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Latent Growth Modeling With Domain-Specific Outcomes Comprised of Mixed Response Types in Intervention Studies

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Abstract

Objective—When several continuous outcome measures of interest are collected across time in experimental studies, the use of standard statistical procedures, such as multivariate analysis of variance or growth curve modeling, can be properly used to assess treatment effects. However, when data consist of mixed responses (e.g., continuous and ordered categorical [ordinal] responses), traditional modeling approaches are no longer appropriate. The purpose of this article is to illustrate the use of a more suitable modeling procedure when mixed responses are collected in longitudinal intervention studies.

Method—Problems with traditional analyses of such data are discussed, as are potential advantages provided by the proposed modeling approach. The application of the multiple-domain latent growth modeling approach with mixed responses is illustrated for experimental designs with data from the SeniorWISE study (McDougall et al., 2010). This multisite randomized trial assessed memory functioning of 265 elderly adults across a 26-month period after receiving either a memory or health promotion training program.

Results—The latent growth models illustrated allow one to examine treatment effects on the growth of multiple mixed outcomes while incorporating associations among multiple responses, which allows for better missing data treatment, greater power, and more accurate control of Type I error. The interpretation of parameters of interest and treatment effects is discussed using the SeniorWISE data.

Conclusions—Multiple-domain latent growth modeling with mixed responses is a flexible statistical modeling tool that can have substantial benefits for applied researchers. As such, the use of this modeling approach is expected to increase.

Keywords

experiments; latent growth model; multiple-domain model; multilevel experimental design; repeated measures

Multiple outcomes collected during intervention studies over several measurement waves is commonly advocated and is becoming more frequent in practice. These multiple outcome measures may consist of mixed response data, such as continuous and ordered categorical responses. While some categorical outcome measures may consist of nominal data in which there is no ordering of the categories (e.g., race/ethnicity, political affiliation), the modeling technique described in the current article assumes a rank order property associated with the categories (e.g., Likert type responses, yes or no responses). With mixed response data, traditional statistical techniques (e.g., multivariate analysis of variance [MANOVA], growth curve models that assume normal responses) are inadequate and introduce added complexities for applied researchers when attempting to analyze the growth trends of participants in their studies. Latent growth curve modeling (LGM) is a structural equation modeling (SEM) technique that allows applied researchers to study individual growth across several measurement waves. The flexibility of LGM allows for the modeling of growth not only with data collected for multiple outcomes but also with mixed response types. Given the flexibilities provided by LGM techniques, the purpose of this article is to (1) explain the primary advantages associated with this multivariate approach compared to using a series of univariate models, (2) describe the LGM technique when multiple outcomes with mixed response types are collected at several measurement waves, and (3) illustrate the application of the LGM technique and interpretation of results using a longitudinal data set with multiple outcomes comprised of mixed response types.

Advantages of Longitudinal Data and Multiple Outcome Measures

Longitudinal designs allow researchers to assess change across time in one or more outcomes. Traditionally, longitudinal designs have been limited to the collection of data at two measurement occasions with a focus on growth either at the group level or at the individual level (Preacher, Wichman, MacCallum, & Briggs, 2008). The collection of data at more than two measurement occasions across time offers researchers in the social and behavioral sciences invaluable information concerning individuals' growth over time, such as the evaluation of the appropriate trajectory of growth, the detection of interindividual or systematic variability in growth, the assessment of background variables as meaningful predictors of growth, and increased precision and reliability associated with the measurement of growth (T. E. Duncan, Duncan, & Strycker, 2006; Willett & Sayer, 1994).

More important, for experimental research, collecting data across time for multiple outcomes allows for a more comprehensive understanding of the effects of a treatment. For example, it is oftentimes hypothesized that a treatment will affect participants in related yet different domains of interest (e.g., depression, anxiety, and drug use). In addition, interventionists may find that a treatment affects growth in certain outcome measures (e.g., performance at school) and not others (e.g., family conflict). Further, Whiston and Campbell (2010, p. 13) endorsed collecting multiple outcomes when conducting clinical trials in the

field of counseling by noting that the best assessment of therapeutic change often involves the use of “multiple measures that draw relevant information from diverse sources.”

When intervention researchers collect longitudinal data on several outcomes, they may choose to analyze data using a series of univariate growth curve models, which is attractive because it simplifies data analysis. However, the simultaneous estimation of multiple outcomes—particularly using a modeling approach that incorporates the degree of association among the multiple outcomes—is advantageous for several reasons. These advantages are similar to those for multivariate multilevel models with cross-sectional data (Heck, Thomas, & Tabata, 2010; Hox, 2010; Snijders & Bosker 2012). First, the multivariate approach we discuss will generally provide for more robust treatment of missing data. It is well known that if a univariate multilevel growth model were used to assess change across time, such an analysis would incorporate information from participants who provide partial data for that particular outcome, given the (now standard) use of maximum-likelihood estimation. Such an analysis is considered more robust than an analysis that would remove cases having any missing outcome data, assuming the missing outcome data at later time points are related to observations made at earlier time points, consistent with a pattern that is known as missing at random, as opposed to the more stringent missing completely at random pattern.

However, this univariate growth curve analysis would have no way of incorporating information from other outcome variables not included in the analysis, introducing potential bias in estimating parameters. That is, if missingness in a given outcome is also uniquely related to observations from other outcome variables (which seems like a realistic scenario), the univariate analysis model will provide biased parameter estimates, with the degree of bias based on the degree of missingness and the association among the multiple outcomes. The multivariate modeling approach presented here, on the other hand, incorporates information from all outcomes included in the analysis model, providing for more robust missing data treatment and improved estimation of effects. Such an inclusive approach to handling missing data is widely recommended in the literature (Collins, Schafer, & Kam, 2001; Graham, 2003; Rubin, 1996; Schlomer, Bauman, & Card, 2010).

In addition to providing for improved estimation when there are missing outcome data (which seems inevitable in longitudinal designs), the multivariate growth modeling approach discussed here will provide more power to test explanatory variables of interest than separate univariate analysis. Enders (2010, p. 129) explained that using additional variables in the analysis model that are related to variables having missing data, as the multivariate approach does, improves power by “recapturing some of the lost information” in the variables having missing data. Snijders and Bosker (2012) noted that this greater power offered by the multivariate approach will be evident in the test of the effect of a given explanatory on a specific dependent variable, as the respective standard error (e.g., of the treatment effect) will be smaller in the multivariate approach. They note that this advantage will be greater when the different outcome variables are more highly correlated and when the degree of missingness in the outcomes is greater.

Third, using a single omnibus multivariate test, for example, of the treatment effect can guard against the inflation of the familywise Type I error rate as opposed to analyzing each of the outcome measures individually in univariate models. The proposed multivariate model allows for such a test. To implement this test, one compares the fit of two models: one that specifies, for example, no treatment effects on any outcome and one that relaxes the constraints of no treatment effects and estimates such effects. Such a test will “avoid the danger of capitalization on chance which is inherent in carrying out a separate test for each dependent variable” (Snijders & Bosker, 2012, p. 283). We illustrate the use of such an omnibus test later in the article.

In addition to these mostly technical benefits, using a multivariate growth model can shed more light on study findings than use of separate univariate growth models. In particular, use of multivariate analysis is necessary to estimate correlations among the growth curve parameters for the different outcomes. For example, with the multivariate approach, it is possible to estimate the correlation between two different outcomes (e.g., motivation and achievement) at final status for the treatment and control groups or to estimate the correlation between status for one outcome and growth in another. For example, did those having initially more motivation tend to have greater achievement growth across time? Is this association present in both the treatment and control groups? Such associations may be of intrinsic interest, and this information is not available in separate univariate growth modeling. In addition, the multivariate latent growth model can, of course, be used to assess if treatment effects are present at final status, for example, and for growth across time for each outcome, while simultaneously adjusting for the associations among the mixed outcomes. We illustrate the ability of the multivariate modeling procedure to address such substantive research questions later in the article.

Mixed Response Data Considerations

In order to capture information concerning the impact of a treatment on multiple domains of interest across time, data may consist of continuous response types as well as ordered categorical response types. For instance, mixed response data types were collected by Brody et al. (2006), who conducted a cluster randomized trial across seven consecutive weeks in which the effectiveness of a prevention program designed to deter alcohol use was examined among African American rural adolescents. Participants responded to questions concerning their perceptions of alcohol use using a Likert-scale ranging from 3 to 4 ordered, category response options. Participants also responded either yes or no to questions concerning alcohol consumption. While aggregated outcome scores were ultimately used in Brody et al. study, researchers may be interested in examining growth trends using responses that consist of ordered categories as well as responses that are assumed to be continuous in nature.

While mixed responses are often collected in experimental settings, traditional statistical methods are not equipped to analyze such data. Specifically, multivariate analysis methods that assume normal responses (i.e., MANOVA, growth curve modeling with normal responses) is not well suited to analyzing mixed response data, primarily because (a) predicted probabilities associated with a categorical outcome variable are often nonlinearly related to explanatory variables and (b) predicted probabilities associated with the outcome

(e.g., probabilities of alcohol use) may exceed values of zero and one with such an analysis. As such, techniques that assume that probabilities are linearly related to a set of explanatory variables may provide poor estimates of effects and, subsequently, poor statistical inferences (Long, 1997; Tabachnick & Fidell, 2007). Consequently, advanced statistical techniques are necessary to enable interventionists to examine growth trends using mixed response data types. Latent growth modeling (LGM) is a structural equation modeling (SEM) technique that may be used when modeling longitudinal growth across time at both the group and individual levels. The subsequent sections introduce the basic latent growth model with a single outcome and its extension for use with multiple outcomes comprised of mixed response data types. Subsequently, the application of this multiple-domain latent growth model (MDLGM) to a real longitudinal data set with mixed, multiple outcome measures is presented.

Latent Growth Model With a Single Outcome Repeatedly Measured

Traditionally, the basic latent growth model is a modified confirmatory factor analysis model in which repeated measures of an observed outcome variable are indicators of both an intercept and slope factor. The intercept factor signifies the amount of the outcome variable at a temporal reference point, and the slope factor denotes the rate of change in the outcome variable. A linear latent growth model with a manifest variable measured at three time points with equal intervals between measurement occasions is depicted in Figure 1 (see online Supplemental Material A for equations associated with this model). The parameters of interest in a latent growth model include the mean and disturbance variance associated with intercept and slope factors as well as the covariance between the intercept and slope disturbances. The mean of the intercept factor, μ_{α} , represents the average value of the manifest outcome variable at the temporal reference point (e.g., initial measurement occasion). The variance of the intercept factor disturbance, $\sigma_{\zeta_{\alpha_i}}^2$, indicates the degree to which individual variability on the manifest variable exists at the temporal reference point. The mean of the slope factor, μ_{β} , represents the average growth rate (linear, in this case) on the manifest variable across time, and the variance of the slope factor disturbance, $\sigma_{\zeta_{\beta_i}}^2$, indicates the degree to which individual variability exists with respect to the growth trajectory across time. The covariance between the intercept and slope factors' disturbances, $\sigma_{\zeta_{\alpha_i}\zeta_{\beta_i}}$, reveals if there is a relationship between individuals' scores on the observed outcome variable at the temporal reference point and their growth trajectory.

The model presented in Figure 1 is parameterized by way of the slope factor loadings, which resulted in the intercept representing the initial amount of the observed variable and growth was modeled as linear across time. Various time-coding and centering methods may be implemented that would result in different interpretations of the parameters of interest (e.g., see Blozis & Cho, 2008; Hancock & Lawrence, 2006; Mehta & West, 2000; and Stoolmiller, 1995). The growth trajectory may also be modeled as nonlinear using various parameterizations (e.g., see Blozis, 2004; and Browne, 1993; Lawrence & Hancock, 1998; Stoolmiller, 1995; Stoolmiller, Duncan, Bank, & Patterson, 1993).

As described and illustrated in Figure 1, the latent growth modeling approach in SEM is different from the multilevel or hierarchical linear modeling (HLM) approach, in which repeated measures for an individual at Level 1 are nested within individuals at Level 2. In contrast, a latent growth model is a single-level model in which the “outcomes are considered as multivariate data” (Heck & Thomas, 2009, p. 178). The nesting or clustering of data (e.g., cluster groups, intervention sites), however, can be accounted for in a latent growth model. The number of hierarchical levels when using the SEM approach will simply be one less than the number of hierarchical levels when using the standard HLM approach.

Latent Growth Model With Multiple Domain-Specific Responses

The extension of the basic latent growth model to a latent growth model with multiple domain-specific responses is fairly straightforward and has been given several different names. For instance, this type of model may be denoted as a parallel process model (Cheong, MacKinnon, & Khoo, 2003), an associative latent growth model (S. C. Duncan & Duncan, 1994; Tisak & Meredith, 1990), a simultaneous growth model (Curran, Harford, & Muthén, 1996), a cross-domain individual growth model (Willett & Sayer, 1994), or a multiple-domain model (Byrne & Crombie, 2003), to name a few. We refer to this model as a multiple-domain latent growth model (MDLGM) in order to recognize that it allows for the modeling of the interrelationships among growth in more than one outcome variable, which provide information concerning different domains of interest across time. While the MDLGM may be easily extended for use with multiple, repeatedly measured variables, we discuss the MDLGM with two outcome variables measured across time for simplicity. This model is depicted in Figure 2.

The same parameters of interest in the basic latent growth model with a single outcome measure are estimated in the MDLGM with multiple outcome measures. Thus, it will capture the mean and disturbance variance associated with the intercept and slope factors as well as the covariance between the intercept and slope factor disturbances for each of the two outcome variables measured repeatedly. In addition, it will capture the covariances among intercept factor disturbances across the domains, slope factor disturbances across the domains, and covariances among intercept and slope factor disturbances across the domains. Figure 2 illustrates an MDLGM model patterning a linear trajectory with two domain-specific outcome variables measured at three time points with equal intervals between measurement occasions. It is important to note that the MDLGM is not the same as the multivariate latent growth model, also referred to as the curve-of-factors model (McArdle, 1988), in which multiple item response variables repeatedly measured load onto first-order factors for each measurement occasion, which subsequently load onto intercept and slope factors. However, the multiple-domain model could be extended for use in a multivariate latent growth model.

MDLGM in Intervention Studies

The models described earlier are oftentimes referred to as unconditional models because predictor variables are not included. When individual variability has been detected in the intercept and slope parameters, researchers often introduce predictors to help explain this

variability. These predictors may be time-invariant in nature (i.e., measured at a single time) or time-varying in nature (i.e., measured at multiple times; see Stoel, van den Wittenboer, & Hox, 2004, and Willett & Keiley, 2000, for more information concerning the inclusion of predictors). Further, these predictor variables may be latent or observed variables.

For longitudinal experimental designs, the MDLGM may be used to assess treatment effects with respect to the intercept and slope factors in intervention studies. Specifically, a group code variable, which is simply a dummy-coded variable indicating group membership (e.g., 0 = control; 1 = treatment), is included in the model as a predictor variable of the intercept and slope factors for both domains of interest (see Figure 3). The direct effect from the group code variable to an intercept factor would denote the degree to which the treatment group is higher or lower than the control group on the domain-specific outcome measure at the temporal reference point (e.g., beginning of the study). The direct effect from the group code variable to a slope factor would signify the degree to which the treatment group's growth trajectory differed from the control group's growth trajectory.

Ordered Categorical Outcome Measures

The most widely implemented estimation procedure in structural equation modeling (SEM)—and this is generally the default estimator in SEM software packages (e.g., AMOS, EQS, LISREL, and Mplus)—is maximum likelihood (ML). ML estimation is based on the assumption of multivariate normality among the observed variables. When the assumption of multivariate normality is violated, parameter estimates tend to become biased (Bollen, 1989). Thus, the treatment of ordered categorical outcome data as normally distributed would violate this assumption, leading to inaccurate parameter estimates, and the use of a different estimation procedure is required. The latent growth model equation with ordered categorical outcome data is presented in online Supplemental Material B.

With an ordered categorical outcome in SEM, two general methods of parameter estimation are available. These two methods are weighted least squares (WLS) estimation and full information maximum likelihood (FIML) estimation. Currently, FIML estimation is available in LISREL (Version 9.1; Jöreskog & Sörbom, 2005–2013) and in Mplus (Version 7.1; L. K. Muthén & Muthén, 1998–2013) software packages with ordered categorical outcome data. While FIML estimation is available in EQS (Version 6.1; Bentler, 2004) software, it is presently restricted to estimation with continuous response data.

It is important to note that regular/full WLS estimation, sometimes referred to as asymptotically distribution free estimation (Browne, 1984), requires exceptionally large sample sizes for accurate chi-square model fit test statistics and parameter estimates (Finney & DiStefano, 2006; Hu, Bentler, & Kano, 1992; Loehlin, 2004). Consequently, robust WLS estimation approaches were developed (see B. Muthén, du Toit, & Spisic, in press, for more information concerning robust WLS) and have been shown to perform better than full WLS with respect to chi-square test statistic and parameter estimate accuracy (Flora & Curran, 2004; Forero & Maydeu-Olivares, 2009). At this time, robust WLS estimation approaches are available in both LISREL (Version 9.1; Jöreskog & Sörbom, 2005–2013) and Mplus (Version 7.1; L. K. Muthén & Muthén, 1998–2013) software packages. Mplus provides two

robust WLS estimation procedure options, which are WLS mean-adjusted (WLSM) and WLS mean- and variance-adjusted (WLSMV) estimation. WLSMV is the default estimator when ordered categorical outcome variables are modeled. Diagonally weighted least squares (DWLS) estimation is the robust WLS estimator option available in LISREL. In EQS (Version 6.1; Bentler, 2004), two estimation options are available when ordered categorical data are modeled, including maximum-likelihood estimation with robust test statistics (ML-ROBUST) and arbitrary distribution generalized least squares (AGLS) estimation. When observed outcome variables are classified as categorical in EQS, ML-ROBUST is the default estimator.

When selecting WLSM or WLSMV estimation in Mplus, DWLS estimation in LISREL, or ML-ROBUST estimation in EQS with ordered categorical outcomes, a probit link function is used to link the ordered categorical outcome variables to their underlying continuous latent factor. When selecting FIML estimation in Mplus or LISREL with ordered categorical data, a logit or probit link function may be selected. The selection of the link function largely depends upon the distributional assumption of the residuals associated with the underlying continuous latent responses. When using a probit link function, the residuals are assumed to be normally distributed, whereas they are logistically distributed when using a logit link function.

Another consideration when using Mplus with ordered categorical outcomes in latent growth models is the type of parameterization employed, which determines which model parameters are estimated. Two types of parameterizations are available in Mplus, types that differ with respect to the treatment of the residual variances associated with the underlying continuous latent responses during estimation. Delta is the default parameterization method employed in latent growth models with ordered categorical outcomes. The alternative parameterization is the Theta parameterization (see B. Muthén & Asparouhov, 2002, for a more detailed explanation of the Delta and Theta parameterizations). In the subsequent illustrations, we employed the default Delta parameterization in Mplus, which has been shown to outperform the Theta parameterization during estimation under certain conditions (B. Muthén & Asparouhov, 2002). The mean of the intercept factor is commonly set to equal a value of zero when employing either of the parameterizations. Additionally, the variance of the intercept factor, the mean and variance of the slope factor, and the covariance between the intercept and slope factors are estimated when implementing either of the parameterizations.

Illustration

Data from the SeniorWISE (Wisdom is Simply Exploration) intervention study (McDougall et al., 2010) were used to illustrate the parameterization of the MDLGM with mixed response types. Mplus software (Version 7.1; L. K. Muthén & Muthén, 1998–2013) was employed to estimate parameters in the MDLGM demonstrations. Model fit was assessed using the chi-square test of overall fit. Several global fit indices were also used to evaluate overall model fit, including the comparative fit index (CFI), the Tucker–Lewis index (TLI), the root-mean-square error of approximation (RMSEA), and the standardized root-mean-square residual (SRMR) or the weighted root-mean-square residual (WRMR) with ordered categorical outcomes.

Participants

The SeniorWISE study is a multisite randomized study in which the memory performance of 265 elderly adults (aged 65 years or older who met inclusion criteria) across 26 months was examined after being randomly assigned to either a memory training program (treatment/intervention condition; $n = 135$) or a health promotion training program (control/comparison condition; $n = 130$) for 12 sessions. The participants were trained in 22 different treatment and control classes within seven different community sites. Note that the analysis first illustrated here does not taken into account the clustering of participants within classes or sites but features the more typical case where repeated measures are nested within persons. Later in the article, we discuss a more proper multilevel analysis of these data (with the multilevel MDLGM). The overall ages of participants ranged from 65 to 94 years. The mean age of participants at the baseline measurement occasion (Wave 1) in the memory training (treatment) and in the health promotion training (control) group was 74.83 years ($SD = 6.22$) and 74.69 years ($SD = 5.74$), respectively. The majority of participants were female (77%) and White (72%). Data were collected during five measurement waves (baseline, 2 months, 6 months, 14 months, and 26 months) and contained information concerning various components of memory (e.g., metamemory, memory self-efficacy, and functioning in activities of daily life).

As commonly seen in longitudinal studies, there was some attrition over the five data collection waves. For instance, at Wave 2, there were 127 out of the original 135 participants in the treatment group and 117 out of the original 130 participants in the control group. At Wave 5, 108 participants remained in the treatment group and 101 participants remained in the control group. McDougall et al. (2010) noted a high retention rate of 79% while documenting reasons for participant attrition. While the missing data patterns are not examined exhaustively here, data are assumed to be missing at random, and thus, full information maximum likelihood (FIML) was implemented in Mplus to deal with missing data. Interested readers are referred to McDougall et al. (2010) for more information concerning the SeniorWISE study features.

Measures

While various outcome measures were collected during the five measurement waves of the SeniorWISE study, we decided to focus on two outcome measures in order to demonstrate the MDLGM with mixed data response types. The Social Functioning subscale of the Short Form-36 Health Survey (SF-36; Ware, Kosinski, & Keller, 1994), which assesses functional health on eight dimensions, was selected to represent the continuous outcome measure because of its general linear trend across time and the divergence of scores between the control and treatment groups across time. The Memory Complaints subscale of a revised Metamemory in Adulthood (MIA; Dixon, Hultsch, & Hertzog, 1988) questionnaire was selected to represent the ordered categorical outcome measure. The Memory Complaints subscale score was computed as the average of 21 items assessing participants' perceptions of the stability of their memory capabilities and ranged from a value of zero to five. McDougall, Becker, and Arheart (2006) suggested that scores of 2.5 and greater were indicative of greater stability and fewer memory complaints. Accordingly, to illustrate analysis with an ordered categorical outcome, this outcome measure was dichotomized such

that participants with scores of 2.49 and less were coded as having more memory complaints (coded as 0), and participants with scores of 2.5 or greater were coded as having fewer memory complaints (coded as 1). This outcome measure was selected because treatment effects were demonstrated in McDougall et al. (2010) from baseline to postclass and from baseline to end of study assessments.

Initial Model Testing of Assumptions in Each Group

A sequence of steps should be followed prior to using the MDLGM for intervention studies in order to assess certain assumptions associated with the model. First, it is important to determine the shape of the growth trajectory in each intervention group for each of the specific outcome measures to be included in the MDLGM. Individual plots of the social functioning outcome, averages of the social functioning outcome, and proportions of those with fewer memory complaints at each of the five time points were graphed for control and treatment participants separately. The plots illustrated a general linear growth trajectory for both outcome measures in each of the groups.

Next, the domain-specific outcome measures should be modeled independently in each intervention group separately to assess model fit and possible model misspecification. Accordingly, a linear latent growth model for the social functioning continuous outcome and a linear latent growth model for the dichotomized memory complaints outcome were fit to the data independently for both control and treatment participants. Because the timing of the measurement waves occurred at baseline, 2 months, 6 months, 14 months, and 26 months, the slope factor loadings were set to -26 , -14 , -6 , -2 , and 0 for measurement Waves 1, 2, 3, 4, and 5, respectively, to coincide with the unequal measurement occasions. As a result, the intercept was modeled to represent the final amount of the outcome measures, which would serve as the most interesting time point to compare the control and treatment groups following an intervention. Note that an alternate specification involves setting the factor loadings to 0 , 2 , 6 , 14 , and 26 . In this case, the intercept reflects initial status for a given outcome, while the linear growth parameter remains the same as in the previous specification. If one were interested in examining treatment and control differences focused on growth (as opposed to growth *and* final status as obtained with the current model), this latter specification can be used. Table 1 contains model fit information for all illustrated models, and Table 2 contains parameter estimates of interest for the unconditional models analyzed in each group. The unconditional models for each domain fit the data adequately in the control and treatment groups.

Multiple-Domain Latent Growth Model (MDLGM)

Because the linear latent growth models for each of the specific domains (social functioning and memory complaints) fit the data well in both the control and treatment groups, linear growth for both of the outcomes in both groups was deemed feasible. The next step was to jointly analyze both domain-specific outcomes within each intervention group separately. The MDLGM with mixed response types fit the control and the treatment participant data well (see Table 1).

The results from the linear latent growth models did not change substantially (see Table 3 for parameter estimates of interest). For instance, the mean of social functioning at the final measurement occasion ($\hat{\mu}_{\alpha} = 80.749$) was significantly greater than zero, and there was significant variability in the final measurement of social functioning among control participants ($\hat{\sigma}_{\zeta_{\alpha_i}}^2 = 162.425$). The mean growth rate ($\hat{\mu}_{\beta} = -.200$) indicated a significant decrease in linear growth (on average) across time in the social functioning outcome. There was, however, no significant variability in the decreasing rates of social functioning ($\hat{\sigma}_{\zeta_{\beta_i}}^2 = .193$) among control participants. While the relationship between the control participants' social functioning at the final measurement wave and their growth trajectory in social functioning was positive, the covariance was not statistically significant ($\hat{\sigma}_{\zeta_{\alpha_i}\zeta_{\beta_i}} = 1.124$), with a corresponding correlation ($\hat{\rho}_{\zeta_{\alpha_i}\zeta_{\beta_i}}$) of .217. The mean for ordered categorical outcomes is fixed to a value of zero at the temporal reference point by default in Mplus with either the Delta or Theta parameterization. Hence, the mean for the dichotomized memory complaints outcome at the final measurement occasion was equal to zero. Nonetheless, there was significant variability in the final measurement of memory complaints among control participants ($\hat{\sigma}_{\zeta_{\alpha_i}}^2 = .650$). While the average growth rate was positive ($\hat{\mu}_{\beta} = .004$), indicating that the probability of participants with fewer memory complaints increased across time, this improvement was not significantly different from zero. The variance of the growth in memory complaints was fixed to a value of zero because of estimation difficulties in which it was estimated to be negative. Because the variance of the growth in memory complaints was set to equal zero, no covariance among the final status and growth in memory complaints was computed.

As with the control participants, the treatment group's mean social functioning at the final measurement occasion ($\hat{\mu}_{\alpha} = 82.948$) was significantly greater than zero, and there was significant variability in the final measurement of social functioning among treatment participants ($\hat{\sigma}_{\zeta_{\alpha_i}}^2 = 249.229$). The mean growth rate ($\hat{\mu}_{\beta} = -.287$) indicated a significant decrease in linear growth (on average) across time in the social functioning outcome, and there was significant variability in the decreasing rates of social functioning ($\hat{\sigma}_{\zeta_{\beta_i}}^2 = .314$) among treatment participants. The relationship between the treatment participants' social functioning at the final measurement wave and their growth trajectory in social functioning was positive ($\hat{\sigma}_{\zeta_{\alpha_i}\zeta_{\beta_i}} = 5.373$), with a corresponding correlation ($\hat{\rho}_{\zeta_{\alpha_i}\zeta_{\beta_i}}$) of .607. This covariance was also statistically significant, indicating that treatment participants with low social functioning at the last measurement occasion tended to experience less growth in social functioning across measurement waves. Again, the mean for the dichotomized memory complaints outcome is fixed to a value of zero by default in Mplus, but there was significant variability in the final measurement of memory complaints among treatment participants ($\hat{\sigma}_{\zeta_{\alpha_i}}^2 = .521$). Although the average growth rate for memory complaints was positive ($\hat{\mu}_{\beta} = .009$), it was not statistically significantly different from zero. Similar to the model for control participants, the variance of the growth in memory complaints was fixed

to a value of zero and thus did not vary among treatment participants due to estimation problems. Consequently, no covariance among the final status and growth in memory complaints was computed.

In a typical MDLGM, all covariances among domain-specific intercepts, domain-specific slopes, and covariances among intercepts and slopes across the domains are estimated via their disturbances (see Figure 2). In the current illustration, however, no covariances involving the linear growth of the dichotomized memory complaints outcome was estimated because its variance was set to equal zero for proper estimation. Hence, the new parameter estimates of interest include the covariance between the domain-specific outcomes at the final measurement occasion and the covariance between the final status for memory complaints and the linear growth for social functioning (see Table 3). For instance, the covariance between the final status of social functioning and memory complaints was not statistically significant for the control group ($\hat{\sigma}_{\zeta_{\alpha_i(1)}\zeta_{\alpha_i(2)}} = 2.285$; $\hat{\rho}_{\zeta_{\alpha_i(1)}\zeta_{\alpha_i(2)}} = .224$) yet was statistically significant for the treatment group ($\hat{\sigma}_{\zeta_{\alpha_i(1)}\zeta_{\alpha_i(2)}} = 3.109$; $\hat{\rho}_{\zeta_{\alpha_i(1)}\zeta_{\alpha_i(2)}} = .273$).

Thus, treatment participants with higher social functioning at the final measurement occasion tended to report fewer memory complaints at the final measurement occasion. While the negative covariance among the growth in the social functioning and the final status of memory complaints denotes that participants with fewer memory complaints at the final measurement occasion tended to experience less growth in social functioning across time, it was not statistically significant in either the control ($\hat{\sigma}_{\zeta_{\beta_i(1)}\zeta_{\alpha_i(2)}} = -.057$;

$\hat{\rho}_{\zeta_{\beta_i(1)}\zeta_{\alpha_i(2)}} = -.162$) or treatment ($\hat{\sigma}_{\zeta_{\beta_i(1)}\zeta_{\alpha_i(2)}} = -.037$; $\hat{\rho}_{\zeta_{\beta_i(1)}\zeta_{\alpha_i(2)}} = -.091$) group.

Simultaneous Multiple-Domain Latent Growth Models (MDLGMs)—Omnibus Treatment Effect

Because the MDLGM fit the data well in both intervention groups, the next step was to conduct an omnibus test for treatment effects on final status and growth for both domains simultaneously. This was accomplished by comparing the fit of nested MDLGMs. Specifically, the model in which the direct effects of the intervention group variable on final status and growth for social functioning and memory complaints are constrained to values equal to zero (termed, here, as the simultaneous unconditional MDLGM) was nested in the model in which the direct effects of the intervention group variable on final status and growth for both domains were freely estimated (termed, here, as the simultaneous conditional MDLGM). The omnibus test for the treatment effect on the set of outcomes in both domains was calculated by way of the chi-square difference test (χ^2) between the two models with the degrees of freedom () equal to the difference in the degrees of freedom for the two models. A statistically significant χ^2 would suggest that treatment and control groups differ significantly on at least one of the following outcomes: (1) final status on social functioning, (2) final status on memory complaints, (3) growth of social functioning, or (4) growth of memory complaints.

It is important to note that the DIFFTEST option in Mplus was implemented to correctly compare the nested MGLDMs, since WLSMV estimation was used (L. K. Muthén & Muthén, 1998–2013). This was carried out by first running the simultaneous conditional

MDLGM (see Figure 3) and saving the derivatives for use in the χ^2 test (see online Supplemental Material C for the Mplus code to run the simultaneous conditional MDLGM). This model fit the data well (see Table 1). The simultaneous unconditional MDLGM, which used the saved derivatives from the conditional model to calculate the χ^2 test (see online Supplemental Material D for the Mplus code to run the simultaneous unconditional MDLGM), was subsequently analyzed. This model also fit the data well (see Table 1). The χ^2 test between the two nested simultaneous MDLGMs ($\chi^2 = 6.726$, $df = 4$, $p > .05$) was not statistically significant. Thus, there was no significant overall treatment effect, meaning that treatment and control groups did not differ significantly on final status or growth of social functioning or memory complaints.

Although there was no significant overall treatment effect, interpretation of the parameters of interest in the simultaneous conditional MDLGM is provided for illustrative purposes. The parameters of interest in the simultaneous conditional MDLGM include the direct effect of the intervention group variable on final status and growth for both domains (see Figure 3). As expected (given the results of the omnibus test for the treatment effect), these individual direct effects on either of the domain's final status and growth were not statistically significant (see Table 4 for parameter estimates of interest). Accordingly, there are no significant differences between the control and treatment groups with respect to social functioning and memory complaints at the final measurement stage, nor are there significant differences between the control and treatment groups with respect to the growth trajectories of social functioning and memory complaints. If these effects were statistically significant, the positive treatment effect on both the social functioning ($\gamma_{\alpha(1)} = 2.465$) and memory complaints ($\gamma_{\alpha(2)} = .157$), respectively, would denote that the participants in the treatment group tended to have higher social functioning and fewer memory complaints than did participants in the control group at the conclusion of the study. The negative effect of the treatment on the growth of social functioning ($\gamma_{\alpha(1)} = -.077$) would signify that participants in the treatment group tended to experience lower rates of change in social functioning than did participants in the control group. Further, the positive treatment effect on the growth of memory complaints ($\gamma_{\beta(2)} = .005$) would indicate that participants in the treatment group tended to have fewer memory complaints across time than did control participants.

Simultaneous Conditional Multilevel MDLGM

In the SeniorWISE study, the treatment was completed by classes (or clusters) of participants who were randomly assigned to a treatment or control class within each of seven sites. For simplicity, this multilevel structure was ignored in the previous illustrations. Ignoring this dependency among observations may lead to inaccurate test statistics and, thus, incorrect conclusions. Given that researchers may encounter data similar to that in the SeniorWISE study, a multilevel MDLGM was also analyzed for illustration. As previously stated, the participants in the SeniorWISE study were trained in 22 different treatment and control classes (or clusters) within seven different community sites. Because there were not enough sites to analyze with a multilevel model, the dependency among participants in the 22 classes was modeled in the simultaneous conditional MDLGM. Mplus is able to model this dependency in the MDLGM with the TWOLEVEL approach (see online Supplemental

Material E for Mplus code to run the simultaneous conditional MDLGM with the TWOLEVEL approach to account for the clustering).

It is important to note that maximum likelihood robust (MLR) is the default estimator in Mplus when using categorical outcomes with the TWOLEVEL option to account for dependency, which implements a numerical integration algorithm that requires more computational resources as the complexity of the model and sample size increase. WLSMV estimation was used in the multilevel MDLGM illustration to reduce computation time as well as to match previous findings in the former MDLGM illustrations.

The conditional multilevel MDLGM used the intervention group variable as a predictor of final status and growth for both domains at the class- or between-level model. The conditional multilevel MDLGM fit the data fairly well (see Table 1). In multilevel models, one SRMR fit index is provided for the within-group, or individual, level and one SRMR fit index is provided for the between-group, or cluster, level. The results in Table 1 indicate that the model fits the individual-level data better than the class-level data. The remaining fit indices (i.e., CFI, TLI, and RMSEA) provide global fit values for the fit of both the within- and between-level models. It must be noted that because the sample size at the within-level is generally larger than the sample size at the between-level, these fit indices tend to be more heavily influenced by the fit of the within-level model to the data. There are methods to separately evaluate the fit of the within- and between-level models to the data, but these would require a lengthy discussion that is beyond the scope of the current article (see Ryu & West, 2009, for more information concerning fit indices with multilevel SEM).

The parameter estimates for the simultaneous conditional multilevel MDLGM are provided in Table 5. There was no statistically significant variability in the final measurement of social functioning or memory complaints between classes. Residual intraclass correlations associated with each of the outcome measures at each measurement occasion for the two domains ranged from .000 to .07144. The effect of the treatment on adult final status and growth for both domains was not statistically significant (see Table 5). Hence, there were no significant treatment effects on the outcomes of interest.

Discussion

The purpose of this article was to provide various illustrations of and demonstrate the flexibility of latent growth modeling (LGM) with multiple outcomes comprised of mixed response types in the context of intervention studies. In particular, the multiple-domain latent growth model (MDLGM) was illustrated using data from the multisite randomized SeniorWISE study in which elderly participants' memory performance was evaluated across 26 months after attending either a health training (control) program or a memory training (treatment) program. LGM allows for the assessment of the type of growth trajectory in an outcome measure of interest. Linear growth was supported in the model demonstrations for both the continuous social functioning outcome measure and the dichotomized memory complaints outcome measure across the five different measurement waves for both control and treatment participant groups. It is important to note that if the functional form of the growth trajectories differed across groups (e.g., linear in one group and nonlinear in the

other), the MDLGM would not be an appropriate modeling technique, because it combines data from both groups. In this case, one would need to model the different types of growth in each group using the multiple-group modeling approach, which would allow for different functional forms of the growth trajectories across groups.

Parameters of interest in the LGM include the average of the outcome variable at a temporal reference point and the average growth rate across time in the outcome variable. The last measurement occasion was selected as the temporal reference point in the illustrations because it would be of most interest to compare treatment groups with respect to the outcome measures at the conclusion of the intervention study. While the selection of the temporal reference point may appear to be arbitrary, interpretations will change depending upon the temporal reference point, and it should be selected with regard to the relevant research questions of a study. LGM also allows for the examination of individual variability in the outcome of interest at the temporal reference point and in the growth trajectories among participants. When outcome measures are continuous, the interpretations are more straightforward than when the outcomes are ordered categorically. The interpretations involve the probabilities or proportions of those with higher category responses when modeling ordered categorical outcome variables. Nonetheless, one can answer important research questions similarly when modeling ordered categorical outcomes as when modeling continuous outcome measures in LGMs.

The central question in intervention studies concerns treatment effects with respect to the outcome measures. The MDLGM with the intervention group variable included as a predictor will allow researchers to explore this question. While the lack of significant treatment effects in the current illustrations is not the general conclusion researchers want to find, but the results still demonstrate important findings in the context of the study for the domains examined.

In general, when conducting multivariate analysis (e.g., traditional MANOVA), researchers may follow up a significant multivariate test with individual univariate tests for each dependent variable, which then does not take the correlated responses into account, or use descriptive discriminant analysis, which forms composite variables but takes the correlations among outcomes into account. The decision to use discriminant analysis versus individual ANOVAs depends upon the research question of interest (Warner, 2013), and this debate is beyond the scope of this article. In our illustration, the MDLGM was not followed up with separate univariate analyses to assess the growth processes for each outcome separately. While the MDLGM does not form composite variables, as does discriminant analysis, all parameters, with MDLGM, are estimated simultaneously (see Tables 4 and 5), including the impact of explanatory variables on each outcome of interest. Hence, separate univariate analyses to assess the growth processes for each outcome are not necessary. Further, as previously described, the parameter estimates from separate univariate analyses may be different from MDLGM because the univariate analyses ignore the relationships among outcomes, whereas MDLGM takes these associations into account. As such, use of MDLGM offers a more robust missing data treatment as well as potentially more power to detect effects of interest than use of univariate analyses. Thus, we do not recommend

conducting separate univariate analyses unless one is only interested in the growth processes of a single outcome independent of the relationships with other outcome measures.

Further, the MDLGM may be extended with more than two groups by including additional dummy-coded predictor variables. The MDLGM may also be extended to situations in which more than two domains are modeled. The outcome measures may be continuous, ordinal, or a combination of continuous and ordered categorical response types. The MDLGM may also model different hypotheses about causality. For instance, researchers could hypothesize that one of the domain-specific growth model's intercept and slope factors may directly affect another domain-specific growth model's intercept and slope factors.

As with all statistical applications, the assumptions associated with the technique should be assessed. The time between each of the five measurement waves in our illustration were unevenly spaced and were modeled as such by employing fixed slope factor loadings representing these unevenly spaced intervals. The treatment of measurement waves as fixed or variable has different connotations. If participants were not measured at fairly comparable times during a measurement wave, fixing the slope factor loadings may lead to inaccurate conclusions concerning growth. Mplus will allow for the modeling of individually varying measurement times and should be implemented if there is variability with respect to measurement schedules among participants.

In addition, two related, yet distinct, approaches are available when assessing the effectiveness of treatment programs across time. One approach is housed in the multilevel or hierarchical linear modeling (HLM) arena, whereas the other is housed in the structural equation modeling (SEM) arena. Both HLM and SEM techniques can provide similar results with respect to the effectiveness of treatment. The HLM approach to analyze multiple outcomes with mixed responses is a multivariate multilevel model (Goldstein, Carpenter, Kenward, & Levin, 2009). Currently, the often used HLM software program (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2011) is not capable of modeling mixed outcomes. While such an analysis can be conducted using the MLwiN software program (Rasbash, Browne, Healy, Cameron, & Charlton, 2012), readers of this journal may be less familiar with that software program, which is the reason we focused on SEM software. The approach presented in this article is a SEM technique and may be conducted with commonly used SEM software programs (e.g., EQS, LISREL, and Mplus). Aside from software differences, the MDLGM approach is advantageous because it can readily incorporate latent variables, which offsets the impact of measurement error (attenuation of power and/or parameter estimates) that is encountered when using observed variables.

In sum, the MDLGM extends the LGM for multiple domain-specific outcomes. The MDLGM not only allows for a more comprehensive evaluation of the impact of a treatment program with the inclusion of multiple growth processes, it also offers some beneficial statistical properties, including better treatment of missing data, increased statistical power, and improved Type I error protection. The flexibility of MGLDM to model various types of response data (continuous and ordered categorical), to include covariates (either latent or observed), and to model the dependency among observations makes it a strong

methodological contender when examining the impact of intervention programs. In conclusion, it is hoped that the illustrations of the MDLGM provided in this article will help applied researchers when analyzing multiple outcomes in intervention studies.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.
Linear latent growth model for an observed outcome variable at three equally spaced measurement occasions.

Figure 2.

Unconditional multiple-domain latent growth model. Domain-specific outcome measures are differentiated with the subscripts (1) and (2).

Figure 3.

Conditional multiple-domain latent growth model. Domain-specific outcome measures are differentiated with the subscripts (1) and (2). Treatment effects are assessed via the direct effect of the group code variable on the domain-specific intercept and slope factors.

Table 1

Model Fit Information for All Illustrated Models

Estimating model	df	χ^2 ^a	Global fit indices				
			CFI	TLI	RMSEA (90% CI)	SRMR	WRMR
Unconditional SF LGM—Control	10	13.415	.965	.965	.051 (.000, .115)	.092	
Unconditional SF LGM—Treatment	10	6.681	1.000	1.025	.000 (.000, .066)	.054	
Unconditional MC LGM—Control	8	7.473	1.000	1.001	.000 (.000, .098)		.491 ^b
Unconditional MC LGM—Treatment	8	6.137	1.000	1.004	.000 (.000, .084)		.465 ^b
Unconditional MDLGM—Control	41	36.864	1.000	1.005	.000 (.000, .051)		.595 ^b
Unconditional MDLGM—Treatment	41	35.161	1.000	1.014	.000 (.000, .045)		.591 ^b
Simultaneous conditional MDLGM	47	38.962	1.000	1.008	.000 (.000, .028)		.557 ^b
Simultaneous unconditional MDLGM	51	48.494	1.000	1.002	.000 (.000, .036)		.687 ^b
Simultaneous conditional multilevel MDLGM	100	82.227	1.000	1.051	.000	W: .051	.429
						B: 1.346	

Note. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; WRMR = weighted root-mean-square residual; SF = social functioning; LGM = latent growth model; MC = memory complaints; MDLGM = multiple-domain latent growth model; W = value for within-level; B = value for between-level.

^aThe model chi-square was not statistically significant.

^bWRMR with categorical outcomes is computed in Mplus instead of the SRMR.

Table 2

Parameter Estimates (Standard Errors) for the Unconditional Models in Each Group

Parameter	Social functioning (Continuous)	Memory complaints (Dichotomous)
Control group		
Means		
Intercept	80.684 (1.610) *	.000 (.000) ^a
Slope	-.207 (.075) *	-.002 (.004)
Variances		
Intercept	165.749 (42.690) *	.712 (.097) *
Slope	.184 (.134)	.000 (.000) ^b
Covariance	1.124 (1.682)	—
Correlation	.204	—
Treatment group		
Means		
Intercept	82.866 (1.696) *	.000 (.000) ^a
Slope	-.297 (.074) *	.005 (.005)
Variances		
Intercept	251.020 (46.814) *	.593 (.120) *
Slope	.286 (.118) *	.000 (.000) ^b
Covariance	5.259 (1.789) *	—
Correlation	.621	—

Note. Dashes indicate not estimated because slope factor variance was set to zero.

^aFixed to zero in Mplus.

^bSet to zero for model estimation purposes.

* $p < .05$.

Table 3

Parameter Estimates (Standard Errors) for the MDLGM in Each Group

Parameter	Social functioning (Continuous)	Memory complaints (Dichotomous)	MDLGM covariances
Control group			
Means			
Intercept	80.749 (2.248) *	.000 (.000) ^a	
Slope	-.200 (.105)	.004 (.004)	
Variances			
Intercept	162.425 (47.750) *	.650 (.104) *	
Slope	.193 (.138)	.000 (.000) ^b	
Covariance	1.124 (1.749)	—	
Correlation	.217	—	
SF intercept and MC intercept			2.285 (1.559)
SF slope and MC intercept			-.057 (.068)
Treatment group			
Means			
Intercept	82.948 (2.420) *	.000 (.000) ^a	
Slope	-.287 (.133) *	.009 (.006)	
Variances			
Intercept	249.229 (45.040) *	.521 (.124) *	
Slope	.314 (.120) *	.000 (.000) ^b	
Covariance	5.373 (1.700) *	—	
Correlation	.607	—	
SF intercept and MC intercept			3.109 (1.326) *
SF slope and MC intercept			-.037 (.064)

Note. Dashes indicate not estimated because slope factor was set to zero. MDLGM = multiple-domain latent growth model; SF = Social Functioning; MC = Memory Complaints.

^a Fixed to zero in Mplus.

^b Set to zero for model estimation purposes.

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Table 4

Parameter Estimates (Standard Errors) for the Simultaneous Conditional MDLGM

Parameter	Social functioning (Continuous)	Memory complaints (Dichotomous)	MDLGM covariances
Means			
Intercept	80.546 (1.958) *	.000 (.000) ^a	
Slope	-.210 (.087) *	.004 (.004)	
Variances			
Intercept	212.701 (32.743) *	.602 (.083) *	
Slope	.245 (.094) *	.000 (.000) ^b	
Covariance	3.392 (1.240) *	—	
Correlation	.470	—	
Treatment effects			
Intercept	2.465 (2.457)	.157 (.128)	
Slope	-.077 (.112)	.005 (.006)	
SF intercept and MC intercept			2.634 (1.044)
SF slope and MC intercept			-.054 (.048)

Note. Dashes indicate not estimated because slope factor was set to zero. MDLGM = multiple-domain latent growth model; SF = Social Functioning; MC = Memory Complaints.

^aFixed to zero in Mplus.

^bSet to zero for model estimation purposes.

* $p < .05$.

Table 5

Parameter Estimates (Standard Errors) for the Multilevel MDLGM

Parameter	Social functioning (Continuous)	Memory complaints (Dichotomous)	MDLGM covariances
Between-level			
Means			
Intercept	79.907 (2.588) *	.000 (.000) ^a	
Slope	-.236 (.076) *	.014 (.008)	
Variances			
Intercept	3.393 (18.620)	.053 (.212)	
Slope	.001 (.029)	.000 (.000) ^b	
Covariance	.081 (.613)	—	
Correlation	1.000	—	
Treatment effects			
Intercept	2.602 (3.412)	.357 (.336)	
Slope	-.071 (.160)	.011 (.015)	
SF intercept and MC intercept			.176(1.245)
SF slope and MC intercept			.000 (.085)
Within-level			
Variances			
Intercept	215.879 (38.702) *	2.663 (.482) *	
Slope	.276 (.102) *	.000 (.000) ^b	
Covariance	3.701 (1.266) *	—	
Correlation	.479	—	
MDLGM covariances			
SF intercept and MC intercept			4.754 (1.957) *
SF slope and MC intercept			-.144 (.160)

Note. Dashes indicate not estimated because slope factor was set to zero. MDLGM = multiple-domain latent growth model; SF = Social Functioning; MC = Memory Complaints.

^aFixed to zero in Mplus.

^bSet to zero for model estimation purposes.

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