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# Using latent growth curve modeling in clinical treatment research: An example comparing guided self-change and cognitive behavioral therapy treatments for bulimia nervosa[1]

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**ABSTRACT**. This experimental study demonstrates the usefulness of multi-group piece-wise latent growth curve models (LGCM) in clinical research, particularly for assessing and comparing treatment effects. Sixty-two female patients (*M* age = 28.1; *SD* = 8.00) with bulimia nervosa were randomly assigned to a) a guided self-change treatment (GSC) involving a self-care manual plus 8 bi-weekly sessions of cognitive behavioral therapy or b) 16 weekly sessions of cognitive behavioral therapy (CBT). Both groups showed significant improvements in treatment outcomes during treatment, although CBT showed greater improvements. However, GSC evidenced more continued

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improvement post-treatment. Both programs showed variability in effectiveness during the treatment period on at least one outcome, while GSC showed greater variability than CBT during follow-up on two outcomes. Baseline levels on treatment outcomes were related to follow-up improvement levels, particularly for GCS. LGCM provided a rich analysis of these data, and addressed important questions regarding differences in the effectiveness of the two treatment programs.

**KEYWORDS**. Bulimia nervosa. Guided self-change. Cognitive behavioral therapy. Latent growth curve modeling. Experimental study.

**RESUMEN**. Este estudio experimental muestra la utilidad de los modelos multigrupo de curva de crecimiento latente por etapas en investigación clínica, concretamente en la evaluación y comparación de los efectos de tratamiento. Sesenta y dos pacientes femeninas (media de edad = 28,1; *DT* = 8) con bulimia nerviosa fueron asignadas al azar a: a) un auto-tratamiento guiado compuesto por un manual de autocuidados más ocho sesiones quincenales de terapia cognitivo conductual (TCC), o b) a 16 sesiones semanales de terapia cognitivo conductual (TCC). Ambos grupos mostraron mejorías significativas durante el tratamiento, aunque la TCC mostró mayor mejoría. Sin embargo, el tratamiento auto-guiado evidenció una mejoría más continuada después del tratamiento. Ambos programas mostraron variabilidad en la eficacia durante el tratamiento al menos en un resultado, mientras que el auto-tratamiento mostró una mayor variabilidad que la TCC durante el seguimiento en dos resultados. Los niveles de la línea de base estaban relacionados con los niveles en el seguimiento, particularmente en el tratamiento auto-guiado. Los modelos de curva latente ofrecen un análisis rico de estos datos y resuelven importantes cuestiones sobre las diferencias en la efectividad de los dos programas de tratamiento.

**PALABRAS CLAVE**. Bulimia nerviosa. Tratamiento auto-guiado. Terapia cognitivo conductual. Modelado de curva de crecimiento latente. Estudio experimental.

Many of the most fundamental research questions in clinical research pertain to change in treatment outcomes over time, and comparisons of various treatment methods. Such questions may include: a) Do patients show improvement on treatment outcomes during treatment?; b) Do patients show continued improvement, or at least maintenance of levels achieved, post-treatment?; c) To what extent are there individual differences in treatment effectiveness?; d) Is baseline status on treatment outcomes related to individual differences in treatment effectiveness?; e) Does progress during treatment predict post-treatment progress?; and f) Do certain treatment methods differ in terms of their relative standing on questions 1-5? New statistical techniques have emerged for analyzing change that provide more flexibility than traditional methods such as repeated measures analysis of variance. One such technique is Latent Growth Curve Modeling (LGCM), which emerged within the structural equation modeling framework (McArdle and Nesselroade, 2002). This technique provides an effective and elegant way to statistically test the six research questions above, but is not yet widely used in clinical

research. In fact, in some areas of the clinical literature, such as eating disorders treatment research, no studies to date (that we are aware of) have utilized LGCM. Further, this methodology has received only limited use in clinical treatment research more broadly (for an example of a recent exception, see Frosch, Stein, and Shoptaw, 2002). Rather, most clinical treatment studies use repeated-measures ANOVA (*e.g.*, Carter *et al*., 2003; Thiels, Schmidt, Treasure, and Garthe, 2003), cross-lagged regression (*e.g.*, Fichter, Quadflieg, and Rehm, 2003), chi-square (*e.g.*, Cooper, Coker, and Fleming, 1996; Palmer, Birchall, McGrain, and Sullivan, 2002), or other traditional techniques. While these techniques can yield useful information about predictors and patterns of change, there are a number of advantages to using newer approaches modeling change like LGCM.

The purpose of the present experimental study (Montero and León, 2007; Ramos-Álvarez, Moreno-Fernández, Valdés-Conroy, and Catena, 2008) was to demonstrate the use of LGCM in clinical research, and particularly for assessing treatment effects and comparing effects of different treatment modalities. Specifically, LGCM was used to compare the treatment effects of guided self-change (GSC) with those of standard cognitive behavioral therapy (CBT) in the treatment of bulimia nervosa (BN). While strong evidence has been gathered for the effectiveness of CBT (Shapiro *et al*., 2007), some researchers (*e.g*., Thiels, Schmidt, Treasure, Garthe, and Troop, 1998) are interested in exploring self-help treatments (many based on CBT principals) that are as effective as other treatments, but more efficient for patients in terms of time and money. However, the evidence for these self-help treatments (GSC) is still equivocal (for reviews, see Shapiro *et al*., 2007; Sysko and Walsch, 2008). GSC generally leads to positive outcomes for patients, but its relative effectiveness compared to other treatments remains unclear. It is hoped that the present study, in addition to presented a promising statistical technique, will also yield insight helpful for evaluating self-help treatments.

*An overview of Latent Growth Curve Modeling*

Latent Growth Curve Modeling (LGCM) combines elements of repeated measures ANOVA and confirmatory factor analysis (within structural equation modeling), and is ideal for investigation of interindividual differences in intraindividual change over time (Duncan and Duncan, 2004; Duncan, Duncan, and Strycker, 2006; McArdle and Bell, 2000; McArdle and Nesselroade, 2002). Essentially, LGCM is a special case of confirmatory factor analysis where the observed measures are the factor indicators, and the factors represent the attributes of the latent or unobserved growth trajectories. A «latent» variable (or factor) is unobserved, and thus signifies something we think exists in the real world but we cannot directly measure (*i.e.*, it is the construct of interest). The observed measures are what we use to try to capture the latent variable, but measures are imperfect and subject to measurement error. LGCM provides a modeling framework that estimates individual latent or true growth trajectories while accounting for measurement error. The observed scores on the repeated measures are thus considered a function of latent growth factors as well as occasion-specific measurement error.

If we have measured an observed variable *Y* at multiple occasions (occasions are indicated by *t* in brackets) on a sample of individuals (individuals are indicated by the subscript *n*), we write the equation for a linear latent growth curve model as:

$$Y[t]_n = y_{l,n} + A[t]y_{s,n} + e[t]_n$$

where $y_l$ represents an individual's initial level (the intercept) and $y_s$ represents that individual's linear change over time (the slope). The intercept and slope are latent factors, and are the two key characteristics of an individual growth curve. *A*[t] represents the factor loadings for the latent slope factor – these are often called «basis weights» or «basis coefficients», and they serve to define the shape of change over time. Lastly, *e*[t] represents the residuals or errors of prediction at each occasion. Therefore, this equation suggests that an individual's score at a given occasion is a function of their true initial level, their true trajectory of change, plus some deviation of their observed score from that true trajectory of change. Hence, this is essentially a regression equation predicting the observed scores, with a regression line intercept and slope, and the deviation of each score from the regression line.

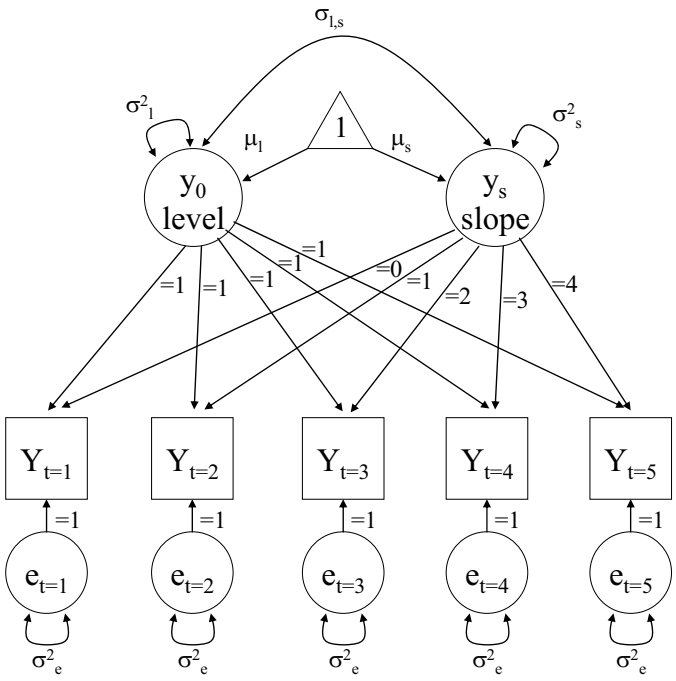
The LGCM presented in equation format above is constant within an individual, meaning that it is constant across all occasions of measurement (i.e., a persons intercept and slope do not change over time). However, the magnitude of the level and slope do vary across individuals in a sample or group. Thus, $y_0$ and $y_s$ can be represented as:

$$y_l = \mu_l + \sigma_{ln}$$
$$y_s = \mu_s + \sigma_{sn}$$

where $\mu_l$ represents the group mean intercept and $\mu_s$ the mean slope, while ó$_{ln}$ represents individual deviations from the mean intercept and $\sigma_{sn}$ deviations from the mean slope.

The equations above can also be transposed into path diagram format (see Figure 1). In path diagrams, circles indicate latent or unobserved variables, squares represent observed variables, one-headed arrows are interpreted as regression paths, and two-headed arrows as variances and covariances (McArdle, 2005). As seen Figure 1, a basic LGCM model has two growth factors: the intercept or level growth factor and the slope or rate of change growth factor. In models where linear growth is specified, the intercept and slope are analogous to those in the algebraic equation for a straight line. LGCM essentially estimates a regression line (which in this case is a growth trajectory) for each individual with an intercept and slope based on his or her observed scores across the repeated measures – the intercept typically being interpreted as the estimated true baseline or initial status, and the slope being the estimated true rate of change over time. Then, LGCM estimates the group intercept and slope means, as well as the variances and covariances for these parameters.

**FIGURE 1**. Linear latent growth curve model.




Similar to classical confirmatory factor analysis, LGCM includes factor loadings which indicate the relative weighting of each observed variable on the factors (see Figure 1) (Duncan and Duncan, 2004; McArdle and Bell, 2000; McArdle and Nesselroade, 2002). Given that an individual's intercept is constant across time (*i.e.*, one's initial status cannot change with time), the factor loadings for the intercept growth factor are set to 1.0 for each occasion. The factor loadings for the slope growth factor specify the shape of the growth curve. For example, to estimate linear growth across 5 occasions, the slope factor loadings might be fixed at 0, 1, 2, 3, and 4. This sets the intercept at the first occasion, allowing it to be interpreted as initial status.

*Strengths of Latent Growth Curve Modeling*

Methodologists have identified several benefits to using LGCM for assessing change (Duncan and Duncan, 2004; Duncan *et al*., 2006; McArdle and Bell, 2000). Stull (2008) compares LGCM and regression models with change scores for analyses of clinical treatment data. Here we focus on comparing LGCM to repeated-measures ANOVA, since prior analyses of the present data (Thiels *et al*., 1998, 2003) were done using this traditional method (for other comparisons of LGCM and repeated-measures ANOVA not specific to clinical research, see Duncan and Duncan, 2004; Duncan *et al*., 2006). First, LGCM allows for estimation of average growth trajectories (mean intercepts and slopes) as well as individual differences in these trajectories (intercept and slope variances).

Repeated-measures ANOVA, on the other hand, assesses only mean growth patterns, treating variability in growth patterns as error. Essentially, LGCM estimates growth curves separately for each individual, and then estimates the group means and variances of the growth factors. Estimates of variation in growth trajectories in clinical research yield information regarding the reliability of treatment effectiveness that is not available using repeated-measures ANOVA. In other words, growth factor variances tell researchers the degree to which treatment programs work the same for everyone, or are more or less effective for certain people. Estimates of the covariance between the growth factors indicate whether initial base-line status on treatment outcomes is related to rate of improvement during treatment, giving information about which specific individuals the treatment might be most effective for (*e.g.*, those with more severe bulimia symptoms).

Second, LGCM has considerable analytic flexibility. For example, complex growth processes can be tested as a single model. Such growth processes, if they can be modeled using repeated-measures ANOVA (and some cannot), require multiple models. The present data include assessments of treatment outcomes during and following treatment. These are two distinct periods of potential change in treatment outcomes, and thus, analyzing them separately can yield useful information about progression during treatment as well as maintenance of improvements post-treatment. In the present study, LGCM provided a framework for more systematically assessing treatment and follow-up change separately, but doing so in the context of a single model (details of this model are discussed later). The same analyses in repeated-measures ANOVA would require two models, one for the treatment phase and one for follow-up.

Third, LGCM can be conducted using Full Information Maximum Likelihood Estimation methods to estimate parameters, which incorporates the generally preferred method for handling missing data (Enders, 2001). In repeated-measures ANOVA, at worst cases with missing data are deleted, and at best missing data are imputed prior to analyses. Maximum Likelihood parameter estimation does not impute values for missing data; rather, it estimates the model parameters using all information that is available. Thus, LGCM takes advantage of all available data, instead of deleting cases with incompleteness. This is important in clinical research because sample sizes are often small and participants frequently drop out resulting in loss of critical data (Shapiro *et al*., 2007).

Fourth, LGCM estimates the growth factors separately from occasion-specific measurement error, allowing researchers to better estimate the true growth trajectory for a given construct. At each measurement occasion, study variables are measured with some error. However, in LGCM, by explicitly modeling these occasion-specific measurement errors, we are able to get an estimate of the true growth trajectory of the study variables across time (Duncan and Duncan, 2004; McArdle and Bell, 2000; McArdle and Nesselroade, 2002). In this sense, the latent or «true» growth trajectories are like regression lines, with occasion-specific measurement errors being like errors of prediction.

Fifth, some research suggests that LGCM has more statistical power to detect group differences in growth trajectories than repeated measures ANOVA (Fan, 2003). Therefore, in many situations LGCM may not require as large a sample size as repeated measures ANOVA in order to yield comparable power. This is important given that many clinical trials involve relatively small samples (*e.g.*, less than 50 participants per treatment group; Shapiro *et al*., 2007).

In short, LGCM clearly has a number of advantages over traditional techniques, such as repeated-measures ANOVA, for analyzing change. These strengths of LGCM make it an ideal analytic strategy in many cases for examining clinical treatment data. However, it should be noted that in some cases there are ways to modify repeated-measures ANOVA models to help overcome some of the limitations noted above (Duncan *et al*., 2006).

*Comparing Latent Growth Curve Modeling and Multi-Level Modeling*

While LGCM emerged within structural equation modeling (SEM), a similar technique for growth analysis was developed recently within the Multi-level Modeling (MLM) framework (a.k.a., random-effects linear regression, mixed-effects linear regression, or hierarchical linear modeling; Singer and Willett, 2003). Mathematically, these two approaches to growth analysis can be made equivalent – both are instances of the general linear model (for more detailed comparisons of the two approaches, see Chou, Bentler, and Pentz, 1998; Ghisletta and Lindenberger, 2004; Schulenberg and Maggs, 2001; Stoel, van Den Wittenboer, and Hox, 2003). Because of this, both allow for estimation of intercept and slope means (fixed effects) and variances (random effects). Further, if equivalent models are estimated the parameter estimates will be identical. Nevertheless, growth analyses in SEM and MLM use different modeling frameworks and generally are estimated using different types of software programs. MLM uses a regression model framework whereas SEM involves a latent variable framework. Thus, in MLM time is a variable in the dataset and an independent variable in the regression model, whereas in LGCM time is represented by the factor loadings on the latent growth factors (intercept and slope). This leads to a number of differences between the two approaches, and thus relative strengths and limitations of each (see the reviews cited above for more extensive discussions of these strengths and limitations). Although LGCM is not always the best approach, it is the most flexible approach in most cases. For example, an important relative strength of LGCM for clinical research is that it is more flexible in terms of multi-group analyses, and allows for group comparisons on intercept and slope means, variances, and covariances (in MLM only means can be compared across groups). Similarly, LGCM generally handles complex growth models more easily, such as those involving multiple phases of change (*i.e.*, piecewise growth models), predictors and outcomes of change, and multiple change processes (*e.g.*, bivariate growth models).

*The present study*

The first purpose of the present experimental study (Montero y León, 2007; Ramos-Álvarez *et al*., 2008) was to demonstrate the usefulness of LGCM in clinical research by showing how it is unique in its capacity to address the critical questions regarding treatment effectiveness outlined earlier. A second purpose was to elucidate information about the relative effectiveness of GSC and CBT bulimia nervosa treatments not yielded by previous comparisons conducted using other approaches for analyzing change. Prior studies have examined the effectiveness of self-help approaches to treating bulimia nervosa (e.g., Bailer *et al*., 2004; Carter and Fairburn, 1998; Carter *et al*., 2003; Cooper *et al*., 1996; Ghaderi and Scott, 2003; Loeb, Wilson, Gilbert, and Labouvie, 2000; Palmer

*et al*., 2002; Pritchard, Bergin, and Wade, 2004; Thiels *et al*., 1998, 2003; for a recent review, see Sysko and Walsch, 2008). However, to our knowledge none have used LGCM, and very few have used multi-level regression growth analysis (*e.g.*, Bailer *et al*., 2004).

The study by Bailer and colleagues (Bailer *et al*., 2004) is not only one of the few studies of self-help treatments for bulimia nervosa that used a growth modeling technique, but to our knowledge it is also one of the few studies to separately model treatment and post-treatment change. However, they did so using two separate models, one for treatment change and one for post-treatment change. Additionally, they could not assess group differences in within-group variance in growth trajectories, nor were they able to look at links between initial status and change over time. Thus, it was hoped that the present study would make both methodological and substantive contributions to the eating disorders literature.

## Method

Detailed descriptions of the sample and procedures can be found in previous reports of these data (Thiels *et al*., 1998, 2003). This study was approved by the ethics committee of the University of Münster. In addition to the data reported in the present study, there are data available at a 4-year follow-up (Thiels *et al*., 2003). However, there was a long time span between the 6-month follow-up (the fifth occasion in the present analysis) and this 4-year follow-up where data were not collected. It is unclear what the developmental trajectory of the study outcomes was during this time period; thus, it did not seem feasible to include the 4-year follow-up data in the growth models estimated.

### *Participants*

Family physicians, psychiatrists, gynecologists and various counseling services in and around Bielefeld, a town with 320,000 inhabitants in Germany, were invited to refer patients aged 15 years or more who complained of symptoms suggestive of bulimia nervosa (the clinical picture of which was briefly described). An article about the service in a local newspaper led to several self referrals. Of those females who contacted the researchers, 62 ($M$ age = 28.1, $SD$ = 8.00) were included in the study. They fulfilled DSM-III-R criteria for BN and gave written informed consent on a form approved by the ethics committee of the University of Münster after complete description of the study. All the assessments were done by the second author or the therapists involved in this study for patients whom they did not treat. The therapists were trained to use the instruments mentioned below by the second author. She is an experienced psychiatrist who had received detailed training at the Maudsley Hospital, Institute of Psychiatry and MRC Institute of Social Psychiatry in London. Bulimia nervosa was diagnosed using the edition 11.5 D of the Eating Disorder Examination (EDE, Fairburn, Unpublished manuscript provided by the author). This investigator-based semistructured interview covers the clinical picture of bulimia nervosa. It assesses in detail the interviewee's state during the preceding month, both in terms of behavior as well as attitudes. The Structured Clinical Interview for DSM-III-R (Spitzer, Williams, Gibbon, and First, 1990) was used to determine additional psychiatric morbidity at the first assessment only.

Each patient was assigned to either the cognitive behavioral therapy treatment group or the guided self-change treatment group (31 patients to each group), with assignment depending on the patients' order of entry into the trial. There were no significant differences between treatment groups on any demographic or clinical variables such as age, duration and severity of bulimia nervosa, or comorbidity. Please see previous reports of these data for more detailed information on the sample (Thiels *et al*., 1998, 2003).

Thirteen subjects (21 %) dropped out during the treatment phase of the study, 9/31 (29%) from GSC and 4/31 (13%) from CBT. The difference was not statistically significant, Yates corrected $\chi^2_{(1)} = 1.56$ ($p = 0.21$). Fourteen (23%) of the original study group were not assessed for follow-up. There were no significant differences between the groups in terms of the proportion of patients responding to the follow-up: 23/31 (74%) of the GSC *vs*. 25/31 (81%) of the CBT group responded to the follow-up. Those who were not assessed at follow-up differed from patients who completed the follow-up assessment only on the following clinical or demographic features; they had marginally higher scores ($t_{(60)} = 1.99$; $p = .051$) on the Bulimic Investigatory Test Edinburgh (BITE; Henderson and Freeman, 1987) at first assessment. Regarding the effect of treatment, patients who did not complete the follow-up assessment improved as much as the rest on all measures.

*Instruments*

The present study examined only three of the outcomes used by Thiels *et al*. (1998, 2003; results on other outcomes can be obtained from the first author). Bulimia nervosa symptoms and severity were assessed using the 33-item self-report Bulimic Investigatory Test Edinburgh (BITE; Henderson and Freeman, 1987), which includes questions about eating habits, concerns about body shape, and concerns about weight. Depression was measured using the 21-item self-report Beck Depression Inventory (BDI; Beck, Ward, Mendelson, Mock, and Erbaugh, 1961); each item presents four statements and asks participants to select the one which best describes the way they have been feeling the last week. Positive self-concept was assessed using the 30-item self-report Self-Concept Questionnaire (SCQ; Robson, 1989), which taps the attitudes people have about themselves by having them rate the extent to which they agree with 30 statements.

*Procedure*

Guided self-change (GSC) and Cognitive behavior therapy (CBT) were carried out on an individual outpatient basis. The treatment programs consisted of either 8 bi-weekly treatment sessions plus a self-care manual or 16 weekly treatment sessions. Thus, the duration of the two treatments was similar, but the time spent with a therapist was halved in GSC compared to CBT. One of the patients was already in psychodynamic psychotherapy when she sought help for her eating disorder. No other patient had psychotherapy or treatment with psychoactive drugs during the study. CBT followed treatment guidelines outlined in the literature (Fairburn, Marcus, and Wilson, 1993; Freeman, 1995). In GSC, less time was spent on the educational and skills training aspect compared to CBT as these were covered in the self help manual. Generally, therapy

sessions were used to help and encourage the use of the book and to tackle obstacles such as poor motivation, depression, or acute crises. Except for the drop-outs, patients received all planned sessions. The therapists were very flexible in the scheduling of sessions in order to accommodate holidays, sickness or other reasons for the postponement of treatment sessions or assessments. Each therapist was trained to implement the forms of treatment described above. During the treatment phase of the study, the therapists met once a week with the second author to discuss hurdles in using the treatments. Each treated equal numbers from the two treatment conditions. Treatment fidelity was not formally assessed. At the end of either treatment, therapist and patient reviewed progress and discussed further treatment options. Additional therapy was one of the outcome measures. Assessments were carried out on five occasions: at baseline, mid-treatment, end of therapy, 3-month follow-up, and 6-month follow-up. Please see previous reports of these data for more detailed information on the procedures (Thiels *et al*., 1998, 2003).

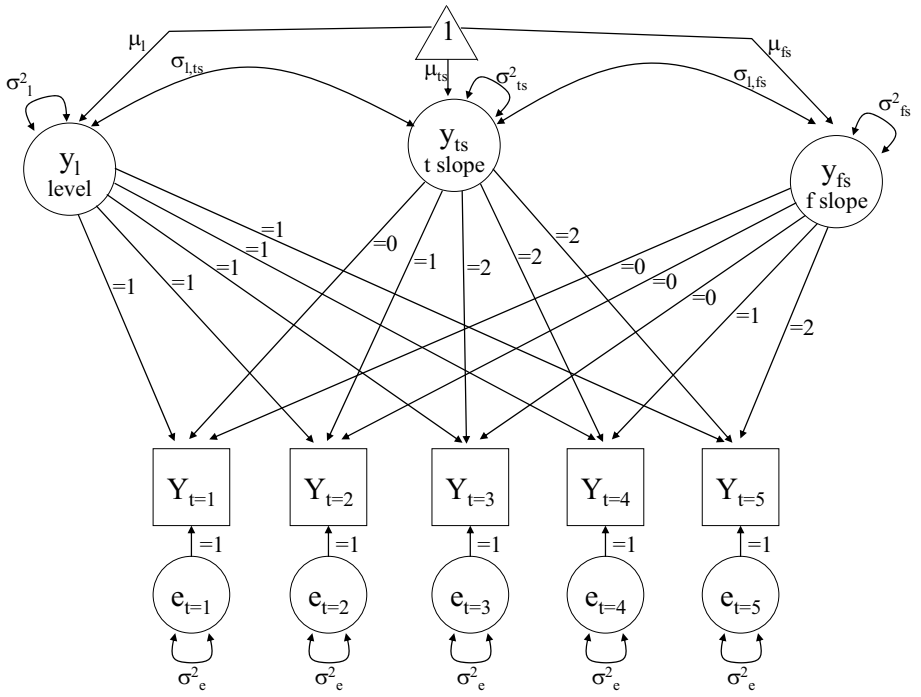
*Analysis plan*

In the basic latent growth curve model there is one latent slope factor that represents the rate of change in a given construct over a certain number of measurement occasions. However, the present study involved two distinct periods of measurement: treatment and post-treatment, as is often the case in clinical research. These two periods of time may be qualitatively different; people might exhibit different change trajectories across treatment than they do post-treatment. Thus, a simple linear growth curve model with a single latent slope variable may not fully capture the pattern of change. Rather, change over the five measurement occasions of the present study may best be captured using two latent slope factors: a treatment slope factor and a post-treatment slope factor (see Figure 2). The equation for this model is

$$Y[t]_n = y_{l,n} + A[t]y_{ts,n} + A[t]y_{fs,n} + e[t]_n$$

where $y_{ts}$ represents the treatment slope and $y_{fs}$ represents the post-treatment slope. This approach is called «piece-wise latent growth curve modeling» (Duncan and Duncan, 2004; Khoo, 2001; Wang, Siegal, Falck, Carlson, and Rahman, 1999). The treatment slope growth factor assessed change from baseline to T3 (since treatment ended at T3), with factor loadings of 0, 1, 2, 2, 2, while the post-treatment slope assessed change from T3 to T5, with factor loadings of 0, 0, 0, 1, 2 (see Figure 2). These factor loadings were specified such that the intercept was set at T1, allowing the intercept factor to be interpreted as initial status. The loadings for the treatment slope factor only change from T1 to T3, while the loadings for the post-treatment (follow-up) slope only changed from T3 to T5 – thus modeling growth across the five occasions in two segments.

**FIGURE 2**. Piece-wise latent growth curve model.




Given our interest in comparing growth for two treatment groups, we used a multi-group piece-wise latent growth curve modeling approach to fit piece-wise latent growth curves to the individual-level data, estimate means and variances of the latent growth factors (initial status, treatment slope, and post-treatment slope), and test for treatment group differences on the growth factor means and variances (Duncan and Duncan, 2004; Khoo, 2001; Wang *et al*., 1999). When structural equation models (such as LGCMs) are estimated, fit indexes can be obtained that indicate the degree to which the data fit the model specified by the researcher. In multi-group analyses, these fit indexes are used to compare the fit of models where certain parameters (*e.g.*, level and slope means) are constrained to be equal across groups to other models where the same parameters are allowed to differ across groups. When the best-fitting model is found, it should reveal which parameters are significantly different across groups. In the present study, the following sequence of model comparisons was used to assess treatment group differences in the growth factor means and variances:

First, an initial multi-group model (where the latent growth curves were simultaneously estimated for both groups) was estimated where all the parameters were constrained to be equal across groups. This initial «constrained model» is essentially the same as estimating the growth model on the entire sample combined, and serves as a baseline for comparing less constrained models where various parameters are allowed to differ across groups.

Second, a multi-group model was estimated where the means for all three latent growth factors (level, treatment slope, and post-treatment slope) were allowed to vary. In cases where this «free means model» fit better than the constrained model, additional follow-up models were estimated allowing only one of the three slope factor means to be freed at a time, in order to better isolate which parameter(s) differed across.

Third, a multi-group model was estimated allowing the means, variances, and covariances of the three growth factors to vary across groups. In situations where this «free variances model» fit better than the constrained or free means models, additional follow-up models were estimated allowing only one of the slope factor variances and corresponding covariances to be freed at a time, in order to isolate which parameter(s) differed across groups.

The parameters in each of the models outlined above were estimated using full information maximum likelihood (FIML) estimation procedures using the structural equation modeling software Mplus 3.12 (Muthén and Muthén, 1998-2005). The $\chi^2$ statistic was the key indicator of model fit. Specifically, the $\chi^2$ value for each of the less-constrained models was compared against that of the previous more-constrained model using $\chi^2$ difference tests. For example, to determine treatment differences in the latent growth factor means on the BITE, the $\chi^2$ value for the model freeing the growth factor means was compared against the $\chi^2$ value for the baseline model where the growth factor means were constrained to be equal across treatment groups. A significant $\chi^2$ difference would suggest that the treatment groups differed on one or more of the three growth factor means. Then, comparisons of three follow-up models (freeing one of the three latent growth factor means in each model) with the baseline would pinpoint which of these three parameters was significantly different across treatments.

## Results

*Preliminary analyses*

Table 1 presents descriptive statistics (means and standard deviations) for the study variables by treatment group. Skewness and kurtosis values for all study variables were within appropriate range (less than an absolute value of 2).

**TABLE 1**. Means and standard deviations.

| | *CBT Group (n = 31)* | | *GSC Group (n = 31)* | | *Overall (N = 62)* | |
|---|---|---|---|---|---|---|
| *Variables* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Bulimia Severity T1 | 32.00 | 5.63 | 34.13 | 8.44 | 33.06 | 7.20 |
| Bulimia Severity T2 | 24.43 | 9.25 | 25.57 | 10.74 | 24.94 | 9.86 |
| Bulimia Severity T3 | 16.78 | 12.60 | 23.05 | 12.24 | 19.37 | 12.70 |
| Bulimia Severity T4 | 13.81 | 10.40 | 23.19 | 11.75 | 17.86 | 11.82 |
| Bulimia Severity T5 | 15.36 | 14.15 | 18.22 | 12.47 | 16.73 | 13.31 |
| Depression T1 | 22.35 | 9.88 | 19.48 | 8.61 | 20.92 | 9.31 |
| Depression T2 | 12.07 | 8.82 | 15.57 | 9.05 | 13.65 | 9.01 |
| Depression T3 | 9.56 | 8.78 | 11.42 | 10.04 | 10.33 | 9.25 |
| Depression T4 | 9.11 | 8.99 | 11.31 | 9.29 | 10.11 | 9.06 |
| Depression T5 | 11.36 | 10.53 | 10.17 | 9.90 | 10.79 | 10.14 |
| Self-Concept T1 | 96.32 | 26.85 | 103.81 | 24.05 | 100.06 | 25.56 |

**TABLE 1**. Means and standard deviations *(Cont.)*.

| | *CBT Group (n = 31)* | | *GSC Group (n = 31)* | | *Overall (N = 62)* | |
|---|---|---|---|---|---|---|
| *Variables* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Self-Concept T2 | 112.18 | 22.63 | 116.43 | 30.19 | 114.10 | 26.12 |
| Self-Concept T3 | 118.85 | 28.11 | 125.63 | 27.64 | 121.65 | 27.81 |
| Self-Concept T4 | 123.95 | 26.81 | 128.06 | 28.52 | 125.73 | 27.25 |
| Self-Concept T5 | 121.56 | 31.33 | 139.30 | 33.51 | 130.06 | 33.27 |

*Multiple-Group Piece-Wise Growth Models*

Piece-wise growth models were conducted for each of the three study outcomes, following the procedures outlined earlier. Parameter estimates for the best-fitting model for each outcome are presented in Table 2. Plots of the estimated growth trajectories for each outcome by group are shown in Figures 3-5.

**TABLE 2**. Best-fitting multi-group piece-wise growth models for bulimia severity, depression, and self-concept.

| *Variables* | *Initial Status (IS) Mean (Variance)* | *Treatment Slope (TS) Mean (Variance)* | *Follow-Up Slope (FS) Mean (Variance)* | *IS and TS Covariance* | *IS and FS Covariance* | *TS and FS Covariance* | *Model Fit Indexes* |
|---|---|---|---|---|---|---|---|
| Bulimia Severity | | | | | | | $\chi^2_{(27)} = 55.36$; $p = .001$; |
| CBT | 32.03* (38.17*) | -6.78* [a] (14.26*) | -1.59 (36.42*) | 8.29 | -19.93* | -5.04 | CFI = .86; RMSEA = .18 |
| GSC | 33.34* (same) | -3.33* [a] (same) | -3.48* (same) | same | same | same | |
| Depression | | | | | | | $\chi^2_{(20)} = 46.73$; $p = .001$; |
| CBT | 21.18* (62.10* [a]) | -5.83* [b] (12.59) | 1.38 (8.73 [a]) | -7.32 [a] | 4.15 [a] | -4.49 [a] | CFI = .86; |
| GSC | 19.45* (52.61* [a]) | -2.43* [b] (7.52) | -2.21* (23.32* [a]) | 4.16 [a] | -32.30* [a] | 1.00 [a] | RMSEA = .21 |
| Self-Concept | | | | | | | $\chi^2_{(20)} = 38.42$; $p = .01$; |
| CBT | 97.72* (517.37*) | 11.98* (68.95) | .69 [a] (29.99 [a]) | -15.87 | 45.07 [a] | 17.22 [a] | CFI = .92; RMSEA = .17 |
| GSC | 104.36* (529.60*) | 7.56* (78.39*) | 9.53* [a] (289.33* [a]) | -24.86 | -200.35* [a] | 2.46 [a] | |

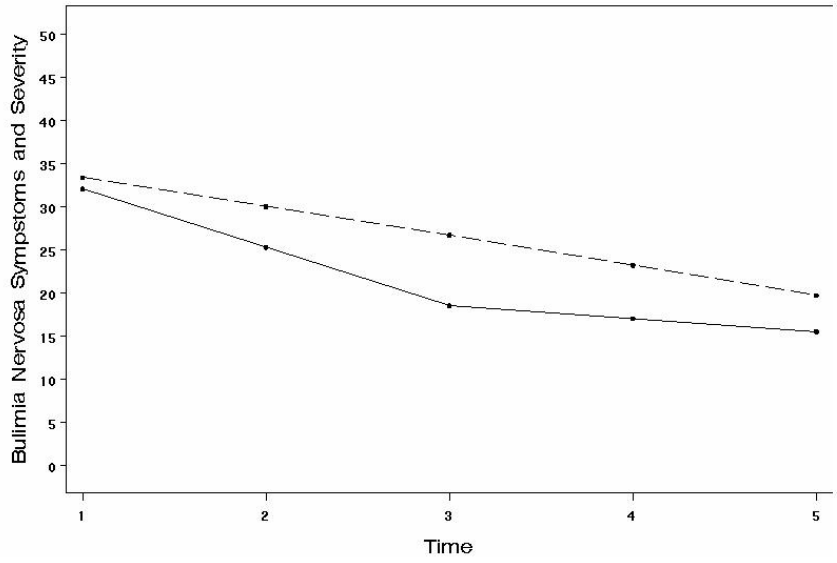
*Notes.* $N = 62$ (CBT $n = 31$; GSC $n = 31$); All parameter estimates are unstandardized coefficients; * $p < .05$; [a] parameter value differs significantly ($p < .05$) across treatment groups as indicated by multi-group model comparisons; [b] parameter value differs marginally ($p < .10$) across treatment groups as indicated by multi-group model comparisons.

*Bulimia nervosa (BITE)*

The best-fitting model for self-report bulimia nervosa symptom severity was the free-means model, indicating that the groups differed on one or more of the growth factor means but not on the variances and covariances. In this model, both groups showed a significant negative treatment slope, while only GSC had a significant negative post-treatment slope. Follow-up analyses indicated that the groups differed specifically on treatment slope in that the slope was more negative for CBT. Hence, even though the GSC post-treatment slope was significantly different from zero, it was not significantly

different from the CBT post-treatment slope. Thus, both treatment programs were effective at reducing self-reported number and severity of bulimia nervosa symptoms while patients were in treatment, but the CBT treatment group showed the most improvement. Further, the GSC group showed continued improvement through post-treatment, although this was not significantly different from that of the CBT group. In terms of variances and covariance, although these did not differ significantly across groups, the variances for initial status, treatment slope, and post-treatment slope were significantly positive, while the covariance of initial status and post-treatment slope was significantly negative. Thus, there was significant individual variation in the effectiveness during treatment and post-treatment, and GSC patients reporting more severe bulimia nervosa symptoms at the start of treatment showed the greatest post-treatment improvements.

**FIGURE 3**. Estimated growth trajectories for bulimia nervosa symptoms and severity by treatment group.



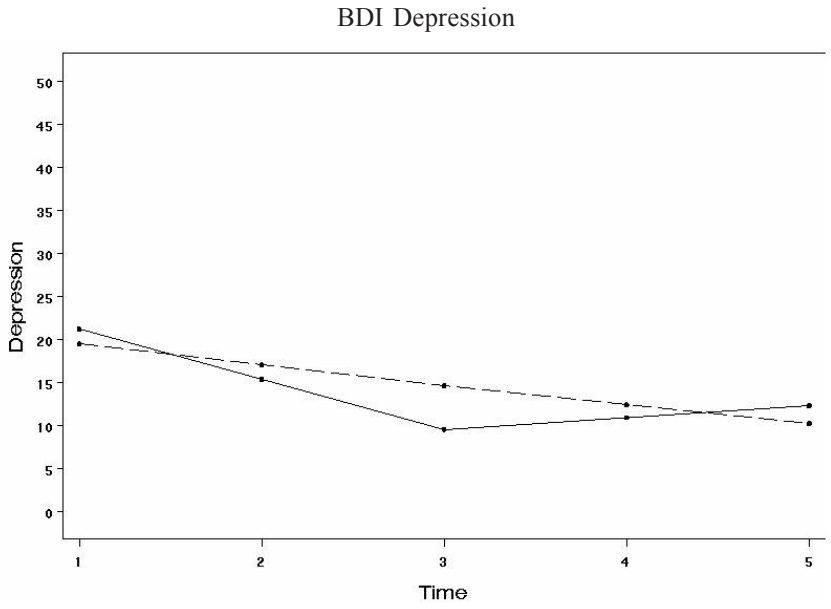

---------- Guided self-change; ———— Cognitive behavioral therapy

*Depression (BDI)*

For depression, the best-fitting model was the free-variances model, indicating that the groups differed both in terms of the growth factor means, variances, and covariances. Both groups showed a significant negative treatment slope while only the GSC group also had a significant negative post-treatment slope. Additionally, both groups had significant initial status variance, and the GSC group also had significant post-treatment slope variance and a significant negative covariance between initial status and post-treatment slope. Follow-up analyses indicated that for the growth factor means, the

improvement in model fit was due to group differences in the treatment slope mean (although the $\chi^2$ difference test for independently freeing the treatment slope mean was only marginally significant). For the growth factor variances and covariances, follow-up analyses indicated group differences on initial status and post-treatment slope variances and associated covariances. In short, both treatment programs were effective at reducing depressive symptoms during treatment, but the CBT showed moderately greater decreases in reported depression. Moreover, while the GSC treatment program resulted in continued significant improvements on depression post-treatment, these improvements were not significantly greater than for the CBT group. Treatment effectiveness during post-treatment varied more in the GSC group, and for this group, patients with higher levels of depression at the start of treatment showed the greatest improvements during post-treatment.

**FIGURE 4**. Estimated growth trajectories for depression by treatment group.



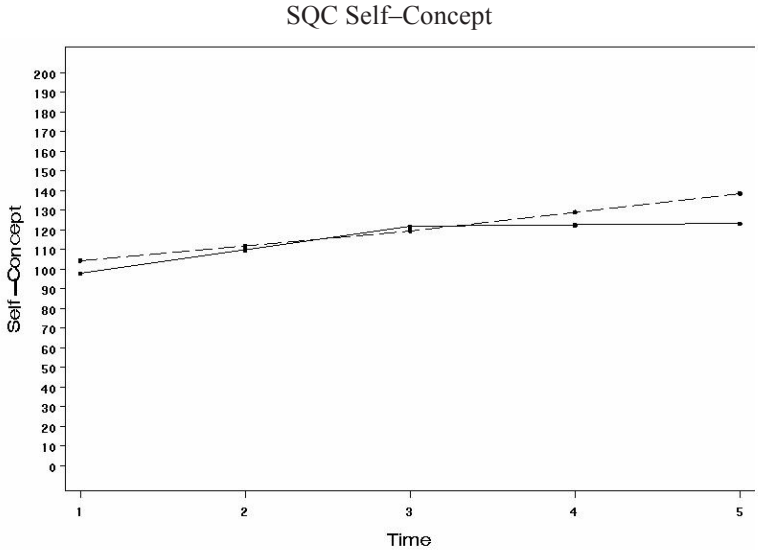

---------- Guided self-change; ———— Cognitive behavioral therapy

*Self-concept (SCQ)*

The best-fitting model for self-concept was also the free-variances model, indicating that the groups differed on both the growth factor means and the variance and covariance. Both groups had a significant positive treatment slope, while only the GSC group had a significant positive post-treatment slope. Both groups had significant initial status

variance, while GSC also had significant variances for the treatment and post-treatment slopes, as well as a significant negative covariance between initial status and post-treatment slope. Follow-up models indicated group differences on post-treatment slope mean and variance, and associated covariances. More particularly, the GSC group showed a more positive post-treatment slope and more post-treatment variance, as well as a negative covariance between initial status and post-treatment slope. In short, while both treatment programs were effective at improving self-concept, only the GSC group showed continued post-treatment improvements. However, the GSC group also showed the greatest individual differences in treatment effectiveness, at least in terms of post-treatment effects. Lastly, for the GSC group, those with the highest self-concept at the start of treatment showed the least improvements during post-treatment.

**FIGURE 5**. Estimated growth trajectories for self-concept by treatment group.




---------- Guided self-change; ———— Cognitive behavioral therapy

## Discussion

The purpose of the present study was to demonstrate the usefulness of employing latent growth curve modeling (LGCM) for assessing and comparing effects of clinical treatment programs. An empirical example was given whereby five waves of repeated measures data from two bulimia nervosa treatment programs (Guided Self-Change and Cognitive Behavioral Therapy) were reanalyzed using LGCM. A multi-group piece-wise LGCM technique was used to address the important questions of clinical research listed previously. Thus, in addition to the methodological contribution of the present study, it was hope that this research would yield novel information regarding the relative effectiveness of GSC and CBT for treating bulimia nervosa.

One benefit of using a LGCM approach is that complex models of growth can be tested in a single model. In the present study, treatment and post-treatment changes were differentiated and modeled separately but simultaneously in a single piece-wise latent growth curve model. Previous analyses of the present data using repeated measures ANOVA, which assessed overall change in treatment outcomes from the first to last occasion, did not find any group differences in change in treatment outcomes except that subjects in the CBT group appeared to have a faster reduction in the levels of depression than those in the GSC group (Thiels *et al*., 1998). By using the piece-wise growth modeling approach which separated treatment and post-treatment change, a number of group differences emerged. Both treatment programs led to significant improvements (*i.e.*, decreases in bulimia severity and depression and increases in self-concept) in patient outcomes during the treatment period, with the CBT group demonstrating greater improvements during treatment on bulimia severity, and marginally better improvements on depression. Across post-treatment, the GSC group (but not the CBT group) showed significant continued improvements post-treatment on all three outcomes, yet the groups only differed significantly on self-concept improvement in that the GSC group showed greater continued increases. To our knowledge, this is the first study comparing CBT and GSC eating disorder treatments to reveal such treatment group differences.

Another major benefit of LGCM is that it allows researchers to not only estimate mean or average change, but individual variation in change trajectories within the sample or within sample groups (and comparison of this variation across groups). This tells researchers the degree to which a treatment is more effective for certain individuals than others, or is consistently effective across individuals. In the present study, both groups had significant individual variation on initial status for all three outcomes. Both groups also showed significant variation in treatment slope for bulimia severity, while only the GSC group evidenced significant treatment slope variation on self-concept – although not significantly greater variation than CBT. In terms of the post-treatment slope, the CBT group again showed individual differences in change only for bulimia severity. However, significant post-treatment slope variation for the GSC group was discovered on all three outcomes – with the GSC group showing more inter-individual differences during post-treatment on depression and self-concept. Given that repeated measures ANOVA does not allow for examination of variation in change, none of these findings was available in previous presentations of these data (Thiels *et al*., 1998, 2003). Further, although a multi-level regression growth analysis could have revealed these variations in change, it could not have elucidated the treatment group differences. Such findings are important because they pinpoint which treatments may be more consistently effective at eliciting change in which outcomes, and across which time frames (treatment *versus* post-treatment).

In addition to getting estimates of the degree to which individuals vary from the mean, LGCM allows researchers to get estimates of the degree to which initial status on outcomes is related to change in those outcomes over time. This enables researchers to characterize the individuals for whom a treatment program may be the most effective. In the present study, baseline status on the outcomes was not significantly related to

progress during treatment in either group on any of the outcomes. However, baseline levels were negatively related to post-treatment bulimia severity change for both groups. Further, for GSC only, patients with higher baseline levels of depression showed greater post-treatment decreases, while those higher on baseline self-concept showed the less self-concept increases. Lastly, degree of improvement during treatment was not related to degree of improvement during post-treatment for either group on any outcome. In short, it seems that the more severe the case of bulimia nervosa, the higher the negative emotional well-being, and the lower the positive emotional well-being, the more likely the patient will be to benefit from treatment. These revealing results were not captured in previous analyses of these data using repeated measures ANOVA (Thiels *et al*., 1998, 2003). Further, these results would not be available using a multi-level regression growth modeling approach.

Taken together, these findings suggest several possible implications regarding these two bulimia nervosa treatment programs. First, in line with prior studies (for review, see Sysko and Walsh, 2008), GSC was shown to be an effective treatment for bulimia nervosa in that it led to significant improvements in all study outcomes across treatment and post-treatment. Second, while CBT seemed to be more effective at leading to improvements while patients were in treatment, GSC more often led to greater continued improvement post-treatment. It is possible that CBT led to greater improvements during treatment because of the more intensive protocol involved (weekly versus biweekly therapy sessions). The greater post-treatment improvements for GSC may have stemmed from its more extensive focus on education and skill-building, which equipped patients with the knowledge and abilities necessary for continued self-improvement. However, these findings are only partly congruent with those of Bailer and colleagues (Bailer *et al*., 2004). Out of 17 outcomes assessed, they found greater improvements across treatment for GSC on four outcomes, and greater improvements across post-treatment for CBT on one outcome. These different findings could potentially be due to sample differences, treatment administration differences, or the fact that different outcome measures were used. Regardless, results from these studies suggest that GSC may not only be «as effective as» CBT, but may actually have some potential added benefits, in addition to its being more cost-efficient.

There are two additional implications that emerged due to the capacity of LGCM to assess inter-individual variability in growth trajectories. First, GSC showed more individual variation in treatment effectiveness across post-treatment. In other words, there was a wider range of change trajectories during post-treatment than for patients in CBT. Although the higher level of self-direction achieved by GSC may have led to more improvement during post-treatment «on average», it might also explain the greater individual differences in its effectiveness. Some individuals may have been more self-motivated, or more competent at learning recovery skills than others. Second, GSC led to greater improvement post-treatment for those with more extensive bulimia symptoms and depression at base-line. It is possible that the more serious one's psychopathology, the more critical it is to develop long-term recovery skills – and it seems the GSC may be more effective at fostering these skills. Once again, it should be highlighted that group differences in variation in treatment effectiveness and in relations between initial status and rate of change can best be examined using LGCM.

The empirical example presented in the present study, although fruitful, was limited in several ways. First, the sample size was relatively small. Although small sample sizes are common in clinical research, LGCM is more stable (more reliable across samples) at larger sample sizes (this is true for most statistical techniques). Secondly, the time between assessments was only approximately uniform across occasions or study participants. This is a limitation in the present study because LGCM assumes uniformity in timing of measurement (which is a relative weakness of LGCM, because MLM growth analysis does not assume uniform measurement intervals).

In summary, LGCM proved to be a useful approach for analyzing repeated measures clinical treatment data – capturing information available about change and providing for comparisons of treatment effectiveness. In terms of clinical implications, the present analyses found (in line with prior research) that GSC (a more economical treatment option) may not only be as effective as CBT, but may in some ways be more effective – in that it led to more continued post-treatment improvements. Additionally, the LGCM approach revealed information about CBT and GSC not available from prior research using other analytic techniques. In particular, we found that GSC showed greater individual variability in post-treatment change than CBT on two of the outcomes, and that baseline levels of treatment outcomes were related to post-treatment rates of improvement for both groups on bulimia severity and for GSC only on depression and self-concept. Thus, this empirical demonstration highlighted the great amount of information that can be gleaned using LGCM in treatment evaluation research.

More specifically in terms of the analytic approach presented, LGCM provided an elegant way to separately but simultaneously model treatment and post-treatment change in outcomes. Additionally, it enabled the estimation of average change in the outcomes during treatment and post-treatment, as well as the within-group individual variability in change. Further, it provided a means for assessing links between base-line status and degree of improvement during treatment and post-treatment. Lastly, it allowed for the complete sample of patients do be utilized, so no information was lost due to missing data.

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