Patient Profiling
An Application of Random Coefficient Regression Models to Depicting the Response of a Patient to Outpatient Psychotherapy

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ABSTRACT

Adaptive treatment planning is a dynamic process that is dependent on valid, systematic assessments. The dosage and phase models provide theoretical bases for the development of such "patient-focused" information. Given an underlying mathematical regularity to the recovery process, growth modeling techniques can be used to determine an expected treatment response for every patient. By mapping the patient's actual status against such an expected change trajectory, it is possible to address the most clinically relevant question, "Is this treatment working?"

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All research designs, whether experimental or naturalistic, require constructive replication to test competing hypotheses as well as generalizability. However, even if a treatment for a given psychological disorder has been shown to be clearly effective, no treatment has been shown to work for everyone. Studies have invariably demonstrated extensive overlap of outcome score distributions of treatment and control group (Chassan, 1967; Howard, Krause, & Vessey, 1994) and reliable variation in outcomes among patients within assigned conditions (Lambert & Bergin, 1994; Lyons & Howard, 1991). Thus, even if tests of average effects yield statistically significant differences between treatment and control conditions or between alternative treatments, estimates of differential success probabilities for the single case are invariably modest and imprecise.
In the actual conduct of treatments, clinicians are most concerned with the question "Is this patient's condition responding to the treatment that is being applied?" In practice, given that the patient has sought amelioration of some (appropriate) malady, it is the clinician's responsibility to provide appropriate treatment. It is not enough for the practitioner to know that a particular treatment can work (efficacy) or does work (effectiveness) "on the average." The practitioner needs to select the most promising treatment for the particular patient and then to determine whether the selected treatment is providing sufficient benefit to that patient. To make such assessments, the clinician must have valid, systematic information about the patient's condition during treatment—information based on "patient-focused" research (Howard, Moras, Brill, Martinovich, & Lutz, 1996). In what follows, we describe the theoretical background and operationalization of a system for providing such systematic feedback about a patient's progress in outpatient psychotherapy.

Theoretical Background

The system we propose is a top-down approach. Rather than identifying particular treatments for particular diagnoses (a bottom-up approach), the psychotherapies are viewed as a class of treatments defined by overlapping techniques, mechanisms of action, and desired outcomes. Instead of focusing outcomes assessment on goals associated with particular diagnoses, outcomes are measured by summing items related to many disorders. Although clinical trials are useful for demonstrating promising new treatments for particular diagnoses, a top-down approach is a more practical first step for monitoring outcomes on a large scale (where the accurate diagnostic tailoring of outcomes assessments often is not feasible or seen as clinically relevant).

Earlier work suggested that the general response of patients to treatment was lawful. On the basis of a meta-analysis, Howard, Kopta, Krause, and Orlinsky (1986) described a dosage model of psychotherapeutic effectiveness that demonstrated a linear relationship between the log of the number of sessions and the normalized probability of patient improvement. This log-normal relationship is quite common in psychology (e.g., the acquisition of learning over trials and the Weber-Fechner-Stevens law of just noticeable differences between physical stimuli). Subsequent work (e.g., Kadera, Lambert, & Andrews, 1996; Kopta, Howard, Lowry, & Beutler, 1994; Maling, Gurtman, & Howard, 1995; Pilkonis & Frank, 1988; Simons, Gordon, Monroe, & Thase, 1995) provided evidence of the differential responsiveness of various symptoms and syndromes. All of this indicated that the "true" course of recovery could be described by a log-normal curve and that the actual progress of a patient could be compared with a hypothetical true course that would be expected for that patient.

Why does the log-normal model fit? One approach to this question is to formulate a model for the concept "illness." The model that we use (Howard, Lueger, & Kolden, 1997) describes three components–feeling ill, showing symptoms, and suffering a disability in functioning. We used this model to arrive at a sequential, three-phase conception of the healing process (Howard, Lueger, Maling, & Martinovich, 1993): (a) remoralization, the enhancement of well-being, which is usually accomplished within a few sessions; (b) remediation, the attainment of symptomatic relief, which is accomplished more gradually; and (c) rehabilitation, the unlearning of troublesome, maladaptive, long-standing behaviors and the establishing of new ways of dealing with various aspects of life, which occurs even more gradually. Thus, the decelerating curve of improvement could be attributed to a sequential increment in the difficulty of accomplishing these goals over the course of treatment. For these three phase concepts, patient self-report scales (Subjective Well-being, Current Symptoms, and Current Life Functioning) were developed, which could be summed to form an overall Mental Health Index (MHI; for psychometric properties, see Sperry, Brill, Howard, &
Patient Profiling and the Determination of Progress

Given a measure such as the MHI, it is relatively straightforward to plot the course of treatment for a patient. This simply entails periodic repeated assessments. However, every patient does not have the same "expected" course. This expected course may be tailored to fit each patient on the basis of that patient's clinical characteristics (e.g., severity or chronicity of condition).

Assuming an underlying log-linear course of recovery, each patient's MHI may be modeled as a function of session number (S) as follows:

\[ MHI(S) \text{ is the observed MHI score at a particular session. The } \pi_0i \text{ parameter (intercept) is a patient's expected MHI at the first session. The } \pi_1i \text{ parameter (slope) is the expected change in MHI per log } 10 \text{ of session number. The random error term (r}_{it} \text{ refers to normally distributed deviations away from expected values for patient } i \text{ at session } t. \] This model is referred to as a Level 1 model.

It is possible to search for predictors of intercept and slope parameters by constructing Level 2 models, in which Level 1 coefficients (i.e., intercepts and slopes) are dependent variables. A "random coefficient" approach (i.e., hierarchical linear modeling [HLM]) is particularly appropriate for this task (Bryk & Raudenbush, 1992). The "random effect" in these models refers to the reliability of unexplained variability in slopes and intercepts, whereas the "fixed effect" refers to the effect of factors influencing average slope or intercept. The dispersion of random effects is represented by a variance—covariance matrix (of slopes and intercepts); thus, error components may covary and have unequal variances. Because session number is treated as a random variable, there is no need to exclude cases from analyses that do not share information at all of a fixed set of sessions. Cases may vary considerably in the number and timing of assessments (Nich & Carroll, 1997). This is a great advantage, given the inherent difficulty in acquiring data at many predetermined moments in clinical settings.

Random coefficient approaches include a number of advantages over traditional regression techniques for estimating treatment response as a function of session number. Traditional regression analyses are limited by assumptions of (a) linearity, (b) normality, (c) homoscedasticity, and (d) independence of errors. The first two of these assumptions are maintained in HLM, but the second two are modified, applying only within each person's data across time. In addition, random coefficient models estimate random effects (individual differences in outcomes and rates of change) and allow for inferential tests of the reliability of these individual differences. Thus, HLM may be used to determine if a group of patients responds in a plausibly homogeneous manner to a given treatment. Finally, because HLM estimates slopes and intercepts for every case regardless of length of treatment, fixed effects for session number are less influenced by individual differences in treatment duration. With other regression models, session effects may be confounded with duration.

Method and Procedures

Instrument and Data Collection
The HLM technique was applied to data from a diverse national sample of therapists, settings, and psychotherapy patients whose treatment was being managed with the assistance of the Compass tracking system (Sperry et al., 1996). Compass data were used by therapists and case managers as part of a feedback system designed to assess treatment progress as it unfolded in practice. At the time of these analyses, the patients and therapists had completed the Compass questionnaire, which includes the MHI scales, at a minimum of three therapy sessions, including the first session.

The MHI has an internal consistency of .87 and a (3- to 4-week) test—retest stability of .82. The average MHI has been shown to be significantly lower for psychotherapy patients than for nonpatients (Sperry et al., 1996). For the present analyses, the MHI was converted to T scores ($M = 50$, $SD = 10$) based on Session 1 norms from over 16,000 patients. MHI T scores below 60 are more representative of a patient population than a nonpatient population (i.e., would be considered outside "normal range"; see Jacobson & Truax, 1991). This criterion provided one basis for identifying medically necessary and successful treatments during ongoing psychotherapies.

Therapists and Patients

The therapist sample included 364 therapists in the national provider network of a managed care company. We have little specific information about these therapists, but we know they varied in professional background and theoretical orientation. The patient sample included 890 psychotherapy outpatients beginning therapy below normal range. Seventy-three percent were female. The average age was 37.4 years ($SD = 9.7$ years). Fifty-eight percent were married; 23% were single; and 19% were separated, divorced, or widowed. Eighty-nine percent were White. Seventy-one percent were employed full time. Seventy-six percent had some college education. These statistics are reasonably representative of psychotherapy outpatients in the United States (cf. Vessey & Howard, 1993).

Data Analysis Strategy

Variation in patient intercepts ($\pi_{0i}$) was initially modeled as an additive function of Session 1 scores on the three MHI scales ($X_{1i}$ to $X_{3i}$), and variation in patient slopes ($\pi_{1i}$) was modeled as a constant plus random effect:

\[ \beta_{00} + \beta_{10} + \gamma_{1i} \]

Each $\beta_{...}$ term is a fixed effect coefficient specifying the relationship between a Session 1 predictor and a parameter in Equation 1. When all predictors are expressed in mean deviation form (i.e., the mean of case means is subtracted from each score), $\beta_{00}$ and $\beta_{10}$ are interpreted as the "average" intercept and slope, respectively. Therefore, predictor variables were expressed in mean deviation form in all analyses. The $\gamma_{1i}$ term represents a random effect (i.e., between patient variation in slopes). Because $\pi_{0i}$ represents the overall MHI at the first session, the Session 1 MHI scale scores ($X_{1i}$ to $X_{3i}$) extract all reliable variation when entered into the Level 2 model predicting intercept; therefore, no random effect is included in Equation 2. Because no random effect is included for the intercept term, the dispersion of random effects is not
represented by a variance—covariance matrix (of slopes and intercepts) but is simply \( \text{Var}(\&ugr;_{1i}) = \sigma^2 \). \\

This "unconditional" base model was augmented by using the Session 1 MHI scales to predict slope variation. That is, Equation 3 was augmented as follows:

\[
\text{In this "conditional" model, the } &ugr;_{1i} \text{ term represents slope variation not explained by factors } X_1, \ldots, X_3. \text{ The above model was further augmented by entering patient self-reports of (a) prior psychotherapy, (b) chronicity of presenting problem, (c) expected treatment efficacy, and (e) therapist ratings of intake symptoms and functioning. This final model (Equation 5) includes three intercept and seven slope predictors and a two-part "error" term ( } \varepsilon = &ugr;_{1i} \log_{10}(S) + r_{it} \).
\]

where we assume,

\[
E(r_{it}) = 0, \text{ and } \text{Var}(r_{it}) = \sigma^2_r, \text{ and } \text{Var}(v_{1i}) = \sigma^2_v.
\]

Of the four added predictors, three were patient ratings of the following questions on anchored rating scales: (a) "How much counseling or psychotherapy have you had in the past?" (b) "How long has the problem for which you are presently seeking treatment been a concern to you?" and (c) "When you finish counseling or psychotherapy, how well do you feel that you will be getting along emotionally and psychologically?" The fourth predictor, the therapist-rated Global Assessment Scale (GAS), is Endicott, Spitzer, Fleiss, and Cohen's (1976) 100-point anchored rating scale (subsequently modified and included in the Diagnostic and Statistical Manual of Mental Disorders [4th ed., American Psychiatric Association, 1994] as Axis V).

**Analyses and Results**

The fixed effect estimates for the unconditional base model (Equations 2 and 3) indicated an average MHI at the first session of 45.3 and a mean rate of change of 6.01 MHI points per log_{10} of session number. This corresponds to a mean change of more than 0.50 SDs over the first 10 sessions. For the slope parameter, the unconditional base model yielded an average reliability of .82 and a variance estimate of 48.5. The inclusion of the Session 1 MHI component scale scores reduced slope variation by 18%, from \( \sigma^2 \approx 48.5 \) to \( \sigma^2 \approx 39.7 \). Substantial reliable variation in residual slopes remained (average reliability = .79).

The final augmented model included four additional predictors of slope variation, reducing the slope variance component from 39.7 to 37.6, an additional 5% reduction. Overall, the seven slope predictors accounted for 22% of the variation in growth rates, after partialing out all reliable intercept variance. Chronicity and treatment expectations each accounted for significant variation if entered as a sixth predictor (after GAS, prior psychotherapy, and MHI scales), but each did not account for significant unique variation after including the other. Thus, the final model included a "treatment expectations minus chronicity" predictor, constraining the coefficient preceding chronicity to be the negative value of the coefficient preceding...
treatment expectations. This "negative" constraint reverse-scales chronicity, so that a single coefficient could be estimated for both predictors. Coefficients and inferential tests are presented in Table 1.

The MHI scales and the MHI itself were converted to T scores based on Session 1 data, then expressed in mean deviation form; therefore, fixed effect coefficients for subjective well-being, symptoms, and functioning are effect sizes expressed in standard deviation units based on Session 1 norms. For example, a patient who is 1 SD above the mean at Session 1 on subjective well-being is predicted to be 3.8 MHI points above the mean of 45.3 at Session 1 and his or her rate of change is −2.6 MHI points per log_{10} of session number below the mean of 6.02. On the basis of the fixed effect coefficients for the three MHI component scales at Session 1, higher baseline status was related to a slower rate of change. This effect was reversed for initial clinician ratings of global patient status. Patients perceived by the therapist as initially less symptomatic were estimated to improve slightly faster (by 0.81 MHI points per log_{10} of session number for each 1 SD on GAS), controlling for other predictors. Prior psychotherapy and problem chronicity were related to slower improvement, and positive treatment expectations were related to more rapid improvement.

Classification of Treatment Success and Failure

To classify cases as treatment successes or failures, we used a reliability-based improvement criterion (cf. Jacobson & Truax, 1991). Specifically, we defined reliable improvement as a change of 1.28 SEM s from reliability-adjusted intake MHI. When calculated from internal consistency reliability, standard error of measurement represents the standard deviation of observed scores around a theoretical true score. Assuming normally distributed measurement error, we may be 90% confident that if an observed score falls more than 1.28 SEM s above some value, the true score is indeed above that value.

Applying the reliable improvement criterion to the HLM predictions for each patient at intake versus various sessions during treatment, we were able to estimate the number of sessions needed for reliable improvement. Fifty percent of the patient sample showed reliable improvement by Session 6, 60% by Session 10, 69% by Session 26, and 74% by Session 52. This pattern is reasonably consistent with prior dose—response studies of psychotherapy effects (cf. Howard et al., 1986).


To more fully evaluate the predictive power of this modeling technique, we repeatedly randomly split our sample of 890 cases into halves, using a predictive model based on the first half to estimate ordinary least squares (OLS) and empirical Bayes (EB) slopes in the second half (see Bryk & Raudenbush, 1992, for a detailed description of EB estimation). EB estimation gives more weight to slope data based on more information (i.e., more assessments across a broader range of sessions). On average, the proportion of variation in OLS slopes accounted for by the predictive model was between 24% and 29% (95% confidence interval). For EB slopes, the corresponding estimate was between 36% and 42%. These results show that although the present method accounted for considerable variation in slopes, substantial and reliable slope variation remained unexplained. Therefore, we chose to use expected trajectories from the model to monitor progress in ongoing individual therapies and to use error estimates from the model to make informed judgments about where in this "unexplained" space an individual therapy resides.

Given a system for generating expected treatment response trajectories and for estimating the variation around these trajectories, we may develop actuarial criteria for detecting treatment success or failure. The random effect estimate from the final model may be used to describe residual deviations away from...
predicted values. Whereas traditional regression analyses presume homoscedasticity, residual deviations in the random coefficient model may covary with session number. The variance of score values around each fitted growth function is the variance of the linear composite \( \varepsilon = \varepsilon_1 \log_{10}(S) + r_{it} \). Because \( \text{Cov}(\varepsilon_1, r_{it}) = 0 \), the "error" variance and residual standard deviation at session \( S \) are

An unlimited number of rational failure-detection criteria may be applied to early estimates of patient status. The strategy that we selected was to specify an empirically based "failure boundary" below the log-linear growth function given by estimated fixed effect coefficients (in Table 1). Because residual deviations were plausibly normally distributed, the residual standard deviation may be used to generate a 25th-percentile bound below expected values for any session for any patient. This threshold is approximately 0.675 SDs (time varying) below expected values based on clinical characteristics. The computation is

The failure boundary provides one potentially useful marker for the early detection of treatment failures. We evaluated the usefulness of the boundary by examining the relationship between single and repeated lowest quartile scores and eventual treatment success, as defined by our reliable change criterion. For patients who remained in therapy for at least 10 sessions (\( n = 450 \)), we found that counting the number of scores below the failure boundary before the 10th session was a useful method for predicting reliable improvement by the last session. For patients with no subthreshold scores (\( n = 303 \)), the probability of reliable improvement was .65. For patients with one subthreshold score (\( n = 128 \)), this probability decreased to .46. For patients with at least two subthreshold scores by Session 10 (\( n = 19 \)), the probability of reliable improvement by the final session was .36.

We also considered the interval from Sessions 10 to 18 for longer term patients, who continued in therapy beyond the 18th session (\( n = 233 \)). In this cohort, of the patients with no subthreshold scores in the interval (\( n = 141 \)), 68% showed reliable improvement by the final session. For patients with one subthreshold score (\( n = 71 \)), 49% showed reliable improvement. For patients with two or more subthreshold scores (\( n = 21 \)), only 24% showed reliable improvement. These results have useful decision support implications for treatment planning for the individual case. One value below the failure boundary suggests continued observation because there is still almost a 50-50 chance of reliable improvement despite such an event. Two such values, however, imply a threefold increase in the odds of treatment failure and, therefore, a need for reevaluation of the current strategy.

These progress indicators, as well as other potential indicators, provide useful tools for matching the patient to his or her uniquely optimal treatment. Instead of making resource allocation decisions entirely on the basis of cost, clinical information systems and indicators such as these allow practitioners and case managers to take into account actual treatment progress as it occurs. Such a system has the potential to benefit patients, therapists, and sponsors because resources can be rationally allocated in such a way as to maximize treatment gains given limited treatment resources.

**Monitoring Treatment Response: Two Examples**

Figure 1 describes a successful psychotherapy case in our sample. At intake, the patient, a 19-year-old
single woman, was diagnosed as meeting criteria for a major depressive episode superimposed on underlying dysthymia. The patient began psychotherapy with an MHI score more than 1 SD below that of the average outpatient. This initial status was also 2 SDs below normal range, as defined by Jacobson and Truax's (1991) Criterion c. In addition to the observed data, the figure depicts an expected trajectory, the failure boundary, and the normal-range boundary in percentile ranks based on Session 1 norms. These reference lines allow judgments concerning whether observed incremental improvements are proceeding as expected.

At Session 1, the patient reported several years of recurring depressive symptoms, one prior 4-month outpatient psychotherapy experience, and an expectation that she would feel much the way she would like to after treatment. The observed response pattern surpassed the predicted response based on the HLM model. At each assessment (Sessions 5, 9, 17, and 25), the patient's overall status showed improvement. From a case management perspective, these data justified continued commitment of treatment resources for this patient. By Session 25, however, the patient's MHI score began looking more representative of that found in a nonpatient population. At this point, the outcomes pattern justified continued monitoring for stabilization followed by consultation with the therapist regarding termination. After scores stabilize in the normal range, the medical necessity of treatment (and thus, third-party contractual obligations) become an issue.

**Figure 2** describes another predicted successful psychotherapy case in our sample. At intake, the patient, a 34-year-old married man, was diagnosed with an adjustment disorder with mixed emotional features. The patient reported acute symptomatic distress primarily within the 2 months before the first session, no prior outpatient psychotherapy experience, and an expectation that he would feel fairly well after treatment but not entirely the way he would like to feel.

At intake, this patient's MHI score was well below normal range. The expected trajectory indicated that improvement into normal range was likely. At the first assessment point (Session 2), the patient's response pattern followed the expected course; however, at the next assessment (Session 8), the patient's scores fell well below expectations. A consultation with the therapist and treatment strategy reevaluation was called for. This consultation and reevaluation led to the conclusion that a more active participation by the patient's wife might be helpful. Couples therapy was initiated at Session 11, and the assessment at Session 15 indicated good progress. By Session 21, the patient's MHI had improved substantially, roughly up to a level consistent with the expected trajectory based on his intake characteristics. In this case, the data indicated both the medical necessity of treatment and the fact that the initial treatment plan was not working.

**Summary and Conclusions**

A rational approach to the allocation of treatment resources would require the determination that treatment is necessary (i.e., the patient is ill), that treatment is appropriate (i.e., the illness is known to respond to this treatment), and that the patient is responding to the treatment. In such a system, assessments from patients and therapists must be obtained periodically during treatment. On the basis of an appropriate database, it can be determined if a particular patient meets a medical necessity requirement for treatment.

Given the patient's initial clinical characteristics (e.g., severity or chronicity), a graph can be drawn that depicts the expected course of response to a particular treatment for that patient. If this graph indicates that outpatient psychotherapy is a reasonable course of action (i.e., this patient is expected to respond to this kind of treatment), the decision to use this approach is well informed, having been tailored to the presenting characteristics of the patient. Once outpatient psychotherapy is initiated, treatment progress may be evaluated by repeatedly assessing the patient's status and comparing these data to the patient's expected
progress.

Comparing these observations with expected and failure trajectories based on each patient's unique presenting characteristics enhances the decision-support value of these observations. In this way, a patient who is not responding (or who is responding too slowly on the basis of a comparison with reference trajectories) can be identified and further consultation can be ordered. In addition, patients who are responding as expected, but who need further sessions to reach a desired outcome, would have these sessions authorized. Finally, if a patient is expected not to reach normal range, but subnormal expected improvement is substantial, the bar may be lowered to a point below normal range for evaluating outcomes for that case.

Basing our methods on established paradigms for examining psychotherapy processes and outcomes (the illness model, the three-phase model, and the log-normal dose—effect model), we have demonstrated how treatment progress may be monitored. It is important to recognize that the present technique is a first step in patient-focused outcomes evaluation, but there is much room for improvement. The present technique begins at a global level, but in time, it may be possible to construct multivariable models in which the outcomes variables monitored are tailored to unique treatment goals for each case (which may depend on diagnostic formulation, environmental circumstances, available treatment options, etc.).

The model we have described could be used to estimate how many sessions are expected to be enough to reach a desired level on some outcome indicator; however, for the technique to be useful, we need to decide which goals we are pursuing (i.e., enough to accomplish what?). In addition, "enough" could mean (a) clinical improvement, (b) no longer meeting criteria for medical necessity or for a psychiatric diagnosis, (c) as much improvement as would be expected for this particular patient, (d) enough improvement to minimize the likelihood of reoccurrence or reentry into treatment, or (e) enough to ensure normal functioning. As we develop better evidence about specific aspects of effectiveness and dosage and address the thorny issue of medical necessity, we will gradually develop a more specific answer. We have made some progress, however, and at this point we are able to provide one practical answer with regard to the treatment of any individual patient.

References


after treatment for mood, anxiety, and personality disorders: Toward a core battery (pp. 263—281). Washington, DC: American Psychological Association.)


### Table 1. Conditional Log-Linear Model of Growth in the Mental Health Index as a Function of Seven Presenting Characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
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<th>p</th>
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<tbody>
<tr>
<td>Initial severity</td>
<td>0.320</td>
<td>0.05</td>
<td>6.41</td>
<td>&lt;.001</td>
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<tr>
<td>Initial variability</td>
<td>0.170</td>
<td>0.03</td>
<td>5.28</td>
<td>&lt;.001</td>
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<tr>
<td>Gender</td>
<td>-0.030</td>
<td>0.02</td>
<td>-1.59</td>
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<tr>
<td>Race</td>
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<td>0.02</td>
<td>-1.28</td>
<td>.200</td>
</tr>
<tr>
<td>Global impression</td>
<td>0.010</td>
<td>0.01</td>
<td>1.21</td>
<td>.228</td>
</tr>
<tr>
<td>Education</td>
<td>0.020</td>
<td>0.02</td>
<td>1.15</td>
<td>.249</td>
</tr>
<tr>
<td>Time</td>
<td>0.030</td>
<td>0.01</td>
<td>3.13</td>
<td>&lt;.001</td>
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</table>

Random effects: Variance components

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<th>Variance</th>
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<th>p</th>
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</thead>
<tbody>
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<td>.009</td>
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<tr>
<td>Initial (t)</td>
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<tr>
<td>Residual (e)</td>
<td>2.46</td>
<td>253</td>
<td>.000</td>
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Note: OLS = ordinary least squares.
Figure 1. Treatment course for a case in which outcomes data validated the treatment strategy.

Figure 2. Treatment course for a case in which outcomes data led to a change in treatment strategy.