ADAPTIVE MODELING OF PROGRESS IN OUTPATIENT PSYCHOTHERAPY

Wolfgang Lutz
Department of Psychology, University of Berne

Eshkol Rafaeli
Department of Psychology, New York University

Kenneth I. Howard
Department of Psychology, Northwestern University

Zoran Martinovich
Department of Psychiatry, Northwestern University Medical School

All professional services require adaptive decision making, that is, modifications based on diagnostic configuration and an ongoing assessment of progress or accomplishment of goals. In the delivery of clinical services, outcome monitoring (i.e., repeated assessments of a patient's response to treatment and recurrent revisions of outcome expectations based on the observed treatment response) can be used to support this sort of adaptive decision making. The authors describe a model for determining the expected treatment response of a patient based on presenting characteristics and information collected over the course of treatment. They also discuss how this information could be used to support clinical decisions regarding treatment selection and modification.

Two research methodologies have guided mental health service evaluation: the randomized clinical trial and the quasi-experimental or naturalistic study. Randomized clinical trial methodology is focused on internal validity and a confirmatory-deductive research goal. Random assignment to treatment and control groups and standardized procedures are used to ensure that any observed mean outcome differences can be unambiguously attributed to the influence of the independent variable (i.e., treatment).

Mainly because of threats to external validity (e.g., generalizability with regard to actual clinical settings [Seligman, 1995], outcome overlap between treatment groups [Howard, Krause, & Vessey, 1994], and data attrition, many have advocated the primary or at least supplemental use of quasi-experimental methods (Barlow, 1996; Beutler, 1998; Goldfried & Wolfe, 1998; Howard, Moras, Brill, Martinovich, & Lutz, 1996; Kopta, Lueger, Saunders, & Howard, 1999; Lambert, 1998; Newman & Tejeda,

1996; Seligman, 1995). In quasi-experimental or naturalistic research, large representative samples of diverse patients, therapists, and settings must be sampled to ensure generalizability. To deal with threats to internal validity, post hoc tests are conducted to reject plausible alternative explanations for observed treatment effects.

Because the methodological strengths and weaknesses of naturalistic studies and clinical trials complement each other, optimal scientific support for the efficacy and effectiveness of a treatment should be based on consistent findings across both kinds of **treatment-focused** (i.e., "Does this treatment work?") designs. However, even if a treatment has such empirical support, what specific prognosis is implied for an individual patient? So far, no treatment has proven to be 100% successful for patients with a specific disorder, and most empirically supported treatments fall far short of such an ambitious goal (i.e., an effect size of 3.0 or greater). Thus, estimates of success probabilities based on treatment-focused research have to be augmented by empirical research strategies, which allow monitoring of the treatment progress of the patient actually treated.

This research strategy cannot be established by conducting time-limited studies or patient assessments as is usual for efficacy or effectiveness studies. It has to be established based on data continually collected from the actual clinical practice of each patient (Lambert, 2001; Lutz, 2002). A pragmatic case-based approach is needed that starts with individual cases and builds up to a large database of treated cases, which allows for the possibility of making use of previous experience (Fishman, 1999). This information can then be used to systematically support, learn about, and improve the treatment of incoming patients.

In addition to the initial decision about which treatment to try first for a particular patient with a particular diagnosis or set of symptoms, intervention decisions should be based on "real-time" information about the process and progress of treatment being delivered to the patient (i.e., on **patient-focused** information: "Is this treatment working in this case?"). Given dependable information that the patient is making enough progress, the therapist is likely to continue the treatment. Given dependable information that the patient is not making enough progress, the therapist is likely to modify the treatment (e.g., Barkham et al., 2001; Beutler, 2001; Grawe, 1998, 2002; Kordy, Hannöver, & Richard, 2001; Lambert, 2001; Lueger et al., 2001).

The ongoing debate about limited treatment implications of psychotherapy research to clinical practice has drawn attention to the "scientist-practitioner gap" (e.g., Goldfried & Wolfe, 1998; Lutz, 2002; Newman & Tejeda, 1996). Clinicians have often complained that mental health researchers fail to produce research relevant to the decisions they must make in clinical practice. Researchers have often complained that clinicians ignore the appropriate research literature. In one study (Strupp, 1996) scientist-practitioners indicated that research had had little impact on their own practices. In one effort to narrow this gap, Howard et al. (1996) and Lutz, Martinovich, and Howard (1999) introduced an outcomes monitoring strategy, the expected treatment response (ETR) method, that can be used to supplement decision making based on treatment-focused research with repeated patient-focused outcomes assessments. The ETR method was developed from the dosage and phase models of psychotherapy.

The dosage model describes a general response pattern of patient outcomes to therapeutic interventions. On the basis of a meta-analysis, Howard, Kopta, Krause, and Orlinsky (1986) concluded that a patient's treatment response tends to follow a logarithmic curve, with rapid improvement over the first few sessions of therapy and diminishing rates of improvement over subsequent sessions. Additional work provided evidence for differential patterns of treatment response for various psycho-

logical symptoms (Barkham, Rees, & Stiles, 1996; Kopta, Howard, Lowry, & Beutler, 1994), interpersonal problems (e.g., Horowitz, Rosenberg, Baer, Ureño, & Villaseñor, 1988; Maling, Gurtman, & Howard, 1995), and diagnoses (Howard et al., 1986; Pilkonis & Frank, 1988).

The phase model of psychotherapy (Howard, Lueger, Maling, & Martinovich, 1993) posits that the goals of therapy change over the course of treatment, and that associated therapy outcomes improve at different rates and in a stochastically causally sequential fashion. In this model, recovery from psychiatric illness is composed of three sequential phases: (a) remoralization (the enhancement of subjective well-being), which facilitates (b) remediation (the attainment of symptomatic relief), which in turn facilitates (c) rehabilitation (the unlearning of pervasive, maladaptive patterns of functioning and the learning of more adaptive approaches). Remoralizing patients (i.e., imbuing them with a sense of hope and a willingness to address and remedy problems) is viewed as necessary but not sufficient to achieve symptomatic relief; and both remoralization and remediation are necessary but not sufficient to attain rehabilitation of maladaptive patterns. The log-linear response pattern, therefore, could be attributed to this sequential change pattern, with changes in subjective well-being driving rapid early improvement and the increasing difficulty of subsequent treatment goals leading to a decelerating pattern of change (Martinovich, 1998).

Empirical research on the phase and the dosage models has relied primarily on aggregated data estimating response patterns for the "average" patient. However, patterns of improvement for individuals vary substantially from each other and from average trends. Individual variance cannot be seen simply as error variance because it almost always reflects real individual differences (e.g., Krause, Howard, & Lutz, 1998; Lyons & Howard, 1991; Martinovich, 1998). In an attempt to model these individual differences, we describe treatment response as a log-linear function relating mental health to the amount of therapy (measured by number of sessions).[1] Individual change patterns across sessions can be modeled for each patient, and the resulting between-patient variation in these change patterns can be predicted by initial patient characteristics (for details, see Lutz et al., 1999). With repeated measures of outcome and course-related presenting characteristics on a sufficiently large sample of patients, it is possible to develop an appropriate statistical model and to apply it to any new patient based on presenting clinical characteristics. The expected course of treatment generated from such a model would thus be tailored to the presenting characteristics of that individual case. Given such an expectation, ongoing therapeutic effectiveness can be assessed by tracking the patient's actual progress in comparison to his or her expected response to treatment (ETR). The observed variance in the model could be used to develop an "action" or "re-evaluation" boundary below the predicted course of treatment. Outcome scale scores crossing such a boundary would not be on the expected track, and the implications of such events for eventual treatment success may be estimated. Thus, these events would suggest a

---

[1]The cited meta-analyses by Howard et al. (1986) showed a consistent pattern across all studies in the analysis of the most rapid response phase early in therapy. This consistent curvilinear pattern is parsimoniously approximated by log-linear transformations of session number, as in the present case. Ample evidence suggests that change patterns on outcome variables in therapy are often (usually) not linear and better approximated by some kind of concave downward but monotonic increasing math model. A log-linear transformation of time is just one such way of trying to approximate this; there are many others. Even so, the log-linear model is widely used in this area of research (e.g., Gibbons et al., 1993; Lambert et al., 2001).

need to reevaluate the treatment strategy and would provide a basis for prioritizing case reviews. However, expected courses based on initial information become less accurate as the time frame into which they are projected becomes longer. Taking this under consideration, the impact of the actual treatment or process changes should be used to remodel and, if necessary, correct the original expected courses.

This is the goal of the current study, which expands on the previous work and describes an extended ETR model that develops treatment-progress expectations based on presenting characteristics but also adapts these expectations to course and process changes within ongoing treatments. This method provides a pragmatic case-based approach, because treatment goals and expected outcomes may change during the course of treatment (Fishman, 1999; Orlinsky, Grawe, & Parks, 1994). A repeated worsening or improvement in such ETRs has implications for quantifying the ongoing clinical significance of treatment effects for the individual case.

In this study we begin examining the potential clinical utility of this approach and illustrate it with examples of patients whose responses were monitored by means of repeated assessments during treatment. Finally, we discuss the possibilities and limitations of that method and answer unaddressed research questions.

Methods and Procedures

Therapists and Patients

The patient sample included 75 psychotherapy outpatients from a national provider network of a managed-care company (Integra, Inc.). The patients began therapy below the "normal range" on a Mental Health Index (Howard et al., 1993). They were treated by 53 different therapists. Although we have little information regarding the therapists, we know that they were of diverse backgrounds and theoretical orientations. Seventy-eight percent of the patients were female, 87% were white, and their average age was 35.2 years (SD = 8.9, range = 19–58). Forty-six percent of the patients were married, 34% were single, and 20% were separated, divorced, or widowed. Seventy-four percent were employed full time and 77% had at least some college education. The demographic characteristics of this subsample are reasonably representative of psychotherapy outpatients in the United States (cf. Vessey & Howard, 1993) but represent a sample of patients with at least 14 and up to 52 (see later discussion) sessions of therapy.

Instruments

The Mental Health Index (MHI) is a self-report outcome measure obtained by averaging three equally weighted scales: Subjective Well-Being (4 items), Current Symptoms (40 items), and Current Life Functioning (24 items). The overall scale is based on 68 items and has a Cronbach's alpha of .87 and a 3- to 4-week early therapy test–retest reliability of .82. The 4-item Subjective Well-Being scale contains questions on distress, energy and health, emotional and psychological adjustment, and current life satisfaction. The internal consistency of the Subjective Well-Being scale was .79 and the 3- to 4-week test–retest reliability was .82. The 40-item Current Symptoms scale includes symptoms from seven *Diagnostic and Statistical Manual of Mental Disorders* (fourth edition; *DSM-IV*; American Psychiatric Association, 1994) diagnoses (depression, anxiety, obsessive–compulsive, adjustment, bipolar, phobia,

and substance abuse disorders). The Cronbach's alpha of the Current Symptoms scale was .95 and the 3- to 4-week test–retest correlation was .85. The 24-item Current Life Functioning scale represents six areas of life functioning: self-management, work/school/homemaker, social and leisure, intimacy, family, and health. The internal consistency was .93 and the 3- to 4-week test–retest reliability was .76. (For more detailed information on the measures, see Howard, Brill, Lueger, O'Mahoney, & Grissom, 1995; Lueger et al., 2001; Sperry, Brill, Howard, & Grissom, 1996.) For the current analyses, the MHI is expressed in *t* scores (with a mean of 50 and a standard deviation of 10) based on first session norms from more than 16,000 patients. The average MHI has been shown to be significantly lower for psychotherapy patients than for nonpatients (Sperry et al., 1996). MHI scores below 60 are more representative of a patient population than of a nonpatient population (i.e., would be considered to be below the "normal" range; Howard et al., 1996; Jacobson & Truax, 1991; Martinovich, Howard, & Saunders, 1996; Schulte, 1995). The MHI was completed as part of the COMPASS information tracking system (see Howard et al., 1995; Lueger et al., 2001; Sperry et al., 1996), which is used for monitoring and managing individual psychotherapy cases based on both patients' and clinicians' ratings of therapy outcomes and processes.

Data Collection

The 75 patients had completed the COMPASS questionnaires for the first session and for a minimum of four subsequent sessions. At least one assessment occurred within each of the following session ranges: 3–6, 9–12, and after the 12th session (ranging from Session 14 to Session 52; with 30.88 sessions on average and a standard deviation of 11.49 sessions; lower quartile = 21; median = 28; upper quartile = 42); 72 patients had two or more assessments after the 12th session.

Analyses and Results

First, using growth curve modeling (Bryk & Raudenbush, 1992; Raudenbush, 2001), each patient's progress over the course of psychotherapy was modeled as a linear function of the log of session number. For each patient, such a model yields an intercept and slope parameter. The intercept in this function represents the patient's expected MHI score at intake. The slope parameter is the expected change in MHI per log of session number for that patient. The statistical procedures used are described in detail in Lutz et al. (1999).

To further enhance this conditional model, which provides us with a predicted course based on presenting information, we developed models using the patient's subsequent response to treatment to modify these predictions. The goal was to develop higher order conditional models, progressively including up-to-date outcome data to improve the original predictions. In the current example, we used information collected in the following session ranges: 3–6 (Assessment 2) and 7–12 (Assessment 3). The first conditional model (based on presenting information) uses all repeated measurements to estimate each patient's progress over the course of treatment. The second conditional model uses all repeated measurements, except Assessment 2 data, which is included as a predictor in the conditional model. The third conditional model uses all repeated measures except Assessment 2 and Assessment 3 data because both are used as predictors.

The first conditional model included three intercept and six slope predictors previously demonstrated to predict rates of change (Lutz et al., 1999). In addition to Subjective Well-Being, Current Symptoms, and Current Life Functioning scores (intercept and slope predictors), we used the patient-reported anchored ratings of (a) prior psychotherapy ("How much counseling or psychotherapy have you had in the past?") and (b) the difference between ratings of treatment expectations ("When you finish counseling or psychotherapy, how well do you feel that you will be getting along emotionally and psychologically?") and chronicity ("How long has the problem for which you are presently seeking treatment been a concern to you?"), and (c) a therapist-rated predictor, the Global Assessment Scale (GAS; Endicott, Spitzer, Fleiss, & Cohen, 1976), was also included as a slope predictor. This is a 100-point anchored rating scale (included as Axis V of the *DSM-IV*; American Psychiatric Association, 1994).

The second conditional model augmented the first conditional model by adding two predictors: (a) a change score (Assessment 2 – Assessment 1) and (b) a dichotomous "failure score" indicating whether scores fell above or below a "re-evaluation boundary" (Lutz et al., 1999) at the second assessment (1 = above, 2 = below). This re-evaluation boundary is essentially a 25th percentile bound below the expected trajectory estimated from the variance components in the regression model. The third conditional model also augmented the first conditional model, but added three predictors: (a) a change score (Assessment 3 – Assessment 1); (b) the slope of the regression of all data from Assessment 1 to Assessment 3 on session number; and (c) a trichotomous "failure score" indicating how often scores fell below a re-evaluation boundary (1 = no failure; 2 = below the boundary at either Assessment 2 or 3; 3 = below the boundary at both assessment points).

The fixed-effect estimates for the unconditional base model indicated an average MHI at the first session of 45.9 for this sample and a mean rate of change of 4.88 MHI points per Log10 of session number (Table 1). This corresponds to a mean change of almost half a standard deviation within the first 10 sessions. For the slope parameter, the model yielded an average reliability of .89 and an estimated variance of the individual slopes of 31.09.

The first conditional model (Table 2) reduced this variance to 21.11, thus accounting for 32% of the variance in the slopes. With the exception of treatment expectations and chronicity, all patient-rated predictors as well as the therapist-rated GAS accounted for significantly unique variation in patient response slopes.

TABLE 1. Unconditional Log-Linear Model of Growth in Mental Health Index

Fixed effect	Variable	Coefficient	SE	t	p
For intercept (π_{0i})	Intercept (β_{00})	45.52	0.47	95.90	<.001
	Subjective Well-Being (β_{01})	0.26	0.07	3.97	<.001
	Symptoms (β_{02})	0.38	0.06	6.45	<.001
	Functioning (β_{03})	0.29	0.05	6.01	<.001
For slope (π_{1i})	Intercept (β_{10})	4.18	0.78	5.31	<.001

Random effect	Variance component	χ^2	df	p	
For slope (υ_{1i})	31.09	771.46	74	<.001	
Level 1 error (r_{it})	23.08				

Note. Reliability of ordinary least squares regression coefficient estimate for slope is .89.

TABLE 2. Conditional Model of Growth as a Function of Presenting Characteristics in Session 1

Fixed effect	Variable	Coefficient	SE	t	p
For intercept (π_{0i})	Intercept (β_{00})	45.49	0.47	96.34	<.001
	Subjective Well-Being (β_{01})	0.32	0.08	4.25	<.001
	Symptoms (β_{02})	0.45	0.07	6.58	<.001
	Functioning (β_{03})	0.34	0.06	6.02	<.001
For slope (π_{1i})	Intercept (β_{10})	4.24	0.70	6.08	<.001
	Subjective Well-Being (β_{11})	−0.23	0.12	−2.01	<.050
	Symptoms (β_{12})	−0.26	0.10	−2.50	<.050
	Functioning (β_{13})	−0.18	0.09	−2.08	<.050
	Global Assessment (β_{14})	0.15	0.06	2.31	<.050
	Prior psychotherapy (β_{15})	−0.09	0.34	−0.28	<.050
	Treatment expectations minus chronicity (β_{16})	0.27	0.35	0.78	*ns*

Random effect	Variance component	χ^2	df	p	
For slope (υ_{1i})	21.11	489.67	68	<.001	
Level 1 error (r_{it})	22.85				

Note. Reliability of ordinary least squares regression coefficient estimate for slope: .85.

Next, we compared the second conditional model to the first conditional model by including treatment progress predictors (based on Assessment 2). Table 3a shows only the results for the two added predictors. The second conditional model reduced the variance to 12.23, accounting for 58% of the variance in the unconditional base model and 42% of the variance remaining in the first conditional model. Of the added predictors, only the change score uniquely contributed to this reduction, $t(66) = 4.77$, $p < .001$.

Finally, we augmented the first conditional model by adding three treatment progress predictors based on Assessment 2 and 3 data. Table 3b shows only the results for the three added predictors. The third conditional model reduced the variance to 8.42, thus accounting for 73% of the variance in the unconditional base model and 60% of the variance in slopes. Of the added predictors, only the slope predictor uniquely contributed to this reduction, $t(65) = 5.51$, $p < .001$.

To cross-validate these findings and to compute confidence bounds around these estimates of explained variance, we used a bootstrap method (cf. Fox, 1997; Neter,

TABLE 3a. Conditional Model 2 Based on Assessment 2 Data (Between Sessions 3–6)

Fixed effect	Variable	Coefficient	SE	t	p
For slope (π_{1i})	Change from 1 to 2 (β_{17})	0.55	0.12	4.77	<.001
	Failure score 2 (β_{18})	1.93	1.54	1.26	*ns*

Random effect	Variance component	π^2	df	p	
For slope (υ_{1i})	12.23	321.26	66	<.001	
Level 1 error (r_{it})	22.59				

Note. Reliability of ordinary least squares (OLS) regression coefficient estimate for slope: .76.

TABLE 3b. Conditional Model 3 Based on Assessment 3 Data (Between Sessions 7–12)

Fixed effect	Variable	Coefficient	SE	t	p
For slope (π_{1i})	Change from 1 to 3 (β_{17})	−0.12	0.08	−1.33	ns
	Slope from 1 to 3 (β_{18})	0.58	0.10	5.51	<.001
	Failure score 3 (β_{19})	1.33	0.82	1.62	ns
Random effect	Variance component	χ^2	df	p	
For slope (υ_{1i})	8.42	230.67	65	<.001	
Level 1 error (r_{it})	21.43				

Note. Reliability of OLS regression coefficient estimate for slope: .66.

Kutner, Nachtsheim, & Wasserman, 1996). For each of the three conditional models, we formed 100 bootstrap samples by randomly drawing, and replacing, the 75 patients from our original sample. We then computed the unconditional and conditional models on these 300 samples and noted the explained variance in individual slopes. The means, standard deviations, and distributions of these proportions of explained variances in slopes are presented in Table 4. As is apparent, despite moderate variability in the proportion of explained variance in slope, there is a consistent improvement in the explanatory power of our models as additional information (from Assessment 2 or 3) is included.

Clinical Utility: Case Examples

To illustrate the utility of the adaptive treatment response model, we provide two case examples using adaptive re-evaluation boundaries. In the first case, an initial positive response resulted in more ambitious expectations of treatment progress. In the second case, early negative response patterns led to progressively lower progress expectations. For each patient, new ETR curves and re-evaluation boundaries were generated after the fourth and ninth sessions and added to the graphic reports of the treatment course. Although the following data show the full course of treatment for each patient, graphic reports were available after each of the designated sessions.

TABLE 4. Descriptive Statistics of Explained Variance Proportions in Bootstrap Samples

Variable	Conditional Model 1	Conditional Model 2	Conditional Model 3
M	.37	.64	.74
SD	.09	.09	.10
Maximum	.61	.87	.98
95%	.55	.77	.91
75%	.42	.71	.81
Median	.37	.64	.74
25%	.32	.56	.68
5%	.23	.49	.58
Minimum	.16	.33	.44

Note. Each bootstrap distribution consists of 100 samples of $N = 75$.

Patient A was a 41-year-old divorced woman diagnosed with major depression. Symptoms of depression had been troubling her for more than 2 years. She reported a prior psychotherapy experience lasting between 6 and 12 months. She expected to feel "much the way I would want to" at the culmination of therapy. This patient presented with a very low MHI (9th percentile) relative to other patients at intake. Her (intake-based) ETR indicated that improvement was expected, but improvement into the normal range did not appear likely.

The sequence of ETRs and re-evaluation boundaries are presented in Figure 1 (along with Patient A's actual observed MHIs and a normal range boundary). At the second assessment (Session 4), the patient's MHI clearly exceeded the original re-evaluation boundary, and this resulted in a revised, steeper re-evaluation trajectory. At the third assessment (Session 9), the patient's MHI again exceeded the new prediction, and an even steeper re-evaluation boundary was estimated.

The recurrent increase in the slope of expected trajectories suggests that the treatment course is repeatedly exceeding revised expectations without periodic setbacks. If the current adaptive model was incorporated into an efficient outcomes monitoring and feedback system, information like that presented in Figure 1 could be an invaluable tool for improving treatment quality. Patient A was not expected to benefit much from individual psychotherapy. This would alert the clinician (case manager) to pay close attention to the actual progress of this patient. Given the revised expectations for this patient based on her actual response to treatment, there was every reason to continue the treatment without significant modification or further review.

Patient B (Figure 2) was a 40-year-old married man diagnosed with undifferentiated attention deficit disorder. Symptoms of this condition had been troubling him for much of his life. He had received no prior psychotherapy and expected to feel "much the way I would want to" after completing a course of therapy. At intake, this
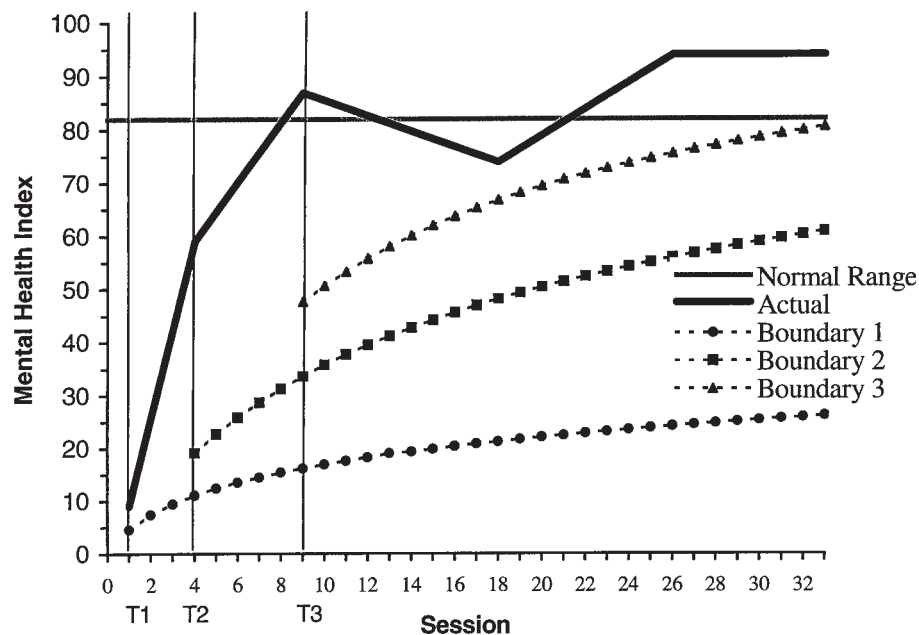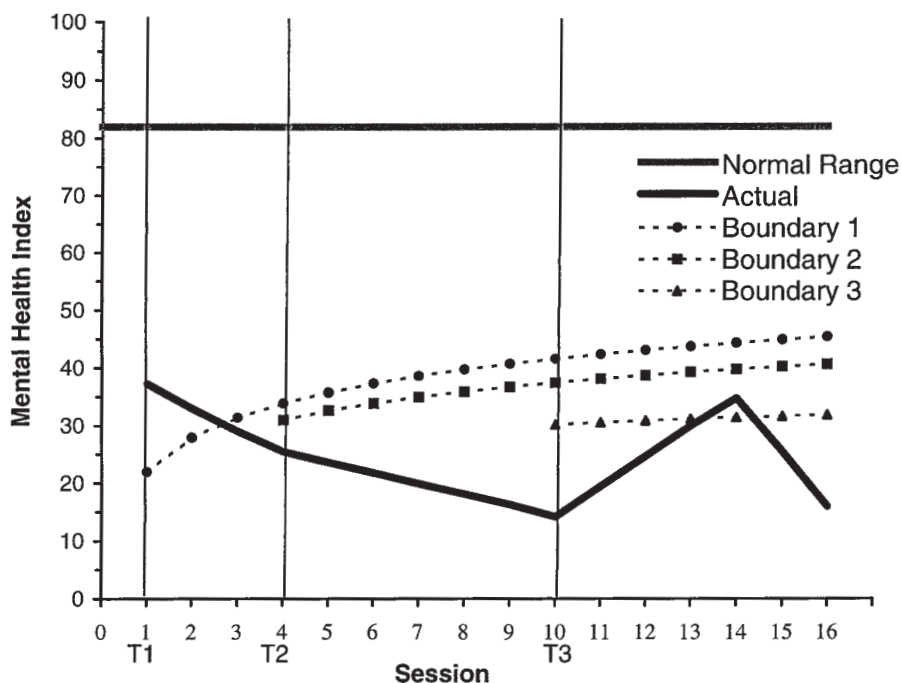

FIGURE 1. Treatment response course for Patient A.

FIGURE 2. Treament response course for Patient B.

patient's MHI was a little below average (38th percentile). On the basis of his intake information, improvement was expected but improvement into normal range did not appear likely. At the second assessment, the patient's MHI dropped below the first re-evaluation boundary (down to the 26th percentile). The low score led to a revised expected trajectory and lower re-evaluation boundary, but some improvement was still expected. At the third assessment (Session 10), the patient's MHI status again deteriorated (down to the 15th percentile), falling below the second re-evaluation boundary. At this point, the predictive model suggested that the patient was not likely to respond to the current therapy.

At several points, the data represented in Figure 2 suggest (and sometimes compel) a modification of the existing treatment strategy. The first drop below the re-evaluation boundary suggests that some change in the treatment process may help, but the expected trajectory still indicated that some eventual improvement was the expected outcome for the current treatment. It certainly is plausible that early symptom exacerbation may co-occur with a new focus on sensitive or painful areas in one's life. If working through that material is a part of the effective process of therapy, an initial increase in symptoms may not necessarily bode ill for the broader course of treatment. Given that Patient B demonstrated such an early decline, it may or may not have been appropriate to continue the particular treatment without changing its aims or processes. An awareness of this pattern (by the clinician, supervisor, patient, and so on) would lead to an evaluation of its meaning.

Although the initial negative response did not necessarily indicate that the treatment was failing, Patient B did not respond to treatment well after this initial period of symptom exacerbation. Instead, his course was repeatedly poorer than expected despite a gradual adaptive lowering of those expectations. This response pattern

compels some substantial effort to find an explanation for the decline and address this cause in a revised treatment plan. This pattern clearly indicated the need for some modification of the patient's treatment regimen.

Discussion

We have described the rationale, statistical and graphic procedures, and potential benefits of an adaptive ETR method for monitoring treatment effects and prioritizing case review for outpatient psychotherapy services. With further investigation, this technique may make it possible for case managers, clinicians, and supervisors (and perhaps patients and payers) to represent treatment goals in a common language (an interpretable global outcomes instrument based on a variety of mental health goals) and to repeatedly evaluate and calibrate treatment progress using empirically based prospective criteria (Castonguay, 2000; Lutz, Martinovich, Howard, & Leon, 2002).

Adaptive Modeling Using the MHI

For treatments designed for homogeneous patient groups, such as those defined by specific diagnoses or empirically based problem clusters, one can often identify some primary symptom (e.g., panic attacks for panic disorder, depressed mood for major depression). When a single primary symptom or functioning goal can be specified, it is possible to apply the ETR method to that specific outcome component (Lueger, Lutz, & Howard, 2000; Lutz, Lowry, Kopta, Einstein, & Howard, 2001). However, we have chosen to begin at a more global level. On the basis of previous research, we used a composite mental health measure that equally weighs subjective distress, a diverse array of symptoms, and the interference of distressing symptoms with a number of life functioning areas. We did so for several reasons.

First, because particular goals change over the course of therapy and desired outcomes vary from stakeholder to stakeholder, it is difficult to find a single symptom or functioning criterion that is always relevant to evaluating progress for any one patient at all times. However, although stakeholders vary in their emphasis on particular treatment goals (e.g., employers may be primarily interested in work functioning whereas patients may be more interested in subjective well-being and symptom reduction), all have some use for a global measure reflecting these diverse but correlated interests. In addition, a high global mental health score would indicate that the therapeutic work has dealt with some rehabilitation issues (instead of just ameliorating severe subjective or symptomatic distress).

Second, a measure targeting a specific diagnosis or syndrome (although useful for research on homogeneous clinical trials samples) often fails to capture the range of treatment goals suggested by complex patient presentations in the real world. Mental health service recipients often present with comorbid diagnoses and a variety of covarying symptom and functioning problems. Although the global index is relevant to all cases and reflects the extent to which numerous covarying problems are present, it should be acknowledged that a more detailed assessment of goals specific to the individual case would be a valuable addition to the current system. As noted, however, this is a complex task, because psychotherapy goals tend to be redefined as the therapy proceeds. We present an initial attempt to tackle the complexity of such changing goals. In the future, adaptive ETR models should be modified so that they

reflect the outcome measures most relevant at the time of assessment for the individual case (Beutler, 2001).

Because the present system is intended to target the outpatient psychotherapy population more generally, monitoring a broad continuum of presenting problems is advisable. In this way, we may compare patients with each other with respect to their overall level of mental health needs and make rational judgments about resource allocation, providing more services for those in greater need and fewer services for those in less need. Although the current system does not identify the right treatment, it can be helpful in clarifying whether a treatment is or is not working. For example, in Patient B's case, at the time of this assessment, the treatment being offered did not seem to be working for this patient. At the same time, the continuous presence of distressing symptoms and functional impairment (worse than is typically found in most patients presenting for mental health services) also provided clear evidence of a need for treatment. When various stakeholders share this information, communication among those stakeholders may be improved, rational discussions concerning resource allocation may ensue, and clinical expertise may be mustered to address the most difficult cases and to find alternative treatments.

Adaptive ETR is a technique that can be carried out with various instruments. In using the MHI in this investigation, our wish was to illustrate the benefit of a theoretically derived tracking system. Other instruments addressing the same or different dimensions of improvement may yield important validation of ETR when analyzed using adaptive modeling.

The Use of Adaptive ETR Information

Several treatment characteristics may be affected by feedback to the therapist. One of these is the therapist's expectation regarding the patient's prognosis, an expectation that may carry with it some self-fulfillment. For example, it is possible that a therapist receiving feedback of a poorer prognosis will be less hopeful in making interventions, contributing in subtle ways to the poor outcome (cf. Harris, 1994). It is important to note, however, that self-fulfilling prophecies, to the degree that they take place in psychotherapy, can occur without adaptive ETR feedback. Indeed, in the absence of such feedback, therapists are likely to be using less structured and less valid information in constructing prophecies. Thus, although adaptive ETR feedback may not eliminate the occurrence of prophecies, it may make them more accurate.

Some research on the usage of ETR information has already begun. For example, a recent randomized, controlled experiment evaluating the effects of outcome feedback to therapists demonstrated that a simple, global outcome report led to longer treatments for patients who were not responding and shorter treatments for patients who were demonstrating a favorable response (Lambert, Hansen, & Finch, 2001). In this study, outcome feedback led to a more efficient use of services, with more services allocated to patients with greater mental health needs.

It is also important to consider the empirical and ethical aspects of providing adaptive ETR information to patients themselves or of withholding this information from them. On the one hand, disheartening prophecies may affect patients' commitment and involvement in therapy and may also be misinterpreted. On the other hand, patients should have a right to such information and perhaps their treatment options. Moreover, providing outcome feedback to the client would be very consistent with several treatment approaches. The extension of such a system could be adapted to several treatments and treatment modalities (e.g., individual therapy, couple therapy,

group therapy, and family therapy). It could help to support decisions about the optimal treatment or treatment modality at the beginning of treatment as well as for the treatment process (Lutz, 2002; Lutz & Grawe, 2000).

Does outcome feedback result in more efficient and more effective mental health services? We believe the answer to this question depends on a number of factors (e.g., the quantity and quality of feedback; the participation of various stakeholders, including patients, in the process; the development of a clinical culture supportive of outcomes monitoring). Given this variety of potential mediating factors, an important task for future patient-focused research is to evaluate how best to design and implement outcome feedback systems.

Repeated and adaptive ETR graphic reports represent one of many possible descriptive outcome monitoring/feedback tools. We should note that, although the sample used in these models is demographically representative, it included patients selected to have at least 14 treatment sessions (i.e., averaging 30.9 sessions and at times having as many as 52 sessions). The applicability of the system is not yet empirically investigated for patients outside this range.

Furthermore, a variety of possible improvements to the current system or alternative monitoring tools ought to be considered in future research. The possibilities for such improvements include (a) using more frequent, perhaps session-by-session, monitoring and feedback; (b) including multivariable assessments of patient progress reports; (c) developing (empirically based) verbal reports describing and interpreting changes in patient status; (d) developing specialized reports for different stakeholders; and (e) identifying unique factors associated with treatment response within a given provider, patient group, or treatment setting and developing models and reports incorporating these factors.

Summary

Whereas our previous ETR models have defined expected courses entirely on the basis of presenting characteristics, the current approach modifies expectations as therapy proceeds. Thus, the current system is more responsive to the process of psychotherapy, which often includes a redefining of treatment goals during treatment. In addition, as more and more data are acquired on an individual case, an adaptive ETR strategy yields a clearer and clearer prediction of the success or failure of the current treatment. Thus, pending further investigation, adaptive ETR models hold promise for addressing the central question of patient-focused research: Is the current treatment working for this patient?

Clearly, many questions remain open in this newly developing field of patient-focused research and should be empirically addressed (cf. Beutler, 2001; Grawe, 1998; Lambert, 2001; Lutz, 2002). For example, more research is needed to find the best fitting growth functions for specific subgroups of patients. Similarly, a more stringent strategy of data disaggregation is needed to identify the representative subsample of already treated patients appropriate for the comparison of a new patient (Krause et al., 1998; Lutz, 2002; Martinovich, 1998). Furthermore, the validity of this approach should be further evaluated by examining the probability that treatments will lead to increased success when the observed course is compared with the adaptively modified projected course. Most important, validity would be demonstrated by showing that change in treatment strategy or modality for a nonimproving patient increases the probability of a positive treatment outcome (Kordy & Percevic, 2000). Finally,

research about the implementation of such concepts into clinical practice and the negotiability of such concepts should be conducted (Barkham et al., 2001).

The ultimate goal of this research program is to develop an empirically based, rational system for clinical decision making. We hope that this system, once fully developed, will allow the use of a patient's intake information to create ETRs for the available treatments, so that clinicians can be aided in making decisions about which treatment to initiate for that particular patient (Grawe, 2002; Schulte & Eifert, 2002). Through monitoring, this system would also provide information about the patient's response to the selected treatment. If that response is adequate, the treatment should be continued; if the response indicates a high probability of treatment failure, the treatment should be modified. Although further research on this topic is necessary, we hope to have demonstrated how such an approach could be helpful to maximize patient benefit and rationalize the allocation of clinical resources.

References

American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders* (4th ed.). Washington, DC: Author.

Barkham, M., Margison, F., Leach, C., Lucock, M., Mellor-Clark, J., Evans, C., et al. (2001). Service profiling and outcomes benchmarking using CORE-OM: Toward practice-based evidence in psychological therapies. *Journal of Consulting and Clinical Psychology, 69,* 184–196.

Barkham, M., Rees, A., & Stiles, W. B. (1996). Dose-effect relations in time-unlimited psychotherapy. *Journal of Consulting and Clinical Psychology, 64,* 927–935.

Barlow, D. H. (1996). Health care policy, psychotherapy research and the future of psychotherapy. *American Psychologist, 51,* 1050–1058.

Beutler, L. (1998). Identifying empirically supported treatments: What if we didn't? *Journal of Consulting and Clinical Psychology, 66,* 113–120.

Beutler, L. (2001). Comparisons among quality assurance systems: From outcome assessment to clinical utility. *Journal of Consulting and Clinical Psychology, 69,* 197–204.

Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchical linear models: Applications and data analysis methods.* Newbury Park, CA: Sage.

Castonguay, L. G. (2000). Training in psychotherapy integration: Introduction to current efforts and future visions. *Journal of Psychotherapy Integration, 10,* 229–232.

Endicott, J., Spitzer, R. L., Fleiss, J. L., & Cohen, J. (1976). The Global Assessment Scale: Procedure for measuring overall severity of psychiatric disturbance. *Archives of General Psychiatry, 33,* 766–771.

Fishman, D. B. (1999). *The case for pragmatic psychology.* New York: New York University Press.

Fox, J. (1997). *Applied regression analysis, linear models, and related methods.* Thousand Oaks, CA: Sage.

Gibbons, R. D., Hedeker, D., Elkin, I., Waterneaux, C., Kraemer, H., Greenhouse, J. B., et al. (1993). Some conceptual and statistical issues in analysis of longitudinal psychiatric data. *Archives of General Psychiatry, 50,* 739–750.

Goldfried, M. R., & Wolfe, B. E. (1998). Toward a more clinically valid approach to therapy research. *Journal of Consulting and Clinical Psychology, 66,* 143–150.

Grawe, K. (1998). Research-informed psychotherapy. *Psychotherapy Research, 7,* 1–19.

Grawe, K. (2002). *Psychological therapy.* Seattle, WA: Hogrefe.

Harris, M. J. (1994). Self-fulfilling prophecies in the clinical context: Review and implications for clinical practice. *Applied & Preventive Psychology, 3,* 145–158.

Horowitz, L. M., Rosenberg, S. E., Baer, B. A., Ureño, G., & Villaseñor, V. S. (1988). Inventory of interpersonal problems: Psychometric properties and clinical applications. *Journal of Consulting and Clinical Psychology, 56,* 885–892.

Howard, K. I., Brill, P. L., Lueger, R. J., O'Mahoney, M. T., & Grissom, G. R. (1995). *Integrating outpatient tracking assessment.* Philadelphia: Compass Information Services, Inc.

Howard, K. I., Kopta, S. M, Krause, M. S., & Orlinsky, D. E. (1986). The dose–response relationship in psychotherapy. *American Psychologist, 41,* 159–164.

Howard, K. I., Krause, M. S., & Vessey, J. (1994). Analysis of clinical trial data: The problem of outcome overlap. *Psychotherapy, 31,* 302–307.

Howard, K. I., Lueger, R. J., Maling, M. S., & Martinovich, Z. (1993). A phase model of psychotherapy: Causal mediation of outcome. *Jour-*

nal of Consulting and Clinical Psychology, 61, 678–685.

Howard, K. I., Moras, K., Brill, P. L., Martinovich, Z., & Lutz, W. (1996). The evaluation of psychotherapy: Efficacy, effectiveness, and patient progress. *American Psychologist, 51,* 1059–1064.

Jacobson, N. S., & Truax, P. (1991). Clinical significance: A statistical approach to defining meaningful change in psychotherapy research. *Journal of Consulting and Clinical Psychology, 59,* 12–19.

Kopta, S. M., Howard, K. I., Lowry, J. L., & Beutler, L. E. (1994). Patterns of symptomatic recovery in time-unlimited psychotherapy. *Journal of Clinical and Consulting Psychology, 62,* 1009–1016.

Kopta, S. M., Lueger, R. J., Saunders, S. M., & Howard, K. I. (1999). Individual psychotherapy outcome and process research: Challenges leading to greater turmoil or a positive transition. *Annual Review of Psychology, 50,* 441–469.

Kordy, H., Hannöver, W., & Richard, M. (2001). Computer-assisted feedback-driven quality management for psychotherapy: The Stuttgart-Heidelberg model. *Journal of Consulting and Clinical Psychology, 69,* 173–183.

Kordy, H., & Percevic, R. (2000, June). *Means for the optimization of psychotherapy provision: Early treatment response–Conceptualization, operationalization, and validation.* Paper presented at the 31st Annual International Meeting of the Society for Psychotherapy Research, Chicago.

Krause, M. S., Howard, K. I., & Lutz, W. (1998). Exploring individual change. *Journal of Consulting and Clinical Psychology, 66,* 838–845.

Lambert, M. J. (1998). Manual-based treatment and clinical practice: Hangman of life or promising development? *Clinical Psychology, Science and Practice, 5,* 391–395.

Lambert, M. J. (2001). Psychotherapy outcome and quality improvement: Introduction to the special section on patient-focused research. *Journal of Consulting and Clinical Psychology, 69,* 147–149.

Lambert, M. J., Hansen, N. B., & Finch, A. E. (2001). Patient-focused research: Using patient outcome data to enhance treatment effects. *Journal of Consulting and Clinical Psychology, 69,* 159–172.

Lueger, R. J., Howard, K. I., Martinovich, Z., Lutz, W., Anderson, E., & Grissom, G. (2001). Assessing treatment progress with individualized models of predicted response. *Journal of Consulting and Clinical Psychology, 69,* 150–158.

Lueger, R. J., Lutz, W., & Howard, K. I. (2000). The predicted and observed course of psychotherapy for anxiety and mood disorders. *Journal of Nervous and Mental Disease, 188,* 127–134.

Lutz, W. (2002). Patient-focused psychotherapy research and individual treatment progress as scientific groundwork for an empirically based clinical practice. *Psychotherapy Research.*

Lutz, W., & Grawe, K. (2000, June). *Adaptive treatment response models in individual-, couple-, group- or mixed settings.* Paper presented at the 31st Annual International Meeting of the Society for Psychotherapy Research, Chicago.

Lutz, W., Lowry, J., Kopta, M., Einstein, A. D., & Howard, K. I. (2001). Prediction of dose–response relations based on patient characteristics. *Journal of Clinical Psychology, 57,* 889–900.

Lutz, W., Martinovich, Z., & Howard, K. I. (1999). Patient profiling: An application of random coefficient regression models to depicting the response of a patient to outpatient psychotherapy. *Journal of Consulting and Clinical Psychology, 67,* 571–577.

Lutz, W., Martinovich, Z., Howard, K. I., & Leon, S. C. (2002). Outcomes management, expected treatment response and severity adjusted provider profiling in outpatient psychotherapy. *Journal of Clinical Psychology, 58,* 1291–1304.

Lyons, J. S., & Howard, K. I. (1991). Main effects analysis in clinical research: Statistical guidelines for disaggregating treatment groups. *Journal of Consulting and Clinical Psychology, 59,* 745–748.

Maling, M. S., Gurtman, M. B., & Howard, K. I. (1995). The response of interpersonal problems to varying doses of psychotherapy. *Psychotherapy Research, 5,* 63–75.

Martinovich, Z. (1998). *Evaluating a phase model of psychotherapy outcome: An application of hierarchical logistic modeling.* Unpublished doctoral dissertation, Northwestern University.

Martinovich, Z., Howard, K. I., & Saunders, S. (1996). Some comments on "assessing clinical significance." *Psychotherapy Research, 6,* 124–132.

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied linear statistical models.* Boston: McGraw-Hill.

Newman, F. L., & Tejeda, M. J. (1996). The need for research that is designed to support decisions in the delivery of mental health services. *American Psychologist, 51,* 1040–1049.

Orlinsky, D. E., Grawe, K., & Parks, B. K. (1994). Process and outcome in psychotherapy–noch einmal. In A. E. Bergin & S. L. Garfield (Eds.), *Handbook of psychotherapy and behavior change* (pp. 270–376). New York: Wiley.

Pilkonis, P. A., & Frank, E. (1988). Personality pathology in recurrent depression: Nature, prevalence, and relationship to treatment response. *American Journal of Psychiatry, 145,* 435–441.

Raudenbush, S. W. (2001). Comparing personal trajectories and drawing causal inferences from longitudinal data. *Annual Review of Psychology, 52,* 501–525.

Schulte, D. (1995). How treatment success could be assessed. *Psychotherapy Research, 5,* 281–296.

Schulte, D., & Eifert, G. H. (2002). What to do when manuals fail? The dual model of psychotherapy. *Clinical Psychology: Science and Practice, 9,* 312–328.

Seligman, M. E. (1995). The effectiveness of psychotherapy: The *Consumer Reports* study. *American Psychologist, 50,* 965–974.

Sperry, L., Brill, P., Howard, K. I., & Grissom, G. (1996). *Treatment outcomes in psychotherapy and psychiatric interventions.* New York: Brunner/Mazel.

Strupp, H. H. (1996). Some salient lessons from research and practice. *Psychotherapy, 33,* 135–138.

Vessey, J. T., & Howard, K. I. (1993). Who seeks psychotherapy? *Psychotherapy, 30,* 546–553.

Zusammenfassung

Alle professionellen Dienstleistungen erfordern adaptive Entscheidungen, d.h. Modifikationen, die auf diagnostischen Ergebnissen in einem fortlaufenden Beurteilungsprozess, gemäss der ereichten Ziele, basiert sind. Bei klinischen Dienstleistungen kann 'Ergebnismonitoring', d.h. die wiederholte Beurteilung der Reaktion eines Patienten auf die Behandlung und die Revision von Zielerwartungen aufgrund der beobachteten Reaktion auf die Behandlung, zu dieser Form der adaptiven Entscheidungsfindung benutzt werden. Die Autoren beschreiben ein Modell zur Bestimmung des erwarteten Behandlungserfolges von Patienten, das auf Informationen, die während der Behandlung gewonnen wurden, beruht. In der Diskussion gehen sie darauf ein, wie diese Informationen für klinische Entscheidungen in bezug auf die Therapieform und ihre eventuelle Modifikation benutzt werden kann.

Résumé

Tous les services professionnels nécessitent une prise de décisions adéquate, à savoir, des modifications basées sur la configuration diagnostique et sur l'évaluation continue du progrès ou de l'atteinte des objectifs. Dans l'offre de services cliniques, le monitoring des résultats (c-à-d, des évaluations répétées de la réponse au traitement d'un patient et de révisions récurrentes des résultats attendus, basées sur la réponse au traitement observée) peut être utilisé pour étayer ce type de prise de décision adaptative. Les auteurs présentent un modèle pour déterminer la réponse au traitement attendue d'un patient basé sur les caractéristiques de présentation et sur des informations assemblées au cours du traitement. Ils discutent également de quelle façon cette information pourrait être utilisée pour étayer des décisions cliniques au sujet du choix et de la modification du traitement.

Resumen

Todos los servicios profesionales requieren decisiones adaptativas, esto es, modificaciones basadas en diagnósticos y en evaluaciones del progreso o del cumplimiento de objetivos. En la prestación de servicios clínicos, se pueden utilizar monitoreos de resultados (esto es, evaluaciones repetidas de la respuesta del paciente al tratamiento y revisiones repetidas de las expectativas de rendimiento basadas en la respuesta observada al tratamiento) para apoyar esta toma de decisión adaptativa. Los autores describen un modelo para determinar la respuesta esperada al tratamiento de un paciente basada en la presentación de características iniciales y en la información obtenida durante el curso del tratamiento. También discuten cómo podría utilizarse esta información para avalar decisiones clínicas referentes a la selección y modificación del tratamiento.

Resumo

Todos os profissionais necessitam de tomar decisões adaptativas, isto é, modificações baseadas em configurações de diagnóstico e avaliações contínuas do progresso ou em função de objectivos atingidos. Na prestação de serviços clínicos, a monitorização dos resultados (i.e., avaliações repetidas das respostas dos pacientes ao tratamento e revisões recorrentes das expectativas de resultados baseadas nas respostas ao tratamento observadas) pode ser utilizada para apoiar este tipo de tomada de decisão adaptativa. Os autores descrevem um modelo para determinar as respostas esperadas ao tratamento de um paciente

baseadas nas suas características iniciais e informação recolhida durante o tratamento. Também discutem como esta informação pode ser utilizada para apoiar a decisão clínica relativa à selecção e modificação do tratamento.

Sommario

Tutti i sevizi professionali richiedono un processo decisionale adattativo, ovvero, modifiche basate sulla configurazione diagnostica e sulla valutazione in corso dei progressi fatti per raggiungere gli obiettivi preposti, o del raggiungimento degli obiettivi stessi. Nella fornitura dei servizi clinici, il monitoraggio degli esiti (valutazioni ripetute della risposta al trattamento da parte del paziente e revisioni ricorrenti delle aspettative sull'esito, in base alla risposta al trattamento osservato) può essere utilizzato per avallare questo tipo di processo decisionale adattativo. Gli autori descrivono un modello per determinare la risposta attesa di un paziente al trattamento, in base alle caratteristiche particolari e alle informazioni raccolte durante l'arco del trattamento. Essi trattano, inoltre, il modo in cui queste informazioni possono essere utilizzate per sostenere decisioni cliniche relative alla selezione e modifica del trattamento.