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Relationship to CBT outcome and dropout of decision support tools of the written case formulation, list of treatment goals and plot of symptom scores

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ABSTRACT

Many patients who receive cognitive behavior therapy (CBT) for mood and anxiety disorders fail to respond or drop out of treatment. We tested the hypotheses that therapist use of each of three decision support tools, a *written case formulation*, a *list of treatment goals*, and a *plot of symptom scores*, was associated with improved outcome and reduced dropout in naturalistic CBT provided to 845 patients in a private practice setting. We conducted regression analyses to test the hypotheses that the presence of each tool in the clinical record was associated with lower end-of-treatment scores on the Beck Depression Inventory (BDI) and the Burns Anxiety Inventory (BurnsAI), and lower rates of premature and uncollaborative dropout. We found that the presence of a *written case formulation* in the clinical record was associated with lower rates of both types of dropout. A *list of treatment goals* was associated with lower end-of-treatment scores on the BDI and the BurnsAI, and a lower rate of uncollaborative but a higher rate of premature dropout. A *plot of symptom scores* was associated with lower end-of-treatment scores on the BDI, and lower rates of both types of dropout. Results suggest that therapist use of a written case formulation, list of treatment goals, and a plot of symptom scores can contribute to improved outcome and reduced dropout in CBT.

Despite its strong evidence base, many patients who receive cognitive behavior therapy (CBT) for mood and anxiety and related disorders fail to respond to it. For example, Cuipers et al. (2014) reported that response rates of empirically-supported treatments for major depressive disorder ranged from 44% to 53%. In addition, many patients terminate treatment prematurely and thus fail to receive a full dose of treatment. Fernandez et al. (2015), in a meta-analysis, reported that more than 25% of patients dropped out of cognitive behavioral therapy (CBT).

Clinicians who use the methods of evidence-based practice rely on a range of strategies and decision support tools to guide decision-making and solve problems that can otherwise lead to nonresponse and dropout (American Psychological Association, 2006). First, clinicians of all theoretical orientations view the *case formulation* as a key tool (Eells, 2007). The case formulation describes the factors that appear to cause and maintain a particular patient's particular symptoms and problems, and it thus identifies the treatment targets and guides the therapist's efforts to overcome problems that can arise in treatment. Despite its importance to practitioners, the case formulation is under-studied, and we have little information about the relationship of the case formulation to outcome and dropout (Persons & Hong, 2016). Second, cognitive behavioral therapists develop with their patients an agreed-upon *list of treatment goals*. The list of treatment goals individualizes the treatment and focuses it on concrete, specific, achievable objectives. A shared list of goals is considered to be part of the therapeutic alliance (Bordin, 1994), and we know that the alliance is related to both outcome (Horvath et al., 2011) and dropout (Roos, J. & Werbart, A., 2013), but we don't know whether the strategy of writing down a list of the patient's concrete, specific treatment goals and using them to guide treatment affects outcome and dropout.

Third, evidence-based practitioners rely on a *plot of symptom scores*. The patient completes a symptom scale before the session, and the therapist and patient together review the plot showing the trajectory of scores and use it to guide decision-making. A recent review showed that measurement-based care, defined as "the systematic evaluation of patient symptoms before or during each clinical encounter to inform behavioral health treatment" leads to improved psychotherapy outcome (Lewis et al., 2018). But only one of the samples that Lewis et al. reviewed were American samples of outpatients with mood and anxiety disorders (Hawkins et al., 2004). All three of these tools (the case formulation, the list of treatment goals, and progress monitoring data)

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represent elements of evidence-based practice as defined by the American Psychological Association (2006), and appear in widely-used clinical manuals (J. S. Beck, 1995; Eells, 2007; Persons, 2008), but little is known about their contribution to outcome and dropout in routine clinical practice. More empirical support is needed for these tools that are widely viewed as core elements of evidence-based practice.

To address this gap in the literature, we tested the hypotheses that therapist use of each of the decision support tools of the *written case formulation*, *list of treatment goals*, and *plot of symptom scores* were associated with improved outcome and reduced dropout in a large sample of patients who received naturalistic cognitive behavior therapy (CBT) for symptoms of depression and anxiety in a private practice setting. We studied outcome as defined by scores on two symptom measures at the end of treatment: the Beck Depression Inventory and the Burns Anxiety Inventory. We studied dropout as defined in two ways. We studied *premature dropout*, defined as ending treatment before, in the therapist's judgment, the treatment has been tried for long enough to help the patient accomplish their treatment goals, and *uncollaborative dropout*, defined as ending treatment against the therapist's advice or without discussing the termination with the therapist. We predicted that the presence in the clinical record of a *written case formulation*, a *list of treatment goals*, and a *plot of scores on a measure of depression or anxiety* would be associated with improved outcome and reduced premature and uncollaborative dropout.

1. Method

1.1. Participants

Participants were 845 adults who received individual naturalistic cognitive behavior therapy during the years 1981–2009 from the second author or one of 20 therapists at the group private practice she established in 1995. All participants gave written consent for data from their clinical record to be used for research purposes. The procedures used to establish and maintain the Persons Archival Database we studied in this investigation were reviewed and approved by the Behavioral Health Research Collective Institutional Review Board. The Persons Archival Database is a completely de-identified database, and no master code list links the data in the database to the names of the patients in the database.

Patients in the sample had an average age of 36.2 years (SD = 12.3) and had completed an average of 16.6 years (SD = 2.6) of education. Patients identified as 58.6% female and 41.2% male; 0.2% were of unspecified gender. 80.9% patients were Caucasian, 2.5% were African American, 2.6% were Hispanic, 6.3% were Asian, 1.9% were of other ethnicity, and 5.8% were of unspecified ethnicity. 20.0% of patients received adjunctive psychosocial treatment (e.g., group therapy or couple therapy), 63.2% did not, and 16.8% were unspecified. 50.7% of patients received adjunctive pharmacotherapy, while 38.1% did not, and 11.1% were unspecified. 86.4% of patients had an anxiety or depressive disorder or both. Diagnoses were assigned by the treating therapist based on the most current version of the Diagnostic and Statistical Manual of Mental Disorders at the time the patient was treated. Patients were treated by one of twenty therapists.[1]

The 845 patients studied here were drawn from a database of 1469 adult patients. Patients were excluded from the larger sample if they had incorrect or missing data describing how many total sessions they completed (n = 14) or sought consultation only, not treatment (n = 24). Most importantly, patients were excluded if they had fewer than three sessions in the database (n = 586). We excluded these cases so that the computations required to carry out the multiple imputation strategy we used to interpolate missing data could be carried out in a reasonable length of time, and so we could use the same patient sample for all data analyses we conducted. If patients completed more than one course of treatment, only the first course was analyzed to simplify analysis.

1.2. Treatment

Treatment consisted of individual cognitive behavior therapy (CBT), typically provided weekly and based on a case formulation-driven mode of treatment (Persons, 1989, 2008). The case formulation-driven mode of treatment called for the therapist to develop, with the patient, an individualized formulation of the case and a written list of treatment goals, to make a plot in each session of scores on symptoms relevant to the patient's treatment goals, and to use these three tools to guide decision-making in therapy. However, therapists worked in a group private practice, not a clinic, and there was no policy or requirement in the practice that clinicians use these decision support tools, and thus therapists made their own decisions about use of the tools. The most common symptom measures used by the therapists in the practice were the Beck Depression Inventory and the Burns Anxiety Inventory, and therefore we selected those two scales as our outcome measures for this study. Treatment was naturalistic because it did not depend on a protocol that described a pre-determined number and frequency of sessions, and it allowed the therapist to make adjustments in the treatment (e.g., increasing session frequency or adding adjunctive psychosocial treatment, such as couple therapy, or adjunctive pharmacotherapy) based on the results of the progress monitoring data and other factors (e.g., the patient's preference). Treatment was open-ended in duration and ended ideally when patient and therapist agreed that the patient had reached the patient's goals but sometimes ended for other reasons (e.g., the patient moved, the therapist left the practice, the patient felt they had accomplished all that could be done in the therapy, or the patient ended treatment against the therapist's advice). Most therapists were Ph.D. psychologists; one was an L.C. S.W. The mean (and standard deviation) of the length of treatment in days was 286.0 (SD = 573.9), and the number of sessions was 24.0 (SD = 32.7).

1.3. Measures

Symptoms of depression. We assessed symptoms of depression with the original version of the Beck Depression Inventory (A. T. Beck et al., 1961). The BDI is a widely-used, 21-item self-report measure of the severity of depressive symptoms that has been shown to have good internal consistency ($\alpha = 0.86$ for psychiatric patients) and good convergence with other measures of depressive symptoms (A. T. Beck et al., 1988). Total score could range from 0 to 63.

Symptoms of anxiety. We assessed symptoms of anxiety with the Burns Anxiety Inventory (BurnsAI), a 33-item self-report inventory measuring 6 anxious feelings (e.g., anxiety, nervousness, worry or fear), 11 anxious thoughts (e.g., feeling that you're on the verge of losing control) and 16 physical symptoms (e.g., a lump in the throat). Each symptom was rated on a 0 to 3 scale ranging from 0 (not at all) to 3 (a lot). Total score could range from 0 to 99. Burns and Eidelson (1998) reported, in a sample of 483 outpatients, that the BurnsAI had a Cronbach's alpha of 0.94, indicating high internal consistency, and it was correlated 0.86 ($p < 0.001$) with the Anxiety subscale of the Symptom Check List-90 (Derogatis et al., 1976). We used the BurnsAI because it covered the full range of anxious symptoms we observed in our patients, its classification of anxiety symptoms as feelings, thoughts, or physical symptoms was clinically helpful, and it was sensitive to change.

Premature dropout. Premature dropout was coded as present (a score of 1) when, after treatment ended and the database was being

[1] Of the 845 patients, 2 were seen by Therapist 1; 107 by Therapist 2; 23 by Therapist 3; 20 by Therapist 4; 3 by Therapist 5; 25 by Therapist 6; 2 by Therapist 7; 1 by Therapist 8; 70 by Therapist 9; 54 by Therapist 10; 16 by Therapist 11; 16 by Therapist 12; 3 by Therapist 13; 315 by Therapist 14 (last author); 28 by Therapist 15; 66 by Therapist 16; 3 by Therapist 17; 42 by Therapist 18; 12 by Therapist 19; 36 by Therapist 20; and 1 by an unspecified therapist.

assembled, the patient's therapist answered "no" to the question: "Has the therapy been given a fair shake/tried for long enough to help patient accomplish their treatment goals?" Reasons for the therapist's judgment that termination was premature varied widely from case to case depending on the patient's treatment goals.

Uncollaborative dropout. Uncollaborative dropout was coded as present (a score of 1), when, after treatment ended and the database was being assembled, the patient's therapist answered "no" to the question: "Did the patient and therapist work well together on the termination, agree on it and discuss it fully?" The termination was coded as uncollaborative, for example, if the patient ended treatment by simply cancelling a session and never rescheduling it.

Premature and uncollaborative dropout were not mutually exclusive, and each patient received a score of 1 (yes) or 0 (no) for each type of dropout.

Therapist use of decision support tools: written case formulation, list of treatment goals, and plot. To assess therapist use of the decision support tools of case formulation-driven CBT, the therapist reviewed each patient's clinical record after treatment had ended, and coded each tool (written case formulation, list of treatment goals, or plot of behavior or symptoms) 1 if it was present, and 0 if it was not present. Therapists used a coding manual to make these coding decisions. The coding manual called for a code of 1 on the *case formulation* item "if there was a written case formulation of any quality in the chart, and 0 otherwise. This should be a written formulation of the case, not just a brief mini-formulation, e.g., a Thought Record or diagram of a panic cycle." The coding manual called for a code of 1 on the *list of treatment goals* if "the goals or objectives of treatment are stated in the clinical chart prior to the termination note. . . . This is not the goals/objectives for what the patient wants to accomplish between one session and another but must be the Goals or Objectives of *treatment*. The word 'Goals' or 'Objectives' must appear, and there should be a list, except in rare cases where there is a single goal. It is not sufficient to state, 'The patient seeks treatment to work on OCD symptoms,' or similar." *Plot* was coded 1 if a plot of scores on the Beck Depression Inventory or Burns Anxiety Inventory appeared in the chart with at least one score entered on the plot, and 0 otherwise.

1.4. Data analysis

We tested the hypotheses that the presence in the clinical record of the three decision support tools (case formulation, treatment goals, and plot), was associated with lower end-of-treatment scores on the Beck Depression Inventory and Burns Anxiety Inventory, and reduced likelihood of premature and uncollaborative dropout. We conducted a linear regression to predict each outcome variable (end-of-treatment symptom scores on the Beck Depression Inventory (BDI) and the Burns Anxiety Inventory (BurnsAI)), and we conducted a logistic regression to predict each dropout variable (premature and uncollaborative dropout). In each analysis, the independent variables were the three decision support tools (coded 0/1 to indicate whether the tool was present in the clinical record), the number of sessions the patient spent in therapy, and the identity of the patient's therapist. In the analyses of end-of-treatment BDI and BurnsAI scores, we also controlled for the patient's score on the measure in the first session. We included all the decision support tools in the regressions in order to examine the effect of each tool on outcome and dropout while controlling for the contributions of the other tools.

To control for therapist identity, we included therapist as a variable in the regression analyses. Thus, our analyses examined the relationship between the decision tools and outcome/dropout *within each therapist's caseload*. To enter therapist identity into the regressions, we created one dummy-coded categorical variable (coded 0–1) for each of the 20 therapists. Rather than report effects for each individual therapist, we reported a cumulative result of the effect of therapist identity on the dependent variable. To do that, for each regression analysis, we compared two nested models, one including the therapist variable and one without the therapist variable. We computed the *p*-value using the F distribution for each regression to determine whether the larger model that included the therapist variable was statistically significantly different from the smaller model that did not include the therapist variable.

We handled the therapist variable as a fixed effect rather than a random effect. Our rationale for this decision was two-fold. Random-effects and fixed-effects models usually give similar results, and random-effects models require making an assumption (Gardiner et al., 2009) that we did not believe was justified, the assumption that therapist effects are uncorrelated with therapist propensity to use the decision support tools we are studying.

As an additional aid to understanding the relationship between the decision support tools and the dropout variables, we computed a measure of correlation between each independent variable and each dropout variable, the Jaccard similarity coefficient (Jaccard index). The Jaccard index ranges from 0 to 1, with 1 indicating maximal similarity.

Effect size. Because our sample size was so large, very small effects could be statistically significant. Therefore, we calculated effect sizes. In the linear regressions examining the relationship between the tools and outcome, we used the change in adjusted R^2 (designated as ΔR^2) as an effect size. Adjusted R^2, the coefficient of determination adjusted for the number of variables, is a statistical measure of how much variance a regression model explains. We calculated the ΔR^2 by subtracting the adjusted R^2 of a regression model that omitted the variable of interest (case formulation, treatment goals, or plot) from the adjusted R^2 of the model that included the variable of interest.

In the logistic regressions examining the relationship between the tools and dropout, we used the odds ratio ($e^{\text{Est.}}$) as an effect size. The odds ratio describes the relative odds of the dependent variable (premature or uncollaborative dropout) occurring given the inclusion of the specified independent variable. We are most interested in the odds ratio ($e^{\text{Est.}}$) for each decision support tool parameter of the regressions, which indicates the estimated odds of a premature/uncollaborative dropout by a patient whose clinical record has the decision support tool (case formulation, list of treatment goals, or plot) as compared to the odds of dropout by a patient whose chart does not have the decision support tool. To increase the interpretability of the odds ratio, we converted the odds ratio to a relative risk ratio for a baseline risk level, using as the baseline risk level the percentage of patients in our sample who dropped out prematurely or uncollaboratively.

We carried out the analyses using R Core Team (2018) and Python (Python Software Foundation, n.d.), using Jupyter Notebooks (Project Jupyter, n.d.), and used the packages Amelia II (Honaker et al., 2012) and Zelig (R Core Team, 2007) to conduct the multiple imputations analyses.

2. Results

2.1. Preliminary analyses

Missing data. Our dataset contained 845 patients with 15987 sessions of data. 104 patients (12.3%) were missing data about case formulation, 100 patients (11.8%) were missing data about treatment goals, and 88 patients (10.4%) were missing data about plot. 70 patients (8.3%) did not have any BDI scores, and 8427 sessions (52.7%) did not have a BDI score. 177 patients (20.9%) did not have any BurnsAI scores, and 10,357 sessions (64.8%) did not have a BurnsAI score. 91 patients (10.8%) were missing data about premature dropout, and 83 patients (9.8%) were missing data about uncollaborative dropout. Data about the decision support tools and dropout were missing when we were unable to interview the treating therapist to obtain this information. BDI and Burns AI scores were missing when we could not locate the medical record or when the therapist did not monitor outcome with a symptom scale or selected another measure (e.g., the YBOCS or a daily log of skin-picking behavior) to monitor outcome.

Multiple imputation. To handle missing data, we used the statistical technique of multiple imputation (Enders, 2017). In this approach, missing data were estimated from existing data multiple times (multiple "imputations") with some degree of randomness, and these multiple estimates were pooled for a final result. By averaging multiple randomized imputations, we can incorporate the variance of estimated values, so that estimates that the system has low confidence in will have high variance, and estimates that are highly supported by the existing data will have low variance. This strategy reduces bias in the estimated values. We used the package Amelia II (Honaker et al., 2012) to carry out the imputations. We computed five imputations. To improve our imputed values, we incorporated our data's structure into the imputation model. Specifically, we modeled our data as time series within patient cross-sections, meaning we assumed that patients' values would vary over time, and that each patient could have a different starting point and rate of change. Amelia II modeled patients' patterns by computing first-order polynomial regressions for each patient, using session number to represent time. We included the following as variables for each patient: number of sessions in treatment, number of days in treatment, age, number of years of education, gender, ethnicity, whether adjunctive pharmacotherapy was provided, whether adjunctive psychosocial treatment was provided, whether they had a depression-related diagnosis, whether they had an anxiety-related diagnosis, the identity of their therapist (numerically coded), whether they had a written case formulation in their chart, whether they had a list of treatment goals in their chart, whether they had a plot of symptom scores in their chart, whether they were coded as a premature dropout, whether they were coded as an uncollaborative dropout, and their BDI and BurnsAI scores for each session. Imputed BDI and BurnsAI scores were lower-bounded at 0 and upper-bounded at the maximum score for each measure, and the number of sessions, days in treatment, age, and years of education were lower-bounded at 0, 0, 18 and 0 respectively. All missing data for these variables were imputed. Final BDI and BurnsAI scores were determined after this multiple imputation analysis. To speed up computation, we used a ridge prior that was set to 10% of the total number of sessions (for details on Amelia II's statistical options, including ridge priors, see Honaker et al. (2012)).

Reliability of coding for therapist decision support tools: written case formulation, list of treatment goals, and plot. To evaluate the inter-rater reliability of coding of the clinical record for presence of a written case formulation, a list of treatment goals, and a plot of symptom data, we conducted a small study of clinical records of 20 patients treated by the last author during the years 2008–2020. These records were randomly selected from a larger database the last author has collected. Patients gave consent for use of their records for research purposes, and this study was reviewed by the IRB of the Behavioral Health Research Collective. We were unable to conduct this study using the data from the Persons Archival Database used in the present study because no master code list exists to link the patient clinical record to the data in the Persons Archival Database. Two authors (R.C. and J.B.P.) rated each of the 20 clinical records using the same coding manual (described on page 9) that therapists used to rate these variables in the Persons Archival Database. The two therapists showed nearly perfect agreement on ratings of the presence in the clinical record of all three decision support tools: a written case formulation, a list of treatment goals, and a plot of symptom data. The clinicians agreed on 19 of 20 ratings of a written case formulation, 19 of 20 ratings of a list of treatment goals, and 20 of 20 ratings of a plot of progress monitoring data, indicating that the presence in the clinical record of the decision support tools in the clinical record can be reliably rated.

Therapist use of the decision support tools. We had data about the presence of a written case formulation (present or absent) for 741 participants; of those 741 cases, 581 (78%) had a written case formulation in the chart. We had data for 745 participants about the presence of a list of treatment goals; of those 745 cases, 505 (68%) had a list of treatment goals in the chart. We had data for 757 participants about the presence of a plot of BDI or BurnsAI data; of those 757 cases, 424 (56%) had a plot in the chart.

Patient outcome. Table 1 presents imputed scores on the Beck Depression Inventory and Burns Anxiety Inventory for all patients, and for patients whose charts did and did not include a case formulation, list of treatment goals, and plot. (The equivalent information for the original data, before the multiple imputation procedure, is presented in Supplementary Table 1.)

Patient dropout. We had data on premature dropout for 754 patients; of those, 394 (52%) were premature dropouts. We had data on uncollaborative dropout for 762 patients; of those, 231 (30%) were uncollaborative dropouts. These percentages were used as "baseline risk" estimates for the relative risk ratio calculations for each type of dropout.

2.2. *The effect of decision support tools on outcome and dropout*

We hypothesized that the presence in the clinical record of decision support tools of case formulation, treatment goals, and plot would be associated with reduced end-of-treatment BDI and BurnsAI scores, and reduced premature and uncollaborative dropout. To test our hypotheses about end-of-treatment BDI and BurnsAI scores, we conducted a linear regression for each symptom score, where the dependent variable was the end-of-treatment score on the symptom measure, and the independent variables were the three decision support tools (coded as present or absent), the initial score on the symptom measure, the identity of the therapist, and the total number of sessions of treatment. To test our hypotheses about dropout, we conducted a logistic regression for each type of dropout, where the dependent variable was premature or uncollaborative dropout, and the independent variables were the decision support tools (coded as present or absent), the identity of the therapist, and the total number of sessions of treatment. We multiplied all p values by four to Bonferroni-correct for the number of regression analyses. Table 2 reports the results of these regressions. We examine results for outcome and dropout in turn.

Outcome. First we examine the degree to which the presence of the decision support tools in the clinical record was related to improved patient outcome on the Beck Depression Inventory (Table 2). We found that Treatment Goals ($\beta = -1.4, p = 0.007$) and Plot ($\beta = -1.6, p = 0.04$) but not Case Formulation ($\beta = -0.6$, $p = 0.6$) were statistically significant predictors of end-of-treatment Beck Depression Inventory (all p

Table 1
Estimated means and standard deviations (S.D.) of initial and final outcome scores of subcategories of patients, after multiple imputation replaced missing data. Lower scores indicate fewer symptoms.

n = 845	Beck Depression Inventory		Burns Anxiety Inventory	
	Initial Score	Final Score	Initial Score	Final Score
	Mean ± S.D.	Mean ± S.D.	Mean ± S.D.	Mean ± S.D.
All Patients	17.45 ± 8.89	12.03 ± 9.02	28.79 ± 15.61	19.98 ± 14.62
Sorted by Tool				
Case Formulation				
Present	17.16 ± 8.41	11.66 ± 8.68	28.55 ± 15.58	19.73 ± 14.52
Absent	18.53 ± 10.41	13.35 ± 10.08	29.65 ± 15.73	20.89 ± 14.98
Treatment Goals				
Present	17.22 ± 8.64	11.48 ± 8.72	28.36 ± 15.84	18.62 ± 14.42
Absent	17.93 ± 9.37	13.16 ± 9.54	29.65 ± 15.12	22.77 ± 14.64
Plot				
Present	18.21 ± 8.87	12.01 ± 9.00	29.96 ± 15.52	19.64 ± 14.48
Absent	16.48 ± 8.83	12.04 ± 9.07	27.29 ± 15.62	20.41 ± 14.80

Table 2

Parameter estimates for linear and logistic regression models predicting outcome and dropout from the decision support tools of a written case formulation, list of treatment goals, and plot of symptom scores.

n = 845	Beck Depression Inventory Est. ± S.E.	ΔR^2	*p*	Burns Anxiety Inventory Est. ± S.E.	ΔR^2	*p*	Premature Est. ± S.E.	$e^{Est.}$	*p*	Uncollaborative Est. ± S.E.	$e^{Est.}$	*p*
Intercept	−2.5 ± 2.7		1.4	5.3 ± 7.3		1.9	2.8 ± 0.6		0	1.3 ± 0.3		4e-4
Case Formulation	−0.6 ± 0.4	4e-4	0.6	0.09 ± 1.8	9e-4	3.8	−0.5 ± 0.08	0.6	0	−0.3 ± 0.07	0.8	4e-4
Treatment Goals	−1.4 ± 0.4	0.005	7e-3	−4.2 ± 1.6	0.02	0.04	0.3 ± 0.05	1.3	0	−0.4 ± 0.05	0.7	0
Plot	−1.6 ± 0.6	0.007	0.04	−3.4 ± 1.5	0.01	0.09	−0.4 ± 0.05	0.7	0	−0.6 ± 0.05	0.5	0
Total # Sessions	4e-4 ± 0.007		3.8	−0.001 ± 0.01		3.8	−0.01 ± 6e-4		0	−0.002 ± 3e-4		0
Initial Score	0.3 ± 0.04		0	0.3 ± 0.02		0						
Therapist	*F*(19,76.3) = 8.3		0	*F*(19,76.1) = 3.9		0	*F*(19,10901.4) = 85.8		0	*F*(19,463.4) = 20.5		0

Note. All *p*-values were Bonferroni-corrected for the number of regression analyses. A *p*-value of 0 represents significance at <0.0001. ΔR^2 signifies the difference between adjusted R^2 for the full regression model, and adjusted R^2 for the regression model without the decision support tool. $e^{Est.}$ is the odds ratio. Both ΔR^2 and $e^{Est.}$ are effect size measures. Reported ΔR^2 are means over the five imputations; means ± standard errors across imputations are as follows: Case formulation/BDI: 4e-4 ± 1e-4; Treatment Goals/BDI: 0.0047 ± 0.0013; Plot/BDI: 0.0068 ± 0.0019; Case formulation/BurnsAI: 9e-4 ± 5e-4; Treatment Goals/BurnsAI: 0.017 ± 0.0053; Plot/BurnsAI: 0.0113 ± 0.0038. Confidence intervals around odds ratios are as follows: Case formulation/Premature Dropout: 0.58, CI = [0.50,0.67]; Treatment Goals/Premature Dropout: 1.31, CI = [1.19,1.44]; Plot/Premature Dropout: 0.66, CI = [0.60,0.72]; Case formulation/Uncollaborative Dropout: 0.76, CI = [0.67,0.87]; Treatment Goals/Uncollaborative Dropout: 0.70, CI = [0.63,0.77]; Plot/Uncollaborative Dropout: 0.53, CI = [0.48,0.59].

values are Bonferroni-corrected). These beta coefficients indicate that we would expect that patients whose clinical record included a list of treatment goals would have an end-of-treatment BDI score that was 1.4 points lower on average compared to patients whose clinical record did not include a list of treatment goals, and that patients whose clinical record included a plot of symptoms would have an end-of-treatment BDI score that was 1.6 points lower. So although statistically significant, the effects of the Treatment Goals and Plot variables on end-of-treatment BDI score were small, about 1.5 points on the Beck Depression Inventory. The measure of effect size, ΔR^2, reported in Table 2 also shows that the effects of Treatment Goals and Plot on end-of-treatment BDI scores were small.

For the Burns Anxiety Inventory, our linear regression analysis showed that Treatment Goals was a statistically significant predictor of end-of-treatment score on the Burns Anxiety Inventory ($\beta = -4.2$, $p = 0.04$), but not Plot ($\beta = -3.4$, $p = 0.09$) or Case Formulation ($\beta = 0.09$, $p = 3.8$) (all *p* values were multiplied by 4 to Bonferroni-correct for the total number of regression analyses). These beta coefficients indicate that we would expect that patients whose clinical record included a list of treatment goals would have an end-of-treatment BurnsAI score that was 4.2 points lower on average (fewer symptoms) than patients whose clinical record did not include a list of treatment goals. As the size of the beta coefficient indicates, the effect of the Treatment Goals variable on end-of-treatment Burns Anxiety Inventory score was small (the score on the measure ranges from 0 to 99). The measure of effect size, ΔR^2, reported in Table 2 also shows that the effect of Treatment Goals on end-of-treatment BurnsAI score was small.

In both the BDI and BurnsAI analyses, the initial score on the measure and therapist identity were statistically significant predictors of the end-of-treatment score on the measure ($p < 0.0001$), but total number of therapy sessions and the intercept parameters were not.

In sum, two decision support tools, Treatment Goals and Plot, were statistically significantly related to end-of-treatment scores on one or two of the outcome measures. Treatment Goals was a statistically significant predictor of both end-of-treatment BDI and Burns AI scores, and Plot was a statistically significant predictor of end-of-treatment BDI score. All effects were small in size.

Dropout. First we examine the degree to which the presence of the decision support tools in the clinical record was related to Premature dropout. As predicted and shown in Table 2, Case Formulation ($\beta = -0.5$, $p < 0.0001$) and Plot ($\beta = -0.4$, $p < 0.0001$) were statistically significantly related to reduced Premature dropout compared to when these tools were not present in the clinical record. However, contrary to prediction, Treatment Goals was positively related to Premature dropout ($\beta = 0.3$, $p < 0.0001$), indicating that a list of Treatment Goals was in the chart was statistically significantly related to *increased* premature dropout.

The effect sizes (estimated odds ratios) of the decision support tools on Premature dropout were 0.6 for Case Formulation, 1.3 for Treatment Goals, and 0.7 for Plot. The fact that the odds ratio for Case Formulation was less than one indicates that if patients had a case formulation in their clinical record, they were *less* likely to drop out prematurely than if they did not have a case formulation in their clinical record; the same is true for Plot. The fact that the odds ratio for Treatment Goals was greater than one indicates that if patients had a list of treatment goals in their clinical record, they were *more* likely to drop out prematurely than if they did not have a list of treatment goals in the clinical record. Another way to consider the odds ratio is to convert it to a risk ratio for a given baseline risk level. Using a baseline risk level of premature dropout of 52% and the odds ratios generated from our model fit, we calculated that a patient whose chart had a case formulation was 0.74 times as likely to drop out prematurely as a patient without a case formulation, a patient whose chart had a list of treatment goals was 1.13 times as likely to drop out prematurely as a patient without a list of treatment goals, and a patient whose chart had a plot was 0.80 times as likely to drop out prematurely as a patient without a plot.

Next we examine the degree to which the presence of the decision support tools in the clinical record was related to Uncollaborative dropout. As Table 2 shows, Case Formulation ($\beta = -0.3$, $p = 0.0004$), Treatment Goals ($\beta = -0.4$, $p < 0.0001$), and Plot ($\beta = -0.6$, $p < 0.0001$) were each statistically significantly related to Uncollaborative dropout in the predicted direction, indicating that the presence of a case formulation, a list of treatment goals, or a plot in the clinical record each predicted reduced uncollaborative dropout compared to when these tools were not present in the clinical record.

As reported in Table 2, the estimated odds ratios for Case Formulation, Treatment Goals, and Plot were 0.8, 0.7, and 0.5, respectively. The fact that all odds ratios were less than one indicates that patients with each of these tools in their clinical record were less likely to drop out uncollaboratively than patients without each of these tools. Using a baseline risk level of uncollaborative dropout of 30%, and the model-derived odds ratios, we calculated that patients who had a case formulation were 0.82 times as likely to drop out uncollaboratively as patients without a case formulation, 0.77 times as likely to drop out uncollaboratively as patients without a list of treatment goals, and 0.62 times as likely to drop out uncollaboratively as patients without a plot.

The total number of sessions a patient completed ($p < 0.0001$), the therapist identity ($p < 0.0001$), and the intercept parameter ($p_{premature} < 0.0001$, $p_{uncollaborative} = 0.0004$) were all statistically significant predictors of both types of dropout.

The mean Jaccard index across imputations for the relationship between the decision support tools and Premature dropout was 0.31, 0.36, and 0.27, for Case Formulation, Treatment Goals, and Plot, respectively. The mean Jaccard index across imputations for the relationship between the decision support tools and Uncollaborative dropout was 0.22, 0.17, and 0.18, respectively, for Case Formulation, Treatment Goals, and Plot, respectively. These indices describe the relationship between each decision support tool and type of dropout, separate from the presence of the other tools, therapist, or number of sessions.

In sum, Case Formulation, Treatment Goals, and Plot each predicted statistically significant reductions in both Premature and Uncollaborative dropout, with the exception that, contrary to our prediction, Treatment Goals predicted an *increased* rate of Premature dropout.

3. Discussion

We found that all three of the decision support tools we studied, a written case formulation, a list of treatment goals, and a plot of symptom scores, were associated with improved outcome and/or reduced dropout in our sample of outpatients treated with naturalistic CBT in a private practice setting. Tools had differing effects on dropout and outcome. We found that two of the three decision support tools we studied, a list of treatment goals, and a plot of symptom scores, were associated with improved outcome. Patients whose medical record included a written list of treatment goals had lower end-of-treatment scores on the Beck Depression Inventory and Burns Anxiety Inventory than patients whose medical record did not include a list of treatment goals. Patients whose medical record included a plot of symptom scores had lower end-of-treatment scores on the Beck Depression Inventory than patients whose medical record did not include a plot. Effects of the decision support tools on outcome were statistically significant but small. The tools with statistically significant effects were associated with expected average reductions in the end-of-treatment BDI score of 1.4 points (a written list of treatment goals) and 1.6 points (a plot of symptom scores), and an expected average reduction in the end-of-treatment BurnsAI score of 4.2 points (a written list of treatment goals). These small effects are similar to the small effects of decision support tools seen in some other studies (e. g., Delgadillo et al., 2018; Kendrick et al., 2016), and several of the studies reviewed by Lewis et al. (2018). We might have obtained larger effects if we had been able to measure the degree to which therapists actually used each tool; instead, we had only an indirect measure of the therapist's use of the tool, namely whether the tool was present in the clinical record. Therapists may have had a written formulation in the chart, for example, but not relied on it in their work, or they may have relied on a case formulation without writing it down. We might have also obtained larger effects if we had assessed the quality of the case formulation; Abel et al. (2016) showed that therapist competence in case conceptualization was related to sudden gains in patients with treatment-resistant depression. And the list of treatment goals might have been more convincingly related to outcome if we had assessed outcome by assessing progress toward the goals on the list. Unfortunately, our field has not yet developed a strong measure for assessing progress toward idiographic goals. Also, there is some evidence that decision support tools contribute more to outcome when the patient begins treatment with a poor outcome than when early progress is good (cf. Lambert et al., 2005; Vittengl et al., 2019) and that the currently-available tools are most effective at predicting deterioration than outcome (e.g., Delgadillo et al., 2018; Lambert & Shimokawa, 2011).

The decision support tools we studied were more predictive of dropout than of outcome in our sample. All three tools were statistically significantly related to a lower rate of both types of outcome we studied, with the exception that a list of treatment goals was a statistically significant predictor of a *higher* rate of premature termination. Based on our model-derived odds ratios and estimated baseline sample rates, we calculated that patients were 0.74 or 0.80 times as likely to drop out prematurely when the clinical record had a written case formulation or a plot of symptom scores, respectively. We calculated that patients were 0.82, 0.77, or 0.62 times as likely to drop out uncollaboratively when the clinical record had a written case formulation, list of treatment goals, or plot of symptom scores, respectively.

Contrary to our prediction, we calculated that patients whose chart included a list of treatment goals were *more* likely (1.13 times more likely) to drop out prematurely than patients whose chart did not include a list of treatment goals. Perhaps this finding resulted from the fact that the rating of whether the dropout was premature was made by the therapist, and perhaps the therapist who had a written list of the patient's treatment goals in the chart was more likely to be aware of the patient's unmet goals and to rate the patient who wanted to end treatment before accomplishing all of their goals as ending treatment prematurely. Relatedly, therapists seem often to have more goals for patients than do the patients themselves. This is reflected by the fact that in our sample (in which patients were only included if they had had at least three therapy sessions), a very large proportion of patients were judged by the therapist to have terminated prematurely (52% of the patients for whom we had premature dropout data) yet had completed a substantial number of therapy sessions (mean $\pm$ std.err of 16.3 ± 0.9) at the time they terminated treatment. (For all patients in the sample, the mean $\pm$ std.err was 24.0 ± 1.1 sessions.)

We speculate that the effects of the tools on outcome and dropout was mediated at least in part by the beneficial effects of the use of the tools on the therapeutic alliance. Notice that all of the decision support tools we studied entailed a written document that therapist and patient could review together and use to guide treatment. Thus, the sharing of the case formulation (Kuyken et al., 2009) and the list of treatment goals, and the collaborative discussion of progress and decision-making, may all contribute to the development of a strong therapeutic alliance. (For example, one of the last author's patients, a business executive, volunteered that the author's practice of collecting and reviewing outcome data conveyed a willingness to be held accountable that increased his respect for her.) This notion is consistent with the facts that agreement on the tasks and goals of therapy is widely viewed as an element of the therapeutic alliance (Bordin, 1994), and uncollaborative dropout would seem to be the quintessential example of an alliance rupture (Safran et al., 2011). A strong alliance has been shown to be related to both improved outcome (Horvath et al., 2011) and reduced dropout (Roos & Werbart, 2013).

Of the three tools we studied in our sample, the one that most aligned with our predictions was the plot of symptom scores, which predicted reduced end-of-treatment Beck Depression Inventory score, marginally predicted reduced end-of-treatment Burns Anxiety Inventory score ($p = 0.09$), and predicted lower rates of both types of dropout. This observation is consistent with a growing body of studies showing that measurement-based care and routine outcome monitoring are associated with improved outcome (see reviews by Carlier et al., 2012; Goodman et al., 2013; Lewis et al., 2018) and reduced dropout (Janse et al., 2020; meta-analysis by; de Jong et al., 2012).

The data analyzed in the present study were collected over a long time period that ended more than 10 years ago (1981–2009). Many changes occurred in our field over this time period, including changes in therapists' training, the development of new interventions and new diagnostic systems, and the advent of online tools for the medical record and progress monitoring. The question of whether these developments have implications for our results is worth considering. However, our hypotheses and data analyses were constructed in such a way that insulates our findings from these changes. We tested the hypothesis that therapist use of decision support tools of a written case formulation, a list of treatment goals, and a plot of symptom scores affected outcome and dropout. These questions remain of interest today. In fact, our study provides some empirical support for the treatment utility of online tools that make it easier for clinicians to maintain a useful clinical record that includes a written case formulation and a list of treatment goals, and to collect and plot progress monitoring data.

Our study has several limitations. Use of the decision support tools was not randomly assigned, and as a result we cannot conclude that the therapist's use of a formulation, plot, and treatment goals *caused* the effects on outcome and dropout that we observed. However, because we controlled for the main effect of therapist in our analyses, we can rule out the competing account that the decision support tools were related to outcome and dropout because the use of the tools reflects the conscientiousness or skill level of the therapist rather than the use of the tools.

Several limitations affect our independent variables, the decision support tools. We do not have any information about the content or adequacy of the case formulations or lists of treatment goals; we have only a rating of whether the tool was present in the clinical record. Therapists may have used a case formulation to guide the treatment even if a written formulation was not present in the clinical record. And the fact that the clinical record included a plot does not indicate that the therapist reviewed the plot with the patient. We also have no information about when in the course of treatment the tools were developed and the degree to which the therapist used the tool to guide the treatment.

Another limitation is that results cannot be assumed to generalize to therapists other than the ones studied here, who are not typical of therapists in the community. All of these therapists collected and plotted symptom data for at least some of their patients; in contrast, less than 20% of providers use measurement-based care (Lewis et al., 2018). This fact limits the generalizability of our findings, as does the fact that patients were a homogeneous group of highly educated predominantly White adults who paid high fees for their treatment.

Strengths of our investigation include our study of a sample of patients with multiple comorbidities who received treatment in a clinical rather than a research setting, and the fact that most of the data we studied here were collected in the course of routine clinical practice, both of which are research strategies that increase the external validity of our findings (Weisz et al., 2014). Additional strengths of our study include our focus on key elements of evidence-based practice (American Psychological Association, 2006), and our examination of a large sample of private practice patients that are infrequently represented in the research literature. A final strength of our study is that the decision support tools we studied (the written case formulation, the list of treatment goals, and the plot of symptom scores) can be used by any psychotherapist of any discipline or psychotherapy orientation to treat patients who seek treatment for any disorder or presenting problem.

Author declaration template

There are no financial conflicts of interest.

CRediT authorship contribution statement

Vael Gates: devised and conducted the data analysis and wrote most of the Results section and some of the Discussion. **Megan Hsiao:** made major contributions to organizing and cleaning the database. **Garret G. Zieve:** assisted with the database organization, cleaning, and coding. **Rebecca Coury:** assisted with coding for the inter-rater reliability study. **Jacqueline B. Persons:** collected the data and drafted the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.brat.2021.103874.

References

Abel, A., Hayes, A. M., Henley, W., & Kuyken, W. (2016). Sudden gains in cognitive–behavior therapy for treatment-resistant depression: Processes of change. *Journal of Consulting and Clinical Psychology, 84*(8), 726–737. https://doi.org/10.1037/ccp0000101. PsycINFO.

American Psychological Association. (2006). Evidence-based practice in psychology. *American Psychologist, 61*(4), 271–285.

Beck, J. S. (1995). *Cognitive therapy: Basics and beyond. Guilford press*.

Beck, A. T., Steer, R. A., & Garbin, M. G. (1988). Psychometric properties of the Beck depression inventory: Twenty-five years of evaluation. *Clinical Psychology Review, 8*, 77–100. https://doi.org/10.1016/0272-7358(88)90050-5.

Beck, A. T., Ward, C. H., Mendelsohn, M., Mock, J., & Erbaugh, J. (1961). An inventory for measuring depression. *Archives of General Psychiatry, 4*, 561–571. https://doi.org/10.1001/archpsyc.1961.01710120031004.

Bordin, E. S. (1994). Theory and research on the therapeutic working alliance: New directions. In A. O. Horvath, & L. S. Greenberg (Eds.), *The working alliance: Theory research and practice. Wiley*.

Burns, D. D., & Eidelson, R. J. (1998). Why are depression and anxiety correlated? A test of the tripartite model. *Journal of Consulting and Clinical Psychology, 66*(3), 461.

Carlier, I. V. E., Meuldijk, D., Van Vliet, I. M., Van Fenema, E., Van der Wee, N. J. A., & Zitman, F. G. (2012). Routine outcome monitoring and feedback on physical or mental health status: Evidence and theory. *Journal of Evaluation in Clinical Practice, 18*(1), 104–110. https://doi.org/10.1111/j.1365-2753.2010.01543.x.

Cuijpers, P., Karyotaki, E., Weitz, E., Andersson, G., Hollon, S. D., & van Straten, A. (2014). The effects of psychotherapies for major depression in adults on remission, recovery and improvement: A meta-analysis. *Journal of Affective Disorders, 159*, 118–126. https://doi.org/10.1016/j.jad.2014.02.026.

Delgadillo, J., de Jong, K., Lucock, M., Lutz, W., Rubel, J., Gilbody, S., Ali, S., Aguirre, E., Appleton, M., Nevin, J., O'Hayon, H., Patel, U., Sainty, A., Spencer, P., & McMillan, D. (2018). Feedback-informed treatment versus usual psychological treatment for depression and anxiety: A multisite, open-label, cluster randomised controlled trial. *The Lancet Psychiatry, 5*, 564–572. https://doi.org/10.1016/S2215-0366(18)30162-7.

Derogatis, L. R., Rickels, K., & Rock, A. F. (1976). The SCL-90 and the MMPI: A step in the validation of a new self-report scale. *The British Journal of Psychiatry, 128*(3), 280–289.

Eells, T. D. (Ed.). (2007). *Handbook of psychotherapy case formulation (2nd ed.). Guilford*.

Enders, C. K. (2017). Multiple imputation as a flexible tool for missing data handling in clinical research. *Behaviour Research and Therapy, 98*, 4–18. https://doi.org/10.1016/j.brat.2016.11.008.

Fernandez, E., Salem, D., Swift, J. K., & Ramtahal, N. (2015). Meta-analysis of dropout from cognitive behavioral therapy: Magnitude, timing, and moderators. *Journal of Consulting and Clinical Psychology, 83*(6), 1108–1122. https://doi.org/10.1037/ccp0000044.

Gardiner, J. C., Luo, Z., & Roman, L. A. (2009). Fixed effects, random effects and GEE: What are the differences? *Statistics in Medicine, 28*(2), 221–239. https://doi.org/10.1002/sim.3478.

Goodman, J. D., McKay, J. R., & DePhilippis, D. (2013). Progress monitoring in mental health and addiction treatment: A means of improving care. *Professional Psychology: Research and Practice, 44*(4), 231–246. https://doi.org/10.1037/a0032605.

Hawkins, E. J., Lambert, M. J., Vermeersch, D. A., Slade, K. L., & Tuttle, K. C. (2004). The therapeutic effects of providing patient progress information to therapists and patients. *Psychotherapy Research, 14*(3), 308–327. https://doi.org/10.1093/ptr/kph027.

Honaker, J., King, G., & Blackwell, M. (2012). Amelia II: A Program for Missing Data (1.6.2) [Computer Software]. https://gking.harvard.edu/amelia.

Horvath, A. O., Del Re, A. C., Flückiger, C., & Symonds, D. (2011). Alliance in individual psychotherapy. *Psychotherapy, 48*(1), 9.

Janse, P. D., de Jong, K., Veerkamp, C., van Dijk, M. K., Hutschemaekers, G. J. M., & Verbraak, M. J. P. M. (2020). The effect of feedback-informed cognitive behavioral therapy on treatment outcome: A randomized controlled trial. *Journal of Consulting and Clinical Psychology, 88*(9), 818–828. https://doi.org/10.1037/ccp0000549.

de Jong, K., van Sluis, P., Nugter, M. A., Heiser, W. J., & Spinhoven, P. (2012). Understanding the differential impact of outcome monitoring: Therapist variables that moderate feedback effects in a randomized clinical trial. *Psychotherapy Research, 22*(4), 464–474. https://doi.org/10.1080/10503307.2012.673023. PsycINFO.

Kuyken, W., Padesky, C. A., & Dudley, R. (2009). *Collaborative case conceptualization. Guilford*.

Lambert, M. J., Harmon, C., Slade, K., Whipple, J. L., & Hawkins, E. J. (2005). Providing feedback to psychotherapists on their patients' progress: Clinical results and practice suggestions. *Journal of Clinical Psychology, 61*(2), 165–174. https://doi.org/10.1002/jclp.20113.

Lambert, M. J., & Shimokawa, K. (2011). Collecting client feedback. *Psychotherapy, 48* (1), 72–79. https://doi.org/10.1037/a0022238.

Lewis, C. C., Boyd, M., Puspitasari, A., Navarro, E., Howard, J., Kassab, H., … Douglas, S. (2018). Implementing measurement-based care in behavioral health: A review. *JAMA Psychiatry, 76*(3), 324–335. https://doi.org/10.1001/jamapsychiatry.2018.3329.

Persons, J. B. (1989). *Cognitive therapy in practice: A case formulation approach. Norton & company*.

Persons, J. B. (2008). *The case formulation approach to cognitive-behavior therapy. Guilford*.

Persons, J. B., & Hong, J. J. (2016). Case formulation and the outcome of cognitive behavior therapy. In N. Tarrier, & J. Johnson (Eds.), *Case formulation in cognitive behaviour therapy* (2nd ed., pp. 14–37) Routledge.

Project Jupyter. (n.d.). Jupyter Notebook. https://jupyter.org.

Python Software Foundation. (n.d.).Python Language Reference (3.6.5) [Computer software]. http://python.org.

R Core Team. (2007). ls: Least squares regression for continuous dependent variables. http://zeligproject.org.

R Core Team. (2018). R: A language and environment for statistical computing. R foundation for statistical computing. https://www.r-project.org/.

Roos, J., & Werbart, A. (2013). Therapist and relationship factors influencing dropout from individual psychotherapy: A literature review. *Psychotherapy Research, 23*, 394–418. https://doi.org/10.1080/10503307.2013.776628.

Safran, J. D., Muran, J. C., & Eubanks-Carter, C. (2011). Repairing alliance ruptures. *Psychotherapy, 48*(1), 80–87. https://doi.org/10.1037/a0022140. PsycINFO.

Vittengl, J. R., Clark, L. A., Thase, M. E., & Jarrett, R. B. (2019). Estimating outcome probabilities from early symptom changes in cognitive therapy for recurrent depression. *Journal of Consulting and Clinical Psychology, 87*(6), 510.

Weisz, J. R., Ng, M. Y., & Bearman, S. K. (2014). Odd couple? Re-envisioning the relation between science and practice in the dissemination-implementation era. *Clinical Psychological Science, 2*(1), 58–74. https://doi.org/10.1177/2167702613501307.