The Relationship Between Dropout and Outcome in Naturalistic Cognitive Behavior Therapy

Garret G. Zieve

University of California, Berkeley

Jacqueline B. Persons
Lisa Ann D. Yu

Oakland Cognitive Behavior Therapy Center

Dropout from psychotherapy is frequent and limits the benefits patients can receive from treatment. The study of factors associated with dropout has the potential to yield strategies to reduce it. This study analyzed data from a large sample of adults ($N = 1,092$) receiving naturalistic cognitive behavioral therapy (CBT) to test the hypotheses that dropouts, as compared to completers, had (1) higher symptom severity at treatment termination, (2) a slower rate of symptom change during treatment, and (3) a higher odds that the therapist rated treatment as ending for reasons related to poor outcome. Results showed that although dropouts ended treatment with higher symptom severity than completers, dropouts and completers did not differ in their rate of symptom change during treatment, suggesting that dropouts had higher symptom severity at termination because they received fewer sessions of treatment, not because their symptoms changed at a slower rate. Dropout was also associated with a higher odds of having a therapist-rated termination reason indicating a poor outcome, suggesting that dropout is more likely if patients are dissatisfied with some aspect of the therapy outcome or process. These findings suggest that strategies for monitoring and enhancing patient satisfaction with the process and outcome of treatment may help patients stay in treatment longer and end treatment with fewer symptoms than if they had dropped out.

DROPOUT FROM PSYCHOTHERAPY is an important phenomenon because it is frequent, with dropout rates ranging from about 20% (Swift, Greenberg, Tompkins, & Parkin, 2017; Swift, Greenberg, Whipple, & Kominiak, 2012) to 47% (Wierzbicki & Pekarik, 1993), and because individuals who drop out receive a smaller dose of a potentially helpful treatment. Dropout also wastes resources and contributes to therapist burnout (Reis & Brown, 1999). The study of factors associated with dropout has the potential to yield strategies to reduce it.

One possible contributor to a patient's decision to drop out is that s/he is not benefitting from treatment. Psychotherapy is costly in terms of both time and money, and can be quite uncomfortable, so if patients are not showing a good response, they may drop out. The hypothesis that dropout is associated with poor outcome is supported by findings showing that lack of early improvement predicted dropout from cognitive behavior therapy

(CBT) for panic disorder provided in a randomized controlled trial (Lutz et al., 2014) and from naturalistic CBT for depression (Schindler, Hiller, & Witthoft, 2013), the finding that patients who showed less symptom reduction over the course of treatment for depression in an outpatient clinic in the U.K. were more likely to drop out (Cahill et al., 2003), and the finding that poor outcome at the 12-week point of treatment was associated with premature discontinuation of naturalistic CBT for depression (Burns & Nolen-Hoeksema, 1992). Thus, several studies support the hypothesis that poor outcome is associated with dropout from psychotherapy. This hypothesis is not supported by Arnow et al. (2007), who found no relationship between early improvement and dropout from psychotherapy and pharmacotherapy for chronic depression provided in a randomized controlled trial.

However, the opposite hypothesis might be true. Patients may drop out of psychotherapy because they are doing well and no longer need treatment. Quite a bit of symptom change can occur in only a few sessions (Crits-Christoph et al., 2001; Schindler et al., 2013) or even a single session. Bloom (2001) reported, based on a review of 40 papers, that "Between one-third and one-half of randomly selected clients seen in single-session psychotherapy report being sufficiently helped by the experience so that the therapeutic episode can be terminated" (p. 75). Manthei (1995) reported that 61% of clients who attended only one counseling session reported some or substantial improvement in the problem for which they had sought counseling. Hansen, Hoogduin, Schaap, and de Haan (1992) showed that dropouts from treatment of obsessive-compulsive disorder had less severe symptoms at the termination of treatment than those who completed treatment. Szafranski, Smith, Gros, and Resick, (2017) found that up to 55% of patients who dropped out of treatment for PTSD showed clinically significant change or met good end-state symptomatology criteria. Thus, patients may drop out of psychotherapy because they have gotten their needs met and do not need further treatment.

Thus, dropout from psychotherapy might be related to either poor or good outcome. Surprisingly little research has examined the relationship between dropout and outcome. None of the large meta-analyses of predictors of dropout investigate outcome as a predictor of dropout (Fernandez, Salem, Swift, & Ramtahal, 2015; Swift et al., 2017; Swift et al., 2012; Wierzbicki & Pekarik, 1993). It is important to understand the relationship between dropout and outcome, as strategies for handling dropout related to good outcome likely differ from those the therapist might use to handle dropout related to poor outcome. To address this gap in the literature, we examined the relationship between dropout and outcome of treatment of symptoms of depression and anxiety in a large sample of private practice patients treated with CBT.

The term dropout is defined in the psychotherapy research literature in a wide range of ways, including whether the patient failed to complete the entire treatment protocol or number of sessions authorized by the insurance company, attended only one or a handful of sessions, failed to collaborate with the therapist on treatment termination, or failed, in the therapist's judgment, to complete an adequate number of sessions. To increase the generalizability of our findings, we studied the relationship between outcome and dropout as defined in three ways. We defined early dropout as attending three or fewer sessions, premature dropout as ending treatment before the therapist believed was indicated (regardless of the number of sessions completed), and uncollaborative dropout as termination in which the therapist rates that termination occurred without the patient and therapist discussing and/or agreeing on the termination decision. The clearest example of uncollaborative dropout, and one with which all therapists are familiar, is the patient who simply does not appear for a scheduled session and does not respond to the therapist's efforts to contact him or her. This type of behavior likely fits the definition of what Safran and Muran (Safran, Muran, & Eubanks-Carter, 2011) term an alliance rupture. We know that psychotherapy outcome is related to the treatment dose (number of sessions; Howard, Kopta, Krause, & Orlinsky, 1986) and to the quality of the therapeutic alliance (Martin, Garske, & Davis, 2000), and therefore we predicted that all types of dropout would be associated with poor outcome.

In the current study, we tested the hypotheses that all three types of dropouts, as compared to completers, had (1) higher symptom severity at treatment termination, (2) a slower rate of symptom change during treatment, and (3) a higher odds that the therapist rated treatment as ending for reasons related to poor outcome.

Method

PARTICIPANTS

Data for the current study were drawn from a de-identified archival database comprised of information from 1,472 adult patients who received individual therapy sessions during the years 1981–2009 from the second author or a therapist at the group private practice the second author established in 1995. All patients gave written permission for the use in research of data that were collected as part of their treatment.

Patients were included in the present study if they (a) sought treatment rather than just a consultation, (b) completed at least one of the symptom measures we studied (see Measures section below) at any time during treatment, and (c) did not have missing data for variables describing dropout status (see Measures section below). Analyses of missing data for the variables describing dropout status indicated that data on these variables were missing completely at random, suggesting that excluding cases with missing data on these variables would not bias our analyses (Rubin, 1976). Additionally, to simplify the data analysis, when patients had more than one course of treatment, we studied only the first course of treatment. These inclusion criteria were selected to maximize the sample size without introducing excessive error into the analyses due to extensive missing data.

The sample that met these inclusion criteria consisted of 1,092 of 1,471 (74.24%) patients in the database. Twenty-six patients were excluded because they sought consultation only, 39 patients were excluded because they did not complete at least one of the symptom measures we studied, and 314 patients were excluded because they had one or more missing value in the variables describing dropout status.

The average patient in the sample was 36.61 years of age (SD = 12.59) and had completed 16.60 years of education (SD = 2.56). Most of the sample (60.81%) identified as female. Regarding race, 85.84% identified as Caucasian, 5.48% as Asian, 3.68% as Hispanic, 2.46% as African American, and 2.55% as other race.

Nearly all patients (91.67%) were diagnosed with at least one anxiety or depressive disorder. Psychiatric diagnoses were made on the basis of a clinical interview by the therapist, who used the most current version of the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 1987, 1994, 2000) available at the time the patient was treated. Approximately half of patients (55.18%) received adjunctive pharmacotherapy and some (22.19%) received adjunctive psychosocial treatment.

TREATMENT

Treatment consisted of individual CBT, typically provided weekly. Therapists did not usually adhere to a manualized treatment. Instead, they developed an individualized cognitive-behavioral case formulation and used the formulation and the results of progress monitoring data to make treatment decisions, including to select interventions from the available CBT manuals and other sources (Persons, 2008). Patients completed a Beck Depression Inventory and/or Burns Anxiety Inventory in the waiting room before the session, and the therapist typically plotted the score at the beginning of the session, reviewed the plot with the patient, and used the data to guide decision-making in the session. Treatment was open-ended in duration and ended ideally when patient and therapist agreed that the patient had reached the patient's goals. Patients were treated by the second author or by one of 15 other therapists at the group practice. Most therapists were Ph.D. psychologists; one was an M.S.W.

MEASURES

Symptoms of Depression
We assessed symptoms of depression with the original version of the Beck Depression Inventory (BDI; Beck, Ward, Mendelsohn, Mock, & Erbaugh, 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 (α = 0.86 for psychiatric patients) and good convergence with other measures of depressive symptoms (Beck, Steer, & Garbin, 1988).

Symptoms of Anxiety
We assessed symptoms of anxiety with the Burns Anxiety Inventory (Burns AI), 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*). Burns and Eidelson (1998) reported, in a sample of 483 outpatients, that the Burns AI had a Cronbach's alpha of 0.94, indicating high internal consistency, and it was correlated 0.86 (p < .001) with the Anxiety subscale of the Symptom Check List-90 (Derogatis, Rickels, & Rock, 1976). We used the Burns AI 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.

Early Dropout
A patient was viewed as having an early dropout if s/he completed three or fewer sessions of treatment. Defining dropout as occurring when the patient completes a small number of sessions is a widely used approach in the literature (Swift & Greenberg, 2012), and although no consistent number of sessions is used for this definition, three is a commonly used number.

Uncollaborative Dropout
Uncollaborative dropout was coded if the patient's therapist answered "no" to this 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 cancelled a session and never rescheduled.

Premature Dropout

Premature dropout was coded when the patient's therapist answered "no" to this question: "Has the therapy been given a fair shake/tried for long enough to help patient accomplish his/her 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, which varied extensively and could range from "reducing scores on the BDI to the normal range" to "beginning to date and finding a boyfriend."

These three categories of dropout were not mutually exclusive. For example, the termination was coded as both early and uncollaborative if the therapist rated that the patient discontinued therapy against the therapist's advice before completing 4 sessions.

Reasons for Termination

After treatment ended, the therapist selected up to two reasons for termination for each patient from a list of 19 reasons developed by the second author (although only 12 of these codes were assigned in the current sample). In some cases, therapists coded reasons for termination months to years after treatment ended. Termination reasons were typically assigned based on a review of the clinical record and patient report. Therapists assigned termination reasons from memory if the clinical record was not available. As our aim in the current study was to investigate the relationship between outcome and dropout, we classified each of the 12 possible reasons for termination into one of three categories: (1) reasons indicating a good outcome, (2) reasons indicating a poor outcome, and (3) reasons indicating logistical, financial, or other barriers to treatment.

Four termination reasons indicated a poor outcome: (1) "Patient or therapist unhappy with therapy (e.g., with the results of the therapy, the patient-therapist match, or the treatment plan)"; (2) "Therapist decides s/he doesn't have the expertise to treat the patient and refers the patient out"; (3) "Patient and therapist could not agree on a treatment plan"; and (4) "Patient or therapist believe that therapy has accomplished all that apparently can be done." This last reason was coded when the therapist or patient or both "threw in the towel" and decided that some level of minimal change was all that was going to be achieved, and that prolonging the therapy did not

seem likely to lead to further gains. One termination reason indicated a good outcome: "Patient or therapist satisfied with results." Termination reasons indicating logistical, financial, or other barriers to treatment were: (1) "Patient moved or other issues of geography"; (2) "Clinician left the Center"; (3) "Patient can't afford treatment"; (4) "Patient's schedule changed or other time issues"; (5) "Therapist got ill or went on maternity leave"; and (6) "Patient is pregnant/ill or close family member is ill." Participants coded with "no reason given" were also included in this category.

If the therapist coded both a termination reason indicating poor outcome and a logistical/financial/ other reason, the patient's final termination reason was coded as indicating poor outcome. If the therapist coded both a termination reason indicating good outcome and a logistical/financial/other reason, the patient's final termination reason was coded as indicating good outcome. Fifteen patients were coded with termination reasons indicating both a good outcome and poor outcome; we considered the termination reason to be missing for these patients.

DATA ANALYSIS

We tested the hypothesis that termination symptom severity was greater for dropouts than completers using linear regression analyses of termination symptom severity in which we controlled for intake symptom severity. We tested the hypothesis that rate of symptom change during treatment was slower for dropouts than completers using hierarchical linear modeling (Raudenbush & Bryk, 2002). For both of these hypotheses, we conducted separate analyses for each dropout type (early, uncollaborative, premature) and symptom measure (BDI, Burns AI). The sample size for each test varied based on the data available. Only patients who completed at least one BDI or Burns AI during treatment were included in the analyses of that symptom measure. We used binary logistic regression to test the hypothesis that dropouts were more likely to be coded by the therapist as ending treatment for reasons related to poor outcome. Each type of dropout was entered into a separate logistic regression analysis predicting the odds of each type of termination reason. As a result of the large sample size, many of the tests we conducted were statistically significant with exceedingly small p-values even when the size of the effect was small. Therefore, we present effect sizes to guide the interpretation of our results.

We handled missing data in the linear regression and logistic regression analyses with multiple imputation (Enders, 2017), which involves generating multiple datasets that fill in missing values with a range of plausible values given other observed
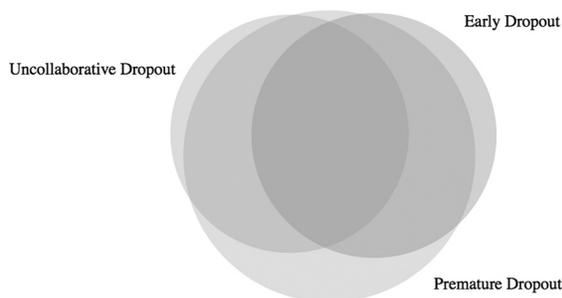
FIGURE 1   Empirical Venn diagram illustrating overlap between types of dropout (N = 1,092).

responses. Statistical tests are then conducted in each imputed dataset and pooled into a final result. Multiple imputation is preferred to the more rudimentary methods of complete case analysis and single imputation, which can produce biased results under a variety of conditions. We used maximum likelihood estimation to handle missing data for the hierarchical linear modeling analyses because there is no established method to apply multiple imputation to time series data when the number of observations varies from case to case. Multiple imputation and maximum likelihood are both considered adequate missing data strategies (Schafer & Graham, 2002), though multiple imputation has the additional benefit of easily incorporating observed responses on auxiliary variables to inform parameter estimates. Simulation studies suggest that these two missing data techniques are asymptotically equivalent, producing increasingly similar parameter estimates as sample size increases (Enders, 2010).

All analyses were completed in R (R Core Team, 2016). Hierarchical linear modeling was conducted using the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018). Multiple imputation was conducted using the mice package (van Buuren & Groothuis-Oudshoorn, 2011).

Results

PRELIMINARY ANALYSES

Missing Data
Among the entire sample of 1,092 patients, 1,014 (92.86%) had at least one BDI score, and 903

(82.69%) had at least one Burns AI score. Among those with at least one BDI score, 665 (64.28%) had a BDI score at the intake session, and 783 (76.84%) had a BDI score at the last session. BDI scores were available for a mean of 64.69% (SD = 31.98%) of sessions. Among those with at least one Burns AI score, 620 (68.66%) had a Burns AI score at the intake session, and 682 (75.53%) had a Burns AI score at the last session. Burns AI scores were available for a mean of 62.55% (SD = 33.26%) of sessions. 1,070 patients (97.98% of the whole sample) were coded with a termination reason.

Dropout Rates and Relationship Between Types of Dropout
Rates of early, uncollaborative, and premature dropout were 37.64%, 33.52%, and 59.52%, respectively. Among the early dropouts, 65.69% received one session, 21.41% received two sessions, and 12.90% received three sessions of treatment. Figure 1 presents an empirical Venn diagram that illustrates the relative sizes and degree of overlap of the three types of dropout. 74.21% of early dropouts and 82.51% of uncollaborative dropouts were also coded as premature dropouts, suggesting that premature dropout may represent a more general category of which early and uncollaborative dropout are subtypes. 14.10% of the sample were coded as all three types of dropout. 26.37% were not coded as any type of dropout.

Duration of Treatment
Table 1 reports the average number of sessions and weeks in treatment for dropouts and completers. Dropouts received fewer sessions and remained in treatment for fewer weeks than completers, across all three types of dropout. Patients who were not coded as any type of dropout (n = 288) received an average of 26.05 sessions (SD = 32.96) over 36.84 weeks (SD = 47.69).

Intake and Termination Symptom Severity
Table 2 reports multiple imputation estimated descriptive statistics for intake and termination symptom scores for all three types of dropouts and

Table 1

Comparisons of treatment duration between dropouts and completers (N = 1,092)

	Early Dropout				Premature Dropout				Uncollaborative Dropout			
	n	M (SD)	t	p	n	M (SD)	t	p	n	M (SD)	t	p
# of Sessions												
Completers	681	20.64 (26.19)	19.08	<0.001	442	20.64 (30.49)	7.87	<0.001	726	15.40 (24.89)	4.62	<0.001
Dropouts	411	1.47 (0.71)			650	8.52 (13.16)			366	9.51 (16.83)		
Weeks in Treatment												
Completers	681	27.64 (36.56)	19.17	<0.001	442	28.08 (42.84)	8.25	<0.001	726	20.69 (35.57)	5.56	<0.001
Dropouts	411	0.73 (1.73)			650	10.33 (17.72)			366	11.20 (20.70)		

Table 2
Estimated Means and Standard Deviations of Intake and Termination Symptom Scores for Dropouts and Completers

	N	Early Dropout			Uncollaborative Dropout			Premature Dropout		
		n	M	SD	n	M	SD	n	M	SD
BDI	1014									
Intake										
Completers		646	19.23	10.04	675	16.94	10.72	410	17.12	11.01
Dropouts		368	14.84	11.68	339	19.03	11.04	604	17.99	10.76
Termination										
Completers		646	10.46	9.10	675	10.65	9.98	410	9.22	10.31
Dropouts		368	14.12	11.52	339	14.04	10.26	604	13.53	9.75
Burns AI	903									
Intake										
Completers		559	31.34	19.02	623	28.89	18.83	358	28.48	18.79
Dropouts		344	26.38	19.63	280	30.71	20.57	545	30.09	19.77
Termination										
Completers		559	16.52	15.10	623	18.09	15.97	358	15.68	14.03
Dropouts		344	24.72	18.97	280	23.09	19.07	545	22.24	18.46

Note. BDI = Beck Depression Inventory; Burns AI = Burns Anxiety Inventory

completers. The intake symptom scores across dropouts and completers for all types of dropout reflect depression in the mild to moderate range (BDI scores of 10 – 18; Beck, Steer, & Garbin, 1988) and anxiety in the moderate range (Burns AI scores of 21 – 30; Burns, 1989). The termination symptom scores for completers reflect depression close to the cutoff for minimal to no depression (BDI scores < 10), and anxiety in the mild range (Burns AI scores of 11 – 20). The termination symptom scores for dropouts (across all types) remained in the mild to moderate range for depression and moderate range for anxiety.

HYPOTHESIS 1. DROPOUTS HAD HIGHER SYMPTOM SEVERITY AT TERMINATION THAN COMPLETERS

Table 3 presents linear regression parameter estimates of the effect of dropout on termination symptom severity, controlling for intake symptom severity. Consistent with our hypothesis, for patients beginning treatment at any given level of symptom severity, dropouts terminated treatment with higher symptom scores than completers. This effect held across all types of dropout and both symptom measures. We calculated Cohen's d for

these effects by dividing the parameter estimates by the pooled standard deviation of symptom scores between dropouts and completers. Effect sizes were in the medium range for early dropout (ds = 0.63 and 0.66 for BDI and Burns AI, respectively), and in the small range for uncollaborative and premature dropout (ds = 0.22 – 0.39), according to established cutoffs for interpreting Cohen's d (Cohen, 1988).

HYPOTHESIS 2. DROPOUTS HAD A SLOWER RATE OF SYMPTOM CHANGE THAN COMPLETERS

Our test of Hypothesis 1 showed that dropouts ended treatment with higher symptom severity than completers. Hypothesis 2 proposes that the reason dropouts had higher symptom severity at termination is that they improved at a slower rate than completers. To test Hypothesis 2, we estimated hierarchical linear models using dropout as a predictor of rate of symptom change across time. As sessions were not always evenly spaced throughout treatment, we measured time by weeks in treatment rather than by session number.

Preliminary model testing suggested that the symptom data contained a slight quadratic trend such that patients started treatment with a faster

Table 3
Linear Regression Parameters for the Effect of Dropout on Termination Symptom Severity, Controlling for Intake Symptom Severity

Measure	N	Early Dropout			Uncollaborative Dropout			Premature Dropout		
		Est.	S.E.	p	Est.	S.E.	p	Est.	S.E.	p
BDI	1014	6.28	0.56	<0.001	2.24	0.57	<0.001	3.88	0.54	<0.001
Burns AI	903	10.9	0.97	<0.001	4.27	1.05	<0.001	5.86	0.98	<0.001

Note. BDI = Beck Depression Inventory; Burns AI = Burns Anxiety Inventory

rate of change, followed by a flatter rate of change later in treatment. However, we selected linear models to test our hypotheses and present our results because: (a) the maximum divergence in model estimated symptom scores over time between linear and quadratic models of symptom change was approximately one point for the BDI and three points on the Burns AI, a clinically negligible difference for both measures, and (b) the linear models yielded the same pattern of results as the quadratic models using fewer parameters.

The use of linear models did, however, require an additional control to our analyses testing for differences in rate of symptom change between early dropouts and completers. Because early dropouts only provided data for up to three sessions at the beginning of treatment, when the rate of symptom change was fastest, they spuriously appeared to have a faster rate of symptom change than completers, despite the only small quadratic trend in the data. Thus, for models testing the effect of early dropout, we only included data for completers from the first three sessions, effectively testing whether dropouts and completers differed in their rate of change in the first three sessions.

Because hierarchical linear modeling assumes that individual rates of change are normally distributed, problems arise if the slopes under investigation are bi-modally or multi-modally distributed. Bi-modality could arise in the context of the current study if some patients dropped out of treatment because they were improving at a fast rate, and others because they were improving at a slow rate. To address this issue, we inspected the distribution of individual symptom change slopes among dropouts and completers and found no evidence of bi-modality.

Table 4 presents results of the hierarchical linear models. The dependent variables in these models are the BDI and Burns AI symptom measures. The Intercept parameter for each model estimates the intake symptom score for completers. The Dropout parameter estimates the difference in the intake symptom scores between dropouts and completers. These parameters reveal that early dropouts started treatment with lower symptom scores than completers (indicated by the negative sign of the Dropout parameter), whereas uncollaborative and premature dropouts started treatment with higher symptom scores than completers (indicated by the positive sign of the Dropout parameters). However, these effects were small, corresponding to Cohen's ds of 0.17 to 0.25, with one exception: the effect of early dropout on intake BDI symptom severity approached a medium effect size ($d = 0.43$).

The Time parameter estimates the average rate of symptom score change per week in treatment for completers. This parameter was statistically significantly different from zero and had a negative sign for all models tested, indicating that the symptom scores for completers improved over time. The Time × Dropout parameter estimates the difference in average rate of symptom score change per week in treatment between dropouts and completers. Contrary to our hypothesis, this parameter was not statistically significant from zero in five out of six models tested, indicating that dropouts and completers did not differ in their rate of symptom change during treatment. The Time × Dropout parameter was negative and statistically significantly different from zero for the model testing the effect of premature dropout on rate of Burns AI change, indicating that premature dropouts improved *faster* than completers on the Burns AI. However,

Table 4

Parameter estimates for hierarchical linear models testing the association between dropout and rate of change

Model Parameters	Early Dropout				Uncollaborative Dropout				Premature Dropout			
	n[a]	Est.	S.E.	p	n	Est.	S.E.	p	n	Est.	S.E.	p
BDI	873				1014				1014			
Intercept		18.99	0.49	<0.001		15.00	0.37	<0.001		14.77	0.47	<0.001
Dropout		-4.36	0.76	<0.001		2.47	0.65	<0.001		1.72	0.62	<0.01
Time		-1.59	0.38	<0.001		-0.22	0.02	<0.001		-0.22	0.02	<0.001
Time x Dropout		0.88	0.54	0.11		-0.02	0.04	0.57		-0.02	0.03	0.46
Burns AI	779				903				903			
Intercept		30.17	0.93	<0.001		25.18	0.68	<0.001		23.71	0.89	<0.001
Dropout		-3.92	1.41	<0.01		3.13	1.24	<0.05		4.12	1.15	<0.001
Time		-1.26	0.88	0.16		-0.43	0.03	<0.001		-0.35	0.04	<0.001
Time x Dropout		-1.18	1.52	0.43		-0.06	0.08	0.48		-0.19	0.06	<0.01

Note. BDI = Beck Depression Inventory; Burns AI = Burns Anxiety Inventory

[a] Analyses compared early dropouts and non-dropouts on rate of change during the first three sessions of treatment, and thus included only patients who had at least one BDI or Burns AI score in the first three sessions of treatment.

the difference in the rate of Burns AI change between premature dropouts and completers was very small, corresponding to approximately one additional point of improvement on the Burns AI over 5 weeks of treatment.

HYPOTHESIS 3. DROPOUTS WERE MORE LIKELY THAN COMPLETERS TO BE RATED BY THE THERAPIST AS ENDING TREATMENT FOR REASONS RELATED TO POOR OUTCOME

Table 5 presents the results of logistic regression analyses examining the effect of dropout on the odds of the patient being rated with termination reasons indicating poor outcome, good outcome, and logistical, financial, or other barriers to treatment. The Est. column displays the standard logistic regression parameter estimates in the form of log-odds and log-odds ratios. For ease of interpretation, the $e^{Est.}$ column displays the corresponding odds and odd-ratios, calculated by exponentiating e with the logistic regression parameter estimates. The $e^{Est.}$ column for the Intercept parameter displays the estimated odds of a completer being rated with the type of termination reason being tested. The $e^{Est.}$ column for the Dropout parameter displays the estimated ratio of the odds of being rated with the type of termination reason for drop-outs as compared to the completers.

Consistent with our hypothesis, each type of dropout, as compared to completers, was statistically significantly associated with a higher odds of being rated with a termination reason indicating a poor outcome (indicated by odds ratios greater than one in the e^{Est} column of the table). Odds ratios for early dropout and premature dropout corresponded to very small effects (Cohen's $d < 0.20$), but the odds ratio for uncollaborative dropout corresponded to a medium effect (Cohen's $d = 0.49$; Chinn, 2000). Dropouts of all types had a smaller odds than completers of being rated with a termination reason indicating a good outcome, as indicated by odds

ratios less than one. Odds ratios ranged from 0.05 to 0.37, corresponding to medium to large Cohen's ds of 0.55 to 1.67. Finally, dropouts of all types had a higher odds of being rated with a termination reason indicating logistical, financial, or other barriers to treatment. Odds ratios for early and uncollaborative dropout corresponded to small effects (Cohen's ds = 0.28 – 0.29), whereas the odds ratio for premature dropout corresponded to a large effect (Cohen's $d = 1.25$).

Discussion

We studied psychotherapy dropout in patients who received naturalistic CBT in a private practice setting. The proportions of patients who dropped out after 3 or fewer sessions (38%) or uncollaboratively (34%) fall within the range of dropout rates reported by meta-analyses of the topic (e.g., Wierzbicki & Pekarik, 1993). However, the premature dropout rate was substantially higher than other dropout rates reported in the literature. Sixty percent of the sample dropped out prematurely, that is, before the therapist judged that the therapy had been tried for long enough to help the patient accomplish her treatment goals. This high rate of premature dropout may reflect the facts that therapists often have more ambitious treatment goals than do patients (Barrett, Chua, Crits-Christoph, Gibbons, & Thompson, 2008), and that private pay therapy may be a significant barrier for many patients. Another contributor to premature dropout may be that often treatment addressed chronic situational factors (e.g., an unhappy job or relationship) in addition to treating the acute episode that brought patients to treatment, and thus required more sessions than standard protocols delivered in randomized trials. Because treatment lasted longer, it was more likely than a shorter treatment to be interrupted by logistical and other barriers to treatment (e.g., therapist or patient goes

Table 5

Logistic regression parameters for the effect of dropout on termination reason (N = 1092)

Parameter	Good Outcome Reason					Poor Outcome Reason					Logistical/Financial/Other Reason				
	Est.	S.E.	$e^{Est.}$	p	d	Est.	S.E.	$e^{Est.}$	p	d^a	Est.	S.E.	$e^{Est.}$	p	d
Early Dropout															
Intercept	-0.53	0.08	0.59	<0.001		-1.20	0.10	0.30	<0.001		-0.38	0.08	0.68	<0.001	
Effect of Dropout	-1.00	0.16	0.37	<0.001	0.55	0.29	0.15	1.34	<0.05	0.16	0.53	0.13	1.70	<0.001	0.29
Uncollaborative Dropout															
Intercept	-0.42	0.08	0.66	<0.001		-1.43	0.10	0.24	<0.001		-0.35	0.08	0.70	<0.001	
Effect of Dropout	-1.76	0.21	0.17	<0.001	0.97	0.89	0.15	2.44	<0.001	0.49	0.50	0.13	1.66	<0.001	0.28
Premature Dropout															
Intercept	0.52	0.10	1.67	<0.001		-1.29	0.12	0.28	<0.001		-1.63	0.13	0.20	<0.001	
Effect of Dropout	-3.02	0.20	0.05	<0.001	1.67	0.33	0.15	1.40	<0.05	0.18	2.26	0.16	9.59	<0.001	1.25

[a] Cohen's d measure of effect size calculated from the logisitic regression parameters (Chinn, 2000).

on maternity leave). Consistent with this interpretation, patients who did not drop out prematurely completed an average of 21 sessions of treatment over 28 weeks. In comparison, the cognitive therapy for depression protocol calls for 16 to 20 sessions over 12 to 16 weeks (Craighead, Johnson, Carey, & Dunlop, 2015). Premature dropouts also had nearly a ten times higher odds of being rated with a termination reason indicating logistical, financial, and other barriers to treatment as compared to completers.

The main goal of our study was to investigate the relationship between dropout and outcome. Results supported our hypothesis that dropouts were more severely symptomatic when treatment ended than were completers. The size of the symptom severity difference at termination between dropouts and completers was not large. Nevertheless, the difference in BDI termination score between dropouts and completers may be a clinically relevant one. Depressed patients who end treatment with residual symptoms are more likely to relapse than those who have recovered completely (van Londen, Molenaar, Goekoop, Zwinderman, & Rooijmans, 1998), and thus there may be an important clinical difference between ending treatment with a BDI score of 9 to 11, which is a score in or near the normal range (Beck et al., 1988) (the mean completer score) and ending treatment with a BDI score of 14, which is a score in the moderate range (the mean dropout score).

Contrary to our hypothesis, dropouts did not differ from completers in their rate of change in symptoms of anxiety or depression over the course of treatment. This finding, coupled with the finding that dropouts received fewer sessions of treatment than completers, suggests that dropouts had higher symptom scores at termination than completers because they received fewer sessions of treatment, not because their symptoms changed at a slower rate.

Also noteworthy is our finding that early dropouts started treatment with lower BDI scores than completers (Cohen's d = 0.43). This may indicate that patients with lower symptom severity may be more ambivalent about seeking treatment and thus quicker to drop out, and highlights the importance of assessing motivation for treatment and discussing termination early in treatment (Davis, 2008).

To add to our understanding of why patients in our sample dropped out, we analyzed therapist-rated reasons for termination. Uncollaborative dropout, but not other types of dropout, was associated with a higher odds of being rated with a termination reason indicating poor outcome,

corresponding to medium effect size (Cohen's d = 0.49). Therapists assigned termination reasons indicating poor outcome when the patient (usually) or therapist (rarely) was dissatisfied with some aspect of the therapy outcome or process. This finding is consistent with work by other investigators pointing to the alliance as a predictor of dropout (Kegel & Flückiger, 2015). Therapists may be able to reduce this type of dropout by carefully monitoring the alliance, perhaps using a web-based feedback system such as that developed by Lambert and colleagues (Harmon et al., 2007), which allows the therapist to get frequent information about the status of the alliance as therapy proceeds. The therapist can also assess the alliance with behavioral observations (e.g., frequent cancellations, low engagement during sessions), and/or standardized tools (e.g., Miller, Duncan, Sorrell, & Brown, 2005). These data can help the therapist take prompt action (e.g., Safran et al., 2011) to resolve any weaknesses or ruptures in an effort to forestall a premature termination.

Our analyses of termination reasons also indicated that all types of dropout, but especially premature dropout, were associated with a higher odds of being rated with a reason indicating logistical, financial, and other barriers to treatment, corresponding to small to large effect sizes (Cohen's ds = 0.28 – 1.25). These factors are particularly salient in a private practice setting in which patients are paying high fees, as in the present study. The large contribution of logistical, financial, and other barriers to treatment highlights the importance of working to reduce attrition by (a) orienting patients at the outset to what can be expected in psychotherapy, including the time and cost involved (Barrett et al., 2008), and (b) working creatively to address logistical barriers (e.g., remote sessions via phone or video-conference). Alternatively, patients may tell the therapist that they are leaving treatment due to logistical, financial, and other barriers to treatment when they are actually dissatisfied with the process of therapy but unable or unwilling to discuss this with the therapist. This possibility highlights the need to routinely monitor and intervene promptly to address problems in the alliance.

This study has several limitations. We could not measure the reliability or validity of therapists' ratings of premature dropout, uncollaborative dropout, or patients' reasons for termination. To obtain accurate information from patients about their reasons for terminating treatment, researchers and clinicians might find it useful to adopt a feedback mechanism that would allow patients to provide information, even anonymously, to their

therapists, about their reasons for ending treatment. The relationship we found between higher symptom severity at termination and therapist-rated premature and uncollaborative dropout may in part be due to the fact that the therapist's ratings of dropout were not always blind to the patient's symptom scores. The association we found between uncollaborative dropout and termination reasons indicating poor outcome may be due to therapists assuming that patients dropped out uncollaboratively because they were unhappy with the process or outcome of therapy. Additionally, because the definition of premature dropout called for the therapist to rate only whether the patient had given the therapy enough time to achieve his/her treatment goals, we could not investigate other factors that might contribute to premature dropout (e.g., terminating before sufficient consolidation of gains). Concern about the contamination of therapists' dropout ratings by awareness of patients' symptom data is mitigated by facts that (a) therapists often made dropout ratings months to years after treatment ended and so were unlikely to remember details of the symptom scores, (b) the symptom score difference between dropouts and completers at termination was small and so may not have been salient to the therapist, and (c) our main finding, that patients who dropped out had worse outcomes but no differential rate of change during treatment, was also found for early dropout, which was assessed with an objective count of the number of sessions the patient completed.

Our study also has several strengths. One is the very large sample. Second, because findings were obtained in a naturalistic study of an unselected sample of patients with a heterogeneous collection of mood and anxiety disorders, results are directly relevant to practitioners working in similar private practice settings. Third, we investigated the relationship between dropout and outcome, which has been little studied. In addition, the consistency of results over all three measures of dropout and symptoms of both anxiety and depression strengthen our confidence in the findings. Finally, the study serves as a model of integrating science and practice (Persons, in press) as a result of the fact that the data reported here were collected for clinical purposes.

CONCLUSION

In summary, our results indicate that although dropouts from naturalistic CBT end treatment with higher symptom severity than completers, dropouts and completers do not differ in their rate of symptom change during treatment. Our results point to the importance of carefully handling the termination phase of treatment (Davis, 2008) and

attending to factors (e.g., problems in the alliance, dissatisfaction with the process of therapy, logistical and financial barriers to treatment) that may lead patients to cut short their trajectories of improvement by dropping out.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest.

References

American Psychiatric Association. (1987). *Diagnostic and statistical manual of mental disorders (DSM-III-R)*. Washington, DC: Author.

American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders (DSM-IV)*. Washington, DC: Author.

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders (DSM-IV-TR)*. Washington DC: Author.

Arnow, B. A., Blasey, C., Manber, R., Constantino, M. J., Markowitz, J. C., Klein, D. N., . . . Rush, A. J. (2007). Dropouts versus completers among chronically depressed outpatients. *Journal of Affective Disorders*, *97*, 197–202. https://doi.org/10.1016/j.jad.2006.06.017

Barrett, M. S., Chua, W. J., Crits-Christoph, P., Gibbons, M. B., & Thompson, D. (2008). Early withdrawal from mental health treatment: Implications for psychotherapy practice. *Psychotherapy: Theory, Research, Practice, Training*, *45*(2), 247–267. https://doi.org/10.1037/0033-3204.45.2.247

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

Bloom, B. L. (2001). Focused single-session psychotherapy: A review of the clinical and research literature. *Brief Treatment and Crisis Intervention*, *1*(1), 75–86. https://doi.org/10.1093/brief-treatment/1.1.75

Burns, D. D. (1989). *The feeling good handbook: Using the new mood therapy in everyday life*. New York, NY: William Morrow and Company.

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), 461–473. https://doi.org/10.1037/0022-006X.66.3.461

Burns, D. D., & Nolen-Hoeksema, S. (1992). Therapeutic empathy and recovery from depression in cognitive-behavioral therapy: a structural equation model. *Journal of Consulting and Clinical Psychology*, *60*(3), 441–449. https://doi.org/10.1037/0022-006X.60.3.441

Cahill, J., Barkham, M., Hardy, G., Rees, A., Shapiro, D. A., Stiles, W. B., & Macaskill, N. (2003). Outcomes of patients completing and not completing cognitive therapy for depression. *British Journal of Clinical Psychology*, *42*(2), 133–143. https://doi.org/10.1348/014466503321903553

Chinn, S. (2000). A simple method for converting an odds ratio to effect size for use in meta-analysis. *Statistics in Medicine*, *19*, 3127–3131. https://doi.org/10.1002/1097-0258(20001130)19:22<3127::AID-SIM784>3.0.CO;2-M

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Craighead, W. E., Johnson, B. N., Carey, S., & Dunlop, B. W. (2015). Psychosocial treatments for major depressive disorder. In P. E. Nathan & J. M. Gorman (Eds.), *A guide to treatments that work* (4th ed., pp. 318–408). New York, NY: Oxford University Press.

Crits-Christoph, P., Connolly, M. B., Gallop, R., Barber, J. P., Tu, X., Gladis, M., & Siqueland, L. (2001). Early improvement during manual-guided cognitive and dynamic psychotherapies predicts 16-week remission status. *Journal of Psychotherapy Practice and Research*, 10, 145–154. PMID:11402077

Davis, D. (2008). *Terminating therapy: A professional guide to ending on a positive note.* Hoboken: John Wiley & Sons.

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. https://doi.org/10.1192/bjp.128.3.280

Enders, C. K. (2010). *Applied missing data analysis.* New York, NY: Guliford Press.

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

Hansen, A. M. D., Hoogduin, C. A. L., Schaap, C., & de Haan, E. (1992). Do drop-outs differ from successfully treated obsessive-compulsives? *Behaviour Research and Therapy*, 30(5), 547–550. https://doi.org/10.1016/0005-7967(92)90040-N

Harmon, S. C., Lambert, M. J., Smart, D. M., Hawkins, E., Nielsen, S. L., Slade, K., & Lutz, W. (2007). Enhancing outcome for potential treatment failures: Therapist-client feedback and clinical support tools. *Psychotherapy Research*, 17(4), 379–392. https://doi.org/10.1080/10503300600702331

Howard, K. I., Kopta, S. M., Krause, M. S., & Orlinsky, D. E. (1986). The dose-effect relationship in psychotherapy. *American Psychologist*, 41, 159–164. https://doi.org/10.1037/0003-066X.41.2.159

Kegel, A. F., & Flückiger, C. (2015). Predicting psychotherapy dropouts: A multilevel approach. *Clinical Psychology & Psychotherapy*, 22(5), 377–386. https://doi.org/10.1002/cpp.1899

Lutz, W., Hofmann, S. G., Rubel, J., Boswell, J. F., Shear, M.K., Gorman, J. M., . . . Barlow, D. H. (2014). Patterns of early change and their relationship to outcome and early treatment termination in patients with panic disorder. *Journal of Consulting and Clinical Psychology*, 82(2), 287–297. https://doi.org/10.1037/a0035535

Manthei, R. J. (1995). A follow-up study of clients who fail to begin counselling or terminate after one session. *International Journal for the Advancement of Counselling*, 18(2), 115–128. https://doi.org/10.1007/BF01421563

Martin, D. J., Garske, J. P., & Davis, M. K. (2000). Relationship of the therapeutic alliance with outcome and other variables: A meta-analytic review. *Journal of Consulting and Clinical Psychology*, 68(3), 438–450. https://doi.org/10.1037/0022-006X.68.3.438

Miller, S. D., Duncan, B. L., Sorrell, R., & Brown, G. S. (2005). The partners for change outcome management system. *Journal of Clinical Psychology*, 61(2), 199–208. https://doi.org/10.1002/jclp.20111

Persons, J. B. (in press). Conducting research in clinical practice. In R. T. C. III (Ed.), *Practice-based research: A guide for clinicians* New York: Taylor & Francis/Routledge.

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

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team. (2018). nlme: Linear and nonlinear mixed effects models. Retrieved from https://cran.r-project.org/package=nlme

R Core Team. (2016). R: A language and environment for statistical computing.Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.r-project.org/

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Reis, B. F., & Brown, L. G. (1999). Reducing psychotherapy dropouts: Maximizing perspective convergence in the psychotherapy dyad. *Psychotherapy: Theory, Research, Practice, Training*, 36(2), 123–136. https://doi.org/10.1037/h0087822

Rubin, D. B. (1976). Inference and missing data. *Biometrika*, 63, 581–592. https://doi.org/10.2307/2335739

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

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods*, 7, 147–177. https://doi.org/10.1037/1082-989X.7.2.147

Schindler, A., Hiller, W., & Witthoft, M. (2013). What predicts outcome, response, and drop-out in CBT of depressive adults? A naturalistic study. *Behavioural and Cognitive Psychotherapy*, 41, 365–370. https://doi.org/10.1017/S1352465812001063

Swift, J. K., & Greenberg, R. P. (2012). Premature discontinuation in adult psychotherapy: A meta-analysis. *Journal of Consulting and Clinical Psychology*, 80(4), 547–559. https://doi.org/10.1037/a0028226

Swift, J. K., Greenberg, R. P., Tompkins, K. A., & Parkin, S. R. (2017). Treatment refusal and premature termination in psychotherapy, pharmacotherapy, and their combination: a meta-analysis of head-to-head comparisons. *Psychotherapy*, 54(1), 47–57. https://doi.org/10.1037/pst0000104

Swift, J. K., Greenberg, R. P., Whipple, J. L., & Kominiak, N. (2012). Practice recommendations for reducing premature termination in therapy. *Professional Psychology: Research and Practice*, 43(4), 379–387. https://doi.org/10.1037/a0028291

Szafranski, D. D., Smith, B. N., Gros, D. F., & Resick, P. A. (2017). High rates of PTSD treatment dropout: A possible red herring? *Journal of Anxiety Disorders*, 47, 91–98. https://doi.org/10.1016/j.janxdis.2017.01.002

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, 45. https://doi.org/10.18637/jss.v045.i03

van Londen, T., Molenaar, R. P. G., Goekoop, J. G., Zwinderman, A. H., & Rooijmans, H. G. M. (1998). Three- to 5-year prospective follow-up of outcome in major depression. *Psychological Medicine*, 28(3), 731–735. https://doi.org/10.1017/S0033291797006466

Wierzbicki, M., & Pekarik, G. (1993). A meta-analysis of psychotherapy dropout. *Professional Psychology: Research and Practice*, 24(2), 190–195. https://doi.org/10.1037/0735-7028.24.2.190