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Therapist Effects and the Impacts of Therapy Nonattendance

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Although dropout from psychotherapy has received substantial attention, the impacts of nonattendance on client outcome across a course of psychotherapy have not been well researched. All in-person psychotherapy treatments require clients to actually attend sessions to generate positive symptomatic results, and missed sessions have at least a time and financial cost. Furthermore, it is plausible that therapist differences exist for client attendance rates. The present study examined impacts of nonattendance, particularly early in a course of treatment, comparing the effects of canceled and no-showed appointments on overall symptom reduction and rate of change while accounting for therapist effects. Using multilevel hierarchical regression, the impact of nonattendance on symptom reduction and rate of change was modeled on 5,253 clients (67.2% female, 72.3% white) across 83 therapists gathered from a practice research network. Results suggested that no-shows, but not cancellations, had negative impacts on the magnitude and rate of symptom change, with larger effects when occurring before the third session. Therapist effects on attendance also were identified; therapists varied greatly on nonattendance percentages of their clients after the third attended session.

Keywords: attendance, outcome, termination, dropout, therapist effects

It is difficult to deliver efficient treatment to psychotherapy clients who infrequently attend appointments. Simply put, if a client does not attend an appointment, they are not receiving potentially beneficial care. Although much research has been devoted to dropout defined as a specific form of last session nonattendance, there has been nearly no research on the impact of multiple nonattended appointments during the process of therapy. These two phenomena are separate: there may be dropouts who attended every session except their last, and infrequent attenders who eventually “complete” a course of treatment and attend their last scheduled session. Clinically speaking, it is conceivable that the efforts of the consistent attender indicate engagement and motivation to benefit from psychotherapy in a way that is lacking for inconsistent attenders. In other words, looking solely at the last appointment may not accurately reflect the client’s commitment to the therapeutic process as a whole.

A high “did not attend” (DNA) rate of a client may especially be damaging during the earliest phase of treatment, given the vital importance of early alliance development (Flückiger, Del Re, Wampold, Symonds, & Horvath, 2012; Horvath, Del Re, Flückiger, & Symonds, 2011). Weaker alliance has been found to be related to smaller positive treatment outcomes and an increased risk of dropout (Sharf, Primavera, & Diener, 2010). Nonattendance during the earliest therapy sessions may disrupt the alliance-building process and inhibit engagement in therapy. Poor attendance during this early period may reflect a lack of engagement, externally or internally based, that may also be predictive of the overall course of treatment. That is, it may be more difficult to “get the ball rolling” if the process of therapy is already stuttering during early treatment.

However, different types of nonattendance may matter: a client “cancellation” is clinically different than a “no-show.” Although both result in a nonattended session, a cancellation involves some client effort and engagement that a no-show lacks. Client cancellation implies communication with the provider some time before the appointment, whereas a no-show represents an extremely late or nonexistent advanced notification. Again, it is plausible that clients who give advance notice are also more engaged in and thinking about therapy, even when they are not with the therapist, thereby putting them in a better position to work in therapy toward their goals. This is not to say that a no-show is equivalent to a disinterested client, but repeated no-shows, even when occurring due to extenuating external circumstances, at the very least may indicate that the client does not have stability in their life optimal for regular psychotherapy.

These subtleties also distinguish client nonattendance from session frequency. As reported by Erekson, Lambert, and Eggett (2015), clients who attended therapy more frequently (weekly

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therapy compared with biweekly) were estimated to recover faster on average, although total change achieved by the end of therapy was nondistinguishable. However, there may be a difference between a therapeutically contracted biweekly schedule of sessions compared with a client who decides on his or her own to attend every other week. That is, regardless of the frequency of sessions agreed upon within a therapeutic dyad, the client who fails or is otherwise unable to honor that agreement may experience overall decreased benefits from therapy.

It is also important to understand if infrequent attendance creates a "stall" on symptom change in therapy, or if it negatively impacts the gains expected of treatment. To borrow language from and expand upon the dose-effect model literature (Howard, Kopta, Krause, & Orlinsky, 1986; Kopta, Howard, Lowry, & Beutler, 1994), it may be that the "dose" of five total sessions attended with nonattended sessions interspersed is less than the "dose" of five sessions attended straight through because timing matters. Just as some medications are only effective when taken regularly in a prescribed way, it may be that beyond the raw number of sessions, the regularity of attendance is important. The unintended protraction of therapy for irregularly attending clients may interfere with optimal treatment: valuable session time may be spent addressing attendance, "catching up" on missed time, or refreshing and reminding clients of themes and/or skills lost in the time between attended sessions. In other words, the process of therapy may be interrupted and the client's rate of change may be diminished. Total change in symptoms and rate of change can therefore be considered distinct ways to measure client change.

Beyond the impact on the client and therapy itself, the potential financial costs of nonattendance are likely quite large. Based on estimates from the medical field, which has produced more research on this issue, estimates place the financial cost of general practitioner appointment DNA rates alone in the U.K. at over 150 million pounds per year (Martin, Perfect, & Mantle, 2005). In terms of hours lost, this may be even more costly for psychotherapy appointments; while in the medical field, patients are scheduled for monthly or longer follow-ups, psychotherapy is often practiced on a weekly basis, and the costs of nonattendance may accumulate more quickly. This is compounded by differences in the structure of treatment: while medical practitioners and hospitals may "overbook" and attempt to replace appointments in the moment, the nature of psychotherapy depends more on structured and timely meetings with specific clients at specific times. In both settings, the nonattendance of scheduled appointments creates a "paradoxical situation" where the health professional is underutilized while also increasing the inefficiency of treatment (Green & Savin, 2008).

Furthermore, it is plausible that different therapists have different overall client attendance patterns. Recent studies have found a therapist effect for dropout rates (Saxon, Barkham, Foster, & Parry, 2016; Zimmermann, Rubel, Page, & Lutz, 2016), but to our knowledge, there has not been a study examining therapist differences in attendance rates. Theoretically it may be that therapists differ in how they address nonattendance with their clients. For example, therapists may vary in how quickly they call clients to reschedule, if at all. Indeed, busy therapists may welcome a "free hour" to catch up on other administrative tasks. They may also address attendance issues differently in-session, with different levels of openness and emphasis on the importance of attendance. For any given therapist, consistent patterns in how nonattendance of scheduled sessions are handled may lead their clients to understand missing sessions as more or less acceptable. Or, therapists may simply differ in their ability to engage their clients and foster a desire to attend sessions.

Perhaps the lack of research on psychotherapy attendance rates is due to the difficulties in gathering longitudinal data from an adequate number of therapists or centers. Although it is difficult to gather continuous appointment data from multiple locations, one way is through practice research networks (PRN), in which clinicians work in collaboration with researchers (Castonguay, Barkham, Lutz, & McAleavey, 2013; Castonguay, Youn, Xiao, Muran, & Barber, 2015). The Center for Collegiate Mental Health (CCMH) is such a PRN that currently involves a nationally representative partnership of university counseling centers. Participating centers use standardized instruments along with appointment attendance information to contribute to an anonymous, aggregate, and large representative dataset that requires no extra effort from its members to collect (Hayes, Locke, & Castonguay, 2011; McAleavey, Lockard, Castonguay, Hayes, & Locke, 2015).

Aside from its size, the CCMH PRN also provides a means to look at a particularly vulnerable treatment setting. Specifically, demand for mental health care at counseling centers is high enough that waitlists are adopted by nearly half of 228 recently surveyed centers, with nearly 90% of center directors reporting concern that their clients may not be getting aid when most helpful (Gallagher, 2011). From a recent meta-analysis, these "university-based clinics" have also been found to have higher dropout rates (30.4%) across all examined clinical settings (Swift & Greenberg, 2012), which when combined with unattended appointments throughout a course of treatment, represent a staggering opportunity cost for client care.

Indeed, this treatment setting may be particularly impacted by nonattendance of clients. College counseling centers have seen an increase in student-client utilization disproportionate to the resources allotted to them; across 93 CCMH center respondents, from 2009 to 2014, the average center saw an increase of 29.6% of students served at their counseling center compared with a 5.6% increase in institutional enrollment (Center for Collegiate Mental Health, 2016; Kadison, 2004; Kadison & DiGeronimo, 2004). To meet their clinical demands and pressures, these treatment centers have frequently adopted various policies, such as wait-lists on a first-come, first-serve basis, clinical triage systems, and assignation of demanding case-loads for each therapist. Although a certain number of cancellations and no-shows may be inevitable, if therapist effects exist for attendance rates, it might be fruitful to understand and develop different practices to improve attendance rates.

The present study aims to explore the impacts of psychotherapy DNA rates of early sessions, in which alliance building may be most important, while accounting for therapist effects. We predicted that a greater nonattendance rate will be associated with diminished overall symptom reduction, and that the timing and the type of nonattendance matters: early nonattendance would be more harmful than later nonattendance and no-shows would be associated with less symptom change than cancellations. We also hypothesized that the rate of change of a client is negatively impacted by nonattendance; that is, the change in symptom reduction per session will be diminished with increasing nonattended sessions.

Finally, we report on the presence of therapist effects for attendance, again with specificity in regards to type (no-shows and cancellations), and timing (early and later in treatment).

Methods

Data Reduction

Participating members of CCMH have their student clientele complete the repeated multidimensional assessment instrument Counseling Center Assessment of Psychological Symptoms (CCAPS), described below. The data were gathered in a naturalistic way from contributing centers, with center autonomy regarding the frequency of administration of the instruments in the spirit of a PRN. The present study was conducted with clients who started and completed a course of therapy (attended at least one therapy session, and were scheduled for at least two) during 2010–2012. To maximize accuracy in capturing clients' change in distress, clients were required to have at least two CCAPS administrations, one each within 14 days of the first and last scheduled appointments to capture the full length of treatment. Clients needed to have their starting score for the Distress Index subscale of the CCAPS fall above the low cutpoint, indicative of a clinically meaningful level of generic distress (described further in instruments). It was expected that a client's starting severity will have great impact on how much they are able to improve and so clients were selected with at least a mild elevation in symptomology (Finch, Lambert, & Schaalje, 2001; Lambert, Hansen, & Finch, 2001). To reliably assess therapist effects, individual therapists were required to have seen at least 30 clients in this 2-year period (Saxon et al., 2016; Soldz, 2006).

Participants

The final dataset composed of 5,253 individual clients and 83 therapists across 22 different counseling centers. The clients averaged 8.63 (SD = 7.64) scheduled and 6.82 (SD = 6.28) attended sessions during their course of psychotherapy. By self-report, 67.2% identified as female, and 72.4% as Caucasian/White. This subset's mean age was 22.43 years (SD = 4.81). Although not specific to this dataset, clients at large were rated by clinicians as having anxiety, depression, specific relationship problems, stress, and family concerns as the five most frequent top concerns on the Clinician Index of Client Concerns, a categorical checklist of 44 client concerns (CCMH, 2015). In regards to therapists, on average they saw 58.65 clients (SD = 24.72), and 79.6% identified as female, 75.5% as Caucasian/White, and with an average age of 39.73 (SD = 11.24).

Instruments

Counseling Center Assessment of Psychological Symptoms. The CCAPS is a self-report measure developed to assess the specific mental health needs of college students (Locke et al., 2011). The 34-item version is designed for repeated use as a tool in clinical practice and has eight subscales measured on a 5-point Likert scale: "Not at all like me" to "Extremely like me." The eight subscales are Depression, Generalized Anxiety, Social Anxiety, Academic Distress, Eating Concerns, Hostility, Alcohol Use, and a Distress Index, which provides an overall level of symptomology by taking key items from multiple scales. Subscale scores are further divided by two cut points—low and high. Scores above the low cutpoint warrant further exploration for potentially problematic or mildly severe symptoms; scores below this point are closer to a nonclinical population. The high cutpoint represents a high likelihood of some clinical problem in that subscale area. As previously mentioned, the present study was conducted with clients with starting scores at least over the low cutpoint on the DI, 1.21 on the 5-point scale, equivalent to the 34th percentile of scores (Center for Collegiate Mental Health, 2012). More generally, the average DI score has been reported as 1.64 (SD = .84) for the clinical population. The CCAPS has demonstrated good internal consistency and test–retest reliability, and its individual subscales have shown good concurrent validity (Locke et al., 2011; McAleavey et al., 2012). The CCAPS data for this study were administered and stored electronically using Titanium software.

Statistical Analyses

The total number of nonattended sessions were calculated for early treatment, defined as appointment attendance prior to the third attended session, and for continued treatment, defined as attendance post third attended session. These numbers were separated into client no-shows and client cancellations separately to assess the impact of types of nonattendance. Cancelled appointments were considered as those labeled as either "cancelled" or "rescheduled" in the electronic medical records system, indicating some communication between client and therapist (or receptionist) regarding absence. For analyses using percentages, the number of no-shows or cancellations was divided by the total number of attended sessions for a given client. Rate of change was operationalized as the total change in DI score from first to last session divided by the number of attended sessions.

On average, clients first DI score was 2.12 (SD = .566) and their last was 1.50 (SD = .776), with an average change of .622 (SD = .743). We report the attendance percentage by session of the clients in the dataset in Table 1, up through the 15th session (i.e., the percentage of first, second, third, etc. appointments that were labeled as attended through the electronic medical record system).

Table 1
Attendance of In-Treatment Clients

Session number	% Attended	N
1	91.63	5,139
2	83.57	5,139
3	80.57	4,988
4	80.94	4,681
5	78.95	4,324
6	76.91	3,907
7	78.45	3,517
8	76.33	3,164
9	76.94	2,845
10	76.72	2,556
11	78.30	2,295
12	77.63	2,043
13	77.75	1,816
14	76.33	1,631
15	79.53	1,456

To assess for collinearity between predictors, the grand mean correlations of all predictors across therapists were assessed. Continued treatment no-shows and cancellations were highly correlated ($r = .92$, $p < .01$), and so these two variables were additively combined into a "continued treatment nonattendance" variable. This aggregate variable was correlated at $r = .95$ with its constituents ($p < .001$). There was a high correlation between total therapy sessions and continued treatment attendance variables—this was expected, as nonattended sessions are expected to accrue as treatment length increases. The complete correlation matrix is presented in Table 2, along with means and standard deviations.

The first set of analyses involved total DI change as predicted by the three DNA variables: raw number of early cancellations and no-shows, and continued treatment nonattended sessions. To assess the appropriateness of multilevel modeling with therapists as a nesting variable, a likelihood ratio test was conducted comparing the null single-level model (without therapist grouping or predictors) with the null multilevel model (with therapist grouping, still without predictors). Second, the client's grand mean centered starting DI score and total number of sessions was added to control for initial client severity and length of treatment, and compared with the null multilevel model. Next, the client level DNA predictor variables were added individually and hierarchically, with each successive new model compared with the previous model using a likelihood ratio test for model improvement. Insignificant variable additions were dropped, and the next variable was tested until all three variables were assessed. Finally, these variables were tested in a random effects model, allowing the impact of DNA predictor variables to vary across therapists. This hierarchical testing of variables was then repeated for the second set of analyses, with DI rate of change as the outcome.

Finally, to test for the existence of therapist effects on attendance variables, three null multilevel models were fitted to the same dataset, each with a different nonattendance variable as an outcome: percentage of early no-shows and cancellations, and percentage of continued treatment nonattended sessions. All therapist effects were calculated as intraclass correlation coefficients (ICCs), a proportion of total variance due to differences between therapists (Steele, 2008). To obtain the ICC, the variation between therapists σ_u^2 is divided by the total variance (variation between therapists, σ_u^2, added to variation within therapists, σ_e^2). Analyses were conducted in R version 3.3.1 (R Core Team, 2016) using the package lme4.

Results

For the first set of analyses relating to total client DI change, therapist effects were present; when compared with the empty single level model, the addition of therapist grouping was found to be significant ($\chi^2(1, 5253) = 28.31$, $p < .001$). The ICC was calculated to be 2.12%; therapists accounted for 2.12% of the variance in the outcome of clients' total DI change. All the predictor variables were found to improve model fit, except for early treatment cancellations. The random effects models were not found to be significant improvements to preceding models. The results of the log likelihood ratio tests are presented in Table 3. Note that the "Comparison Step" column denotes which models are being compared.

In the final model, presented in Table 4, each point higher of client initial DI score increased amount of total change by .47, and each attended therapy appointment by .006. Early treatment no-shows (prior to the third attended session) were found to decrease total change by .117 points per no-showed session, whereas continued treatment nonattendance (cancellations or no-shows after the third attended session) were not found to be significantly impactful.

The second set of analyses on DI rate of change produced a similar direction of results. Therapist effects were found to be significant ($\chi^2(1, 5253) = 347.34$, $p < .001$) and from the ICC calculation accounted for 8.74% of the variance in outcome of client DI rate of change. All the predictor variables, including early treatment cancellations, were found to be significantly improving additions to the hierarchical model, although in the final model statistics, early treatment cancellations were not found to a significant predictor. Summaries of the log likelihood ratio tests for DI rate of change are presented in Table 5. Once again, the random effects models were not found to be significant improvements.

The final model for DI rate of change, shown in Table 6, found each point higher of a client's starting DI increased DI change per session by .063 points, and each attended session decreased change per session by .004. Early treatment no-shows decreased rate of DI change by .014 points per no-showed session, whereas early treatment cancellations were not found to be significant. Nonattended sessions after the third session decreased rate of DI change by .003 points per session.

The final set of analyses examined therapist effects on type and timing of attendance. The therapist effect, ICC, for early treatment

Table 2
Correlation Matrix of Predictor Variable Grand Means Across Therapists

Predictor variable	Initial DI score	Total attended therapy sessions	Early treatment cancels	Early treatment no-shows	Continued treatment cancels	Continued treatment no-shows	Continued treatment nonattendance	Mean	*SD*
Initial DI score	1							2.12	.566
Total attended therapy sessions	.351**	1						6.81	6.19
Early treatment cancels	.118	−.075	1					.38	.69
Early treatment no-shows	.101	−.060	.167	1				.23	.57
Continued treatment cancels	.223	.636**	−.173	−.76	1			.82	1.30
Continued treatment no-shows	.235	.737**	−.193	−.104	.919***	1		.43	1.00
Continued treatment nonattendance	.236	.722**	−.191	−.099	.995***	.955***	1	1.25	1.83

** $p < .01$. *** $p < .001$.

Table 3
Client Total DI Change Model Selection

Step	Variables included	Comparison step	χ^2	Degrees freedom	*p*-value
1	Empty	n/a	n/a	n/a	n/a
2	Initial DI Score, total attended appts	1	629.73	2	<.001
3	Initial DI Score, total attended appts, early treatment no-shows	2	57.18	1	<.001
4[a]	Initial DI Score, total attended appts, early treatment no-shows, early treatment cancellations	3	3.07	1	.072
5	Initial DI Score, total attended appts, early treatment no-shows, continued treatment nonattendance	3	3843.43	1	<.001
6[a]	Initial DI Score, total attended appts, random effects of early treatment no-shows, continued treatment nonattendance	5	5.77	5	.329

Note. $N = 5{,}253$.
[a] A step/variable that was not included in the final model.

no-shows was calculated to be 1.4%, and for early treatment cancellations was 1.1%. For continued treatment nonattendance (sessions extending beyond the third attended session), therapist variance accounted for 45.7% of total variance in client nonattendance rates. In terms of descriptive statistics, it was found that therapists grand mean average for nonattendance after the third session was 12.27% (*SD* = 11.62%). Therapists ranged in nonattendance from 0% to 35.09%, and 26 therapists reported a nonattendance rate of 0%. These 26 therapists were from six different centers, with one center housing 16 of the therapists (61.5%).

Discussion

This study examined the impacts of client DNA rates on symptom reduction and rate of change, with specificity of timing and type of nonattendance and with consideration of therapist variation. That is, does the type and timing of nonattendance impact client outcome or rate of change? And do therapists differ in their overall rates of specific types and timings of client nonattendance? Interestingly, across therapists, their client cancellations and no-shows were extremely highly correlated after the third session. As seen in Table 1, the DNA rate roughly falls between 75% and 80% regardless of session, perhaps reflecting a clinical landscape that nonattendance is a ubiquitous phenomenon that can and does occur irrespective of time in treatment. It is important to note that the inclusion criteria of clients required attendance of at least one session and being scheduled for at least two, indicating the initiation of some form of scheduled therapy. While Session 1 was found to have a 91.6% attendance rate, this is reflective of individuals committed enough to start a course of psychotherapy by attending at least one session. This does not include any individuals who were scheduled but never attended any sessions at all, which represents a different, but also administratively taxing, population that would decrease the overall percentage of attended first sessions.

Table 4
Client Total DI Change Final Model Statistics

Variable	B	Standard error	Significance
Intercept	.722	.016	<.001
Initial DI score	.471	.021	.002
Total attended therapy appts.	.007	.002	.001
Early treatment no-shows	−.117	.022	<.001
Continued treatment nonattendance	−.014	.007	.100

Note. $N = 5{,}253$.

As expected, the combination of a client's starting level of symptoms (as measured by DI score) and treatment length was a significant predictor for both outcomes. Nonetheless, there were also clear patterns of differences between no-shows and cancellations and their timings on both outcomes after controlling for initial DI score and number of sessions. In particular, earlier session no-shows were found to be over eight times as impactful as nonattendance after the third session. For example, two no-showed early treatment sessions would predict less DI change on a magnitude of .234 points, whereas two continued treatment nonattended sessions would be equivalent to a .028 reduction of overall DI change scores (i.e., less overall symptom reduction).

The results of the rate of change analyses suggest similar conclusions. A single early treatment no-show was found to be roughly four times as negatively impactful as a no-show after the third session. It is important to note that the negative effects of no-shows in these analyses are compounded as treatment length increases. For example, given these results, two early no-showed sessions would be predicted to have an equivalent decrease of .028 DI subscale points per session, which becomes an overall DI change decrease of .28 points if treatment lasts 10 sessions. For treatment no-shows after the third session, the same 10 session course would be predicted to result in an overall reduction of only.06 DI change points. Comparatively, neither early nor continued treatment cancellations were found to be significant predictors of either total DI change or rate of change.

In regards to therapist effects on attendance, there was little therapist variance for early treatment attendance variables. These results may suggest that although early nonattendance can impact outcome and rate of change, their occurrence does not drastically vary from therapist to therapist. However, after this important early phase of treatment, our results suggest that therapists vary greatly in nonattendance, with over 40% of client attendance being attributed to therapist variance. With most of the therapist effects literature having been estimated using various outcomes at 5%–8% (Baldwin & Imel, 2013; Lutz, Leon, Martinovich, Lyons, & Stiles, 2007; Saxon & Barkham, 2012), and recent research on therapist effects in dropout having been reported at 5.7% (Zimmermann et al., 2016) and 12.6% (Saxon, Barkham, Foster, & Parry, 2016), therapist effects on attendance variables is an unresearched phenomenon which appears to have great variation be-

Table 5
Client DI Rate of Change Model Selection

Step	Variables included	Comparison step	χ^2	Degrees freedom	*p*-value
1	Empty	n/a	n/a	n/a	n/a
2	Initial DI Score, total attended appts	1	305.90	2	<.001
3	Initial DI Score, total attended appts, early treatment no-shows	2	35.24	1	<.001
4	Initial DI Score, total attended appts, early treatment no-shows, early treatment cancellations	3	14.73	1	<.001
5	Initial DI Score, total attended appts, random effects of early treatment no-shows, early treatment cancellations, continued treatment nonattendance	3	9128.55	1	<.001
6[a]	Initial DI Score, total attended appts, early treatment no-shows, early treatment cancellations, continued treatment nonattendance	5	8.25	9	.501

Note. $N = 5{,}253$.
[a] A step/variable that was not included in the final model.

tween therapists. However, that the random effects models (allowing for the impact of the predictors to vary across therapists) were not significant also suggests that the impact of DNA rates does not differ much between therapists. In other words, although therapists may differ noticeably in the overall rates of their clients' attendance records, the negative impact of any missed session does not differ greatly between therapists.

However, these results should be reported in context and with caution. Although there was a significant and consistent negative impact of no-shows on both overall DI change and rate of change, the size of the effect was small and should not be negatively overinterpreted. In fact, one might argue that the small effect size observed sends a reassuring message—just because a client doesn't show up regularly doesn't mean they are "doomed." Similar to Erekson et al.'s findings regarding scheduled session frequency and outcome, there is little evidence to suggest that nonattendance has a drastic impact on their total symptom change at termination. It may be that irregularly attending clients may simply have to stay in longer in treatment in order to achieve a level of change similar to that of more consistently attending clients; this is consistent with the good-enough level model literature (Barkham et al., 2006; Stiles, Barkham, Connell, & Mellor-Clark, 2008). These findings are also reflected in the different therapist effects for rate of change (8.74%) compared with total DI change (2.12%); there is much more variation in how quickly or efficiently therapists evoke change than in the total amount of change their clients experience.

Also notably, the majority of therapists reporting a striking 0% DNA rate reported from a single center. It may be that a large proportion of attendance variance can actually be attributed to center level effects. That is, center policy regarding client contact, cancellations, and no-show policies may play a larger role in overall client attendance than individual therapist differences. This may especially be true for the college counseling center, where resources may be scarcer and triaging is a premium concern (Gallagher, 2014; Mistler, Reetz, Krylowicz, & Barr, 2012). Compared with independent practice, the college counseling center may be a treatment setting with less room for therapist variation in attendance policy, and center-wide practices, such as text reminders or harsh no-show rules, play an important role in overall attendance. Although it was outside the focus of this paper to thoroughly examine center effects, there were still therapists with low nonattendance rates dispersed in other centers as well, and it remains plausible that therapists do indeed exhibit some variation in their clients' attendance rates. Relatedly, our analyses also found substantially higher therapist variance for DI rate of change compared with overall DI change, highlighting the importance of understanding that the operationalization of therapist effects can have great impact on findings.

All told, these results suggest that nonattendance does matter, and in a specific manner: no-shows, and not cancellations, occurring early, and less so later, in treatment can have a negative impact of client outcome and rate of change. At the same time, it is also suggested that a client who misses frequently will not necessarily "fail" in treatment; it could just take longer. It may be the case that the client who calls in or otherwise communicates desire to cancel or reschedule is engaged in therapy at a different level than one who simply does not show up, and are more likely to inform their therapist of cancellations. Or, it may be that the therapist who is "stood up" repeatedly by a client also has less patience to work with the client in an optimal way, in which there may be room for improvement by adopting more proactive strategies by addressing these issues early in treatment.

Although early nonattendance appears to have a stronger negative clinical impact, it appears that nonattendance in continued treatment has the most administrative and therapist impact. That is, there is a cumulative cost to nonattendance in the form of inefficiency, cost, and time, and it appears that variance in attendance rates can be substantially attributed to sources outside of the client. Regardless of whether the bulk of this variance rests in individual therapist practices or center policies, attendance appears to be an area of research that could unearth important strategies to improve effectiveness of mental health care, particularly for college coun-

Table 6
Client DI Rate of Change Final Model Statistics

	Block	B	Standard error	Significance
1	Intercept	.113	.003	<.001
2	Initial DI score	.063	.003	<.001
3	Total attended therapy appts.	−.004	.000	<.001
4	Early treatment no-shows	−.014	.003	<.001
5	Early treatment cancellations	−.002	.003	.409
6	Continued treatment nonattendance	−.003	.001	.010

Note. $N = 5{,}253$.

seling centers. Therapists could do well to be mindful of the big picture of their clients' attendance patterns, and may benefit from direct and practical changes such as revisiting the therapeutic contract in session or providing client reminders.

Although there is evidence that counseling centers experience a diverse range of psychopathology comparable with outpatient clinics (Benton, Robertson, Tseng, Newton, & Benton, 2003; Twenge et al., 2010), these results may be limited in their generalizability. Clients seen in more traditional outpatient clinics may be in a different phase of life, and may present with concerns less frequently seen at the college counseling center, such as full-time employment, marital disputes, or child rearing. Furthermore, ease of access to mental health care may differ, as it may be easier for a student to visit an on-campus counseling center than for an individual to find time/transportation to visit an outpatient facility.

Center autonomy within the CCMH PRN allows for a by-center decision as to when and how to administer the CCAPS, which led to significant data reduction when assessing DI change. This also includes autonomy over how and when clients' attendance was recorded as "no-show" or "cancelled." Some centers may vary in their definitions of these records. Further, therapists and administrators likely have some discretion in the use of these labels at some schools, increasing the overall noise in the data potentially negatively affecting the effect sizes obtained in our analyses. We were unable to independently confirm the classifications entered by center staff. Although CCMH does indeed collect some therapist demographic variables, there is little reason to suspect that such variables would adequately explain therapist variance. Specifically, across multiple studies, therapist variables such as age, gender, theoretical orientation, degree, and experience have not been found to reliably explain therapist effects (Wampold, Baldwin, Grosse-Holtfort, & Imel, in press). Instead, it may be as yet unexamined variables that help explain therapist differences in attendance, including such things as therapist burnout and workload, and were not able to be assessed in the present study.

Future research should address these limitations by standardizing the classification of attendance ("no-show" or "cancelled") and examining the impact of different reasons for poor attendance. It would also seem indicated to investigate whether or not our findings observed can be replicated in other treatment settings; for example, might private practitioners, whose income depends on client attendance, show different results? In addition, the inclusion of potential moderators, such as therapeutic alliance, may help further clarify the cause and impact of nonattendance. It would also be worthwhile to assess for potential moderators on the client level—might different presenting concerns see a more negative impact with irregular attendance? For example, an anxiety-focused treatment using a manualized treatment may see larger negative impacts if DNA rates are high.

Conclusion

Although client cancellations and no-shows may come with the psychotherapy territory, the impact of nonattendance has not been researched as the singular session impact of a dropout has. Nonattendance at the very least incurs a direct financial cost of time and/or money with potential regularity. Particularly for counseling centers, this can create bottlenecks of wasted resources for a treatment delivery system that already often has to rely on waitlists to provide service.

There was evidence for specificity in type and timing of nonattendance on client outcome, even after controlling for starting symptom severity and overall treatment length, and accounting for therapist effects. No-shows early in treatment were linked to decreased magnitude and rate of symptom reduction, whereas cancellations were not found to be impactful. Nonattendance after early treatment was found to have less overall impact on client symptom change, but did exhibit high therapist variation. Attendance may be a particularly fruitful and actionable area of research, as clients with high DNA rates will use up many more unproductive scheduled clinical hours than a regularly attending client. In the interest of providing the most cost-effective and efficient treatments, it is in the clinician's best interest to consider their clients' attendance issues. Given the presence of therapist effects and potential for center effects, understanding and researching the diversity of practices and policies between therapists and centers may greatly improve the efficiency of psychotherapy delivery.

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