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Therapist Effects on Dropout From a College Counseling Center Practice Research Network

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Dropout has been a pervasive and costly problem in psychotherapy, particularly for college counseling centers. The present study examined potential predictors of dropout using a large data set ($N = 10,147$ clients, 481 therapists) that was gathered through a college counseling center practice research network as a replication and extension of recent findings regarding therapist effects on dropout. The final model resulted in a dropout rate of 15.9% and a therapist effect of 9.51% on dropout variance. Therapist demographic variables were investigated, though none were found to be significant. Variables found to be predictive of increased likelihood of dropping out included higher levels of general presenting concerns, alcohol-related distress, and current financial stress. Ultimately, this study showed that therapists may play an important role in the likelihood of client dropout, and that additional research should be conducted to identify additional predictors, particularly at the therapist and center level.

Public Significance Statement

This study suggests that there are specific variables predictive of dropout for the college counseling demographic in a nationally representative dataset. It also suggests that different therapists experience different rates of dropout.

Keywords: dropout, premature termination, psychotherapy, practice research network, therapist effects

Dropout from psychotherapy, or client-initiated cessation of psychotherapeutic treatment before recovery of symptoms (Hatchett & Park, 2003), is a ubiquitous phenomenon. It can have negative impacts that carry through from the client, to the therapist, to the service agency (Swift, Greenberg, Whipple, & Kominiaik, 2012). It is also fairly common; in their meta-analysis, Swift and Greenberg (2012) found an average 20% dropout rate across treatment settings, with the university-based clinic (including training clinics and counseling centers) having the highest rate at approximately 30%.

Dropout can be defined in several different ways, such as therapist-rated, number of sessions attended (treatment dosage), and last-session nonattendance, each of which changes the calculated rate of dropout (Hatchett & Park, 2003; Pekarik, 1985; Swift & Greenberg, 2012). The present study aims to use a thorough and conservative definition of dropout by combining last-session non-

attendance with failure to achieve a reliable change index (RCI, Jacobson & Truax, 1991) in a global distress score. Such an operationalization reflects a premature cessation of services since the client did not attend the final session despite mutual agreement between therapist and client to do so. It also reflects an empirically based assessment of a client's lack of symptom reduction, as the RCI refers to the minimum change needed between repeated administrations of a measure that is statistically unlikely to be attributed to measurement error. That is, with the present operationalization, we attempted to capture clients who quit treatment unilaterally before they experienced significant reduction of symptoms.

This definition of dropout requires a missed last session, representing a loss of at least one clinical hour, not including the time spent attempting to recontact the client and determine when to terminate the case, a situation that could be further complicated if the client was also in a state of marked distress or crisis prior to the missed session. This emphasizes the administrative and systemic cost of nonattendance as well as the decrease in efficiency of care—a wasted clinical hour means other clients are not getting services in an optimal manner. Within a web of costs, this kind of dropout may be particularly important for counseling centers, which have experienced a growth in demand for services outpacing institutional enrollment growth (Center for Collegiate Mental Health [CCMH], 2015; Xiao et al., in press). Indeed, Carter et al. (2012) have found 90% of 228 surveyed counseling center directors reporting concern that their clients may not be receiving services when most helpful.

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To meet their clinical demands and pressures, many centers adopt various policies such as waitlists on a first-come, first-serve basis, clinical triage systems, and assignment of demanding case-loads for each therapist (Hardy, Weatherford, Locke, Depalma, & D'iuso, 2011). These solutions may be helpful, but each option is also a compromise between individual client needs, therapist morale, and center resources. In other words, the costs of dropouts may be magnified by the current state of the college counseling center, a setting which may also, in turn, benefit the most from focused research to predict dropout. Increasing awareness and understanding of dropout risk factors could provide helpful information to guide clinical and policy discussions (Hatchett, 2004), especially if the information could be used to inform decision making early on in treatment. Considering counseling center resources, this might lead to more effective triage of clients, better informed decisions to spend valuable session time on attendance psychoeducation, or consideration of other methods recommended in the literature to reduce dropout (Hatchett, 2004; Swift et al., 2012).

While several predictors of dropout have indeed been identified, including ethnic minority status, age, personality factors, presenting concerns, past trauma, initial level of distress, education level, socioeconomic status, self-esteem, and hostility (e.g., Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993), a number of these have received mixed support, and most of them have been researched in data sets with limited sample sizes, or in varied treatment settings. The issue is further complicated with findings regarding therapist effects, in which a growing body of research finds 5–8% of the variance in various outcomes to be attributed to therapist differences (Baldwin & Imel, 2013), using statistical methods not implemented in much of the existing body of dropout literature.

Whereas studies have traditionally examined therapist effects for positive treatment outcomes or recovery curves, there is a relative dearth of such research for negative outcomes, such as dropout. However, two recent studies have supported the notion that therapists vary on dropout rates (Saxon, Barkham, Foster, & Parry, 2016; Zimmermann, Rubel, Page, & Lutz, 2016). Respectively, Saxon et al. (2016) and Zimmermann et al. (2016) found therapist effects of 12.6% and 5.7%, a contrast in range that appears quite striking and worth further exploration. Incidentally, the authors of both studies recommended new investigations into therapist effects across alternate treatment sites in order to better understand this phenomenon, which appears to be especially important given the range of their findings: Saxon et al. (2016) reported increased presenting symptom severity, younger age, nonwhite ethnicity, and unemployment (discussed as a potential proxy of socioeconomic status) as client dropout predictors across 35 counseling and clinical psychology services across the United Kingdom, while Zimmermann et al. (2016) identified initial impairment, male gender, lower education, specific personality styles, and negative treatment expectations as client predictors within a sample collected from a single outpatient clinic in Germany. Given Swift and Greenberg's (2012) meta-analytic finding of increased dropout risk at university-based clinics, it seems prudent to further examine therapist effects and dropout specifically within a large college counseling dataset.

Not only would an increased understanding of dropout be of particular importance to counseling centers, it also presents a

unique opportunity to better understand a substantial and clinically meaningful segment of the population, as more than 60% of high school graduates now attend some postsecondary education. Epidemiological work has also found no difference in prevalence of mental disorders between age-matched college students and non-students (Blanco et al., 2008; Gallagher, 2011), and nearly three quarters of all *Diagnostic and Statistical Manual of Mental Disorders* (4th ed.; *DSM-IV*; American Psychiatric Association, 1994) diagnoses occur before age 24 (Kessler et al., 2005), leaving the counseling center a large-scale umbrella to study this important demographic.

One way of collecting such data is through practice research networks (PRNs), in which clinicians work in collaboration with researchers to collect scientifically rigorous and clinically relevant data (Castonguay, Barkham, Lutz, & McAleavey, 2013; Castonguay, Youn, Xiao, Muran, & Barber, 2015). The CCMH is such an infrastructure that currently involves a partnership of over 300 university counseling centers. Using standardized instruments as part of their clinical routine, the CCMH participating centers contribute to an anonymous, aggregate, and large representative dataset that requires no extra effort from its members to collect, allowing for a streamlined opportunity to gather large amounts of clinically relevant naturalistic data from a treatment setting that has been found to have high dropout rates (Hayes, Locke, & Castonguay, 2011). Furthermore, the CCMH dataset provides therapist demographic information, allowing for examination of therapist effects and possible therapist level predictors through multilevel modeling, an extension and exploration of the significant therapist effects findings of Saxon et al. (2016) and Zimmermann et al. (2016).

With this dataset, the present study further aims to replicate and extend their recent findings by clustering their specific findings into three theoretically derived domains, presenting issues, client demographics, and critical concerns, using data collected from the college counseling setting. Presenting issues include, as in the aforementioned studies, a measure of the client's overall distress. In addition, this domain contains measures of alcohol use and eating concerns, which are areas that hold particular significance for the college demographic. Both of these are pervasive on college campuses and linked with many potential negative consequences, including academic attendance/performance, health, and legal issues (Eisenberg, Nicklett, Roeder, & Kirz, 2011; Larimer & Cronce, 2002; Pihl & Stewart, 2013; White & Hingson, 2013).

Client demographics include gender, racial minority status, financial distress, and class standing (as an analog to age), while the critical concerns cluster assesses issues related to harm to self and others. Notably, the items within these three domains have received empirical support through at least one of the separate multilevel analyses of Saxon et al. (2016) and Zimmermann et al. (2016). Conceptually and clinically, each of the three domains also presents a different level of consideration for the therapist in regards to dropout. Within these levels, each variable reflects clinical issues that can increase the risk of drop out (such as the inadequate attunement to acute suffering, gender related individual differences [e.g., internalizing vs. externalizing coping style], developmental and economic challenges, as well as the commission of cultural microaggressions) and/or its negative consequences, such as the lack of adequate treatment of debilitating disorders and

dangerous actions toward self and others (Matud, 2004; Owen, Tao, Imel, Wampold, & Rodolfa, 2014).

Furthermore, because the streamlined nature of data collection of the CCMH PRN allows for the collection of therapist level demographic variables, the current body of dropout research can be extended by testing for potential therapist-level variables impacting dropout. Therefore, the goal of the present study was to examine dropout and therapist effects in college counseling centers using empirically and clinically valuable variables to address two questions: (a) are existing predictors from multilevel dropout analyses replicable in the college demographic setting? and (b) is there a therapist effect for dropout in this setting, and can it be explained using therapist demographic variables?

Method

Participants

The data reduction process is outlined in Table 1. From the complete dataset of CCMH clients seen in individual therapy from 2010–2012, individuals were included if they had attended at least one therapy session, and were scheduled for at least two (i.e., started a course of psychotherapy). They must also have had completed the Standardized Data Set (SDS) and at least two Counseling Center Assessment of Psychological Symptoms (CCAPS) measures; these are further detailed in the instruments section below. To more accurately assess prepost symptom change scores, clients were also required to have their first and last CCAPS occur within 30 days of their first and last scheduled appointments, respectively. Finally, therapists within this dataset must have seen at least 10 clients, resulting in a final dataset of 10,147 unique clients. Of these clients, 15.9% ($n = 1,617$) were categorized as a dropout, having missed their last attended session and failed to achieve an RCI on the Distress Index (DI) subscale described below.

Clients were, on average, 22.62 ($SD = 5.01$) years of age, and 66.7% were female. Additionally, 73.3% self-identified as White/Caucasian, 7.1% as Hispanic/Latino/a, 6.7% as Black/African American, 5.9% as Asian/Asian American, 3.3% as multiracial, and less than 1.5% each as American Indian, Alaskan Native, Native Hawaiian, or other.

Therapists

As stated above, therapists were required to have seen at least 10 unique clients for individual psychotherapy from CCMH data

collected from 2010–2012, amounting to 481 therapists. They were, on average, 56.22 ($SD = 9.58$) years of age, 83.0% were female, 75.3% White/Caucasian, 7.9% Black/African American, 6.8% as Hispanic/Latino/a, 4.0% as Asian/Asian American, 2.7% as multiracial, and less than 1.5% each as American Indian, Alaskan Native, Native Hawaiian, or other. On average, therapists had 14.29% of their clients meet the dropout criteria, with an interquartile range of 7.55% to 23.08%.

Instruments

SDS. The SDS was created from the collective intake materials of 50 counseling centers (Hayes et al., 2011), and its 47 items cover a broad array of client characteristics, such as demographics and mental health history. The items are categorical in response choice.

CCAPS. 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 loads onto eight subscales: Depression, Generalized Anxiety, Social Anxiety, Academic Distress, Eating Concerns, Hostility, Alcohol Use, and a DI which provides an overall level of symptomology by taking key items from multiple scales. It has demonstrated acceptable internal consistency and test–retest reliability, and its individual subscales have shown good concurrent validity (Locke, Bieschke, Castonguay, & Hayes, 2012; McAleavey et al., 2012).

Both the SDS and the CCAPS are administered and stored electronically using Titanium software. To store their own local data and contribute deidentified data, individual centers received approval through local institutional review boards (IRBs), while an additional IRB for analyses of the pooled and deidentified (at both client and center level) data repository covered the present study.

Statistical Analyses

Dropout was defined per client by meeting two criteria: (a) nonattendance of the last scheduled session for an individual's course of therapy as recorded by each center's electronic medical records system, and (b) failure to achieve at least an RCI change on the prepost DI subscale of the CCAPS. Specifically, clients whose last appointment during a course of therapy was marked as "canceled," "rescheduled" without return, or "no-showed" met the first half of the dropout definition, and clients failing to achieve a 0.79 point change on the DI met the second (CCMH, 2012).

A series of multilevel logistic regression models were tested to arrive at the final model. First, the presence of therapist effects was tested and calculated in a null model as an intraclass correlation (also referred to as the variance partition coefficient, for which the variation between therapists is divided by the total variance (variation between therapists, σ_u^2 , added to variation within therapists σ_e^2). For logistic models, σ_e^2 is constant, and calculated as $\pi^2/3$ (Steele, 2008).

A log 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) in a random intercepts model. Next, each of the three clusters of variables, presenting issues, client demographics, and critical concerns, were separately added to this null multilevel model as fixed effects, and then compared with the null multilevel

Table 1
Data Reduction

Data reduction step	<i>N</i>
Scheduled at least one appointment within 2010–2012	121,698
Attended at least 1 therapy session	100,831
Clients who completed the SDS and had at least 2 CCAPS	32,312
First and last CCAPS occurred within 30 days of first and last appointment	14,538
Therapist seen at least 10 clients	10,147

Note. SDS = Standardized Data Set; CCAPS = Counseling Center Assessment of Psychological Symptoms.

model using a log likelihood ratio test (Dayton, 2003). The significant variables from each cluster were retained in a combined model, and then further tested in a random intercepts and random slopes model allowing for the impact of the specific predictor in question to vary across therapists.

Finally, therapist demographic variables were added (Level 2) as fixed effects to explore potential explanatory variables of therapist effects compared with the previous model. These demographic variables were selected based on a review of literature of factors that have been examined (using multilevel analyses) to account for therapist effects in therapy outcome (Wampold, Baldwin, Holtfort, & Imel, in press). They included therapist age, gender, theoretical orientation, experience (measured as years licensed), and degree obtained (e.g., master's, doctorate, etc.). The final model includes only those variables that were found to be significant predictors of dropout. Analyses were conducted in R version 3.3.1 (R Core Team, 2016) using the package lme4 (Bates, Mächler, Bolker, & Walker, 2015).

Results

A therapist-level variance of 9.11% was found in the null model comparisons of a single level to a multilevel model ($\chi^2(1, 10147) = 127.48, p < .001$), indicating the presence of therapist effects. In the next set of analyses each of the three domains of variables (presenting issues, client demographics, and critical concerns) were separately added to the empty multilevel model and tested for significant improvement in model fit. These domain-specific models are presented in Tables 2–4. Briefly, from presenting issues, increases on the Alcohol Use subscale were found to be significantly predictive of increased odds of dropout, while increases in the DI decreased odds. From client demographics, increased financial distress increased odds of dropout, and none of the critical concerns items were predictive of dropout.

The final model, presented in Table 5 resulted in a significant therapist effect of 9.51%, and contains only the statistically significant predictors mentioned above. For the CCAPS subscale continuous variables, the odds ratio represents the expected change for a 1-point increase in the respective subscale (which ranges from 0 to 4). Odds ratios are reported in comparison to the reference group listed first for categorical variables. Specifically, in the final model, each point increase on the Alcohol Use subscale increased the odds of dropping out by 17.9%, while a point increase in the DI was associated with an 18.5% decrease in dropout odds. For the item “current financial situation,” those who indicated “never stressful” had 0.643 times the odds, or 35.7% decreased odds of dropping out compared with those who indicated the reference group, “always stressful.”

Table 2
Multilevel Logistic Regression of Presenting Issues

CCAPS subscale	<i>p</i> value	<i>SE</i>	<i>OR</i>
Alcohol Use	<.001	.030	1.176
Eating Concerns	.245	.025	1.029
Distress Index	<.001	.038	.832

Note. *N* = 10,147. CCAPS = Counseling Center Assessment of Psychological Symptoms; *OR* = odds ratio.

Table 3
Multilevel Logistic Regression of Client Demographics

Predictor	<i>p</i> value	<i>SE</i>	<i>OR</i>
Academic class			
Freshman			Reference
Sophomore	.391	.091	.924
Junior	.114	.085	1.144
Senior	.289	.087	.912
Graduate student	.059	.099	.830
Ethnicity			
Nonracial ethnic minority			Reference
Racial ethnic minority	.859	.065	1.012
Current financial distress			
Always stressful			Reference
Often stressful	.693	.091	1.037
Sometimes stressful	.303	.083	.918
Rarely stressful	.003	.093	.760
Never stressful	.002	.125	.680
Gender			
Male			Reference
Female	.144	.059	.917

Note. *N* = 10,147. Reference groups for categorical variables labeled as such. *OR* = odds ratio.

This model's predictors were also tested in a random slopes and random intercepts model, but this did not result in a significant improvement. Similarly, therapist level variables of age, gender, theoretical orientation, experience (measured as years licensed), and degree obtained (e.g., master's, doctorate, etc.) were tested in a fixed-effects model with no improvement to model fit.

Discussion

The current study aimed to replicate and extend findings regarding prediction of dropout while accounting for therapist effects in a college counseling PRN. Our final model resulted in a therapist effect of 9.51%, a finding within the range reported by Saxon et al. (2016) and Zimmermann et al. (2016), respectively, 12.6% and 5.7%, lending further support to the notion that therapists play an important role in the rate at which their clients drop out. Collectively, dropout therapist effects appear to be on the high end of the range of the therapist effects literature, which has been estimated using various outcomes at 5–8% (Baldwin & Imel, 2013; Lutz, Leon, Martinovich, Lyons, & Stiles, 2007; Saxon & Barkham, 2012).

However, our efforts to replicate specific client-level predictors within a therapist effects model generated more diverse results. Specifically, out of the 11 variables in three domains selected to match most closely with variables found to be significant in the aforementioned therapist effects studies, only three achieved significance in our study—higher Alcohol Use and higher financial distress were predictive of increased dropout rates, while contrary to prior findings, a higher general DI was actually found to be associated with decreased dropout rates.

This appears to illustrate the importance of replication, particularly with respect to the diversity and heterogeneity of clinical data (Leichsenring et al., 2016). Indeed, our results indicate that some predictors, such as a general measure of distress, may be broken down into more specific components. For example, our study extended upon a general DI replicated in the results of both

Table 4
Multilevel Logistic Regression of Critical Concerns

Predictor	<i>p</i> value	<i>SE</i>	<i>OR</i>
Considered seriously injuring another person	.356	.111	.902
Intentionally caused serious injury to another person	.104	.199	1.382
Purposely injured self without suicidal intent	.747	.071	1.023
Seriously considered attempting suicide	.587	.069	1.038

Note. *N* = 10,147. All predictors dichotomous and compared with null responses. *OR* = odds ratio.

Saxon et al. (2016) and Zimmermann et al. (2016) by adding two subscale measures of presenting issues arguably endemic for the college counseling population, Eating Concerns and Alcohol Use. While Alcohol Use was significantly predictive of dropout, increases in DI actually decreased risk of dropping out, a finding counter to that of both aforementioned studies. It could be that regardless of its clinical utility, a “general” assessment of a client’s level of distress may not always tell the whole story, and more specific areas of concern may be more helpful for predictive purposes. In relation to our sample, it may be that an elevation of distress across multiple areas leads counseling center clients to feel more invested in seeking help and completing treatment, as opposed to those with elevations in Alcohol Use, who may view their potentially problematic drinking habits as more normative, given its high prevalence on campuses and end treatment earlier if therapy focused on alcohol abuse (Larimer & Crounce, 2002; Pihl & Stewart, 2013; White & Hingson, 2013). In general, these results may reflect a difference in client sample characteristics or instrument of measurement (i.e., differences between measures in emphasis of capturing diverse symptoms for calculation of global distress) between the present study and those of Saxon et al. (2016) and Zimmermann et al. (2016).

By the same token, that a client’s distressing financial situation has received consistent support for increasing dropout risk also lends more confidence to its interpretation. It is undeniable that therapy takes time and energy, valuable resources for anyone, but perhaps particularly so for individuals with increased financial difficulties. Unfortunately, our findings further add support for the notion that individuals with the most financial distress are also at a greater risk for dropout compared with those who do not experience these difficulties as much. These findings may hold particular significance for the college counseling demographic; college

can be expensive, and psychotherapy takes time that may prove extra costly for a financially burdened student. Especially if they subjectively experience little to no improvement, clients may make a premature decision to end treatment if money or time is an issue, making open and early discussion with clients regarding treatment engagement, including expectations and client concerns about the financial and time commitments of therapy a notable potential solution.

That we did not find not find significant effects for gender, ethnicity, age (as approximated with academic status), eating concerns, risk to self, and risk to others does not mean that these variables are irredeemably contentious. Each of these variables was selected for their theoretical underpinnings along with their previous empirical support, and may certainly play a role in dropout on a case-to-case basis. It could be that these and other client variables may not be universally applicable across setting and treatment demographics. Notably, it is also possible that differences in dropout operationalization impacted the diverse findings. For instance, Zimmermann et al. (2016) used therapist judgment to categorize consensual termination, while we used a combination of last session nonattendance and failure to achieve some degree of symptom change. While all three of these definitions have strengths and capture some aspects of the construct of dropout, none of them is without limitations, and our usage of a thorough and conservative operationalization may have captured a different client-based aspect of the dropout construct (Hatchett & Park, 2003).

Regardless, and most importantly, the heterogeneity of these client-level dropout predictors in this growing body of research should not undermine the consistent finding of a strong therapist effect despite differences in sample and operationalization. Indeed, the random intercepts and random slopes model was not found to be a significant improvement to our final model, indicating that client-level variance on predictors does not adequately explain the therapist variance (e.g., a high client level of financial distress is more likely to drop out with any therapist). Furthermore, none of the demographic therapist variables tested in this study was found to be a significant explanatory variable for therapist effects in a fixed effects model, consistent with the therapist effects literature at large (Wampold et al., in press). Clearly, the evidence suggests that therapists vary in their clients’ dropout rates, but it is the mechanisms of these differences that is not well understood and may be most important for future research. It will be helpful to more closely examine factors above the traditionally recorded client and therapist demographic variables. Therapists, for example, may differ in their timing of responses and behaviors regarding client cancellations or no-shows, or be more or less open or authoritative in discussing attendance in the therapeutic contract.

Table 5
Multilevel Logistic Regression Final Model

Predictor	<i>p</i> value	<i>SE</i>	<i>OR</i>
CCAPS subscales			
Alcohol Use	<.001	.029	1.179
Distress Index	<.001	.038	.815
Current financial situation			
Always stressful			Reference
Often stressful	.935	.091	.993
Sometimes stressful	.063	.084	.856
Rarely stressful	<.001	.094	.707
Never stressful	<.001	.126	.643

Note. *N* = 10,147. Reference groups for categorical variables labeled as such. CCAPS = Counseling Center Assessment of Psychological Symptoms; *OR* = odds ratio.

There may be insight to be gained from those therapists at the extremes of the “dropout spectrum” who have a very high or very low dropout rate compared with their peers.

It is also plausible that these differences in therapists are due, in some part, to the policies of their work setting. For example, it may be that because of their resource demands, college counseling centers create environments where there are restraints in some of the ways that clinical services are utilized, such as stricter session limits and longer waitlist times, which may impact dropout rates at a different level than a therapist. A therapist can only affect his or her dropout rates so much if the center policy is to terminate clients after two unannounced no-shows. In other words, it is plausible that center effects, as a third level (i.e., clients nested within therapists nested within a counseling center and its policies), might also be an important next direction in understanding the differences in dropout rates and other outcomes. This may particularly be the case for counseling centers because of the necessity for efficiency of treatment due to resource restraints, where local center policy may impact treatment process and outcomes at a greater level than may be expected elsewhere.

Regardless of how and where it is researched, dropout is an issue. It is difficult to gauge the true cost of the 15.9% dropout rate we observed: there is an administrative and financial loss where an appointment was scheduled, left unattended, and there was likely some amount of time spent trying to recontact the client, as well as a clinical loss in failure to complete treatment with individuals who may not have achieved maximum benefit from therapy. However, it is also promising that there is also room to improve the efficiency of treatment, with evidence pointing toward therapists having a substantial contribution to their clients’ dropout rates, and room for exploration in an as-of-yet unexamined center effect.

It is beyond the scope of this paper to thoroughly discuss strategies to reduce and change the rate of dropout, but Swift et al. (2012) have highlighted six ways in which therapists may reduce their dropout rates, including psychoeducation regarding treatment expectations, and incorporating client preferences for treatment. In line with Zimmermann et al.’s (2016) suggestion to implement routine monitoring to provide updated feedback, they also suggest an active assessment and discussion with the client regarding treatment progress, based on the implementation of routine outcome monitoring. Different strategies, of course, are likely to be differentially effective for different clients. Suffice it to say, a therapist might do well to reflect on the outcomes of their patients, and upon finding a high dropout rate, assess potential explanations and solutions. The differences between dropouts due to a mutual understanding with the client that the last session “may not be necessary” and dropouts due to a failure to address client expectations may entail different strategies and solutions.

Limitations

Our conservative two-part operationalization of dropout resulted in an overall 15.9% dropout rate, and incurred a large loss of data from requiring two CCAPS, dropping our sample by roughly two thirds. This is somewhat expected in a naturalistic PRN setting with center autonomy in measure administration, especially with the modal number of attended therapy appointments being one across treatment settings (Gibbons et al., 2010), precluding a second CCAPS administration. As centers are free to dictate (or

leave to the therapist’s judgment) the frequency of CCAPS, this is also further argument for the examination of therapist and center effects. While conservative, our definition also covers two important facets of the dropout construct: failure to alleviate symptoms before the last attended session and failure in communication and attendance of a last mutually agreed upon session.

Despite the breadth covered by the items contained in the SDS and CCAPS, there are important predictors named by Saxon et al. (2016) and Zimmermann et al. (2016) that did not have analogs, specifically, client personality and treatment expectation variables. Unfortunately, neither the SDS nor the CCAPS covers these constructs. While these are “nontraditional” client-level variables, the evidence still suggests that the therapist effect may be best explained at a different level.

The population itself consists of university attendees. Although there is a body of literature suggesting that university students experience similar levels of distress and impairment to other clinical settings (Blanco et al., 2008; Gallagher, 2011), there may still be differences to general outpatient variables. However, given the ubiquitous nature of dropout, it may indeed be helpful to consider the diverse variables afforded by researching in the context of this university-based PRN.

Conclusion

From this study’s large, geographically representative data set, dropout as defined by a combination of last session nonattendance and failure to achieve an RCI in a global distress subscale was found to reach 15.9% in individual psychotherapy in counseling centers, with a therapist effect of 9.51%. Because of the strained resources of this treatment setting, the ability to assess who may drop out of treatment may have significant benefits for the management and quality of care provided. Armed with awareness of variables predicting dropout, clinicians might be better equipped to have front-end conversations about treatment completion, which may impact the delivery of mental health services at multiple levels. Yet, clinicians should be aware that dropout is not only explained by clients’ characteristics. Different therapists do indeed have different dropout rates. In efforts to increase efficiency of care, further research might focus on better understanding the factors that predict why a therapist might have an exceptionally high or low dropout rate, as well as on examining the possible impact that center policies may have on dropout and attendance rates.

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