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Article *in* Psychotherapy Research · May 2020

DOI: 10.1080/10503307.2020.1762948

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Psychotherapy Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tpsr20

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To cite this article: J. Ryan Kilcullen , Louis G. Castonguay , Rebecca A. Janis , Michael N. Hallquist , Jeffrey A. Hayes & Benjamin D. Locke (2021) Predicting future courses of psychotherapy within a grouped LASSO framework, Psychotherapy Research, 31:1, 63-77, DOI: 10.1080/10503307.2020.1762948

To link to this article: https://doi.org/10.1080/10503307.2020.1762948

Psychotherapy Research, 2021
Vol. 31, No. 1, 63–77, https://doi.org/10.1080/10503307.2020.1762948

EMPIRICAL PAPER

Predicting future courses of psychotherapy within a grouped LASSO framework

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(Received 24 December 2019; revised 12 April 2020; accepted 24 April 2020)

Abstract
Objective: There is a paucity of studies examining the experience of clients who undergo multiple courses of psychotherapy. Conducted within a large practice research network, this study demonstrated that returning therapy clients comprise a considerable portion of the clinical population in university counseling settings, and identified variables associated with return to therapy. **Method:** Utilizing data spanning 2013 to 2017, statistical variable selection for predicting return to therapy was conducted via grouped least absolute shrinkage and selection operator (grouped LASSO) applied to logistic regression. The grouped LASSO approach is described in detail to facilitate learning and replication. The paper also addresses methodological considerations related to this approach, such as sample size, generalizability, as well as general strengths and limitations. **Results:** Attendance rate, duration of initial treatment course, social anxiety, perceived social support, academic distress, and alcohol use were identified as predictive of return to therapy. **Conclusions:** Findings could help inform more cost-effective policies for session limits (e.g., extending session limits for clients with social anxiety), referral decisions (e.g., for clients with alcohol use problems), and appointment reminders (based on the association between poor attendance rate and return to therapy). Taking into account the many reasons that can explain why clients do or do not return to therapy, these findings also could inform clinicians' early case conceptualizations and treatment interventions.

Keywords: long-term psychotherapy; process research; statistical methodology; mental health services research

Clinical or methodological significance of this article: Clinical implications pertaining to delivery of mental health care are discussed. Specifically, the findings may inform clinicians' work and administrators' policies pertaining to important issues such as session limits, referrals, and early-treatment considerations (i.e., gauging client engagement). More broadly, clinicians may benefit from empirical work focusing on returning therapy clients. While this clinical population has received little attention in the literature to date, it comprises a considerable portion of clinicians' caseloads. From a methodological perspective, this study offers an in-depth description of how to implement Machine Learning techniques in psychotherapy research, specifically the statistical variable selection method of grouped least absolute shrinkage and selection operator (grouped LASSO). Important issues related to the use and interpretation of grouped LASSO analysis are also discussed.

Introduction

Psychotherapy outcome studies typically focus on change within a single course of treatment. Prominent theories and models of therapeutic change, such as Howard et al.'s (1993) phase model and the dose–response relationship (Kadera et al., 1996), are based on this specific window of health care services. One drawback of confining research in this manner is that it fails to pay attention to the fact that a number of clients return for additional treatment courses. Few studies have investigated clients who return for therapy and what makes a client likely to return. This is unfortunate considering evidence suggesting that clients with prior therapy

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experiences tend to show slower improvement and less engagement compared to first-time treatment-seeking clients (Boswell et al., 2012; Stulz & Lutz, 2007).

Although returning therapy clients are common to clinical practice, the prevalence rates vary across studies—ranging from 14% (Boerema et al., 2016) to 83% (Grenyer et al., 2008). Such variation is in part due to differences between clinical populations being investigated, but also the diverse clinical settings in which these studies have been conducted (Goodman et al., 2001). The aim of the present study was to shed light on returning therapy clients within a particular clinical setting. Specifically, the goals were to assess prevalence rates and identify factors associated with returning therapy clients in university counseling centers (UCCs). Such information may help clinicians assess whether a client will pursue additional therapy down the road, facilitate communication between clinicians and their clients early on in treatment, and possibly aid in case conceptualization and treatment planning. To illustrate this potential clinical utility, it is important to contextualize returning therapy clients, firstly by recognizing that a decision to return to therapy (or to not do so) may have different meanings for clients, and secondly by emphasizing the unique characteristics of the clinical setting and population investigated.

Why a Client May or May Not Return to Therapy

There are many reasons why individuals may return to therapy. Some may have enjoyed the process involved in working with a therapist (e.g., being understood and validated by a mental health professional, developing a new understanding of self and others, etc.) and wish to continue and/or deepen this positive experience. Others may have gained therapeutically—in terms of symptom reduction, for example—from their previous therapy but believe that they would benefit further from additional treatment (e.g., perhaps a problem wasn't fully resolved or a client realizes that it may be worthwhile to address other concerns). On the other hand, different factors can explain why clients may not want to engage in additional therapy. After an initial course of treatment, some individuals may have developed a greater awareness of the depth or severity of a particular problem but decide that they are not ready or willing to work further on such difficulties. Others may wish to receive more treatment, but prefer to seek a different experience than the one they originally received (e.g., the opportunity to return for additional therapy with a different therapist). Of course, some clients do not return to therapy because they feel that their problem was solved at the end of their initial treatment.

As an example, Siddall et al. (1988) found that more than a quarter of clients seen over a 4-month period at an outpatient clinic returned for additional therapy. Of note, among those who returned, 51% found previous therapy helpful and returned for a new problem, 26% found previous therapy helpful and returned for the same problem, 10% found previous therapy not helpful and returned for the same problem, and 6% found previous therapy not helpful and returned for a new problem. In terms of factors associated with returning therapy clients, Siddall et al. (1988) found that diagnoses and symptomatology, namely depression and anxiety; life functioning, namely academic distress and work problems; and interpersonal distress, both intimate and peer relationships, were most commonly endorsed by returning clients.

Clients' decisions regarding returning to therapy may also be influenced by the inherent structure and boundaries of a given type of provider. For example, university counseling centers, which is the clinical setting of investigation in the present study, tend to provide short-term treatment, frequently within a priori session limits (McAleavey et al., 2019). Moreover, UCCs are temporally bound by the academic calendar, which typically imposes interruptions to the provision of services during winter and summer breaks. These parameters likely interact with clients' perceptions of what they could expect from another course of treatment. For example, the aforementioned clients who have become aware of the extensiveness of their problem but are ambivalent about trying to resolve it may feel that additional therapy in the same UCC setting would be limited, insufficient, and thus not worthwhile. Furthermore, in the context of limited resources available to university counseling centers, some clients with severe difficulties may not return because they have been referred out to more specialized and/or long-term services. These considerations need to be taken into account when discussing why some variables may be positively associated with return to therapy and others negatively associated.

How Returning Therapy Clients Might Differ from First-time Treatment Seekers

In addition to recognizing that there are various reasons why clients may or may not return to therapy, it is important to consider whether returning therapy clients differ from first-time treatment-seeking clients. As described below, returning therapy clients have been found to differ on a variety of factors that can be characterized in four conceptual clusters: (i) problem chronicity, (ii) prior utilization, (iii) initial treatment course factors, and (iv) other client characteristics. It should be noted that few studies have been conducted in UCC setting. What have received more attention, in the UCC literature, are constructs that are distinct from but nevertheless related to returning therapy clients—i.e., treatment-seeking behaviors and UCC utilization patterns. These constructs differ from return to therapy in that they are broader—concerning factors leading to individuals pursuing treatment in the case of treatment seeking, and how resources are consumed and by whom in the case of utilization. Yet, they are sufficiently related (i.e., returning therapy clients engage in further treatment seeking and utilize additional services) to suggest that variables associated with them are possible predictors of return to therapy.

Problem chronicity. A study conducted in an outpatient setting suggests that individuals with history of trauma may be likely to undergo multiple treatment courses (McKenna & Todd, 1997). In the UCC setting, client factors indicative of problem chronicity—such as non-suicidal self-injury (NSSI), prior sexual abuse, suicidal ideation—have been linked to greater levels of treatment utilization (Janis, 2017).

Prior utilization. McKenna and Todd (1997) and Siddall et al. (1988) examined separate groups of returning therapy clients in an outpatient setting and both found high rates of prior psychiatric hospitalizations and psychiatric medication use among participants. In comparison to clients not returning to therapy, Janis (2017) found that returning therapy clients with prior counseling experiences had greater utilization rates in subsequent treatment courses in UCCs.

Initial treatment course factors. Diagnoses associated with recurrent episodes such as depression, substance use, post-traumatic stress disorder, and eating disorders have been shown to predict greater therapy utilization and subsequent return to therapy across various treatment settings (Delsignore, 2008; Goodman et al., 2001; Grenyer et al., 2008; Minami et al., 2009; Ronis et al., 1996). In contrast, Minami et al. (2009) also found that substance use and issues pertaining to academic distress were associated with less treatment utilization. Supporting this latter finding, using latent profiling, Nordberg et al. (2016), demonstrated that clients presenting to therapy with substance problems utilized fewer sessions. They also found that clients with eating concerns tended to use more sessions.

In addition to diagnostic variables, treatment-specific factors have been examined and the results are mixed. Some studies have shown that shorter duration is linked with return to therapy (e.g., Boerema et al., 2016) while others (e.g., Horn, 2002) have found that longer initial duration predicts subsequent treatment courses. It may be that these mixed results are in part due to organizational policies. For instance, when session limits are imposed by agencies or insurance companies, clients with more serious problems may not get enough therapy to sufficiently address their concerns. In the absence of session limits, more disturbed clients tend to need and receive longer treatment. Yet these same clients may have chronic mental health issues that require multiple courses of treatment.

Mixed findings also have been observed with regard to pre- to post-changes in symptomatology, as both symptom improvement and non-improvement in prior treatment courses have been associated with return to therapy (Ciarrochi & Deane, 2001; Delsignore, 2008; Horn, 2002). These studies tend to assess prior-treatment outcomes across diverse clinical populations and via aggregated measures of change across several domains of mental health. Such pan-diagnostic and composite approaches may contribute to the mixed findings regarding the association between prior outcomes and receiving additional therapy; it may be that the influence of prior outcomes depends on the specific symptom domain.

Other client characteristics. UCC clients with problems specific to social support (such as intimacy issues) have been shown to utilize more treatment (Minami et al., 2009). Treatment-seeking behavior also has been associated with an individual's social support (Nam & Choi, 2013); however, the directionality of this influence is unclear as both weak and strong social support systems have been demonstrated to predict treatment seeking (Ciarrochi & Deane, 2001; Kahn & Williams, 2003). For ethnic minority clients, it has been shown that perceived lack of support from family members in addition to problem chronicity-related factors increase the likelihood of seeking treatment (Hayes, Youn, et al., 2011). In addition, pressure from one's parents has been linked to clients', especially UCC clients, decision to pursue additional therapy (McKenna & Todd, 1997). Lastly, Kessler et al. (1980) examined additional treatment courses within a psychiatric outpatient setting and found that women utilized significantly more appointments than men and that, perhaps obviously, older clients had greater amounts of utilization than younger clients across gender identities.

The Present Study: Exploration Within a Machine Learning Framework

The aims of the current study were twofold: (i) determine the prevalence rates of returning therapy clients within the UCC setting, and (2) identify client characteristics and treatment-related factors that predict the likelihood of returning to therapy following an initial treatment course. Based on the review of findings above, and as later illustrated in Table III, four conceptual clusters of potential predictors of returning therapy clients were investigated: problem chronicity, prior utilization, initial treatment course, and client characteristics. Two categorical control variables, time of year of last appointment and current academic status, also were included to account for the artificial interruptions in services caused by academic breaks like summer vacation and the possible confound that students early in their collegiate career have more time to return to therapy than more advanced students, respectively.

Two features of the present study are worth mentioning. First is its exploratory nature, which is dictated by the limited literature examining the ability of variables to predict likelihood of return to therapy, especially in the UCC setting, as well as by the mixed findings resulting from research on related topics of utilization and treatment-seeking. Although exploratory, a better understanding of who may or may not return to treatment could provide information that might help clinicians to better address clients' needs and increase the effectiveness of mental health care. Second, modern analyses from machine learning were implemented—specifically, least absolute shrinkage and selection operator (LASSO; Tibshirani, 1996) regression—to examine the importance of a wide range of possible predictors. Such a regularized regression approach allowed us to home in on variables most associated with return to therapy, particularly given the wide variety of predictors with limited and/or mixed empirical evidence. In traditional regression, variables are often deemed informative based on a nominal Type I error rate (usually, 5%). The difficulty is that if one has many plausible predictors of an outcome and relatively little empirical basis for preferring some predictors over others, then the experiment-wise Type I error rate increases unchecked for each variable entered into the model. Although there are many approaches for multiple comparison correction (Shaffer, 1995), regularized regression methods like LASSO are particularly helpful in reducing overfitting—that is, the problem of identifying too many predictors of small effect that would be unlikely to replicate in an independent sample.

Furthermore, LASSO allows for an automated, less arbitrary means to identify statistically meaningful variables when one is interested in identifying a relatively small subset of variables that jointly predict an outcome (Tibshirani, 1996). LASSO regression is most commonly used when there is one outcome variable, but many possible predictors. For example, in genetics research, researchers are often interested in finding a small number of genetic markers that predict an outcome in the context of hundreds or thousands of possibilities (Usai et al., 2009). The strengths of LASSO approaches for variable selection and generalizability have made it a fruitful technique for psychotherapy research (Cohen et al., 2020; Delgadillo et al., 2017; Dwyer et al., 2018). While predictors of psychotherapy outcome often number in the tens, not hundreds, LASSO is nevertheless helpful for such data because it helps reveal large, reproducible predictors of outcome while down-weighting findings that are unduly influenced by collinearity, large sample sizes, or predictors that are less likely to replicate out of sample due to influential cases.

Although the large sample available for this exploratory study merits the use of machine learning methods, attention has been given to the limitations of these methods in capturing and understanding the complexity of the phenomenon investigated, as well as the generalizability of the results obtained to other clinical settings. For instance, one could argue that all predictors of return to therapy merit conceptual attention. Predictors with small effect sizes might be retained in traditional regression models with a sufficiently large sample, but these would often be eliminated in LASSO regression. This argument is relevant to psychotherapy research, particularly practice-oriented research, as statistical variable selection methods like LASSO may lead to identifying replicable predictors of large effect at the expense of potential clinical significance, i.e., statistically weak trends or findings that would be of great value to clinicians and researchers. Others may view this aspect of LASSO approach as a positive, however, because a smaller subset of the vast expanse of potential predictor variables may carry the greatest signal for predicting an outcome, in this case return to therapy. Indeed, regarding clinical decision-making, evidence favors providing clinicians with a few strong signals, rather than an array of weak ones (Dawes et al., 1989). One could argue then that the LASSO promotes clinically informed psychotherapy research through its sparsity.

Methods

Procedure

Data for the present study were obtained through the Center for Collegiate Mental Health (CCMH), which is a practice-research network (PRN) involving multiple stakeholders including service providers, university administrators, psychological researchers, and industry partners. As a collaborative infrastructure regrouping more than 600 college and university counseling centers, CCMH provides a unique opportunity to examine returning therapy clients in the UCC setting across a nationally representative sample (Castonguay et al., 2011; Hayes, Locke, et al., 2011).

The study utilized CCMH data collected from the 2013–2014, 2014–2015, 2015–2016, and 2016–2017 academic years. Based on previous investigations (Horn, 2002; Lefevor et al., 2017; Perry & Howard, 1990), the end of one treatment course and initiation of a new course was determined by an interval of at least 90 days between sessions. A client's initial treatment course was defined as at least 2 attended individual or group therapy sessions within a 90-day period. Return to therapy was not confined to the same criteria as the initial treatment course. Specifically, a client returning for at least 1 attended individual or group therapy session after a period of at least 90 days since the last appointment constituted a returning therapy client. This operationalization enabled the opportunity to capture clients returning, for example, to receive "booster" sessions.

Data Reduction

To reduce the likelihood of false negatives (i.e., clients who could have returned for additional therapy but data from only their initial treatment course is available), UCCs that did not contribute data for all of the four aforementioned years were excluded from the study. Further, only clients initiating treatment during the 2013–2014 or 2014–2015 academic years were included for analysis in order to focus on clients who had the most time to return to therapy for four and three years, respectively, thus reducing the likelihood of including false negatives. This initial dataset consisted of 135,767 clients—comprised of undergraduate and graduate students—receiving treatment across 112 UCCs throughout the United States.

Several data reduction decisions were then made in order to better focus on returning therapy clients, and these steps are summarized in Table I. First, only clients who attended at least two individual or group therapy sessions during their initial treatment courses were included. As shown in Table I, this step resulted in a substantial reduction in client sample size; and this reduction is reflective of the fact that the majority of clients attend only 1 session. This clinical reality of naturalistic data is common not only to the UCC setting (CCMH, 2020) but to routine practice in general (e.g., Hansen et al., 2002). Second, to allow for an assessment of symptoms change, only clients with at least 2 completed administrations of the Counseling Center Assessment of Psychological Symptoms (CCAPS; described in the "Measures" section) were retained. Third, in order to assess initial symptom severity most accurately and permit comparable pre- to post-treatment symptom change scores, the administrations of the CCAPS needed to take place within 14 days of both the first and last sessions of their initial treatment courses. This third decision was made to take into account the fact that there is a variability across CCMH centers regarding the frequency of the administration of the CCAPS. The 14-day window was utilized to make sure that clients who had, for example, a baseline and midpoint CCAPS but no post-treatment CCAPS were not erroneously included as having a score to reflect an end of therapy outcome. The significant reduction in sample size resulting from this step reflects, yet again, the clinical reality of naturalistic, routine data.

Of the 25,970 clients who met the three inclusion criteria above, only those with data present for all of the predictor variables were included. The predictor variables were derived from the Standardized Data Set (SDS; described in the "Measures" section). As with the CCAPS, there is center-wide variability in terms of administration policies. While CCMH encourages the use of several core items (e.g., items pertaining to treatment history, demographics, academic status, etc.), CCMH centers are allowed to implement only portions of the SDS and some

Table I. Data reduction process for study sample.

	Data Reduction Steps	Client N	Center N	Client N Reduction	Center N Reduction
1	Only individual or group therapy sessions	135,767	112	N/A	N/A
2	At least 2 attended first-course sessions	97,068	112	38,699	0
3	At least 2 first-course CCAPS	45,692	109	51,376	3
4	Has CCAPS for first and last session	25,970	105	19,722	4
5	Has SDS	23,570	98	2400	7
6	Responded to core SDS items	16,611	84	6959	14
7	Responded to non-core SDS items	8329	56	8282	28

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

centers do not administer the SDS at all. Most predictor variables come from the list of aforementioned core items but others (i.e., perceived support variables, trauma history, and sexual orientation) were derived from less-frequently administered items. Adding this last step in the data cleaning procedures resulted in a final study sample of 8329 clients across 52 UCCs.

Participants

As Table II reveals, the majority of the clients identified as female (67.07%) and Caucasian/White (73.57%). On average, clients were 22.20 years old ($SD = 4.43$) at the beginning of their initial treatment courses. The average number of attended initial treatment course sessions per client was about 9 ($M = 8.88$). However, course durations varied greatly, ranging from 2 to 109 attended sessions ($SD = 8.28$); the modal number of attended initial sessions per client was 4.

Measures

Counseling Center Assessment of Psychological Symptoms (CCAPS): This multidimensional self-report questionnaire measures psychological distress among clients in UCCs across seven subscales—depression, generalized anxiety, social anxiety, academic distress, eating concerns, alcohol use, and hostility (Locke et al., 2011). The CCAPS subscales demonstrate high convergent validity and strong test-retest reliability (Locke et al., 2012). There is a 62-item version of the CCAPS as well as a 34-item short-form version comprised of items from the CCAPS-62 version. The CCAPS-34 subscales have high correlations above .92 with the corresponding subscales of the CCAPS-62 (CCAPS, 2015 Manual). Because some CCMH centers only administer the CCAPS-34 version and the CCAPS-62 can be scored using only the items from the CCAPS-34 (CCAPS, 2015 Manual), the present study focused on the CCAPS-34 items to ensure that as much CCAPS data as possible were included in analyses. The internal consistency of the CCAPS-34 remained strong in the study sample as Cronbach's alphas ranged from 0.81 (academic distress & generalized anxiety subscales) to 0.89 (eating concerns subscale) at baseline, and from 0.84 (alcohol use & social anxiety subscales) to 0.92 (eating concerns subscale) at post-treatment.

Standardized Data Set (SDS): The SDS is a self-report instrument that collects information on demographics, academics, and mental health history and is typically administered at the beginning of treatment as it captures more stable information (Hayes, Locke, et al., 2011). SDS items were used to assess variables in three of the four predictor clusters: problem chronicity, prior utilization, and client characteristics. See Table III for a full description of predictor variables by conceptual cluster, how they were operationalized, and their respective data sources.

Table II. Client demographics.

Variable	*M*	*SD*
Age (years)	22.20	4.43
Attended Initial Treatment Course Sessions	8.88	8.28
	Percentage	
Gender		
Woman	67.07%	
Man	31.61%	
Transgender	0.41%	
Self-identify	0.91%	
Race/ethnicity		
Caucasian/White	73.57%	
African American/Black	7.98%	
Asian American/Asian	5.98%	
Hispanic/Latino/a	5.98%	
Multiracial	4.48%	
Self-Identify	1.51%	
American Indian or Alaskan Native	0.32%	
Native Hawaiian or Pacific Islander	0.17%	
Current Academic Status		
Freshman/First year	19.59%	
Sophomore	19.13%	
Junior	21.88%	
Senior	21.62%	
Graduate/Professional degree student	16.12%	
Other	1.66%	

Statistical Analyses

The primary outcome variable of interest was whether or not a client returned for a second course of therapy. Because the return to therapy is dichotomous, logistic regression models were used to assess the predictive utility of the four clusters of variables. To identify and select generalizable predictors of return to therapy, logistic regression was used with LASSO regularization implemented in the *gglasso* package (Yang & Zou, 2015) in *R* (R Core Team, 2018). LASSO regularization minimizes misfit of the model to the data based on the model residuals (i.e., prediction error). But unlike standard regression, LASSO regression applies a penalty to the fitted coefficients according to their absolute magnitude such that the coefficient magnitudes of retained variables are shrunk toward zero and weak coefficients are set to zero exactly, thereby dropping

Table III. Predictor variables and their operationalization by conceptual cluster.

Predictor Variables		Operationalization (source of data)
Problem Chronicity	(a) trauma history, non-suicidal self-injury (NSSI), suicidal ideation, prior sexual abuse	Dichotomization (SDS). (a) Present: endorsement of item either once, 2–3 times, 4–5 times, or 5 or more times across the lifespan. Absent: endorsement of "Never" across the lifespan.
Prior Utilization	(a) prior hospitalization for mental health concerns (b) prior counseling, prior psychiatric medication use	Dichotomization (SDS). (a) Present/absent: same criteria as Problem Chronicity variables. (b) Present: endorsement of item either prior to college, after starting college, or both. Absent: endorsement of "Never" across the lifespan.
Initial Treatment Course	(a) symptom severity (b) pre- to post-symptomology change (c) number of initial-course treatment sessions (d) attendance rate	Timepoint measurements (CCAPS). (a) Baseline scores on each of 7 CCAPS-34 subscales. (b) Change scores on each of 7 CCAPS-34 subscales. Appointment information (routine CCMH data). (c) Log-transformed total number of attended sessions per client. (d) Total number of attended sessions divided by number of scheduled sessions (expressed as a percentage).
Other Client Characteristics	(a) gender identification (b) family support, social support (c) ethnicity, sexual orientation	Contrast coding (SDS). (a) contrast 1: men vs. women (i.e., within gender-conforming clients); contrast 2: gender conforming vs. non-conforming (i.e., transgender and self-identifying clients). Unchanged ordinal variables (SDS). (b) Perceived support items scored on Likert scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"). Dichotomization (SDS). (c) Compared individuals identifying within majority-status groups (i.e., Caucasian/White or heterosexual/straight) with minority-status individuals (i.e., clients endorsing any other ethnicity or sexual orientation)
Controls	(a) time of year (ToY) of last session of initial treatment course (b) current academic status	Contrast coding (SDS & Appointment information). (a) Divided ToY into five categories: early & late fall, early & late spring, and summer. Contrast 1: early fall vs. late fall; contrast 2: early spring vs. late spring; contrast 3: fall vs. spring; & contrast 4: summer vs. fall and spring. Dummy coding (SDS). (b) Comparing all academic statuses against the reference group of clients in their first-year (i.e., clients with the most available time to return to therapy).

Note: All continuous and ordinal variables were standardized and mean-centered at zero on a sample-wide level. CCAPS = Counseling Center Assessment of Psychological Symptoms; SDS = Standardized Data Set.

these predictors from the model. This property of LASSO results in a *sparse* solution in which only a subset of the predictors entered into the model is retained in the prediction equation, where the level of sparsity is controlled by the tuning parameter lambda, λ. LASSO regression thus facilitates variable selection and the development of a parsimonious model while also improving the generalizability of a given model to different sample populations.

The *gglasso* package implements a group-LASSO penalized least squares (Yang & Zou, 2015), where "group" refers to a set of variables that must be modeled together such as contrast-coded or dummy-coded variables. In the present study, there were three variable groups that represented categorical variables: (i) time of year of last appointment control variables; (ii) 5 dummy-coded current academic status control variables; and (iii) 2 contrast-coded gender identity variables. All other variables were entered into the model independently. By accounting for the grouping of categorical variables, the penalty term generated by group LASSO is more appropriate than that generated by LASSO in approaches such as glmnet (Friedman et al., 2010) in which categorical variables are all dummy coded and treated as independent.

Cross-validation is often used in machine learning to evaluate a model's performance and determine the optimal model parameters. *K*-fold cross-validation, where *K* corresponds to a number of groups (more than 1) into which the full dataset is randomly divided, is a common procedure for estimating the performance of regularization on the data (see Chapter 2 of Hastie et al. (2015) for more information) and selecting the best λ value. Hastie et al. (2015) note that while data are commonly divided into 5, 10, or *n* groups, these options are not ubiquitous (e.g., Delgadillo et al., 2017). In the present study, fourfold cross validation was used to determine the LASSO penalty term, λ, that minimized the mean cross-validation error. While the decision to implement fourfold cross validation is a less common and somewhat arbitrary approach, it was influenced by considerations (though not formal testing) of variance bias trade off. That is, as the number of groups increases, bias is reduced due to the fact that the evaluated sample size contains more data but variance increases because the evaluative sample then contains less data. This approach tests multiple λ values in each of four random splits of the data. For each λ value, the model error terms (penalized sum of squared residuals) are calculated for each split. Thus, there is variability across λ values (i.e., the multiple different λ values tested) and within λ values (i.e., the variance between the four error terms generated within each subset of the data for a given λ value). Given this within-λ variability, the fourfold cross validation does not always produce the same optimal value (Tibshirani, 1996).

Different λ values can alter the variables retained in the model. Because this inconsistency could hamper the model's generalizability, additional steps to mitigate such inconsistency were applied. First, several initial runs of the fourfold cross validation were conducted to over a broad range of λ values to get an approximate range for the optimal values of λ. Two-hundred and fifty unique λ values spaced evenly within this approximate range were then tested in fourfold cross validation. This cross-validation process was repeated 100 times—i.e., the mean cross-validated error was calculated for each of the 250 unique λ values 100 times. After calculating the average deviance of the 100 repetitions across all 250 λ values, the λ value with the lowest deviance across repeats was chosen as the optimal λ value for LASSO regression because it represents the most consistent and best-fitting penalty term.

This process of repeated cross-validation to estimate performance and decrease variability has been advocated for empirically (see Jung and Hu (2015) and Chapter 3 of Kuhn and Johnson (2019) for details). The decision to implement 100 iterations of the cross-validation was less empirically-driven; rather, it was more influenced by pilot tests of the data and computational efficiency considerations. The optimal λ value identified by the cross-validations showed little variation following tests of, for example, 10 and 20 iterations. Attempts at conducting several hundred iterations proved to be too timely and unwarranted. Thus, 100 iterations seemed to sufficiently minimize variability while also not requiring excessive computational time and efforts.

In selecting the best λ, deviance was used as the measure of model error. Similar to the use sum of squared residuals in ordinary least squares regression, the deviance residual is a statistic for assessing goodness of fit in logistic regressions. It is calculated as negative two times the maximized log-likelihood, and smaller deviance values represent better fit (Friedman et al., 2010). The one-standard error rule was then applied to this optimal λ value to achieve a more stringent penalty term, which results in a more parsimonious LASSO model and a more robust set of coefficients (Melkumova & Shatskikh, 2017). Here, standard error refers to the measurement of the aforementioned within-λ deviance value across the four error terms derived from each subset of the data. In applying the one-standard error rule, the error term corresponding to one-standard error above the mean cross-validated error of the optimal λ is identified. Then, the λ with the corresponding mean cross-validation error term that is closest in magnitude to—but no greater than—this identified value is selected as the final λ value to utilize in the LASSO regression. This one-standard error λ value is larger than the originally identified optimal λ value, thereby applying a stronger penalty on the predictor variable coefficients (i.e., more coefficients are shrunk to zero). Conclusions drawn from the model using the one-standard error rule about the predictors of return to therapy were not substantively different when using the λ with minimal deviance; three additional clinically relevant variables (as opposed to control variables) were retained by the model with the less stringent penalty. These additional variables may best be viewed as weaker or marginal effects that were on the cusp of being retained by the more stringent model reported in this study (additional details on these model comparisons are available from the corresponding author upon request).

After determining the one-standard error λ value, logistic LASSO regression was conducted. As is standard procedure in non-regularized logistic regression, the coefficients for the predictor variables in the logistic model fitted with LASSO regularization were converted from log-odds units to odds ratio via exponentiation to facilitate interpretability. As LASSO is intended for variable selection, all variables with non-zero coefficients were considered to be meaningful predictors of return to therapy. Further, prior to conducting the analyses, all continuous as well as ordinal variables were standardized and mean-centered at zero on a sample-wide level (i.e., across all participants). As such, the predictor variables are transformed to the same scale and odds ratio magnitudes can be ranked and interpreted similarly to effect sizes in non-regularized regression.

Lastly, although the logistic LASSO regression generates parameter estimates for each predictor at the optimal λ, uncertainty in these parameter estimates is difficult to estimate analytically. Likewise, conventional null hypothesis significance tests are not meaningful because the null hypothesis is that a random predictor is unrelated to the outcome, but the LASSO retains variables that are systematically related to the outcome. Consequently, to derive confidence bounds on the estimates of the subset of variables that best predict return to therapy, nonparametric bootstrap resampling was applied to the LASSO models at the optimized lambda (see Hastie et al., 2015, Chapter 6). More specifically, the *gglasso* model with the chosen λ value was estimated in 1000 bootstrapped datasets, where each dataset was created by resampling the original data with replacement, yielding a dataset of the same size (i.e., number of clients). Estimated model coefficients were retained for each bootstrapped dataset, resulting in 1000 coefficient estimates for each of the predictor variables. Then, the sampling distribution of these coefficients was used to derive confidence intervals for all predictors. More specifically, the 95% confidence intervals were derived by identifying the coefficient values corresponding to the 2.5th and 97.5th quantiles; thus, in terms of traditional significance testing, this approach mirrors a two-tailed significance test with a significance threshold of $p < .05$. Due to the LASSO regularization, many of the log-odds coefficients in the bootstrapped samples will be set to zero (i.e., an odds ratio of 1.00) in some of the bootstrapped samples and their distributions largely center at zero in the distribution of resampled coefficients. Likewise, if a predictor related to the outcome only in a handful of the bootstrapped samples, then the bootstrapped odds ratio distribution would be highly skewed and largely surrounding zero. Altogether, it was decided to interpret variables whose bootstrapped log-odds 95% confidence interval did *not* include zero as reliable predictors of return to therapy.

Results

Prevalence: 2500 clients (30.02%; see Table IV) returned for at least one additional course of therapy. The majority of therapy returners returned for one additional treatment course ($N = 1790$); and clients averaged a total of 1.41 courses ($SD = 0.71$). Among clients who returned to therapy, clients attended an average of about seven sessions ($M =$ 7.27) in their second treatment course. As with initial treatment course data, 2nd-course duration varied greatly, ranging from 1 to 82 sessions ($SD =$ 7.70). 467 clients (18.68%) attended only one session in their second treatment course (shedding light on what was referred to earlier as "booster sessions"). 1 was the modal number of 2nd-course sessions and the next 1067 clients (42.68%) attended between 2 and 7 sessions in their second course.

Table IV. Prevalence of returning therapy clients.

	Number of clients (study sample)	Percentage	Number of clients (broader sample)	Percentage
Non-returning client	5829	69.98%	70,848	73.18%
Returning therapy client	2500	30.02%	25,961	26.82%
Number of additional courses				
0	5829	69.98%	70,848	73.18%
1	1790	21.49%	18,901	19.52%
2	550	06.60%	5504	5.69%
3	140	01.68%	1293	1.34%
4	17	00.20%	213	0.22%
5	2	00.02%	41	0.04%
6	1	00.01%	9	0.01%

Note: Study sample $N = 8329$; broader study sample $N = 96{,}809$.

Primary analyses focused on clients with first and last administrations of the CCAPS, which led to the exclusion of many clients. Thus, to ensure that prevalence estimates were similar to the broader population of clients ever having sought UCC treatment, the prevalence of returning to therapy among the broader data of 96,809 clients was calculated. Interestingly, as shown in Table IV, the prevalence rates largely held steady, suggesting that the sample used for primary analyses is representative of the larger UCC clinical population.

Variable selection for return to therapy: Firstly, the approximate range of λ values for regularizing the logistic regression parameter estimates were identified. More specifically, a wide range of λ values were piloted. Based on the results of this, a narrower range between −5.00 and −8.30 (values are log-transformed) was selected for the primary LASSO model cross validation. The primary cross validation tested 250 λ values evenly spaced across this range; and the test of these 250 λ values was repeated 100 times across independent random splits of the data. The λ value that minimized the mean cross-validation error was 0.0004 in log units, yielding an estimated error of 1.05. One standard error above the mean cross-validation error for the optimal λ was

1.06 (standard error = 0.01). The λ value with a corresponding mean cross-validated error closest to, but no greater than, 1.06, was 0.005. Thus, 0.005 represented the one-standard error rule λ value, and the final λ value utilized in the regularized logistic regression. The corresponding regularized model had 10 nonzero coefficients (i.e., variables retained) out of a total of 38 predictors.

Conceptual predictor clusters: Across the four conceptual predictor clusters, 6 of the 29 predictor variables were retained by the LASSO logistic regression as useful in predicting return to therapy. Of the 2 groups control variables pertaining to time of year of last appointment and current academic status (9 variables in total), 4 were retained by the LASSO logistic regression. The control variables are addressed in the "Controls" subsection (but not included in the summarizing Table V, in order to focus on the more clinically-relevant findings). For all retained variables, mean odds ratio values from the bootstrapping method are presented along with the 95% confidence intervals around these means in the following format: (M_{OR} = mean odds ratio, 95% CI [lower bound, upper bound]). Because all predictors were standardized, the relationship reflected by the odds ratio value can be summarized as for each standard deviation increase in the predictor variable, a client's odds of returning to therapy would be expected to increase/decrease by the percentage reflected by the absolute magnitude of the OR value subtracted by 1.00. For example, an odds ratio of 1.15 means that for every standard deviation increase in a given variable, a client's odds of returning to therapy would be expected to increase by 15%.

Problem chronicity & prior utilization: History of trauma, history of sexual abuse, suicidal ideation, and non-suicidal self-injury (NSSI) were not significant predictors of return to therapy. Similarly, none of the prior utilization variables (i.e., prior counseling, psychiatric medication use, or hospitalization) were retained.

Initial treatment course: There were 16 variables in total describing the initial treatment course; of these, 5 were retained. Regarding initial symptom severity, social anxiety was associated with increased likelihood of returning to therapy (M_{OR} = 1.14, 95% CI [1.08, 1.21]). Increased levels of academic distress (M_{OR} = 0.92, 95% CI [0.87, 0.98]), and alcohol use (M_{OR} = 0.94, 95% CI [0.90, 0.99]) were associated with decreased likelihood of returning to therapy. Regarding pre- to post-symptomology change, no variables were retained as predictors of return to therapy.

A positive effect of attended treatment sessions in the initial course was found: a greater number of log-transformed treatment sessions was associated with increased likelihood of returning to therapy (M_{OR} = 1.36, 95% CI [1.28, 1.44]). Because this odds ratio value reflects a relationship with a transformed variable, interpretation is not straightforward and it is not accurate to say that a standard deviation increase in attended sessions is associated with a 36% increase in odds of returning to therapy. Rather, what this finding reflects is that greater number of sessions is associated with increased likelihood of returning to therapy, but that the rate of this increased likelihood of returning decreased as the total number of sessions increased.

Lastly, overall attendance rates were associated with decreased likelihood of returning to therapy (M_{OR} = 0.48, 95% CI [0.46, 0.51]).

Client characteristics: Of the gender, race/ethnicity, sexual orientation, and perceived support variables, only perceived social support was retained by the model. Increased levels of perceived social support (M_{OR} = 1.12, 95% CI [1.06, 1.18]), were associated with increased likelihood of returning to therapy.

Controls: Of the nine total control variables, four were retained. Clients whose last appointment occurred in late spring had increased likelihoods of returning to therapy when compared to those whose last appointments occurred in early spring (M_{OR} = 1.10, 95% CI [1.001, 1.21]). Clients whose last appointment occurred in the summer had decreased likelihoods of returning to therapy when compared to those whose last appointments occurred in fall or spring (M_{OR} = 0.95, 95% CI [0.93, 0.97]). For the current academic status variables, unsurprisingly, seniors had the lowest likelihood of returning to therapy (M_{OR} = 0.40, 95% CI [0.35, 0.46]), followed by graduate students (M_{OR} = 0.67, 95% CI [0.58, 0.77]).

Table V. LASSO logistic regression results: across predictor clusters.

	Odds Ratio	95% Confidence Interval
Attendance rate	0.48	0.46–0.51
Number of initial-course sessions (log-transformed)	1.36	1.28–1.44
Initial social anxiety	1.14	1.08–1.21
Social support	1.12	1.06–1.18
Initial academic distress	0.92	0.87–0.98
Initial alcohol use	0.94	0.90–0.99

Notes: N = 8329; LASSO = Least Absolute Shrinkage and Selection Operator. Odds Ratios presented in order of absolute magnitude to reflect the relative effects of the variables. Confidence intervals were computed using the quantiles of the sampling distributions of the coefficients estimated using nonparametric bootstrapping. Only significant (i.e., 95% confidence interval does not include zero) and non-control variables are displayed.

Discussion

The present study set out to determine the prevalence rate of clients who return for additional courses of therapy in the university counseling center setting and to identify variables that predict return to therapy. The findings revealed that 27–30% of clients returned for at least one additional course of therapy. While this figure is substantially larger than the 14% rate that Boerema et al. (2016) found for clients with depression seen in a routine outpatient facility, it is smaller than the 83% rate observed by Grenyer et al. (2008) at a depression-specific treatment program. Such variability within naturalistic settings suggests an important consideration for research, clinical, and organizational purposes: The rate of returning therapy appears to depend heavily on the clinical settings; settings that can differ in terms of multiple factors, such as the population they serve and the policies that guide their treatment (e.g., session limits, cost of services). The results further show that a number of variables from two of four clusters (i.e., initial treatment course and client characteristics) were either positively or negatively associated with clients' probability of returning for additional courses of therapy. As noted in the introduction, these findings need to be interpreted while recognizing that returning (or not) to therapy may have different meanings for clients, and that specific clinical settings and populations may have particular characteristics. Based on the obtained findings, the present study provides information about longitudinal patterns of utilization and treatment-seeking behaviors from a subset of clients that has received little empirical attention in the psychotherapy outcomes literature.

Understanding why some variables may increase or decrease the likelihood of university clients' return to therapy requires acknowledging the unique developmental challenges frequently faced by college students with regard to their identity and relationships with others. Linked to these development challenges is the finding related to social anxiety. Considering how risk and maintaining factors of social anxiety (e.g., evaluative self-monitoring in social situations) are prevalent in college population (Purdon et al., 2001), it is not surprising that social anxiety has been found to be highly prevalent in the UCC setting, to have a pervasive impact on UCC clients' wellbeing, and to be associated with more severe and additional psychopathology later in life (Schry et al., 2012). The present study indicates that problems related to social anxiety are also difficult to treat. Increased levels of initial severity of symptoms were associated with increases in likelihood of returning to therapy. Interestingly, change in social anxiety severity over the course of treatment was not retained as predictive of return to therapy. This may further highlight that social anxiety is a persistent problem and suggest that clients with social anxiety are likely to return to therapy regardless of how helpful an initial treatment course may be. This possibility is supported by Janis (2017) finding that social anxiety was associated with increased utilization (i.e., additional sessions as well as other services or modalities, like group therapy or psychiatric appointments). Referring back to one of the meanings described in the introduction, one possibility is that many clients with high levels of social anxiety benefitted from treatment but not as much as they wish they had. They therefore may have sought additional treatment because they felt they *could* benefit more from professional help. Relatedly, they may have returned to therapy because the felt that they *should* do so. Since social anxiety is highly stigmatized (Anderson et al., 2015), some socially anxious clients may have been motivated to continue to pursue therapy out of a sense of shame from such difficulties.

Also prevalent in the college population is problematic alcohol use. Unlike social anxiety, however, there is not nearly as much shame and stigma associated with alcohol use on university campuses. College students can talk openly about their drinking habits with little fear for negative social consequences; in fact, doing so may even reinforce such behavior (Perkins & Wechsler, 1996). These developmental and/or cultural issues provide a context to explain, at least in part, why clients with greater levels of alcohol use were less likely to return to therapy in the present study as well as why Janis (2017), Minami et al. (2009), and Nordberg et al. (2016) found that increased alcohol use was associated with lower levels of utilization in the UCC setting. Given that alcohol use is more normative in this population, some UCC clients may understand that they have problematic drinking habits but conclude that the time is not right to try to address this concern—i.e., they may feel that their drinking is part of the college experience and that there is no need to worry about it until they graduate. It may also be that some clients became aware of, and daunted by, the severity of their drinking and were deterred from returning to therapy out of fear of confronting their problem. Additionally, it may be that some clients with high levels of substance use problems were willing to pursue additional treatment at their UCC but were referred out to longer-term, more specialized forms of treatment for alcohol use.

As with alcohol use, increased academic distress was associated with decreased likelihood of returning to therapy. This association may be explained by previous findings showing that subjective distress is amenable to change in a relatively small number of sessions (Howard et al., 1993). Thus, it is possible that many clients with academic distress felt that their difficulties were resolved during therapy and that they did not need additional treatment. Further supporting this possibility are Janis (2017) and Minami et al.'s (2009) results showing that academic distress was negatively associated with utilization rates as well as the evidence showing that UCCs are adept at treating academic distress (Lockard et al., 2012).

Given the agentic (academic and/or professional) and social challenges frequently experienced by young adults, it is not surprising that support from others has been shown to play an important role in their wellbeing (Nordberg et al., 2013). The present study, however, suggests that the facilitative or enhancing value of interpersonal relationships may be complex as clients with *stronger* perceived social support were found to be more likely to return to therapy. While one might expect decreased levels of perceived social support to be associated with a greater need for more therapy, it may be that an individual with strong social support appreciates the value of close, emotional connections and views therapy as an opportunity for an additional intimate relationship. This interpretation aligns nicely with the possibility that individuals may seek additional therapy because they enjoyed and/or benefitted from their initial treatment and want to gain more from the process of therapy.

Like the findings about interpersonal support, the results related to some of the variables pertaining to the initial course of treatment are complex and perhaps even contradictory at first glance. This may again reflect the need to consider that different reasons may lead clients to return, or not return, to therapy. Regarding the duration of clients' initial treatment, results showed that the likelihood that a client returns for additional therapy increased with additional sessions, but that the strength of the relationship between duration and the probability of returning to treatment diminished as treatment duration extended. Taken together, these findings suggest that some of the clients who may have enjoyed and/or benefitted from therapy wanted more of it, but less so as their problems were progressively or sufficiently addressed over the course of their first therapy experience.

The results also showed that poorer attendance rates, which can appear to contrast sharply with the finding pertaining to greater number of sessions received by the clients, were also associated with increased odds of returning to therapy (the magnitude of this finding being quite strong as for every 1-standard deviation decrease in attendance rate, the odds of returning to therapy increased by 52%). Considering the dose effect observed in naturalistic settings (i.e., that more therapeutic change is associated with increased number of session), this finding may indicate that some clients feel that they need to return to therapy because they have not resolved their problems and, thus, seek to make up for the inadequate dose of therapy received during their initial treatment courses.

Limitations and Broader LASSO Considerations

Several limitations of the present study should be mentioned. A primary one is that details of clients' subsequent treatment courses were not examined. For example, it would have been ideal if returning therapy clients completed a measure assessing why they are pursuing additional therapy. Further, though the present study included returning therapy clients attending only 1 session to allow for the possibility of clients returning for booster sessions, it is not possible to determine how many clients returning for one session were doing so for a booster session as opposed to pursuing an entirely new course of treatment. This distinction is important because of the aforementioned clinical reality of UCC and other naturalistic clinical settings that the modal number of sessions attended is often 1. Thus, it would have been helpful if clinicians had indicated in the data whether a client was returning for a booster session or a new course of treatment. Lastly, without this information, it was not possible to examine the possibility that the variables identified as predictive of return to therapy in the present study would be the same for clients returning explicitly for a booster session.

A related limitation is that the initial severity of clients at the beginning of subsequent therapy course was not controlled for; thus, it is not known to what extent the variables identified in the present study predict return to therapy above and beyond presenting symptomology at later therapy. Methodological limitations also deserve attention. Although the derived model is more conservative due to the LASSO implementation, the generalizability of these findings is inevitably bound by the fact that the present study examined a specific clinical population—college-aged clients—receiving therapy in a unique setting—university counseling centers. Further, though the prevalence rates of returning therapy clients were similar in the final data set and the broader, more inclusive data set, this similarity does not mean that these samples could not have varied in other meaningful ways (e.g., demographically, diagnostically, outcome-wise, etc.); and this possibility is important to keep in mind regarding the limits of the study's generalizability. Also, it is not possible to determine whether clients' initial treatment course in the data is their first time receiving therapy within (or outside of) the UCC. Although the prior utilization variables control for this fact to an extent, a client who endorsed prior counseling may have received that therapy at the UCC (e.g., during the 2012–2013 academic year). For some clients, then, it is possible that initial treatment course data actually may represent a subsequent course of therapy. In a similar vein, clients identified as non-returning in the present study may have returned to therapy in the UCC after the examined time period (e.g., in 2017–2018). Lastly, it may have been more meaningful/statistically sound to center predictor variables around within-group means as opposed to grand means. More than one group of clients exists in this data (i.e., clients who do and do not return to therapy) and it is potentially problematic to presume that individual slopes and intercepts would be the same across groups (Chen et al., 2014). The present study did not examine between-group differences in terms of means and variability; thus, implementing within-group centering would have been advantageous by accounting for potential differences in group averages.

Further, LASSO regularization is not without shortcomings. Specifically, multicollinearity among predictor variables can influence LASSO performance. With highly correlated variables, LASSO tends to select only one variable assuming any of these variables are predictive of a given outcome (Chong & Jun, 2005), and the variable selected can differ from sample to sample. In terms of replicability, it is possible that another LASSO model on the same variables might select a different set of meaningful predictors. Correlations among predictors were not examined formally, but it is possible that several of these variables would be highly correlated (i.e., a client with prior hospitalization is likely to have also had prior psychiatric medication use). Further, while the nonparametric bootstrapping method improved the overall statistical soundness of the analysis, it does not necessarily resolve issues relating to collinearity; thus, this possibility ultimately limits the robustness of the retained variables. Also, as addressed earlier, the LASSO penalty term is somewhat sample-dependent; this inconsistency was accounted for as best as possible via the fourfold cross-validation, but this limitation bears repeating as a larger reflection of the uncertainty inherent to the LASSO penalty when it comes to deriving the ideal level of regularization.

Another limitation is that several potentially fruitful predictors were not investigated, such as clients' personality traits and expectancies. Relatedly, a drawback of assessing initial-course treatment outcomes via pre- to post-treatment symptom change is that it neither captures fluctuations in clients' treatment trajectories (e.g., changes in a given clients' symptomology on a session-by-session basis) nor the change in other targets of psychotherapy such as quality of life and wellbeing. Furthermore, therapist effects were not examined in the present study in order to include as many clients as possible and also because of the intertangled nature of longitudinal utilization patterns (i.e., returning therapy clients may have seen several different therapists). These considerations were beyond the scope of the present study and should be considered for future research on returning therapy clients.

Nonetheless, this study provided evidence that returning therapy clients comprise a considerable portion of the UCC clinical population. It also shed light on longitudinal therapy utilization patterns and treatment-seeking behaviors among this group of therapy utilizers that has received little empirical attention to date. In the hands of staff and administrators, the findings could be used to inform policies related to delivery of care, such as session limits and referrals. For example, it may behoove staff and administrators to consider extending session limits for clients presenting with particularly prevalent and difficult problems like social anxiety. Clients with these difficulties may benefit from adjusted session limits—as suggested by the finding that the association between treatment duration and likelihood of returning decreased as the duration expanded—and UCCs may gain from a cost–benefit perspective in that these clients may utilize less resources in the long-term. UCC staff also may consider assessing more thoroughly the extent of problematic drinking behaviors among clients reporting higher levels of alcohol use as well as these client's engagement in therapy and willingness to address these concerns. Clients willing to address these concerns may be particularly well-suited for a referral for long-term, specialized care while those less willing may benefit from a therapy in which the core focus is not on alcohol use. Lastly, given the strong association between attendance rate and return to therapy, clients and UCC staff both may benefit from novel appointment reminders such as automated text messages or emails in addition to traditional reminders via phone call.

Ultimately, though, more research is needed in order to provide more precise and actionable information to guide these policies and recommendations. As mentioned, it is necessary to investigate both client and therapist variables that may contribute to clients' returning for additional courses of treatment. It also is crucial to better understand why some clients return and why some do not. Obviously, return to therapy is not something that clinicians and administrators necessarily want to prevent. There are some clients for whom returning to treatment is indicated and should be welcome. For others, not returning is indicative of an optimal outcome from a treatment course. Yet there may be clients who could benefit from additional therapy but do not pursue it, or others who want more therapy but pursue it at another facility. Having a better understanding of these considerations, as well as the complex networks of factors related to treatment seeking and utilization, would help the field provide more cost-effective interventions to many clients.

References

Anderson, K. N., Jeon, A. B., Blenner, J. A., Wiener, R. L., & Hope, D. A. (2015). How people evaluate others with social anxiety disorder: A comparison to depression and general mental illness stigma. *American Journal of Orthopsychiatry*, *85*(2), 31–138. https://doi.org/10.1037/ort0000046

Boerema, A. M., Cuijpers, P., Beekman, A. T. F., Hellenthal, A., Voorrips, L., & van Straten, A. (2016). Is duration of psychological treatment for depression related to return into treatment? *Social Psychiatry and Psychiatric Epidemiology*, *51*, 1495–1507. DOI 10.1007/s00127-016-1267-7

Boswell, J. F., McAleavey, A. A., Castonguay, L. G., Hayes, J. A., & Locke, B. D. (2012). Previous mental health service utilization and change in clients' depressive symptoms. *Journal of Counseling Psychology*, *59*(3), 368–378. https://doi.org/10.1037/a0028078

Castonguay, L. G., Locke, B. D., & Hayes, J. A. (2011). The center for collegiate mental health: Practice and research working together. *Journal of College Counseling*, *14*(2), 105–119. https://doi.org/10.1080/87568225.2011.556929

CCAPS 2015 Manual. (2015). Center for Collegiate Mental Health.

Center for Collegiate Mental Health. (2020, January). 2019 Annual Report (Publication No. STA 20-244).

Chen, G., Adleman, N. E., Saad, Z. S., Leibenluft, E., & Cox, R. W. (2014). Applications of multivariate modeling to neuroimaging group analysis: A comprehensive alternative to univariate general linear model. *NeuroImage*, *99*, 571–588. https://doi.org/10.1016/j.neuroimage.2014.06.027.

Chong, I., & Jun, C. (2005). Performance of some variable selection methods when multicollinearity is present. *Chemometrics and Intelligent Laboratory Systems*, *78*(1-2), 103–112. https://doi.org/10.1016/j.chemolab.2004.12.011

Ciarrochi, J. V., & Deane, F. P. (2001). Emotional competence and willingness to seek help from professional and nonprofessional sources. *British Journal of Guidance & Counselling*, *29*(2), 233–246. https://doi.org/10.1080/03069880020047157

Cohen, Z. D., Kim, T. T., Van, H. L., Dekker, J., & Driessen, E. (2020). A demonstration of a multi-method variable selection approach for treatment selection: Recommending cognitive–behavioral versus psychodynamic therapy for mild to moderate adult depression. *Psychotherapy Research*, *30*(2), 137–150. https://doi.org/10.1080/10503307.2018.1563312.

Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science*, *243*(4899), 1668–1674. https://doi.org/10.1126/science.2648573

Delgadillo, J., Huey, D., Bennett, H., & McMillan, D. (2017). Case complexity as a guide for psychological treatment selection. *Journal of Consulting and Clinical Psychology*, *85*(9), 835–853. https://doi.org/10.1037/ccp0000231

Delsignore, A. (2008). Does prior psychotherapy experience affect the course of cognitive-behavioural group therapy for social anxiety disorder? *The Canadian Journal of Psychiatry*, *53*(8), 509–516. https://doi.org/10.1177/070674370805300805

Dwyer, D. B., Falkai, P., & Koutsouleris, N. (2018). Machine learning approachers for clinical psychology and psychiatry. *Annual Review of Clinical Psychology*, *14*(1), 91–118. https://doi.org/10.1146/annurev-clinpsy-032816-045037

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, *33*(1), 1–22. https://doi.org/10.18637/jss.v033.i01

Goodman, A. C., Hankin, J. R., Kalist, D. E., Peng, Y., & Spurr, S. J. (2001). Estimating determinants of multiple treatment episodes for substance abusers. *The Journal of Mental Health Policy and Economics*, *4*, 65–77. PMID: 11967467. http://www.econ.wayne.edu/agoodman/Research/PUBS/JMHPE.pdf.

Grenyer, B. F. S., Deane, F. P., & Lewis, K. L. (2008). Treatment history and its relationship to outcome in psychotherapy for depression. *Counselling and Psychotherapy Research*, *8*(1), 21–27. https://doi.org/10.1080/14733140801889055

Hansen, N. B., Lambert, M. J., & Forman, E. M. (2002). The psychotherapy dose-response effect and its implications for treatment delivery services. *Clinical Psychology: Science and Practice*, *9*, 329–343. https://doi.org/10.1093/clipsy.9.3.329

Hastie, T., Tibshirani, R., & Wainwright, M. (2015). *Statistical learning with sparsity: The lasso and generalizations*. CRC Press.

Hayes, J. A., Locke, B. D., & Castonguay, L. G. (2011). The Center for collegiate mental health: Practice and research working together. *Journal of College Counseling*, *14*(2), 101–105. https://doi.org/10.1080/87568225.2011.556929

Hayes, J. A., Youn, S. J., Castonguay, L. G., Locke, B. D., McAleavey, A. A., & Nordberg, S. (2011). Rates and predictors of counseling center use among college students of color. *Journal of College Counseling*, *14*(2), 105–116. https://doi.org/10.1002/j.2161-1882.2011.tb00267.x

Horn, A. (2002). *A longitudinal evaluation of an intermittent model of psychotherapy* [Unpublished doctoral dissertation]. Northwestern University. https://search.proquest.com/psycinfo/docview/305524496/fulltextPDF/370FE5A57AED49DFPQ/1?accountid=13158

Howard, K. I., Lueger, R. J., Maling, M. S., & Martinovich, Z. (1993). A phase model of psychotherapy outcome: Causal mediation of change. *Journal of Consulting and Clinical Psychology*, *61*(4), 678–685. https://doi.org/10.1037/0022-006X.61.4.678

Janis, R. A. (2017). Prediction of psychotherapy treatment utilization [Master's thesis, The Pennsylvania State University, University Park, PA, USA]. Available from The Pennsylvania State University Electronic Theses and Dissertations for Graduate School database at https://etda.libraries.psu.edu/catalog/14803ruj134.

Jung, Y., & Hu, J. (2015). A *K*-fold Averaging cross-validation procedure. *Journal of Nonparametric Statistics*, *27*(2), 167–179. https://doi.org/10.1080/10485252.2015.1010532

Kadera, S. W., Lambert, M. J., & Andrews, A. A. (1996). How much therapy is really enough? A session-by-session analysis of the psychotherapy dose-effect relationship. *The Journal of Psychotherapy Practice and Research*, *5*(2), 132–151. PMID: 22700273. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3330412/pdf/132.pdf.

Kahn, J. H., & Williams, M. N. (2003). The impact of prior counseling on predictors of college counseling center use. *Journal of College Counseling*, *6*(2), 144–154. https://doi.org/10.1002/j.2161-1882.2003.tb00235.x
Kessler, L. G., Steinwachs, D. M., & Hankin, J. R. (1980). Episodes of psychiatric utilization. *Medical Care*, *18*(12), 1219–1227. https://doi.org/10.1097/00005650-198012000-00007. http://www.jstor.org/stable/3764397.
Kuhn, M., & Johnson, K. (2019). *Feature engineering and selection: A practical approach for predictive models*. CRC Press LLC.
Lefevor, G. T., Janis, R. A., & Park, S. Y. (2017). Religious and sexual identities: An intersectional, longitudinal examination of change in therapy. *The Counseling Psychologist*, *45*(3), 387–413. https://doi.org/10.1177/0011000017702721
Lockard, A. J., Hayes, J. A., McAleavey, A. A., & Locke, B. D. (2012). Change in academic distress: Examining differences between a clinical and nonclinical sample of college students. *Journal of College Counseling*, *15*(3), 233–246. https://doi.org/10.1002/j.2161-1882.2012.00018
Locke, B. D., Buzolitz, J. S., Lei, P. W., Boswell, J. F., McAleavey, A. A., Sevig, T. D., Dowis, J. D., & Hayes, J. A. (2011). Development of the counseling center assessment of psychological symptoms-62 (CCAPS-62). *Journal of Counseling Psychology*, *58*(1), 97–109. https://doi.org/10.1037/a0021282
Locke, B. D., McAleavey, A. A., Zhao, Y., Lei, P. W., Hayes, J. A., Castonguay, L. G., Li, H., Tate, R., & Lin, Y. C. (2012). Development and initial validation of the counseling center assessment of psychological symptoms-34. *Measurement and Evaluation in Counseling and Development*, *45*(3), 151–169. https://doi.org/10.1177/0748175611432642
McAleavey, A. A., Youn, S. J., Xiao, H., Castonguay, L. G., Hayes, J. A., & Locke, B. D. (2019). Effectiveness of routine psychotherapy: Methods matters. *Psychotherapy Research*, *29*(2), 139–156. https://doi.org/10.1080/10503307.2017.1395921
McKenna, P., & Todd, D. (1997). Longitudinal utilization of mental health services: A timeline method, nine retrospective accounts, and a preliminary conceptualization. *Psychotherapy Research*, *7*(4), 383–395. https://doi.org/10.1080/10503309712331332093
Melkumova, L. E., & Shatskikh, S. Y. (2017). Comparing ridge and LASSO estimators for data analysis. *Procedia Engineering*, *201*, 746–755. https://doi.org/10.1016/j.proeng.2017.09.615
Minami, T., Davies, D. R., Tierney, S. C., Bettmann, J. E., McAward, S. M., Averill, L. A., Huebner, L. A., Weitzman, L. M., Benbrook, A. R., Serlin, R. C., & Wampold, B. E. (2009). Preliminary evidence on the effectiveness of psychological treatments delivered at a university counseling center. *Journal of Counseling Psychology*, *56*(2), 309–320. https://doi.org/10.1037/a0015398
Nam, S. K., & Choi, S. I. (2013). Psychological factors in college students' attitudes toward seeking professional psychological help: A meta-analysis. *Professional Psychology: Research and Practice*, *44*(1), 37–45. https://doi.org/10.1037/a0029562
Nordberg, S. S., Castonguay, L. G., McAleavey, A. A., Locke, B. D., & Hayes, J. A. (2016). Enhancing feedback for clinical use: Creating and evaluating profiles of clients seeking counseling. *Journal of Counseling Psychology*, *63*(3), 278–293. https://doi.org/10.1037/cou0000147
Nordberg, S. S., Hayes, J. A., McAleavey, A. A., Castonguay, L. G., & Locke, B. D. (2013). Treatment utilization on college campuses: Who seeks help for what? *Journal of College Counseling*, *16*(3), 258–274. https://doi.org/10.1002/j.2161-1882.2013.00041.x
Perkins, H. W., & Wechsler, H. (1996). Variation in perceived college drinking norms and its impact on alcohol abuse: A nationwide study. *Journal of Drug Issues*, *26*(4), 961–974. https://doi.org/10.1177/002204269602600413
Perry, K.J., & Howard, K.I. (1990). *Previous psychotherapy: Relationship to current treatment episode*. Paper presented at the annual meeting of the Society for Psychotherapy Research, Wintergreen, VA.
Purdon, C., Antony, M., Monteiro, S., & Swinson, R. P. (2001). Social anxiety in college students. *Journal of Anxiety Disorders*, *15*(3), 203–215. https://doi.org/10.1016/S0887-6185(01)00059-7
R Core Team. (2018). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/
Ronis, D. L., Bates, E. W., Garfein, A. J., Buit, B. K., Falcon, S. P., & Liberzon, I. (1996). Longitudinal patterns of care for patients with posttraumatic stress disorder. *Journal of Traumatic Stress*, *9*(4), 763–781. https://doi.org/10.1002/jts.2490090407
Schry, A. R., Roberson-Nay, R., & White, S. W. (2012). Measuring social anxiety in college students: A comprehensive evaluation of the psychometric properties of the SPAI-23. *Psychological Assessment*, *24*(4), 846–854. https://doi.org/10.1037/a0027398
Shaffer, J. P. (1995). Multiple hypothesis testing. *Annual Review of Psychology*, *46*, 561–584. https://doi.org/10.1146/annurev.ps.46.020195.003021
Siddall, L. B., Haffey, N. A., & Feinman, J. A. (1988). Intermittent brief psychotherapy in an HMO setting. *American Journal of Psychotherapy*, *42*(1), 96–106. https://doi.org/10.1176/appi.psychotherapy.1988.42.1.96
Stulz, N., & Lutz, W. (2007). Multidimensional patterns of change in outpatient psychotherapy: The phase model revisited. *Journal of Clinical Psychology*, *63*(9), 817–833. https://doi.org/10.1002/jclp.20397
Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B: Methodological*, *58*, 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x
Usai, M. G., Goddard, M. E., & Hayes, B. J. (2009). LASSO with cross-validation for genomic selection. *Genetics Research*, *91*(6), 427–436. https://doi.org/10.1017/S0016672309990334
Yang, Y., & Zou, H. (2015). A fast unified algorithm for solving group-lasso penalize learning problems. *Statistics and Computing*, *25*(8), 1129–1141. https://doi.org/10.1007/s11222-014-9498-5