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PREDICTION OF PSYCHOTHERAPY TREATMENT UTILIZATION

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Abstract

Within university counseling centers, there are increasing needs but few resources to meet those needs. There is also evidence that some clients use more resources than others, often dramatically so. This discrepancy between resource demand and availability leads to the need to identify characteristics of clients who utilize more sessions. This will allow counseling centers to make empirically informed decisions around treatment planning and allocation. The current study employs mixed effects negative binomial regression to identify pretreatment predictors of client session utilization within a university counseling center setting. Additionally, a logistic regression is conducted to identify predictors of membership in a high resource utilization group, defined as the clients who utilize the highest 20% of sessions. Several predictors of both utilization and membership in the high resource utilization group are identified. Clinical implications and implications for future research are discussed.
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Chapter 1

Introduction

In psychotherapy, as in healthcare in general, there are increasing needs but few resources to address them. For example, within one insurance network, only 32.4% of patients diagnosed with a mental illness received subsequent psychotherapy (Harpaz-Rotem, Libby, & Rosenheck, 2012). There is also evidence that some clients use more resources than others, often dramatically so, across many mental health systems (Minami, Serlin, Wampold, Kircher, & Brown, 2008; Pasic, Russo, & Roy-Byrne, 2005). Given the discrepancy between resource demand and resource availability, it becomes important to identify clients who are using more resources than others, as it could prove beneficial for informing policies around session limits and treatment allocation. The examination of factors related to treatment utilization appears to be indicated in a college counseling center setting, as the discrepancy between client resource needs and services available has been clearly demonstrated (The Center for Collegiate Mental Health [CCMH], 2016).

Before identifying such factors, and in order to provide a broader context for our investigation, we present an overview of variables that have been investigated with regard to treatment length and utilization in psychotherapy in general, as well as in other areas of mental health care.

Length of Psychotherapy Treatment

There is some existing work looking at client factors related to psychotherapy treatment length, although few consistent findings emerge. While several studies have identified a positive relationship between years of education and length of treatment
(Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Sue, McKinney, & Allen, 1976), others have found no relationship (Craig & Huffine, 1976; Perry, Bond, & Roy, 2007). With regard to age, two studies have found that older clients utilize more sessions than younger ones (Craig & Huffine, 1976; Sue et al., 1976). This could be due to a maturational process throughout the lifespan that leads older adults to stay in therapy longer and terminate prematurely less often, or it could be indicative of a longer duration of problems prior to treatment. Other studies, however, have found no relationship between age and sessions (Mueller & Pekarik, 2000; Perry et al., 2007), with one additional study finding a negative relationship (Pekarik & Wierzbicki, 1986). Ethnicity has largely been shown to be unrelated to treatment length (Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986), although one study found that racial ethnic minority clients utilized fewer sessions (Sue et al., 1976). The authors suggested that the community mental health system was not responding to the needs of minority clients, causing them to drop out of treatment prematurely and use fewer session. To our knowledge, no study demonstrated a significant relationship between marital status (Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Sue et al., 1976) or gender (Craig & Huffine, 1976; Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Perry et al., 2007; Sue et al., 1976) and treatment length.

Looking beyond demographic variables, studies have shown that clients with personality disorders (Craig & Huffine, 1976; Perry et al., 2007), eating disorders (Mueller & Pekarik, 2000), and psychosis (Craig & Huffine, 1976) generally utilize longer treatments than other clients. In contrast, other diagnoses such as depression and anxiety have not been found to significantly predict treatment length (Perry et al., 2007;
Sue et al., 1976). Two trans-diagnostic issues related to mental health, childhood sexual abuse and emotional neglect, have been found to predict longer treatment length (Mueller & Pekarik, 2000; Perry et al., 2007). Prior therapy, another trans-diagnostic factor, has been found to be related to longer treatments in one study (Pekarik & Wierzbicki, 1986). Another study, however, found both prior therapy and prior psychotropic medication use to be unrelated to length of treatment (Mueller & Pekarik, 2000). Interestingly, Mueller and Pekarik (2000) found that in the context of other significant predictors of treatment length, the client’s expected number of visits was the strongest predictor of actual number of visits, even stronger than the therapist’s prediction of treatment length.

The most consistently identified predictor of treatment length is initial distress or symptom severity (Baldwin, Berkeljon, Atkins, Olsen, & Nielsen, 2009; Brookman-Frazee, Haine, Gabayan, & Garland, 2008; Mueller & Pekarik, 2000; Stiles, Barkham, Connell, & Mellor-Clark, 2008), with more distressed clients utilizing more sessions. However, severity is also related to increased risk of dropping out of treatment, possibly leading to lower utilization of services than if the client had remained in treatment (Boerema et al., 2016). Interestingly, Saltzman and colleagues (1976) identified many client characteristics that discriminated between clients who dropped out of treatment and those who remained, but none of those variables significantly predicted treatment length for clients who remained in treatment. Beyond initial client characteristics, treatment duration has been shown to differ based on change in early sessions. Clients who exhibited early improvement used fewer sessions than clients who did not show early change, especially in clients with high initial impairment (Stulz, Lutz, Leach, Lucock, & Barkham, 2007). Additionally, number of therapy visits has been found to correlate
positively with number of medication visits (Goldenberg, 2002). Number of medication visits may serve as a within treatment indicator of severity, mirroring the findings above, or a propensity for help seeking behavior, leading to more sessions of both kinds.

As a whole, and with the exception of initial distress or severity, past research has failed to identify strong and robust client level predictors of treatment length. This is potentially due to the myriad of possible interaction effects and to the variety of populations and contexts within which client variables have been examined. Looking to such contextual factors, Lutz and colleagues (2015) found that 20% of difference in treatment length could be explained by the number of sessions approved by insurance. After controlling for sessions approved by insurance, therapists accounted for about 9% of the variance in number of sessions. The only client variable related to treatment length in this context was interpersonal distress, which explained only 2% of the variance, with more distressed clients utilizing more sessions.

**Utilization of Other Treatment Services**

In addition to work looking at session utilization within psychotherapy, there has also been relevant research done in other related areas, especially areas in which high utilizing clients prove very costly to the system, such as psychiatric hospitalizations, emergency psychiatric services, and general health care utilization (e.g. Bloom, 1970; Pasic, Russo, & Roy-Byrne, 2005; Saarento, Hakko, & Joukamaa, 1998; Sullivan, Bulik, Forman, & Mezzich, 1993). Research in these settings has frequently demarcated a subgroup of patients as high resource utilizers (HRU), indicating that they account for a disproportionate amount of visits, resources, or costs. For example, in the United States, 50% of health care expenditures are accounted for by 5% of the population (Berk &
Monheit, 2001, Conwell & Cohen, 2002). In psychiatric emergency rooms, a setting more closely related to outpatient psychotherapy, high utilizers (defined as clients with visits two standard deviations above the mean) accounted for 23% of all visits (Pasic et al., 2005). In that setting, prior treatment, especially prior hospitalizations, was associated with an increased likelihood of multiple visits (Arfken et al., 2004; Nurius, 1983; Pasic et al., 2005; Pérez, Minoletti, Blouin, & Blouin, 1987; Spooren, De Bacquer, Van Heeringen, & Jannes, 1997). Specifically, clients who used a high volume of services in a short period of time (acute HRU) were more likely to have prior hospitalizations than more chronic high utilizers (Pasic et al., 2005), indicating that these clients may have a pattern of higher use during periods of crisis. Similarly, prior psychological treatment was also related to increased utilization (Miller, 1968; Pérez et al., 1987). The diagnoses of psychosis and personality disorders were also related to an increased likelihood of being a repeat patient (Saarento et al., 1998; Slaby & Perry, 1980; Spooren et al., 1997), while diagnoses of anxiety and depression were related to a decreased likelihood (Pasic et al., 2005; Saarento et al., 1998; Sullivan et al., 1993). In regards to demographic variables, being male was generally associated with an increased likelihood of being a repeat user of psychiatric ER services (Arfken et al., 2004; Saarento et al., 1998; Spooren et al., 1997; Sullivan et al., 1993), as well as being unmarried (Miller, 1968; Nurius, 1983; Pérez et al., 1987; Slaby & Perry, 1980; Sullivan et al., 1993), and a racial ethnic minority (Arfken et al., 2004; Sullivan et al., 1993).

**Utilization in University Counseling Centers**

As in other mental health care settings, a disproportionate use of services has been observed in university counseling centers (UCCs), with a small percentage of clients
accounting for a disproportionately large percentage of sessions. Across a national sample of over 100 counseling centers, for instance, 10% of clients accounted for about 35% of all scheduled sessions, with 20% of clients using over half of all sessions (CCMH, 2016). Compared to the treatment services reviewed above, however, the paucity of research directly evaluating client predictors of treatment duration is even more pronounced in UCC settings, and to our knowledge, no studies have looked specifically at characteristics of HRU in that setting. Preliminary research has shown that UCC clients who report a lifetime history of threat-to-self characteristics (non-suicidal self-injury, suicidal ideation, etc.) use 20-30% more services than those who do not (CCMH Annual Report, 2015). Minami and colleagues (2009) also found that clients with intimacy issues and anhedonia use more sessions, while substance use issues, loss of productivity and stress are associated with using fewer sessions. Generally consistent to findings in other psychotherapy treatment settings, race/ethnicity, gender and marital status were not significantly related to number of sessions. A positive correlation was observed between age and number of sessions, although it explained less than 1% of the total variance. Surprisingly, suicidality was not related to number of sessions. Another study identified nine latent profiles of presenting symptoms in UCC clients, differentiated primarily by the presence of eating concerns and substance use (Nordberg, Castonguay, Mcaleavey, Locke, & Hayes, 2016). The profiles differed in average treatment length, with averages ranging from 7.34 to 13.03 sessions. Generally, clients with primary or comorbid eating concerns utilized more sessions, while clients with primary substance/alcohol use problems utilized fewer. This relationship between substance use and number of sessions utilized mirrors that found by Minami et al. (2009).
Further investigation of resource utilization is particularly timely for UCCs. There is indeed evidence that increases in UCC service utilization are outpacing growth in university enrollment (CCMH, 2015). Put more simply, a greater percentage of university students are now requesting psychological treatment. Considering the increasing severity of many clinical problems experienced by college students (Xiao, et al., in press), this trend is not likely to decrease in the near future.

**The Center for Collegiate Mental Health**

The Center for Collegiate Mental Health (CCMH), a nationally representative practice research network (PRN), provides a unique setting in which to examine treatment utilization in UCCs (Castonguay, Locke, & Hayes, 2011; Hayes, Locke, & Castonguay, 2011). CCMH is a collaborative partnership infrastructure involving multiple stakeholders, including university administrators, psychological researchers, industry partners, and over 400 UCCs. CCMH fills the primary goals of a PRN by facilitating the collection of information that will both inform clinical practice and advance research on the mental health services provided to UCC clients, while not adding substantial burden to everyday clinical practice.

As one example of a clinically relevant study that can be conducted at CCMH, research on client characteristics related to treatment utilization might provide helpful information for service delivery and policy setting. For example, knowing client characteristics indicative of higher utilization may allow centers to make empirically informed decisions regarding referring out of the center for more long term treatment or adjusting session limits for clients predicted to require longer courses of treatment. Nordberg and colleagues (2016), for instance, suggest that their work on profiles of
presenting symptoms could be used to advocate for extended services for clients with profiles associated with the utilization of more sessions. Additionally, predictions of client treatment length could be further used for treatment planning to estimate how long clients are likely to remain in treatment given their characteristics, and consequently when a given therapist is likely to have an opening. With the hope of providing useful knowledge to address such clinical issues, the goals of this exploratory study are twofold: To identify client characteristics predictive of 1) the number of sessions a client utilizes, and 2) a client being classified as a HRU.

The present study extends the two previous studies examining treatment length in UCCs (Minami et al., 2008; Nordberg et al., 2016) in several ways. Although using similar data to Nordberg and colleagues (2016), which was also collected through CCMH, this study looks directly at the effect of individual predictors of treatment length instead of indirectly examining the average treatment lengths of derived latent profiles. This will allow for conclusions to be made about the contribution of individual predictors to treatment length. It further builds on Minami and colleagues’ (2008) examination of client predictors of treatment length in a large, nationally representative data set, attempting to replicate their findings as well as examining predictors not included in their analyses, including mental health history variables. Most significantly, the current study identifies a subgroup of clients as HRU, as has been done in other mental health settings, and evaluates characteristics that discriminate this subgroup from other clients.

**Hypotheses and Research Questions**

The current study will be guided by several hypotheses predicting the replication of previous findings, as well as questions that have not been addressed by previous
studies. Hypotheses and research questions are the same for analyses predicting both session utilization and membership in the HRU subgroup: predictors hypothesized to be related to increased session utilization are also hypothesized to be predictive of classification as a HRU. Based on research done within CCMH, it is hypothesized that suicidality, prior suicide attempts and prior self-injury will be related to increased utilization (CCMH Annual Report, 2015). As a caveat, however, it should be noted Minami et al. (2009) found suicidality to be a non-significant predictor of session utilization in the context of other predictors. Accordingly, it is possible that suicidality might become non-significant when tested concurrently with other predictors.

Based on research conducted outside of college counseling centers, it is hypothesized that having prior hospitalizations will lead to increased utilization, as prior hospitalizations positively predicted more visits to a psychiatric ER (Arfken et al., 2004; Pasic et al., 2005; Spooren et al., 1997). Hospitalizations likely serve as an indicator of a higher level of chronicity and severity of a client’s mental health problems, causing them to historically utilize the hospital to manage those problems and to utilize more sessions at a UCC to manage them. Additionally, it is hypothesized that having a sexual trauma will be associated with increased utilization, as childhood sexual abuse has been previously shown to be predictive of longer treatments (Mueller & Pekarik, 2000; Perry et al., 2007).

Beyond the above hypotheses based on prior research, several research questions will be explored based on variables with mixed findings or no prior research. Prior therapy and medication use were inconsistently related to psychotherapy session utilization (Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986), but they may serve as
indicators of chronicity and severity of problems, similar to hospitalizations, and were found to be predictive of psychiatric ER visits (Miller, 1968; Pérez et al., 1987).

Furthermore, many demographic variables have received mixed support in the literature. Gender was found to be unrelated to psychotherapy utilization (Craig & Huffine, 1976; Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Perry et al., 2007; Sue et al., 1976); however, men have been found to utilize more psychiatric ER visits (Arfken et al., 2004; Saarento et al., 1998; Spooren et al., 1997; Sullivan et al., 1993). Similarly, ethnicity was an inconsistent predictor of session utilization in psychotherapy (Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Sue et al., 1976), but was found in two studies to predict more psychiatric ER visits (Arfken et al., 2004; Sullivan et al., 1993). Marital status was also found in psychotherapy settings to be non-significantly related to treatment length (Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Sue et al., 1976) but was a significant predictor of psychiatric ER visits (Miller, 1968; Nurius, 1983; Pérez et al., 1987; Slaby & Perry, 1980; Sullivan et al., 1993). In addition, years of education and age have some support as predictors of psychotherapy treatment length (Craig & Huffine, 1976; Minami et al., 2008; Mueller & Pekarik, 2000; Pekarik & Wierzbicki, 1986; Sue et al., 1976); however, both variables suffer from a restricted range in a college sample. These mixed findings lead to the exploration of the following questions:

1. Will prior therapy and medication use be predictive of greater utilization?

2. Do men utilize more sessions than women, and do transgender and gender non-conforming clients use more than cisgender clients?

3. Will being a racial ethnic minority be associated with a greater number of sessions?
4. Will clients in relationships utilize fewer sessions than single, divorced or separated clients?

5. Within the restricted range of college students, will clients in more advanced academic years utilize more sessions?

No identified studies examined disability or sexual orientation as a predictor of utilization. Similarly, no studies within college counseling centers included the time of year that a client starts treatment as a covariate. These research gaps lead to the exploration of three additional questions:

1. Will having a disability be predictive of more session utilization?

2. Will being a sexual minority (non-heterosexual) client be predictive of more session utilization?

3. Given constraints imposed by the academic year, will the time of year a client first presents to the counseling center be related to session utilization?

Finally, initial level of distress or severity has been consistently associated with longer treatment; however, this finding has been based on a unidimensional measure of general distress. The present study has the advantage of measuring distress across seven domains: Depression, generalized anxiety, social anxiety, eating concerns, hostility, alcohol use, and academic distress. Based on prior research conducted specifically in college counseling centers, it is hypothesized that eating concerns will be positively related to utilization (Nordberg et al., 2016), while alcohol use distress will be negatively related to utilization (Minami et al., 2009; Nordberg et al., 2016). Beyond those two domains, this study will explore whether other markers of symptomatology replicate the finding of general distress predicting greater utilization.
Chapter 2

Methods

Procedure

Data for the present study were collected through the Center for Collegiate Mental Health (CCMH), which as mentioned above, is a practice research network of over 400 university and college counseling centers. Participating counseling centers maintain their own IRB and collect data locally as part of clinical routine using standardized measures. The de-identified data is then uploaded to the CCMH data repository. Data collected through CCMH during the 2013-2014 and 2014-2015 academic years are utilized in the current study.

Of the centers contributing data from 2013-2015, the only centers included in the present study are those that have contributed data for both the 2013-2014 and 2014-2015 academic years. This is because our study aims to measure utilization during the one year following clients’ initial appointment. From the date of each client’s initial clinical evaluation, one calendar year of appointment data are included.

Sample

The complete 2013-2015 CCMH data set includes data from 150 UCCs and 183,618 clients. Although CCMH as a network comprises over 400 UCCs, not all contribute data to the centralized database. From the 150 centers contributing data, 129 contributed data for both years. These centers contributed a total of 168,645 clients. In order to be included, clients needed to have an initial evaluation appointment in the 2013-2014 academic year, ensuring that their treatment started in the first year, and allowing
for one full year of data to be included. This step resulted in a reduced data set of 60,939 clients from 118 centers, as many clients began treatment in the 2014-2015 year and were not eligible. Further data cleaning steps included removing clients who did not respond to all predictor items, as well as removing centers with fewer than 25 clients. This was done to ensure that the data from each center was representative in order to create accurate demarcations of the HRU clients. With data from fewer than 25 clients per center, it is unlikely that the data contributed is representative of the center. This resulted in a final data set of 39,806 clients from 82 centers.

**Measures**

**Appointment information.** Information about appointments is recorded through Titanium, an electronic medical record system. This information includes the date of the appointment, the type of appointment (e.g. intake, individual, group, psychiatric, etc), and the client’s attendance status. Appointment information is also used in this study to code the time of year a client first presents for treatment.

**Counseling Center Assessment of Psychological Symptoms (CCAPS).** The CCAPS is a multidimensional self-report instrument intended to measure psychological distress in college counseling centers (Locke et al., 2011). The CCAPS measures distress in seven domains: Depression (6 items), Generalized Anxiety (6 items), Social Anxiety (5 items), Academic Distress (4 items), Eating Concerns (3 items), Alcohol Use (4 items), and Hostility (6 items). The CCAPS has a 62-item version and a 34-item short form composed of items present on the CCAPS-62 version. Consequently, administrations of the CCAPS-62 can be scored as a short form using only the items that appear on the CCAPS-34, which will be done in the present study in order to include the as much
CCAPS data as possible (since some CCMH centers only use the 34 items version). The CCAPS-34 subscales have high correlations above .92 with their corresponding CCAPS-62 subscales (CCAPS 2015 Manual).

The CCAPS-34 subscales show convergence with other criterion measures of depression, anxiety, eating problems, anger, and alcohol use disorders, with all correlations between subscales and criterion measures being greater than .52 (Locke et al., 2012). The subscales also display adequate test-retest reliability, with 1 and 2 week reliability ranging from .74 to .87 (Locke et al., 2012).

In completing the CCAPS, clients are asked to rate themselves over the past two weeks on a Likert scale, from 0 (not at all like me) to 4 (extremely like me). Each subscale is scored by taking the average of the questions that load onto that subscale. As such, higher subscale scores indicate more distress, with scores ranging from 0 to 4. CCAPS items and their corresponding subscales are shown in Appendix A. Each client’s first completed CCAPS administration is included in the present study as a representation of that client’s initial distress in the seven domains captured by the CCAPS.

**Standardized Data Set (SDS).** The SDS collects information on demographics, academics, and mental health history and is most often administered at the beginning of treatment (Hayes et al., 2011). All answer options for SDS questions are presented in Appendix B. Mental health history items ask how many times an event has occurred in a client’s life, from “never” to “more than 5 times.” Responses will be dichotomized for the present analyses based on whether a client reported ever experiencing the event in question.
**Statistical Analyses**

Session utilization, the first outcome of interest, was defined as the total number of sessions for a given client within one year of his or her first appointment. Scheduled sessions regardless of attendance were included, as they represent time the center cannot provide services to another client. Sessions canceled or rescheduled by a counselor or due to the center being closed were omitted. All sessions representing psychotherapy (i.e. individual therapy, group therapy, crisis, etc) were included and weighted equally as one session. Psychiatric sessions were not included, as not all centers in the sample provide psychiatric services. High resource utilization, the second outcome of interest, was defined as the top 20% of utilization. Therefore, clients were classified as HRU if their session utilization was in the top 20% for their center. HRU classification was done after removing clients who began treatment in the second year of data but before clients with incomplete predictor data were removed.

The cleaned data set was split into two even samples, sampling evenly from within the 82 centers represented. Before analyses, the sets were tested for differences on the outcome of session utilization and predictors. One sample was used as a training set for developing predictive models for session utilization and membership in the HRU group, and the second sample was used as a testing set to test the accuracy of the models in a unique sample from that in which they were derived.

**Session Utilization.** The association between predictor variables and session utilization was analyzed using a mixed effects negative binomial regression with a log link function. Negative binomial regression was used instead of a linear regression since the outcome variable, utilization, is a count variable with a highly skewed distribution.
Although Poisson regression is frequently used for count type outcome variables, the Poisson distribution assumes an equal mean and variance of the outcome variable, a condition not met by the utilization variable in the present study, which has a much larger variance than mean (M = 8.68, variance = 71.91). Negative binomial regression allows for greater variance in such “overdispersed” data by including an extra dispersion parameter, making it a better fit for the present analyses (Gardner, Mulvey, & Shaw, 1995). Coefficients from a negative binomial regression are exponentiated to be interpreted as the percent change in the outcome with a one unit change in the predictor, for a categorical variable, or the percent difference in utilization between the two categories of a dichotomous variable. Clients were only represented in the data set if they had at least one scheduled appointment at a center, so there were no values of zero for session utilization. Since the negative binomial distribution assumes zero values are present, each client’s value for session utilization was shifted backward by 1. Predicted values from the model were then shifted forward by 1 in order to align with the original utilization values.

Modeling was conducted using the “lme4” package (Bates, Maechler, Bolker, & Walker, 2015) in the R programming language (R Development Core Team, 2014) using maximum likelihood estimation. Mixed effects modeling accounts for the nesting inherent in the data, as clients are nested within university counseling centers, and prior work has shown a center effect on other outcomes of interest (Lefevor, Janis, & Park, 2017). The model included two levels: clients (level 1) within university counseling centers (level 2). Although clients are also nested within therapists, therapist was not included as a level because clients frequently see more than one therapist, making the
assignment of each client’s variance to only one therapist difficult. Accounting for each client’s multiple therapists would require a cross classified model, which is outside the scope of the current project. The model equation below represents the basic equation for the proposed model:

Level 1: $\log (Utilization_{ij}) = \beta_{0j} + \beta_{1j}(X_{1ij}) + e_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + u_{0j}$

$\beta_{1j} = \gamma_{10}$

where $Utilization_{ij}$ indicates the total sessions for client $i$ in center $j$. The model includes an intercept ($\gamma_{00}$), representing the average utilization for clients at the center average on all predictors, as well as a random intercept ($u_{0j}$), allowing individual centers’ utilization to vary randomly around that intercept. The variance associated with this random intercept ($\sigma_{u0}^2$) indicates the amount of variance in utilization that exists between centers. $X_{1ij}$ represents a client level predictor of utilization, and the effect of that predictor is indicated by $\gamma_{10}$. Residual error is indicated by $e_{ij}$.

The inclusion of a random intercept allows for the calculation of an intraclass correlation coefficient ($\rho$), which can be interpreted as the percentage of variance in utilization accounted for by centers. Between level variance in a negative binomial model was calculated by dividing the between center variance ($\sigma_{u0}^2$) from an empty model by the sum of the between center variance and the dispersion parameter.

**High Resource Group Membership.** Logistic regression was used to predict membership in the HRU group. Since HRUs were identified as the top 20% of clients at each center, each center had an equal percentage of HRU clients, resulting in no between center variance in the rate of a client being classified as a HRU. Consequently, it was not
necessary to utilize a mixed effects model with a random intercept, as in the previous analyses on utilization. A single level logistic regression was used, with membership in the HRU group as the outcome. Similar to the negative binomial model above, coefficients from the logistic regression are also exponentiated, allowing them to be interpreted as the change in odds of being a HRU associated with a one-unit change in the predictor.

**Model fitting.** The training set was used to explore potential models for predicting both utilization and HRU membership. Model fit for the negative binomial model predicting session utilization proceeded by first testing a model with all predictors, then removing predictors with non-significant or small effects and evaluating model fit. The best fitting model was determined by the Bayesian Information Criteria (BIC; Schwarz, 1978), on which smaller values indicate better fit. BIC was favored over AIC due to BIC’s penalty on additional parameters, especially in large sample sizes. AIC and loglikelihood are reported in addition to BIC for reference. Models were also compared using likelihood-ratio tests (LRT) comparing models with additional predictors to the models without the predictors to assess whether the additional predictors improved model fit (Bolker et al., 2009). The LRT tests the null hypothesis that the two nested models do not have significantly different model fit. This is modeled as a Chi-square distribution with degrees of freedom equal to the difference in parameters estimated between the two models. The best fitting model for membership in the HRU group was selected by again testing all predictors and removing non-significant predictors.

The best fitting model found for each outcome was then applied to the testing set to evaluate how well each performed on out of sample prediction, ensuring that the model
was not overfitting the training set. The percent of variance in session utilization explained by the final negative binomial model was calculated by pseudo-$R^2$ (Nakagawa & Schielzeth, 2013). The accuracy of the logistic regression model predicting HRU membership was evaluated by the percentage of clients correctly classified.

**Predictors.** Although the main focus of the analysis was on identifying client predictors associated with utilization, center policy on session limits was first tested as a level two variable in order to control for contextual effects of session limits, if necessary. This decision was based on a study by Lutz et al., (2015), which found that 20% of treatment length could be accounted for by the number of sessions approved by insurance.

Client level predictors of treatment utilization were drawn from the SDS and the CCAPS. The SDS provided mental health history items representing the historical presence or absence of the event, including prior therapy, medication, hospitalization, non-suicidal self-injury (NSSI), suicide attempts, and trauma. Demographic variables, also drawn from the SDS, included gender, sexual orientation, ethnicity, disability status, relationship status, and academic year. Two contrast codes were created for gender: one comparing male and female clients, and one comparing cisgender to gender non-conforming and transgender clients. Sexual orientation was coded to compare heterosexual and non-heterosexual (gay, lesbian, bisexual, questioning, and self-identified) clients. Ethnicity was coded to compare clients identifying as white to clients identifying as racial ethnic minorities. Disability status compared clients registered with the campus disability office to those not registered with a disability. Relationship status compared clients in a relationship (married or serious dating, committed relationship, and
civil union, domestic partnership, or equivalent) to clients not in a relationship (single, separated, divorced, and widowed). Academic year included the categories freshman, sophomore, junior, senior, and other (including graduate student), with freshman as the referent category for analyses. Client rating of current distress includes all seven continuous CCAPS subscales, on which higher scores indicate greater distress. Additionally, a single item from the CCAPS asking about suicidal ideation (“I have thoughts of ending my life”) was included.

Finally, the time of year of the first appointment, which was coded from appointment information, was included to control for differences in the number of sessions a client was able to utilize based on when they first begin services at the counseling center. For example, a client who begins treatment at the beginning of the academic year may be more likely to use more sessions over the course of the year than a client who begins close to the end of an academic year and is constrained by the academic year ending. Time of year was coded into five categories around the academic calendar based on consultation with university counseling center clinicians: early fall (August-October), late fall (November-December), early spring (January-February), late spring (March-April), and summer (May-July).

All predictor variables were included in analyses of both session utilization and HRU membership. Predictors were centered around the UCC means. This centering was done to remove between center variance in predictors that could potentially drive relationships, and therefore allowed the regression coefficients to be interpreted as within counseling center relationships: the effect of the predictor compared to other clients within the same counseling center.
Chapter 3

Results

Table 1 presents descriptives for utilization and the other variables included in the study for both the training and testing sets. Two visual outliers were removed from the sample prior to analyses that were more than 1.5 standard deviations from the next highest value. Clients in the sample had on average 8.68 (SD = 8.48) scheduled appointments in the span of a year. The median number of scheduled appointments was 6, and scheduled appointments ranged from 1 to 93. The modal number of scheduled appointments was 2, and the distribution was highly skewed (figure 1), visually indicating a disproportionate utilization of services. There were no differences between the training set (N = 19,987) and testing set (N = 19,819) on utilization ($F(1, 39804) = .02, p = .902$), or on any of the predictors.

Utilization

Testing for overdispersion showed that a negative binomial model with an extra dispersion parameter (dispersion = 1.08) fit better than a Poisson model (BIC Poisson = 206,501, BIC negative binomial = 122,669; $\chi^2 (1) = 55,500, p < .001$). All subsequent models include an estimated dispersion parameter. In a random intercept only model with no predictors, center accounted for 7% of the variance in utilization. Figure 2 shows the distribution of average center utilization scores, highlighting the variability between centers.

Before proceeding to analyses of client level predictors, session limits was tested as a center level predictor. Out of 82 centers included in the main analysis, 81 provided
information on session limits, and 30 of those centers reported having a session limit policy. Session limits ranged from 7 to 24 sessions, with the most common limit being 12 sessions. The presence of session limits was not a significant predictor of number of sessions (β = -0.03, p = .693) and did not improve model fit (empty BIC = 118,692, session limits BIC = 118,702; χ²(1) = 0.16, p = .693). Session limits was not included in subsequent analyses.

The final, best fitting model established in the training set minimized the BIC and improved fit compared to an empty model (empty model = 122,669, final model = 121,119, χ²(19) = 1737.40, p < .001). This model explained 14% of the variance in utilization, 7% of which is attributable to the client predictors above the center effect previously reported. A model with all possible predictors included also explained 14% of the variance in utilization, indicating that the predictors removed did not explain meaningful variance. Outlined in Appendix C are the exploratory data steps and fit statistics for other candidate models. The final model explained 13.5% of variance in utilization when applied to the testing set, a similar amount of variance explained in the training set, indicating it performs well predicting outside of the sample on which it was developed.

The final model resulted in 13 predictors of utilization. Table 2 presents coefficients for these predictors, as well as exponentiated coefficients, which can be interpreted as the percent change in utilization associated with a one-unit change in the predictor. Because predictors were centered on the UCC means, the coefficients represent within center relationships. All predictors included in the final model were significant at p < .005. Confirming hypotheses, NSSI, sexual trauma, suicidality, and
eating distress were all related to increased utilization, while alcohol use was related to decreased utilization. The presence of prior NSSI increased client utilization on average by 3% ($\beta = .03$), and the presence of prior sexual trauma increased utilization by 5% ($\beta = .05$). Each one-point increase in initial suicidality on a 0 to 4 scale was associated with a 4% increase in utilization ($\beta = .04$). Each one-point increase in eating distress was associated with a 3% increase in utilization ($\beta = .03$), while each one-point increase in alcohol use distress was associated with a 5% decrease in utilization ($\beta = -.06$).

Addressing the exploratory research questions, prior therapy, sexual orientation, race/ethnicity, academic year, time of year of first appointment, and distress related to depression, social anxiety and academics were all significantly related to utilization. Prior therapy was associated with a 10% increase in utilization compared to clients without prior therapy ($\beta = .09$). Non-heterosexual clients utilized 4% more sessions than heterosexual clients ($\beta = .04$), and racial ethnic minority clients utilized 3% more sessions than white clients ($\beta = .03$). For academic year, all comparisons to freshman clients were significant, with sophomores using 11% more sessions ($\beta = .10$), juniors using 19% more sessions ($\beta = .17$), seniors using 7% more sessions ($\beta = .06$), and other students using 24% more sessions ($\beta = .22$). Additionally, for time of year of first appointment, all comparisons to early fall were significant, with clients beginning in early fall utilizing the most sessions, and clients beginning in late spring utilizing the least. Clients beginning in late fall utilized 30% fewer sessions ($\beta = -.35$). Clients beginning in early spring utilized 16% fewer sessions ($\beta = -.18$). Clients beginning in late spring utilized 39% fewer sessions ($\beta = -.49$), and clients beginning in summer utilized 17% fewer sessions ($\beta = -.19$).
For distress, depression and social anxiety were positively related to utilization, while academic distress was negatively related. Each one-point increase in depression was associated with a 7% increase in utilization ($\beta = .06$), and each one-point increase in social anxiety was associated with a 9% increase ($\beta = .08$). For academic distress, each one-point increase was associated with a 6% decrease in utilization ($\beta = -.06$).

Several variables with very small or non-significant effects were not included in the final model. Contrary to hypotheses, prior hospitalization and suicide attempts were not related to utilization after controlling for other variables. Further, no relationship was found between gender and utilization, both in comparing males to females, and males and females to gender non-conforming clients. Similarly, no difference was found between clients in a relationship and single clients. Findings for gender and relationship status replicate previous findings in psychotherapy but differ from findings in a psychiatric ER setting. No significant relationship with utilization was found for disability status, prior medication use, anxiety, and hostility — four variables for which no specific hypotheses were made.

Looking more closely at the predictions, predicted utilization ranged from 2.55 to 31.59 sessions, while actual utilization ranged from 1 to 87, indicating that the predictions do not capture the full range of utilization, and specifically, are not predicting the extreme high utilization observed in the distribution. This reinforces the need for a model aimed specifically at predicting clients who will be disproportionate high resource utilizers, the clients most taxing center resources, which the next analysis addresses.
High Resource Group Membership

Confirming the disproportionate utilization observed in figure 1, HRU clients (defined as the top 20%), accounted for 52% of all services. This subgroup had an average of 21.1 scheduled appointments, while the other 80% had an average of 5.3. Separate descriptives for the top 20% and bottom 80% are displayed in table 1. Interestingly, HRUs and non-HRUs both attended about 80% of sessions on average. The percentage of resources utilized by the HRU group varied by center (figure 3), with the HRU group at the lowest end using only 35% and the highest end using 72% of all resources.

A logistic regression was used to predict membership in the top 20% HRU group (table 3). From that analysis, 15 variables emerged as significant predictors. Similar to the previous analysis of utilization, prior therapy, prior NSSI, prior sexual trauma, suicidality, sexual orientation, racial ethnic minority status, academic year and time of year of first appointment were significant predictors of membership in the HRU group. Additionally, distress in the domains of alcohol use, academic distress, social anxiety, and depression were predictive of HRU group membership. Diverging from the previous model, eating concerns was not a significant predictor, but gender, disability and relationship status emerged as additional significant predictors.

Clients with prior therapy were 19% more likely to be HRUs ($\beta = .18$), and clients with prior NSSI were 7% more likely ($\beta = .07$). Clients with prior sexual traumas were 7% more likely to be HRUs ($\beta = .06$). Non-heterosexual clients were 8% more likely than heterosexual clients to be HRUs ($\beta = .08$), and racial ethnic minority clients were 5% more likely ($\beta = .05$). Similar to the analysis of utilization, freshmen were least likely
to be HRUs. Compared to freshmen, sophomores were 20% more likely ($\beta = .18$), juniors were 35% more likely ($\beta = .30$), seniors were 11% more likely ($\beta = .10$), and other students were 50% more likely to be HRUs ($\beta = .41$). Again, similarly to analysis of utilization, clients beginning treatment in early fall were most likely to be HRUs, and clients beginning in late spring were the least likely. Compared to clients beginning in early fall, clients beginning in late fall were 41% less likely to be HRUs ($\beta = -.53$). Clients beginning in early spring were 36% less likely ($\beta = -.45$) and clients beginning in late spring were 61% less likely ($\beta = -.95$). Finally, clients beginning in summer were 27% less likely to be HRUs ($\beta = -.31$).

In terms of distress, each one-point increase in alcohol use distress was associated with an 11% reduction in the odds of being a HRU ($\beta = -.12$), and each one-point increase in academic distress was associated with a 14% decrease in odds ($\beta = -.15$). A one-point increase in social anxiety was associated with an 18% increase in the odds of being a HRU ($\beta = .17$), and a one-point increase in depression was associated with an 11% increase ($\beta = .10$). Both gender comparisons were significant: females were 4% more likely than males to be HRUs ($\beta = .07$), and gender non-conforming clients were 54% more likely to be HRUs than clients identifying as male of female ($\beta = .43$). Clients with a disability were 4% more likely to be HRUs than clients without ($\beta = .04$), and clients in a relationship were 13% less likely ($\beta = -.14$).

Analyses were also conducted to examine the predictive accuracy of the final model. In the training set, with a cut off value of .25, the model classified 32% of clients as HRUs. It correctly predicted 2,111 out of 4,324 HRUs, for a sensitivity value of 49%. The model also correctly classified 73% of non-HRUs. Overall, the model correctly
classified 67% of clients. Of the clients predicted to be HRUs, 33% of those were correct. The value of .25 was chosen as a conservative cut off. Although decreasing the cut off value results in more HRU clients correctly classified, it also results in a higher false positive rate. Table 4 shows prediction rates at other cut off values. In the testing set, with the same cut off value, the model correctly predicted 2,070 out of 4,189 HRUs, for a sensitivity value of 49%, identical to the value in the training set. Overall, the model correctly classified 68% of clients, and 33% of clients predicted to be HRUs were actually HRUs, also on par with the correct classification rate in the training set.
Chapter 4

Discussion

Similar to trends observed in psychiatric ERs and healthcare generally, there was a disproportionate utilization of services observed in UCCs (e.g. 20% using 50% of services). The goal of the present study was to identify pretreatment client characteristics predictive of treatment utilization generally and high resource utilization specifically. Many hypothesized client characteristics emerged as predictors, as well as several of the exploratory variables. Despite the large number of predictors tested, however, all available client predictors explained relatively little variance in utilization (14%) and did not discriminate between the top 20% and bottom 80% of utilizers with a high degree of accuracy. Following is a review the findings in more detail, including convergence with prior research, as well as some possible clinical implications of those results Limitations of the current study and directions for future research are then presented.

Variation between centers accounted for about 7% of the variance in utilization, approximately equal to the amount explained by client predictors. This center effect is larger than center effects on psychotherapy outcome in CCMH data (Carney, Janis, Xiao, Castonguay, & Locke, 2017), indicating it may be more affected by center policies. Surprisingly, in light of this finding, the presence of center session limits did not explain this variation between centers and was not related to utilization. This may be due to a number of factors. The actual limit on sessions reported by centers with session limits ranged from 7 to 24, and it is possible that utilization differs among centers with limits, while not differing on average between centers with and without limits, or that session
limits only impact utilization below a certain number. Further, session limits typically apply to the number of sessions a client can attend at a center, while the outcome in the current study was number of scheduled sessions. There may be differences in attendance rates between centers with and without session limits such that number of attended sessions differs between schools with and without session limits while number of scheduled appointments does not. Another possibility to explain the null effect of session limits is that session limits may not be enforced for clients with more critical presenting concerns or histories, resulting in no average center effect of session limits. Anecdotally, some centers report exemptions to session limits for student athletes, clients with trauma histories, and clients being seen by trainee therapists.

Outside of further policies related to session limits, there may be other center policies impacting utilization. These include the frequency with which clients are scheduled for appointments and policies around client no shows, such as whether the client is rescheduled after no showing and how many times a client can miss appointments and remain in treatment. Additionally, center practices around referral to additional services within a center may impact utilization. For example, services outside of individual treatment, such as group therapy appointments, are often not counted toward session limits, and centers likely differ on the availability of these services and the frequency with which clients are referred to or provided additional services.

Many of the hypotheses made based on prior research were confirmed, although some predicted relationships did not emerge. Specifically, NSSI, sexual abuse and suicidality were all positively related to utilization and likelihood of being a HRU, while prior hospitalizations and suicide attempts were related to neither. Several relationships
also emerged with predictors for which no hypotheses were made. Namely, prior therapy, sexual orientation, academic year and time of year of first appointment were all related to utilization and odds of being a HRU. In contrast, no relationship was found with either outcome for prior hospitalizations, medication use, or suicide attempts. Of note, very few differences were observed between the two models. Specifically, gender, disability, and relationship status were related only to odds of being a HRU. This difference across models may be due to less stringent criteria for model selection in the logistic regression compared to the mixed effects negative binomial (i.e. significance of predictors vs BIC, which penalizes for additional predictors). This may have resulted in a lower threshold for individual predictors to be included in the HRU model compared to the utilization model.

Several predictors found to be significant of increased utilization represent a type of client with more chronic mental health concerns, namely prior therapy, prior NSSI and prior sexual assault. Clients with these indicators of chronicity are likely to have more severe and longstanding problems that may require more resources to treat. Interestingly, a number of clinically related variables were not found to predict outcome, most likely because of their common variance with these indicators. For instance, prior therapy and prior medication are likely capturing the same domain of pre-treatment care, which could explain why only one of them, prior therapy, emerged as significant. Similarly, prior hospitalizations (which was hypothesized as a predictor due to its relationship with high resource utilization in psychiatric ERs) and prior therapy are both likely to reflect chronicity of mental health concerns. As a lower threshold indicator of chronicity, however, prior therapy may be capturing more clients, which in turn may explain why it
was retained as a significant predictor and hospitalizations was not.

The same issue of common variance may be at play with other variables related to clinical health. Specifically, suicidality, a measure of a client’s suicidal ideation at the beginning of treatment, emerged as a predictor, while prior suicide attempts did not. Suicidality at the start of treatment may have emerged as a predictor due to its more immediate effect on treatment compared to historical suicide attempts, and clients reporting suicidality when starting treatment may be utilizing more sessions as a way to manage acute crises related to their suicidality.

Across the demographic predictors tested, diversity generally predicted more utilization and higher odds of being an HRU, with non-heterosexual and racial ethnic minority clients utilizing more. Further, disability status and a gender non-conforming identity were significant predictors specifically of being a HRU. Taken together, these findings may be a reflection of the impact of stigma and minority stress faced by minority clients (Meyer, 2003). Relationship status was also uniquely predictive of being a HRU, with clients in a relationship being less likely to be HRUs. This is likely representative of these clients having increased social support outside of therapy, which has been shown to moderate life stress (Cobb, 1976).

Academic year was a surprisingly strong predictor, with all other years utilizing more resources than freshman, sometimes dramatically so. Differences between “other” students and freshman corresponded to a 24% difference in utilization and 50% increase in odds of being a HRU. This difference between freshman and other years is consistent with research showing that freshman drop out of treatment at higher rates (Xiao, 2015). This may represent a maturational process that happens throughout college, with more
mature clients sticking with therapy longer and not dropping out. It may also be that clients who present for treatment later in their years at college have been dealing with their mental health problems for longer, tying back to the idea of greater chronicity of mental health problems being related to increased utilization.

The time of year of a client’s first appointment was also a surprisingly strong predictor, and differences between clients starting in early fall and late spring had the largest effect on utilization and likelihood of being a HRU out of all the variables tested (39% and 61% increases, respectively). While tested at the client level, this variable is likely controlling for contextual variables outside of the client, such as center availability at the time the client begins treatment. Clients beginning in early fall have more consecutive school year included in their 1 year period, and many students leave campus over the summer and may be less likely to return to treatment the next fall. A counseling center also has the most free resources available at the beginning of fall, when few clients are already engaging in treatment. As the semester goes on and the counseling center reaches capacity, there are less open resources to allocate to new clients.

The previous finding of general initial distress predicting more utilization did not replicate across all domains of distress tested in the present study. As hypothesized, eating distress was positively related to utilization, although it was not significantly related to odds of being an HRU. Additionally, greater distress in the domains of social anxiety and depression were related to increased utilization and odds of being a HRU. Social anxiety’s relationship to greater utilization mirrors findings for social anxiety and dropout, in which more socially anxious clients drop out of treatment less frequently (Xiao, 2015). It is possible that socially anxiety clients have less social support outside
of treatment, and once they form a bond with their therapist, they may remain in
treatment longer because of the social support it provides. It is also possible that more
serious level of social anxiety and depression take longer to treat. It is notable that
neither anxiety nor hostility had a significant relationship to utilization after controlling
for distress in other domains. Anxiety and depression being highly comorbid and anger
being a frequent clinical feature associated with depression (LeMoulth, Castonguay,
Joorman, & McAleavey, 2013) may explain why anxiety and hostility were not uniquely
related to utilization controlling for depression.

Academic distress also had a negative relationship with utilization and odds of
being HRU, indicating that holding other areas of distress constant, higher academic
distress results in less utilization. Interestingly, academic distress is not significantly
related to utilization in a bivariate analysis but a significant negative relationship emerges
when controlling for other variables. This raises interesting theoretical possibilities for
the negative effect of academic distress on utilization. The phase model of treatment
suggests that the first phase of treatment is a remoralization phase, during which clients,
who often present to treatment with a sense of hopelessness and failure to cope,
experience a renewal of hope and increase in self-efficacy (Howard, Lueger, Maling, &
Martinovich, 1993). For clients experiencing academic distress, this distress may provide
a concrete target of early treatment for which a client can see noticeable change quickly.
The initial remoralization phase offers an opportunity for the client to reappraise and
normalize their academic distress. This increase in hope and self-efficacy in the domain
of academic performance may trigger change in other domains as well, building
therapeutic inertia that leads to more rapid change across domains and a shorter duration
of treatment.

Like academic distress, alcohol use distress was inversely related to utilization and likelihood of being a HRU as hypothesized, although, perhaps for different reasons. Clients presenting with high alcohol use distress may be mandated by their university to attend alcohol related treatment. In this context, clients high on alcohol use may be attending the mandated number of sessions then dropping out of treatment, resulting in lower utilization rates. Even when not mandated to treatment, students with high levels of alcohol use may lack motivation to change, especially given the context of high normative levels of alcohol use in which they live. When confronted with the difficult task of changing this difficult behavior, these students may drop out of treatment. These findings parallel Nordberg’s (2016) client profiles, which showed that profiles defined by primary substance use utilized less on average, while profiles with eating concerns utilized more.

Although each predictor individually corresponded to small changes in utilization, taken together, they result in quite different profiles of client utilization. In a hypothetical example, a freshman client may present to a counseling center in late fall when classes are more stressful with subclinical levels of distress on alcohol, eating, social anxiety, and depression, but elevated academic distress. If this client also has no other factors associated with high utilization (e.g. prior therapy, prior NSSI, suicidality, non-heterosexual orientation, racial ethnic minority status), the client would be predicted to use about 5 sessions. Another client with chronic mental health concerns (e.g. prior therapy, prior NSSI, prior sexual trauma) may present to a counseling center at the beginning of fall semester with elevated eating concerns, social anxiety, depression, and
suicidality and be predicted to use about 17 sessions.

Beyond the profiles developed by Nordberg and colleagues (2016), information on the specific contribution of individual predictors to utilization will allow counseling centers and therapists to better evaluate individual clients, especially ones who do not fit cleanly into one of the profiles. Specifically, Nordberg’s (2016) profiles differentiated between clients only on the basis of CCAPS scores, but clients within each profile may vary significantly on other dimensions. Consequently, the profiles capture types of clients based on initial distress, but do not take into account the demographic and mental health history information also available at the start of treatment. For example, two clients may present with similar initial distress, but one client may have a history of self-injury, suicide attempts and prior treatment, making the two clients look very different clinically. The findings from the current study allow clinicians to build on the previously created profiles to take into account this additional information. Using the findings of the present study in conjunction with the client profiles, a clinician would determine that both clients fall into a profile of clients who on average utilize more sessions, but that the client with mental health history risk factors is likely to utilize even more sessions.

Looking specifically at the analysis of HRUs, one could hypothesize that differences between the HRU and non-HRU groups could be due to different attendance rates, indicating that the groups differ not on their actual dose of treatment but on their attendance behavior while in treatment. This does not appear to be the case, however, as the groups attended at the same rate. Not only are the groups differing in the average sessions that they’re accounting for at a center, they’re also differing on the amount of treatment they’re actually receiving, a meaningful distinction.
Further related to the analysis of HRUs, the decision of where to place the cut off value for prediction has implications for how many clients are predicted to be HRUs. As the cutoff value becomes less stringent, more HRU clients are correctly classified, but the percent of correct positive predictions (e.g. percent of clients predicted to be HRUs who are actually HRUs) decreases, causing less trust in any given positive prediction as the odds that it is accurate decrease. The cost of false positives versus false negatives should be taken into account when setting the cut off value. In this case, the cost of a false positive (i.e. a client being predicted as a HRU but not actually being a HRU) may be that they are given extra resources within a center, or alternatively, referred out of a center for more long-term treatment. The cost of a false negative (i.e. a HRU failing to be classified as such) may be more to the center in terms of planning how to allocate resources. Additionally, such a client may not be referred to additional resources within and outside the center from which the client may especially benefit.

Limitations

Despite the large number of items available from the CCAPS and SDS to include as predictors, there are potentially important predictors not included in the present study. Diagnoses have been frequently tested as predictors of utilization but were not available in the data used in this study to replicate previous findings. Additionally, variables related to client attitudes toward treatment (e.g. expected length of treatment) have some evidence as predictors (Mueller & Pekarik, 2000) and provide an interesting avenue for future replications.

Additionally, the decision to exclude therapists as a level of nesting was an informed one based on a desire to include as many clients as possible and to not remove
clients who saw many therapists during their treatment, as they may be more likely to be high resource utilizers. This decision, however, removed a potentially important source of variance. Finally, all sessions were weighted equally, regardless of their type. This does not take into account how long the sessions were or how many clients were served by that session (e.g. group treatment). Weighting sessions by length and number of clients served may more closely represent the cost of treatment incurred by the center for each client and may result in a different predictive model.

**Future Directions**

The present study and its limitations suggest several routes for future research. Examining client utilization leads naturally to questions of how utilization relates to client outcome. Primarily, do clients who utilize more sessions have better outcomes? Research on the good enough theory of change in therapy suggests that all clients achieve similar amounts of change, but that clients require different numbers of sessions to achieve that change (Barkham et al., 2006; Stiles et al., 2008; Stiles, Barkham, & Wheeler, 2015). This research would suggest that utilization and outcome are largely unrelated, although other studies have found a relationship between number of sessions and outcome below 8 sessions, but no relationship beyond that (Baldwin et al., 2009). This also indicates that there may be a more complex relationship between utilization and outcome beyond a binary related or not. There may be client characteristics that predict for which clients additional session utilization may be beneficial. Further, future research should evaluate whether clients discrepancy from their predicted utilization corresponds to outcome. Most interestingly, do clients who receive less than their predicted number of sessions have poorer outcomes?
Future research should also take into account attendance in linking utilization and outcome, bridging between the cost to the center in terms of hours, the actual dose of treatment a client receives, and the resulting outcome. Looking at a more complete picture of client characteristics, utilization, attendance, and outcome would allow for the possibility of creating client profiles of utilization that more closely mirror clinical experience compared to only taking into account one or two dimensions. This could lead to more actionable treatment recommendations. For example, one profile may represent a type of client who utilizes a lot of sessions but has a high attendance rate, resulting in a good outcome. For this client, it may be recommended to extend session limits. Another profile may be a client who utilizes a lot of sessions but may not attend consistently and does not benefit even from a high volume of sessions within a UCC setting. This may lead to the recommendation of referring the client to resources outside of the center.

Finally, the present analyses included center as a level but did not include therapists within centers. Beyond center policies, therapists’ own policies and unique approaches to treatment likely exert an influence on utilization. As previously mentioned, therapists in training may be exempt from session limits, allowing them to see clients for more sessions in order to gain additional hours of experience. Additionally, therapists may respond differently to missed sessions, causing the clients of some therapists to utilize more sessions due to missed or rescheduled sessions. Confirming this, a CCMH study found that therapists accounted for 45.7% of variance in client attendance rates after the third session (Xiao, Hayes, Castonguay, McAleavey, & Locke, 2017).
Appendix A

Tables

Table 1. Client descriptives

Table 2. Mixed effects negative binomial regression of utilization

Table 3. Logistic regression predicting membership in high resource utilization group

Table 4. Logistic regression cut off values and resulting sensitivity and specificity
<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td>Bottom 80%</td>
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<tr>
<td>Client N</td>
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<tr>
<td>Average scheduled sessions</td>
<td>5.31 (3.77)</td>
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<tr>
<td>Total scheduled sessions</td>
<td>166204</td>
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<tr>
<td>Average percent attended</td>
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<table>
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<td>Alcohol</td>
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<td>Eating</td>
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<tr>
<td>Academics</td>
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<td>Suicidal ideation</td>
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<table>
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<td>Prior hospitalization</td>
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<td>Prior NSSI</td>
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<tr>
<td>Prior sexual trauma</td>
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<td>Woman</td>
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<td>Man</td>
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<tr>
<td>Gender non-conforming</td>
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<td>Year in school</td>
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<td>Junior</td>
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<td>Senior</td>
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<td>Summer</td>
</tr>
</tbody>
</table>
Table 2
Mixed effects negative binomial regression of utilization

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Exponentiated coefficient</th>
<th>SE</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random intercept</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>2.159</td>
<td>8.659</td>
<td>0.038</td>
<td>[2.085, 2.232]</td>
</tr>
<tr>
<td>Variance</td>
<td>0.082</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alcohol</td>
<td>-0.055</td>
<td>0.947</td>
<td>0.038</td>
<td>[-0.069, -0.041]</td>
</tr>
<tr>
<td>Eating</td>
<td>0.032</td>
<td>1.032</td>
<td>0.007</td>
<td>[-0.018, 0.046]</td>
</tr>
<tr>
<td>Academics</td>
<td>-0.056</td>
<td>0.945</td>
<td>0.007</td>
<td>[-0.072, -0.040]</td>
</tr>
<tr>
<td>Social Anxiety</td>
<td>0.081</td>
<td>1.085</td>
<td>0.009</td>
<td>[0.065, 0.098]</td>
</tr>
<tr>
<td>Depression</td>
<td>0.063</td>
<td>1.065</td>
<td>0.009</td>
<td>[0.041, 0.086]</td>
</tr>
<tr>
<td>Suicidality</td>
<td>0.042</td>
<td>1.043</td>
<td>0.012</td>
<td>[0.024, 0.060]</td>
</tr>
<tr>
<td>Prior therapy</td>
<td>0.091</td>
<td>1.095</td>
<td>0.009</td>
<td>[0.077, 0.105]</td>
</tr>
<tr>
<td>Prior NSSI</td>
<td>0.030</td>
<td>1.031</td>
<td>0.007</td>
<td>[0.016, 0.045]</td>
</tr>
<tr>
<td>Prior sexual trauma</td>
<td>0.047</td>
<td>1.048</td>
<td>0.008</td>
<td>[0.034, 0.061]</td>
</tr>
<tr>
<td>Non-heterosexual orientation</td>
<td>0.043</td>
<td>1.044</td>
<td>0.007</td>
<td>[0.029, 0.056]</td>
</tr>
<tr>
<td>Racial ethnic minority</td>
<td>0.032</td>
<td>1.033</td>
<td>0.007</td>
<td>[0.018, 0.046]</td>
</tr>
<tr>
<td>Academic year</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Freshman</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Sophomore</td>
<td>0.101</td>
<td>1.107</td>
<td>0.023</td>
<td>[0.058, 0.145]</td>
</tr>
<tr>
<td>Junior</td>
<td>0.170</td>
<td>1.185</td>
<td>0.022</td>
<td>[0.127, 0.212]</td>
</tr>
<tr>
<td>Senior</td>
<td>0.064</td>
<td>1.067</td>
<td>0.023</td>
<td>[0.021, 0.108]</td>
</tr>
<tr>
<td>Other</td>
<td>0.218</td>
<td>1.243</td>
<td>0.025</td>
<td>[0.169, 0.266]</td>
</tr>
<tr>
<td>Time of year</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Early fall</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Late fall</td>
<td>-0.353</td>
<td>0.703</td>
<td>0.020</td>
<td>[-0.391, -0.315]</td>
</tr>
<tr>
<td>Early spring</td>
<td>-0.177</td>
<td>0.838</td>
<td>0.020</td>
<td>[-0.219, -0.135]</td>
</tr>
<tr>
<td>Late spring</td>
<td>-0.493</td>
<td>0.611</td>
<td>0.022</td>
<td>[-0.532, -0.455]</td>
</tr>
<tr>
<td>Summer</td>
<td>-0.190</td>
<td>0.827</td>
<td>0.027</td>
<td>[-0.241, -0.139]</td>
</tr>
<tr>
<td>Dispersion parameter</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.195</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Alcohol, eating, academics, social anxiety, depression and suicidality are all on a 0-4 scale, with higher numbers corresponding to greater distress. Prior therapy, NSSI (non-suicidal self-injury), sexual trauma are all dichotomous, non-heterosexual orientation, and racial ethnic minority are all dichotomous. Academic year is coded with freshman as the reference category. Time of year is coded with early fall as the reference category. Outcome is utilization, shifted backward by 1. All coefficients are significant \( p < .005 \)
Table 3
Logistic regression predicting membership in high resource utilization group

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>Z value</th>
<th>OR</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.703</td>
<td>0.168</td>
<td>-4.193</td>
<td>0.495</td>
<td>[-1.237, -1.035]</td>
</tr>
<tr>
<td>Alcohol use</td>
<td>-0.117</td>
<td>0.019</td>
<td>-6.157</td>
<td>0.889</td>
<td>[-0.155, -0.080]</td>
</tr>
<tr>
<td>Academics</td>
<td>-0.149</td>
<td>0.021</td>
<td>-6.947</td>
<td>0.862</td>
<td>[-0.191, -0.107]</td>
</tr>
<tr>
<td>Social Anxiety</td>
<td>0.168</td>
<td>0.021</td>
<td>7.838</td>
<td>1.183</td>
<td>[0.126, 0.210]</td>
</tr>
<tr>
<td>Depression</td>
<td>0.101</td>
<td>0.030</td>
<td>3.411</td>
<td>1.106</td>
<td>[0.043, 0.159]</td>
</tr>
<tr>
<td>Suicidality</td>
<td>0.099</td>
<td>0.023</td>
<td>4.324</td>
<td>1.104</td>
<td>[0.054, 0.143]</td>
</tr>
<tr>
<td>Prior therapy</td>
<td>0.176</td>
<td>0.019</td>
<td>9.327</td>
<td>1.192</td>
<td>[0.139, 0.213]</td>
</tr>
<tr>
<td>Prior NSSI</td>
<td>0.072</td>
<td>0.019</td>
<td>3.865</td>
<td>1.074</td>
<td>[0.035, 0.108]</td>
</tr>
<tr>
<td>Prior sexual trauma</td>
<td>0.063</td>
<td>0.018</td>
<td>3.401</td>
<td>1.065</td>
<td>[0.026, 0.099]</td>
</tr>
<tr>
<td>Gender: male/female</td>
<td>0.070</td>
<td>0.020</td>
<td>3.607</td>
<td>1.073</td>
<td>[0.032, 0.109]</td>
</tr>
<tr>
<td>Gender: male &amp; female/gender non-conforming</td>
<td>0.432</td>
<td>0.161</td>
<td>-2.682</td>
<td>1.541</td>
<td>[0.113, 0.745]</td>
</tr>
<tr>
<td>Non-heterosexual orientation</td>
<td>0.078</td>
<td>0.017</td>
<td>4.593</td>
<td>1.081</td>
<td>[0.045, 0.112]</td>
</tr>
<tr>
<td>Disability</td>
<td>0.043</td>
<td>0.017</td>
<td>2.500</td>
<td>1.044</td>
<td>[0.009, 0.076]</td>
</tr>
<tr>
<td>Relationship</td>
<td>-0.144</td>
<td>0.038</td>
<td>-3.817</td>
<td>0.866</td>
<td>[-0.218, -0.07]</td>
</tr>
<tr>
<td>Racial ethnic minority</td>
<td>0.046</td>
<td>0.018</td>
<td>1.047</td>
<td></td>
<td>[0.010, 0.081]</td>
</tr>
</tbody>
</table>

Academic year

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>SE</th>
<th>Z value</th>
<th>OR</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freshman</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sophomore</td>
<td>0.183</td>
<td>0.058</td>
<td>3.131</td>
<td>1.201</td>
<td>[0.069, 0.298]</td>
</tr>
<tr>
<td>Junior</td>
<td>0.300</td>
<td>0.057</td>
<td>5.280</td>
<td>1.350</td>
<td>[0.189, 0.412]</td>
</tr>
<tr>
<td>Senior</td>
<td>0.101</td>
<td>0.059</td>
<td>1.719</td>
<td>1.107</td>
<td>[-0.014, 0.217]</td>
</tr>
<tr>
<td>Other</td>
<td>0.405</td>
<td>0.062</td>
<td>6.516</td>
<td>1.499</td>
<td>[0.283, 0.526]</td>
</tr>
</tbody>
</table>

Time of year

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>SE</th>
<th>Z value</th>
<th>OR</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early Fall</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Late fall</td>
<td>-0.529</td>
<td>0.049</td>
<td>-10.846</td>
<td>0.589</td>
<td>[-0.624, -0.433]</td>
</tr>
<tr>
<td>Early spring</td>
<td>-0.452</td>
<td>0.049</td>
<td>-9.221</td>
<td>0.636</td>
<td>[-0.549, -0.357]</td>
</tr>
<tr>
<td>Late spring</td>
<td>-0.952</td>
<td>0.059</td>
<td>-16.050</td>
<td>0.386</td>
<td>[-1.069, -0.836]</td>
</tr>
<tr>
<td>Summer</td>
<td>-0.312</td>
<td>0.064</td>
<td>-4.912</td>
<td>0.732</td>
<td>[-0.438, -0.188]</td>
</tr>
</tbody>
</table>

Note. Alcohol, eating, academics, social anxiety, depression and suicidality are all on a 0-4 scale, with higher numbers corresponding to greater distress. Prior therapy, NSSI (non-suicidal self-injury), sexual trauma are all dichotomous, non-heterosexual orientation, and racial ethnic minority are all dichotomous. Academic year is coded with freshman as the reference category. Time of year is coded with early fall as the reference category. Outcome is HRU membership. All coefficients are significant p < .005
Table 4

Logistic regression cut off values and resulting sensitivity and specificity

<table>
<thead>
<tr>
<th>Cutoff value</th>
<th>Percent correct</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.20</td>
<td>57.57%</td>
<td>67.88%</td>
<td>54.72%</td>
</tr>
<tr>
<td>0.21</td>
<td>60.06%</td>
<td>63.90%</td>
<td>59.01%</td>
</tr>
<tr>
<td>0.22</td>
<td>62.42%</td>
<td>60.36%</td>
<td>62.98%</td>
</tr>
<tr>
<td>0.23</td>
<td>64.08%</td>
<td>56.41%</td>
<td>66.20%</td>
</tr>
<tr>
<td>0.24</td>
<td>65.91%</td>
<td>52.59%</td>
<td>69.58%</td>
</tr>
<tr>
<td>0.25</td>
<td>67.64%</td>
<td>48.82%</td>
<td>72.83%</td>
</tr>
<tr>
<td>0.26</td>
<td>69.06%</td>
<td>45.05%</td>
<td>75.69%</td>
</tr>
<tr>
<td>0.27</td>
<td>70.26%</td>
<td>41.63%</td>
<td>78.17%</td>
</tr>
<tr>
<td>0.28</td>
<td>71.52%</td>
<td>38.37%</td>
<td>80.67%</td>
</tr>
<tr>
<td>0.29</td>
<td>72.65%</td>
<td>35.22%</td>
<td>82.99%</td>
</tr>
<tr>
<td>0.30</td>
<td>73.61%</td>
<td>32.19%</td>
<td>85.04%</td>
</tr>
</tbody>
</table>

Note. Percent correct indicates the percent of total clients correctly classified. Sensitivity indicates the percent of HRU clients correctly classified. Specificity indicates the percent of non-HRU clients correctly classified.
Appendix B

Figures

Figure 1. Frequency histogram showing the distribution of client utilization

Figure 2. Frequency histogram showing the distribution of center mean utilization

Figure 3. Frequency histogram showing the distribution of center skew in distribution:
   The percent of sessions accounted for by the top 20% of clients at each center
**Figure 1.** Frequency histogram showing the distribution of client utilization.
Figure 2. Frequency histogram showing the distribution of center mean utilization.
Figure 3. Frequency histogram showing the distribution of center skew in distribution: The percent of sessions accounted for by the top 20% of clients at each center.
### Appendix C

#### CCAPS Items and Corresponding Subscales

<table>
<thead>
<tr>
<th>Scale</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression</td>
<td>I don’t enjoy being around people as much as I used to&lt;br&gt;I feel isolated and alone&lt;br&gt;I feel worthless&lt;br&gt;I feel helpless&lt;br&gt;I feel sad all the time&lt;br&gt;I have thoughts of ending my life</td>
</tr>
<tr>
<td>Generalized Anxiety</td>
<td>My heart races for no good reason&lt;br&gt;I am anxious that I might have a panic attack in public&lt;br&gt;I have sleep difficulties&lt;br&gt;My thoughts are racing&lt;br&gt;I have spells of terror or panic&lt;br&gt;I feel tense</td>
</tr>
<tr>
<td>Social Anxiety</td>
<td>I am shy around others&lt;br&gt;I make friends easily&lt;br&gt;I am concerned that other people do not like me&lt;br&gt;I feel uncomfortable around people I don't know&lt;br&gt;I feel self conscious around others</td>
</tr>
<tr>
<td>Academic Distress</td>
<td>I feel confident I can succeed academically&lt;br&gt;I am not able to concentrate as well as usual&lt;br&gt;It's hard to stay motivated for my classes&lt;br&gt;I am unable to keep up with my school work</td>
</tr>
<tr>
<td>Eating Concerns</td>
<td>I feel out of control when I eat&lt;br&gt;I think about food more than I would like to&lt;br&gt;I eat too much</td>
</tr>
<tr>
<td>Hostility</td>
<td>I have difficulty controlling my temper&lt;br&gt;I sometimes feel like breaking or smashing things&lt;br&gt;I get angry easily&lt;br&gt;I am afraid I may lose control and act violently&lt;br&gt;I frequently get into arguments&lt;br&gt;I have thoughts of hurting others</td>
</tr>
<tr>
<td>Alcohol Use</td>
<td>I drink alcohol frequently&lt;br&gt;When I drink alcohol I can't remember what happened&lt;br&gt;I drink more than I should</td>
</tr>
</tbody>
</table>
I have done something I have regretted because of drinking
Appendix D

Standardized Data Set (SDS) Items and Answer Options

Prior therapy:
Please indicate if and when you have had the following experiences: Attended counseling for mental health concerns.
- Never
- Prior to college
- After starting college
- Both

Prior medication:
Please indicate if and when you have had the following experiences: Taken a prescribed medication for mental health concerns.
- Never
- Prior to college
- After starting college
- Both

Prior hospitalization:
Please indicate if and when you have had the following experiences: Been hospitalized for mental health concerns. How many times?
- Never
- 1 time
- 2-3 times
- 4-5 times
- More than 5 times

Prior non-suicidal self-injury (NSSI):
Please indicate if and when you have had the following experiences: Purposely injured yourself without suicidal intent (e.g., cutting, hitting, burning, etc.)
- Never
- 1 time
- 2-3 times
- 4-5 times
- More than 5 times

Prior suicide attempt:
Please indicate if and when you have had the following experiences: Made a suicide attempt
- Never
- 1 time
- 2-3 times
- 4-5 times
- More than 5 times

Prior sexual trauma:
Please indicate if and when you have had the following experiences: Someone had sexual contact with you without your consent (e.g., you were afraid to stop
what was happening, passed out, drugged, drunk, incapacitated, asleep, threatened or physically forced)
- Never
- 1 time
- 2-3 times
- 4-5 times
- More than 5 times

**Disability:**
Are you registered, with the office for disability services on this campus, as having a documented and diagnosed disability?
- Yes
- No

**Gender:**
What is your gender identity?
- Woman
- Man
- Transgender
- Self-identify (please specify):

**Sexual orientation:**
Do you consider yourself to be:
- Heterosexual/Straight
- Lesbian
- Gay
- Bisexual
- Questioning
- Self-identify (please specify):

**Race/ethnicity:**
What is your race/ethnicity?
- African American / Black
- American Indian or Alaskan Native
- Asian American / Asian
- Hispanic / Latino/a
- Native Hawaiian or Pacific Islander
- Multi-racial
- White
- Self-identify (please specify):

**Relationship status:**
Relationship status:
- Single
- Serious dating or committed relationship
- Civil union, domestic partnership, or equivalent
- Married
- Divorced
- Separated
- Widowed

**Academic year:**
Current academic status:
- Freshman / First-year
- Sophomore
- Junior
- Senior
- Graduate / professional degree student
- Non-student
- High-school student taking college classes
- Non-degree student
- Faculty or staff
- Other (please specify)
Appendix C

Exploratory Data Steps for Mixed Effects Negative Binomial Regression of Utilization

Fit criteria for models at each step are included in table 4 in this appendix. Exploratory data analysis began with an empty Poisson model (model 1). A negative binomial model (model 2) provided better fit, and a dispersion parameter was included in subsequent models. All possible predictors were then added to the model (model 3). From this model, hostility, prior medication use, prior hospitalization, and a prior suicide attempts were non-significant and were removed (model 4). Variables were then removed in order of the strength of the coefficients. The comparison of males and females to gender non-conforming clients was the weakest predictor and was removed next (model 5). Disability (model 6), anxiety (model 7), and relationship status (model 8) were then removed, resulting in worse fit according to AIC but equivalent fit according to BIC. Finally, the comparison between males and females was removed (model 9), resulting in the final model used for prediction. NSSI (model 10) and racial ethnic minority status (model 11) were removed but were both added back in, as their removal worsened model fit.

Table 5
Fit criteria for exploratory model steps

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>BIC</th>
<th>Log likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1- empty Poisson</td>
<td>206485.0</td>
<td>206500.8</td>
<td>-103240.5</td>
</tr>
<tr>
<td>Model 2- empty negative binomial</td>
<td>122644.9</td>
<td>122668.6</td>
<td>-61319.4</td>
</tr>
<tr>
<td>Model 3- full model</td>
<td>120917.4</td>
<td>121162.3</td>
<td>-60427.7</td>
</tr>
<tr>
<td>Model 4</td>
<td>120912.1</td>
<td>121125.5</td>
<td>-60429.1</td>
</tr>
<tr>
<td>Model 5</td>
<td>120915.3</td>
<td>121120.7</td>
<td>-60431.6</td>
</tr>
<tr>
<td>Model 6</td>
<td>120923.9</td>
<td>121121.5</td>
<td>-60437.0</td>
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<tr>
<td>Model 7</td>
<td>120929.7</td>
<td>121119.3</td>
<td>-60440.8</td>
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<tr>
<td>Model</td>
<td>Start Year</td>
<td>End Year</td>
<td>AIC</td>
</tr>
<tr>
<td>--------</td>
<td>------------</td>
<td>----------</td>
<td>--------</td>
</tr>
<tr>
<td>Model 8</td>
<td>120936.9</td>
<td>121187</td>
<td>-60445.5</td>
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<tr>
<td>Model 9</td>
<td>120945.4</td>
<td>121193</td>
<td>-60450.7</td>
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<td>Model 10</td>
<td>120959.3</td>
<td>121253</td>
<td>-60458.7</td>
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<td>Model 11</td>
<td>120963.2</td>
<td>121292</td>
<td>-60460.6</td>
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*Note.* AIC = Akaike information criterion; BIC = Bayesian information criterion.
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