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PREDICTING DROPOUT FROM PSYCHOTHERAPY IN CAMPUS CLINICS

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Abstract

Premature termination, or dropout, from psychotherapy has been a pervasive problem for many decades. It can especially a problem at the university counseling center, where there is increased demand for a variety of psychotherapy services at campus centers which can be underfunded. At these centers, a dropout represents an opportunity cost with impacts at the client, therapist, and administrative level where it is most prohibitive. While several predictive factors for dropout have been identified from previous research studies, the current study aims to examine potential predictors using a very large (n=23,144 clients in the final presented model), representative data-set gathered through a practice research network, the Center for Collegiate Mental Health (CCMH), for an in-depth analysis of a specific treatment setting. Using multiple logistic regression, previously empirically validated variables are examined along with clinically derived variables specific to the college counseling demographic, and predictive models for dropout models are presented using these variables available at intake.

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Chapter 1

Introduction

Dropout from psychotherapy has been problematic for many decades. Also referred to as premature termination, dropout is ubiquitous in psychotherapy and can be defined as the client initiated cessation of psychotherapeutic treatment before recovery from their symptoms (Hatchett and Park, 2003). As recently reviewed by Swift, Greenberg, Whipple, and Kominiak (2012), the negative impacts of dropout can carry through from the client, to the therapist, to the provider or service agency. Aside from negative client outcomes (Klein, Stone, Hicks and Pritchard, 2003; Knox, Adrians, Everson, Hess, Hill and Crook-Lyon, 2011;) and frustrating or confusing therapist experiences (Piselli, Halgin, & MacEwan, 2011; Klein et. al., 2003), a dropout also creates a loss of overhead, revenue, and time (Barrett et. al., 2008; Swift et. al., 2012).

Swift and Greenberg’s (2012) meta-analysis of dropout rates suggests that nearly 20% of clients prematurely terminate from psychotherapy. While this may seem an improvement from Wierzbicki and Pekarik’s 1993 finding of a 47% percent dropout rate, Swift and Greenberg (2012) point out that effectiveness studies experience more premature termination (26%) than efficacy studies (17%). It is conceivable that the “real-world” rate of dropout is closer to the findings regarding effectiveness studies. Furthermore, the rates do not change as a function of the year the study was conducted. In other words, while the dropout rate varies across clinical settings, it does not appear to have reduced over time. As Barrett et. al. (2008) describe, the rates have remained comparable to Rogers’ findings in 1951, and dropout “wastes limited mental health resources.” (p. 248).

This might be especially true for those mental health agencies with limited funding, such as university based clinics for students (for this study, "university based clinic" is referring specifically to counseling centers set up for campus students, distinct from university affiliated graduate training clinics). There has been an increase in concern over college student mental health, and for good reason. Colleges are not "safe zones" from mental health issues, nor are they somehow selecting for mentally "healthy" students. Epidemiological studies have indeed found non-distinguishable differences in the prevalence of mental disorders between age-matched college students and non-students (Blanco et. al., 2008; Gallagher, 2012). Furthermore, students are coming in with increasingly more diverse and severe symptoms (Gallagher, 2008; American College Health Association, 2008; Benton et. al. 2003), leading to an increase not only in demand for campus mental health services, but also types of services, including psychiatric, outreach, and training for specific mental health issues (Watkins, Hunt, and Eisenberg 2011).

However, this demand has not seen an equivalent increase of resources for campus clinics (Benton et. al. 2003, Gallagher 2011), leading to adoption of various polices to offload the clinical pressure. Primarily, these involve usage of a wait-list to provide services on a first-come, first-served basis, conducting brief, short-term therapy protocols, assignation of a set case-load for each therapist, and adopting a clinical triage system (Hardy et. al. 2011). While these policies may help in managing clinical demands, several concerns remain. Specifically, waitlist is not likely to be an optimal strategy to address a high starting level of distress, short-term therapy may be insufficient to significantly reduce symptoms and functional problems, set case-loads can lead to therapist burnout, and not all clinics can obtain the resources for triaging and referring out.

The problem of dropout appears to be magnified in college campus counseling settings. As indicated by a recent survey (Gallagher, 2012), nearly half of 228 centers adopted waitlists, and nearly 90% of their directors reported concern that their clients may not be getting help when most helpful. Indeed, time spent on waitlist may be a predictor for dropout (Carter et. al., 2012) and as Hatchett (2004) correctly argued, each premature termination represents time and resources that could have been devoted to one of the many students on a center's waitlist. It is particularly concerning that Swift and Greenberg's (2012) meta-analysis finds the "university-based clinic" to have the highest rate of dropout, at 30.4%, across all clinical settings. While their definition combines the university based training clinic with the university based counseling center, the two share comparable client demographics. With nearly one in three clients dropping out, this seems to be a staggering opportunity cost for any under-resourced campus clinic. Simply put, the cost of a premature termination is heightened by the unique demands that many campus clinics face. The concern has resulted in a body of literature that has dubbed the situation a "crisis" (Kadison, 2004; Kadison & DiGeronimo, 2004).

However, in spite of the high dropout rates, the campus clinic also represents a unique opportunity to capture a particularly important age demographic. Over 60% of high school graduates attend some postsecondary education (Aud and Wilkinson-Flicker, 2013). Coupled with findings that three quarters of DSM-IV diagnoses occur before age 24 (Kessler et. al., 2005), the campus clinic represents a large-scale umbrella to potentially provide services for a high percentage of the population (Hunt, Watkins, and Eisenberg, 2012). The ability to cater to this demographic, however, is tempered by available clinic resources.

Likewise, the usage of prevention techniques for dropout from campus counseling centers is dependent on clinic assets. Hatchett (2004) outlines a number of methods to help in reducing dropout specifically in the campus setting, often involving “interventions” in the early phases of treatment. For example, streamlining and simplifying the intake process, providing psycho-education about therapy to clients, focusing on developing shared goals and tasks, and discussion of treatment length and termination, are all strategies that could be implemented as the client is starting services at the clinic, or in the earliest therapy sessions. Other suggestions may be more appropriately used throughout therapy, such as provision of appointment reminders and checking in with the client’s progress.

Common to all these of strategies is the fact that they are not free. In other words, while all these suggestions could potentially help in reducing dropout, each one also necessitates some expenditure of valuable resources to implement. Altering the intake process or monitoring client progression could mean a structural change of the services provided at the clinic. Appropriate levels of psycho-education most likely involve time, which can be particularly problematic if there are strict session limits set. Even something as simple and reasonable as appointment reminders requires someone to take time to make the call. For the resource-starved center, it may not be feasible or cost-efficient to implement some of these suggestions.

Given these difficulties, it is not surprising that a number of scholars and clinicians have emphasized the importance of increasing awareness of dropout risk factors (e.g., Hatchett, 2004). A prediction tool based on these factors could provide helpful information to guide policy discussions related to the previously mentioned problems faced by most counseling centers. Considering their own resources, it might lead some clinics to get at-risk for dropout clients into treatment sooner, to expend resources specifically for this population, or to refer them somewhere with more resources.

Of course, such a tool would be especially helpful if it could be developed using data from a naturalistic representative sample while also requiring little additional expenditure of resources to collect. The development of a reliable, valid, and easy to implement tool would both reflect and require the integration of science and practice, which is perhaps best exemplified in the practice research network model. Practice research networks have been shown to be an effective way for clinicians to directly contribute to research in an efficient way, and also for researchers to receive invaluable feedback and input from clinicians on the front lines of service (Castonguay, Barkham, Lutz, & McAleavey, 2013; Castonguay, Youn, Xiao, Muran, & Barber, in press). Fortunately, the Center for Collegiate Mental Health (CCMH) is an existing, established practice research network focused specifically on campus based clinics (Castonguay, Locke, and Hayes, 2011).

CCMH is a practice research network that involves a partnership of over 260 schools. Using shared instruments as part of their clinical routine, the CCMH participating centers have contributed to an anonymous, aggregate, and representative dataset that requires no extra effort from its members to collect (Castonguay et al., 2011; Hayes, Locke, and Castonguay, 2011) The primary goal of CCMH is to create a data base that could simultaneously serve both clinical and scientific purpose without overburdening its contributors. With such a dataset, a statistical model for dropout prediction could be generated to give clinicians, administrators, and/or centers a tool to assess dropout risk and act in accordance to their own resources and needs.

The search for dropout predictors has spanned the past five decades. There have been many findings, sometimes conflicting, regarding the characteristics of clients who dropout. Just to name a few, ethnic minority status, age, personality factors, specific diagnoses, past trauma, initial level of distress, education level, socioeconomic status, self-esteem, and hostility, have all been found to be moderators of dropout rates (Draper and Jennings, 2002; McCabe, 2002; Pekarik, 1985; Saxon, Ricketts, and Heywood, 2010; Sharf, Primavera, and Diener, 2010; Swift and Greenberg 2012; Wierzbicki and Pekarik, 1993).

As Swift and Greenberg (2012) note, dropout prediction studies and earlier reviews are mostly conducted with particular client populations receiving specific treatments, reducing generalizability of the findings. While it is certainly an important finding to uncover a "common thread" of premature terminator characteristics across a broad array of mental health provider settings, it is also possible that the college campus setting represents a relatively unique demographic and treatment modality that could be different in its client dropout characteristics. This is especially important given Swift and Greenberg's findings that a younger age and, as previously mentioned, campus mental health services (combining training clinics with campus clinics) experience statistically higher dropout rates.

The Current Study

The university based clinic is an under-researched setting, which is concerning given the increase in higher education enrollment. It presents a unique and socially important setting to examine premature termination, but is not so far removed from previous dropout research as to be independent from it. As such, it seems indicated to create a model that combines previous empirically supported variables while allowing for exploration of other potentially relevant factors. Guided by this assumption, the present study aims to take the current empirically supported individual predictors of premature termination, test them in a predictive model, and fine-tune the model by adding clinically sensible variables for this specific population and setting.

In so doing, the clinical and research benefits become inextricable and mutually informative. A major limitation in the dropout research literature to date has been the difficulty in recruiting large numbers of generalizable participants within a single study. While meta-analyses certainly grant large amounts of information, the aggregated studies can be disparate in demographics, variables examined, and treatment setting. CCMH provides a research opportunity of a large dataset consisting of the specific high-risk university population, generalizable to the US college student. Furthermore, all contributing schools use the same instruments, which consist of a breadth of client characteristics variables that have not yet been examined in the combinatory way this study is aimed to do.

Chapter 2

Methods

Participants

There were 72,695 clients in the final dataset. Clients were all individuals seen at contributing university clinics who were administered at least one of each of the following self-report measures: the Counseling Center Assessment of Psychological Symptoms (CCAPS) and Standardized Data Set (SDS), described in the Instruments section. They were allowed to skip out on any and/or all questions on both the CCAPS and SDS. Unfortunately, the data variable "Client Age" contained impossible and improbable values, such as -7188 and 122.42 years of age, rendering the actual age impossible to accurately report. As an alternate approximation of age, the academic status of clients is reported in Table 2-1. In terms of gender, 65.5 % self-identified as female, 34.5 % as male, .2% as transgender, .4% indicated the desire not to answer, and .4% of the clients did not answer. With respect to ethnicity, 66.9% of clients self identified as Caucasian/White, 7.8% as African American/Black, 7.3% as Hispanic/Latino/a, and 5.2% as Asian American/Asian (see Table 2-2 for client gender and demographic information).

The average number of appointments scheduled was 7.32, with a standard deviation of 6.83, and a mode of 2 sessions scheduled (the mode of actually attended appointments was 1).

Therapists

There were 2,449 unique therapists in the dataset. These were individuals across all contributing centers that were designated as the therapist for a client that completed both the SDS and CCAPS for at least one session. Like the items for clients, therapist items were optional. Among those who responded for this item (948, or 38.7% of all therapists), 68.5% self-identified as female, 30.8% as male, and .3% as choosing not to answer (Table 3-3). Of those who indicated their ethnicity (692, or 73.0% of responding therapists), 28.3% self-identified as White/Caucasian. The next three largest ethnicity categories were African American/Black at 91 therapists (9.6% of respondents), Asian American/Asian at 65 therapists (6.9% of respondents), and Hispanic/Latino/a at 53 therapists (5.6% of respondents). As indicated in Table 3-4, 39.9% of respondents practiced with a Ph.D, 37.1% with some form of a Master's degree (encompassing Masters' of Social Work, Arts, Science, or Education), and 13.1% with a Psy.D. 38.7% of all therapists elected to answer this item.

Instruments

Standardized Data Set (SDS). The SDS was created from the collective intake materials of 50 counseling centers (see Castonguay et al., 2011; Hayes et al., 2011). It contains 47 variables designed to provide a comprehensive demographic snapshot of the incoming client. These variables have been revised beyond dichotomous selections to allow for increased ability to capture the subtle differences between clients. For example, a common answer branch allows for clients to not only specify *if* they've experienced some phenomenon, but also whether it happened before or after starting college, or both. The SDS also contains variables that therapists can complete regarding their own demographic information.

Counseling Center Assessment of Psychological Symptoms (CCAPS). The CCAPS has both a long (CCAPS-62, with 62 items) and short (CCAPS-34, with 34 item) version. They include items loading onto 9 subscales: Depression, Generalized Anxiety, Social Anxiety, Academic Distress, Eating Concerns, Family Distress, Hostility, Substance/Alcohol Use, and a Distress Index which provides an overall level of symptomology by taking key items from multiple scales; the CCAPS-34 does not include the Family Distress subscale or the substance abuse items in the Substance/Alcohol Use subscale, and is designed to balance administrative time with comprehensiveness. Both have been empirically shown to have at least acceptable internal consistency, test-retest reliability, and individual subscales have shown good concurrent validity with more particular associated measures, such as the Beck Depression Inventory (McAleavey et. al., 2013; Locke et. al., 2012).

For the purposes of this study, the CCAPS-34 subscales and the Distress Index were used as analogues for initial distress in various functional domains. The same items are used in both versions, and more counseling centers use the CCAPS-34, presumably for its decreased administration time.

Procedures

The large, aggregated, and relevant dataset is made possible by the nature of the PRN. Each contributing school provides CCAPS and SDS. While contributing centers are given autonomy in the frequency of administration of these instruments, the majority administer both of them at least once for any given client. In general, the CCAPS and SDS are used as part of an intake process administered early in the treatment. Typically, the SDS is administered once, and the CCAPS is used as an assessment tool used according to the centers' policies. The instruments are administered electronically, and the data is stored using Titanium software (Castonguay, Locke, and Hayes, 2011).

Chapter 4

Statistical Analyses

Operationalizing Dropout

One of the major issues identified in the dropout research literature has been selection of the operational definition of dropout itself (Hatchett & Park, 2003; Pekarik, 1985). From an empirical standpoint, dropout can be defined in different ways, including therapist rated, failure to attend the last scheduled appointment, and various treatment length criteria. Depending on the definition used, and as confirmed in the most recent meta-analysis (Swift & Greenberg 2012), the rate of dropout fluctuates from study to study. As Hatchett and Park (2003) have suggested, looking at the last scheduled appointment might be the most accurate way of identifying dropouts. While therapist rated and last-appointment dropouts appear to be measuring a common phenomenon, therapist rated dropouts have the disadvantage of lower reliability due to differences in how therapists view the goals and progress of their therapy. On the other hand, with dropouts determined by looking at the last scheduled appointment, we can be certain that there was at least some agreement between therapist and client to attend one more session, in which the client ultimately did not appear. Therefore, this study used CCMH data to identify dropouts by looking at the last scheduled appointment.

In the CCMH data, the attendance of each individual appointment of every client is recorded. Attendance is a categorical variable, labeling appointments as client no-show, client/therapist rescheduled, client/therapist canceled, or attended appointments. For this study, dropout was defined per client by selecting those individual last appointments in which the client no-showed, rescheduled, or canceled. In other words, dropouts were considered individuals whose therapies which did not end on an attended appointment because of some "client-side issue."

Statistical Model Selection

For the purposes of this study, dropout was treated as the dichotomous dependent variable (as discussed in *Operationalizing Dropout).* As Peng, Lee, and Ingersoll (2002) outline, there are several methods that allow for analysis and prediction of some dichotomous outcome. Logistic regression analysis has been suggested to be at least slightly more accurate in prediction when compared to other traditional methods, such as ordinary least squares (OLS) regression (Pohlmann & Leitner, 2003) and discriminant analysis (Press & Wilson, 1978). This study used multiple logistic regression in an effort to create a prediction model using a selection of variables available through the CCMH dataset. Missing data was handled by list-wise deletion, which has been shown to be more robust than other methods, particularly for regression analysis (Allison, 2002).

Similar to linear regression (Cohen & Cohen, 2013), each regression coefficient value represents an expected unit change in the dependent variable (criterion) given a single unit change in the specific predictor. It is important to note that the regression coefficient values calculated for logistic regression come in the form criterion change in the relatively unintuitive logit scale (Hosmer & Lemeshow, 2004). As such, interpretation of results is often done using the exponential function of these coefficients, known as the odds ratio. Simply put, the odds ratio is a measure of association- it is equivalent to taking odds of occurrence of the outcome (in this case, dropout) given a particular predictor (the various independent variables), divided by the odds of the outcome occurring in the absence of the predictor. Odds in general are simply a measure of likelihood that a particular event takes place.

Regression coefficients in logistic regression adhere to the same significance guidelines in regression. That is, a significance value of .05 or lower is desired to suggest that the result is obtained by chance only 5 times out of 100. For interpretation of significant predictors, the regression coefficients in logistic regression are better explained given an example. In this hypothetical example, for continuous predictor variable age and criterion of dropout, the regression coefficient can be interpreted as follows: "For each unit increase of age (increase of 1 year in the age of the subject), the odds of dropping out increase by [age regression coefficient value]."

Because many of the variables are categorical in nature, dummy coding was used to provide a reference group for which the categorical values are compared. Using dropout as the criterion, and using a categorical gender variable with a reference group of "male", a hypothetical regression coefficient value of 1.5 for a "female" category could be interpreted as such: "Compared to the reference group (males), individuals belonging to this specific gender categorical value (female) are 1.5 times as likely to drop out (females have a 1.5 times the odds of dropping out as males)."

Variable Selection/Prediction models

In this study, there were three tested hierarchical regression models. The cut value for each of the models is set to .500. That is, the model predicted an individual case to be a dropout if the criterion produced by the predictors is valued at greater than .500. This value may be raised to increase the accurate prediction of any individual prediction at the cost of failing to predict a greater percentage of dropouts as such. The first model, the "empirical model," used variables empirically supported in the dropout literature to be moderators of dropout in some context. In other words, at least one study has found each individual variable to be a predictor for dropout. In a sense, this regression model was a "confirmatory" analysis of empirically supported predictors for dropout. The variables in this model include age, ethnic minority status, higher initial distress of client, hostility, past intentional harm to others, education status, and socioeconomic status (Barrett et. al. 2008; Beckham, 1992; Berrigan & Garfield, 1981; Marie Lincoln et. al., 2005; McCabe, 2002; McMurran, Huband, and Overton, 2010; Mennicke, Lent, and Burgoyne, 1988; Lampropoulos, Schneider, and Spengler, 2009; Owen, Imel, Adelson, and Rodolfa, 2012; Pekarik, 1985; Piselli et. al., 2011; Reis & Brown, 2991; Saxon et. al., 2010; Sharf et. al. 2010; Smith et. al., 1995; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). While Swift & Greenberg's recent 2012 meta-analyses found many traditionally supported demographic variables to be non-predictive of dropout, it is possible that the aggregate nature of the meta-analysis may have "washed-out" some specific findings for the college student demographic.

The second model used available CCMH data variables, and included variables that make clinical "sense." This model, the "combined model," used the previous "empirical model" predictors, and added to them a selection of theoretically clustered variables with contentious or unproven empirical support; that is, previously unexamined variables or those with substantial mixed findings.

In an effort to maximize accuracy of prediction, a third model, called the "revised model" used only the significant predictor variables found in the "combined model". By compiling only the significant variables found in the breadth of empirical findings in the first model and clinical variables in the second, the third model should provide the most parsimonious predictive tool.

For each of the three models, variables were entered hierarchically in clusters. This method was used to provide a theoretical framework to structure the entry of the variables and to contextualize the interpretation of the results. The first model included 4 clusters- Initial Severity, Demographics, Alcohol, and Critical Items (severe distress items such as suicidality and homicidality). In the second model, relevant clinical variables were added in some of the clusters of the first model. In addition, 3 new clusters were included- Mental Health Treatment History, Extracurriculars, and Social Support. The final model included variables that were statistically significant from the combined second model. For the present study, all seven clusters retained at least one significant variable in Model 3, and are described in further detail below.

Data analysis was run using SPSS version 22, using the Binary Logistic Regression option. The results of these prediction models can be conceptualized in a 2x2 table, comparing actual and model predicted dropouts and non-dropouts. The models will be judged on values of sensitivity, the proportion of correctly predicted dropouts, and specificity, the proportion of correctly predicted non-dropouts.

The Hosmer-Lemeshow test for goodness of fit for logistic regression models will be used to assess the utility of each added variable block in the hierarchical logistic regression (Hosmer, Lemeshow, & Sturdivant 2013). The null hypothesis, that the model predicted dropout rate does not differ from what actually occurs, is similar to that of a Chi-Squared goodness of fit test. In other words, an insignificant $p>.05$ finding for this test indicates that the model can be stated to have acceptable fit.

Data Reduction

Starting from the complete 2010-2012 CCMH dataset, there were a number of data reduction steps necessary to meaningfully capture dropouts in a prediction model. First and foremost, clients were included *if and only if* they have attended at least 1 therapy session. That is, consistent to the aforementioned definition of dropout, clients must have started some psychotherapeutic treatment, a distinction from therapy "rejecters," who are never seen by a therapist (Swift & Greenberg, 2012).

Next, the client's last session of a given therapy course (a course of therapy is defined as any series of appointments occurring with a maximum of 90 days between any two consecutive sessions) must have been present in the dataset. That is, for any course of therapy, there must have been data on their last appointment's attendance status in order to categorize the subject's dropout status. As defined previously, dropouts were then defined by examining the attendance status of their last scheduled appointment. Clients who canceled, rescheduled, or no showed their last appointments were considered dropouts.

Finally, only those clients who completed both the Standardized Dataset (SDS) and Counseling Center Assessment of Psychological Symptoms (CCAPS) were considered. The data reduction process is outlined in Table 2-5. In the final dataset, dropout rate was calculated to be 41.9% (n= 30,426) out of a total N= 72,695, spanning 107 separate counseling centers.

Chapter 4

Results

A summary of each model's regression coefficients in its final iteration (i.e. with all blocks of variables present) is summarized sequentially in Table 3-1. The regression coefficients can be interpreted as the odds ratios when compared to the reference group listed first. Each model's performance in prediction, sensitivity and specificity is summarized in Table 3-2.

Model 1

The first model consisted of those variables that have received the most empirical support of being predictive of dropout. From a starting sample size of 72,695, list-wise deletion of individuals who were missing data on these variables resulted in a final dataset of 30,145 individuals. From this data, 12,748 individuals, or 42.29%, were dropouts. The Hosmer - Lemeshow test of significance indicated that the addition of the Block 1 and Block 2 variables produced a model with acceptable fit. Blocks 3 and 4 (Alcohol and Critical Items) were not significant improvements of the overall predictability of the model, although the p-value of the 4^{th} block was .050 exactly. In other words, the initial severity Block 1 variables, the demographic Block 2 variables, and possibly the critical items Block 4 variables fail to reject the null hypothesis that there is no difference between actual dropout rate and the model's predicted dropout rate, indicating acceptable fit.

Within each block, there were individual variables which significantly predicted dropout. The categorical variable with the largest between levels impact for risk of dropout was the Block 4 variable "intentionally caused harm to others." Those who endorsed this variable both before and after starting college had 1.65 times the odds of dropping out as someone who had not endorsed this variable at all (or conversely, those who did not endorse this variable dropped out at only .61 times as much as those who endorsed harm to others both before and after starting college.

From the continuous initial severity variables of CCAPS subscales in Block 1, the most impactful variable was social anxiety. For each point increase of social anxiety, individuals were respectively .87 times less likely to dropout out. That is, an elevation on the social anxiety subscale decreased the likelihood of a dropout. Of note, the Distress Index subscale was almost statistically significant ($p = .051$), and its exponent was 1.30. For each point increase on the DI, clients were 1.3 times more likely to dropout.

In its final iteration, this model correctly predicted 2,865 dropouts, for a sensitivity value of 22.5%. This model also correctly predicted 15,098 non-dropouts for a specificity value of 86.8%, setting the model's overall predictive accuracy at 59.6%. In other words, over all classified individuals, there is roughly a 60% chance that he or she is correctly classified using this model. Any given individualwas correctly classified as a dropout 55.5% of the time, and as a non-dropout 60.4% of the time.

Model 2

The second model consisted of all variables from Model 1, with the addition of several variables to the existing blocks, and the addition of three theoretically clustered blocks. From list-wise deletion, the final dataset is set at $n= 20{,}181$, with 8,720 dropouts (43.2%). All seven entered blocks of variables in the model were additions with acceptable fit based on Hosmer-Lemeshow statistics. However, only one variable, "suicidal thoughts prior to starting college," was found to be a significant in the entire second block of Critical Items variables, with those having seriously considered suicide prior to college dropping out less frequently, .88 times that of those who never considered attempting suicide. The previously empirically supported variables of hostility were not found to be significant in this model. However, the corresponding variables used in this dataset may be closer to measuring homicidality, and thus may not be an adequate comparison.

The most impactful categorical variable was an alcohol binge drinking item in Block 3. Individuals who binge drank 6 to 9 times a week dropped out at rates 1.34 times greater than those who did not binge drink at all. Conversely interpreted, those who did not binge drink dropped out at rates .75 times that of those who binge drank 6-9 times a week. The coefficients for those who binge drank greater than 10 times were found to be statistically insignificant. From the continuous variables, the distress index in the CCAPS subscale Block 1 variables was found to be a significant predictor, with each point increase increasing the odds of dropping out by 1.47.

The final iteration of this model correctly predicted 2,572 out of 8,720 actual dropouts, for a sensitivity of 29.5%. It correctly predicted 9,445 out of 11,461 non-dropouts, for a specificity of 82.4%. Its overall accuracy of prediction was 59.5%. This model has an increase of 7% sensitivity at the cost of 4.4% specificity. An individual identified was correctly classified as a dropout 56.1% of the time, and as a non-dropout 60.6% of the time, a minor improvement from Model 1.

Model 3

The final model "trims down" Model 2 by removing 13 insignificant variables to improve the fit of the model. The dataset for this model consisted of n= 23,144 unique clients, with 9,869 dropouts (42.6%). All seven blocks of variables were statistically acceptable additions during the hierarchical addition of variables. All variables had at least one significant level, with the exception of a single item in the social support Block 7: "I get the emotional help I need from my family." In separate analyses not reported here, this item was removed and the model was evaluated to be functionally identical to the present described model.

Being a graduate student was the most impactful categorical variable, with odds of dropping out .67 times those of freshmen (conversely, freshmen drop out 1.49 times that of graduate students). The most impactful continuous initial severity variable was the distress index. Within the model, a one point increase of the DI corresponded to an increase in odds of dropping out by a factor of 1.27.

The final iteration of this last model correctly predicted 2,637 out of 9,869 dropouts for a sensitivity of 26.7%. Its specificity was 84.3%, correctly predicting 11,164 out of 13,245 non-dropouts. Its overall predictive accuracy was 59.7%. Compared to the previous model, this model is 2.8% less sensitive and 1.9% more specific, and is substantially more parsimonious. When an individual is predicted to be a dropout using this model, it was accurate 55.9% of the time. A classified non-dropout had a 60.69% chance of being correctly identified.

Chapter 5

Discussion

Dropout is a pervasive problem in the delivery of mental health services. This problem can be compounded in settings that are faced with limited resources, such as college university centers. The current study aimed to examine variables that were predictive of dropout in previous studies (model 1), explore the impact of under-researched or contentious variables (model 2), and develop a parsimonious predictive model (model 3) for dropout that may offer a university center a flexible tool available at the time of intake. For each model, variables were entered in cluster during hierarchical logistic regression to glean insight on potential patterns of predictive variables.

Model 1

The first model's contained previously supported empirical variables that were largely found to be significant, but with a pattern of nuance within variables and differential impact depending variable level. For example, increased presenting symptoms (which were included in Block 1) was not unified in predicting greater dropout rate. While increased symptomatology on Alcohol Use and Academic distress were both found to be significant predictors of dropout (1.04 and 1.08 times increased odds, respectively), Depression, Generalized Anxiety, Hostility, and Eating Concerns were not found to be predictive of dropout. In contrast, Social Anxiety was preventative, with each point increase decreasing odds by nearly 13%. Similarly, increases on the Distress Index, an "overall measure" of distress, closely approached significance at $p=.051$, and would have been the strongest predictor of dropout, increasing odds of dropping out by 30%. As a whole, the findings showed that presenting concerns variables are predictive of dropout, but the specific concerns provide context for what may make it more or less likely for the individual to terminate prematurely from treatment.

In the same first model, each of the three demographic variables that were included in Block 2 was found to be important in prediction of dropout. Interestingly, as students moved further away from their freshman year, their odds of dropout significantly decreased, up to nearly 30% decreased odds for graduate students when compared to freshman. It may be that from year to year, presenting concerns change such that students are more invested in treatment later in their academic career. As for ethnic minority status, it is not enough to simply state that identifying as an ethnic minority is a risk factor for dropping out. While African-American/Black and Hispanic/Latino/a clients dropped out at rates 1.24 and 1.15 higher, respectively, the majority of ethnic minorities dropped out at rates indistinguishable from Caucasian/White clients. Consistent with previous studies, socioeconomic status (as measured by financial distress) predicted dropout rates. Compared to those who found their current financial situation "always stressful," each step closer to "never stressful" led to a decrease in up to 32% of the odds of dropping out.

Alcohol related variables (included in Block 3 of the first model) were also predictive, as individuals who reported frequent binge-drinking (up to 6-9 times in two weeks) had up to 38% increased odds of dropping out compared to those who did not binge-drink at all. Compared to individuals who did not feel their drinking needed to be reduced, those who felt the need to reduce drinking before entering college dropped out at odds 18% greater.

Finally, among the critical items that were part of the fourth block on model 1, actual "causation of harm to others" was found to increase dropout rates by up to 64% if the individual caused harm both before and after entering college. In contrast, the homicidal ideation variable only approached significance (p=.076) and was found to decrease dropout rates. This perhaps demonstrates the difference between working with those who have already "performed" the critical items in Block 4 when compared to individuals who have thought about it, but have not yet done so. The former group may present with severe interpersonal difficulties which make it difficult to establish and complete a treatment framework, while the latter may be more compelled to complete treatment due to fears or desires not to engage in these serious behaviors.

Model 2

The addition of the clinically derived and contentious variables in Model 2 uncovered several more significant variables predictive of dropout in a university counseling center setting. The majority of significant findings from Model 1 were present in similar magnitude for Model 2, and noteworthy deviations are described below, along with findings from the added variables.

From the initial severity variables of Block 1, there were some shifts in significance. The Distress Index subscale, which approached significance in the first model, was found in this model to significantly increase dropout odds 1.47 times (p=.019), lending support to the idea that an overall more distressed client may be at risk for dropout. Additionally, academic distress increased odds of dropping out by 7.8% per point increase. However social anxiety, and to a lesser extent, eating concerns, were both found to decrease odds of dropping out by 12.7% and 3.1% respectively- it is important to consider the client's presenting concerns.

Block 2 saw the addition of gender and relationship status as demographic variables; the original four variables all retained their significance. There have been mixed findings regarding dropout and gender (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993), but in this data, females were found to drop out at 15% higher odds than males. Combined with the fact that only 34.5% of the full dataset is male, it may be that males are less likely to come in for a variety of reasons, but that once they start therapy, they are also more invested. In terms of relationship status, individuals in committed or serious relationships were found to drop out at 16% increased odds compared to the single individual. Single individuals may find therapy to provide a relationship supportive and important in a way that may already present for those in committed relationships. It should be mentioned that even with the addition of two additional variables, every single demographic variable in Block 2 was found to significant- it may be that these concrete characteristics play a great role in the likelihood of dropout.

The alcohol related variables of Block 3 largely did not change. The odds for dropout increased to 30% for those who felt the need to reduce alcohol use prior to college, and those who felt this need after college started had 11% increased odds; the previous model did find this latter group to be significant.

Added critical items in Block 4 included variables on self-harm, suicide, and trauma. Interestingly, the only variable found to be significant was serious consideration of suicide before college, which decreased odds of dropping out by 12%. It would appear that while certain aspects of these critical items may impact dropout, it is unclear how to interpret a history of such characteristics, and may be more idiosyncratic to the client. Specifically for suicidal ideation, these individuals may be in extreme distress and motivated to seek help.

Mental health history variables included in Block 5 provided interesting new findings. Individuals who had attended counseling for mental health after starting college had roughly 17% decreased odds of dropping out than those who had never attended counseling. Having taken medication for mental health concerns after starting college increased odds of dropping out by approximately 13%-15%, while hospitalizations were not found to predict dropout. It may be that previous experience with college campus counseling gives students specific ideas about what to expect for further college campus counseling. On the other hand, individuals who receive medication may be less likely to complete treatment if they feel the medication is working.

With regards to extracurricular activities, the cluster of variables included in Block 6 shows promise in terms of predicting dropout. Among these variables, participation in 3 or more organized activities (but not two, one, or occasional participation) reduced dropout odds by 16%, and being on an athletic team reduced odds by 18%. These organized activities may provide an entertainment and social component that the third non-significant variable of ROTC membership does not. In order to maintain these rewarding ties, involved individuals may wish to address their perceived mental health concerns. Furthermore, the added time constraints that come with increased activities may highlight mental health difficulties and the motivation to get them resolved.

Finally, the seventh block contained two variables associated with social support. Interestingly, friend support seems more impactful than family support. Those who felt they had more emotional help/support from friends were up to 20% less likely to prematurely terminate than those who strongly felt they did not get support. In contrast, only those who strongly felt they received emotional support from their family had an *increase* in dropout odds of 12% compared to those who did not feel they received support. Given the close interactions of students and friends on campus, it may be more important to assess student friendship social ties than family ties. When students have strong bonds with family, being away from them may have a negative impact.

Model 3

The final model only included variables which were found to be significant from Model 2. This model removed a total of 13 variables (labeled as N.T. [not tested] variables in Table 3-1) mostly concentrated in the critical items of Block 4. The significant findings from Model 2 were present in similar magnitude for Model 3, and noteworthy deviations are described below.

The removal of statistically insignificant presenting concerns resulted in 4 variables in Block 1. Alcohol use and the Distress Index were predictive of dropout at 6.6% and 27.1% increased odds, while eating concerns and social anxiety helped mitigate dropout at 3.1% and 13.5% decreased odds, respectively.

All of the empirically supported and clinically derived demographic variables in Block 2 were retained. Demographic variables do indeed seem to help predict dropout, and no variables were removed from this block during the study. Significant findings were similar in magnitude to those described in Model 2. Similarly, from the alcohol related variables of Block 3, recognition of needing to reduce alcohol use and binge drinking were predictive of increased dropout odds comparable to the previous model. However the item “others expressed concern about your drinking” was removed due to non-significance. In the alcohol-heavy culture of the college university, it may be hard coming to terms about alcohol related problems.

As mentioned previously, the number of variables in Block 4 was the most reduced. Out of the 7 tested variables in the previous model, the current model only contained 1 item, seriously considering attempting suicide, which reduced odds of dropout by up to 16%. This is consistent with the previous model, and may be indicative of severely symptomatic but motivated individuals.

Hospitalization for mental health was excluded from Block 5, and the remaining two variables held to the pattern described in Model 2. Counseling prior to college predicted a decrease of 13.4% odds in dropout, while psychiatric medication use increased odds of dropout by up to 17.4%. Similarly, one variable (ROTC enrollment) was excluded from Block 6, and the remaining two variables followed similar patterns. Participation in athletics reduced odds of dropout by 15%, and in this model, regular participation in at least one regularly attended activity (as opposed to at least three activities, as in the previous model) decreased odds of dropping out by up to 15%. Again, these extracurricular activities may actually provide a framework in which mental health concerns are more apparent, or more important to be resolved.

Finally, the seventh block had included both family and social network support variables, of which only emotional help from social networks was found to be significant, decreasing dropout odds by up to 17%. This is consistent with the previous model, and may even be compared to Block 6, extracurriculars. In some ways, extracurriculars can be viewed as social networks and support systems when one considers the unique demographics and lifestyle of the average college student. All three of the variables in blocks 6 and 7 reduced dropout odds by roughly 15%. It may be that the more involved an individual, the more “eyes” on them to help them recognize mental health issues, and the more help and motivation provided to complete treatment.

Clinical Implications

Interestingly all 3 models sported similar overall accuracies in prediction, with slight shifts in specificity and sensitivity. However, Model 3 did have the highest overall accuracy at 59.7%, along with the best ratio of most statistically significant variables. Using this model there is a 56% chance that an individual is accurately identified when labelled as a dropout. While this model may not capture the majority of dropouts, those identified as dropouts are more likely to dropout. For counseling centers' starved resources, it may then be most clinically useful to direct resources towards these individuals. Even if dropouts are "missed" with this model, resources spent on those individuals identified as dropouts would still be spent attempting to prevent the dropout of 20-30% of individuals that may otherwise be lost. Of course, the cut value for the model itself can be adjusted to have a higher accuracy of individual prediction, but at the cost of missing substantially more potential dropouts.

In addition, the model highlights several variables that can be taken into consideration when assessing dropout risk. Many of the previously supported variables predictive of dropout in different populations still hold true for the college population as examined in the first 4 variable blocks. The categorical nature of the SDS variables also lends a nuance to several variables in comparing different levels of variables. It can be helpful to know that presenting concerns of a client seem to matter most when the client presents with a widespread set of symptoms. It is also perhaps fortunate that the more immutable and easily determined demographic variables seem to be quite reliably predictive of dropout. Similarly encouraging is the finding that many of the critical items, which may have complex meanings for different individuals, are less predictive of dropout than the other variables. Alcohol related symptoms also retain their significance, and perhaps may be even more important in the college setting, where drinking has a notorious presence.

The model also unearths several variables with predictive power that are perhaps unique to the university setting. Previous mental health treatment and psychiatric treatment had different impacts on dropout. There may be something inherently unique about those who started treatment or medication in high school or younger before they venture into college.

Extracurriculars also seem to be a step above a "CV padder" for the college student, with those who participate in more organized activities to also be less to dropout. Perhaps the busyness of their schedules reflects the responsibility or resources needed to see a treatment through. These group activities also reflect a social support network indigenous to college universities. And perhaps unsurprisingly, friends matter more than family when college students are surrounded and enmeshed within their peers.

While it is difficult to make a judgment as to the likelihood of dropping out based on any of these individual statistically significant variables, the knowledge that these clusters of variables exist and do impact dropout may give clinicians a better sense on whether or not dropout is an issue for a given client. There have been several suggestions made to prevent dropout (Swift, Greenberg, Whipple, & Kominiak, 2012; Swift & Greenberg, 2015), and the present study and model may provide variables to consider in the unique college setting when planning a course of therapy or setting administrative guidelines.

Limitations

As mentioned above, the definition of dropout can change the reported rate. Given the nature of the data collected, dropout was defined post hoc by looking at the last session. It was not possible to determine whether the therapist or client would have considered the non-attendance of a last session as a dropout, and these other definitions may have changed the model's prediction characteristics.

Despite the breadth covered by the items contained in the SDS and CCAPS, there are important predictors excluded from the proposed models. Specifically, client personality variables (Schindler, Hiller, and WitthÖft, 2012; Swift and Greenberg, 2012; Sasso and Strunk, 2013) and therapist variables, particularly therapist experience level (Swift and Greenberg, 2012; Roos and Werbart, 2013), have both been found to be predictors for premature termination.

Unfortunately, neither the SDS nor the CCAPS has client personality variables, so it was not possible to examine these important client characteristics. The exclusion of therapist variables was an informed decision. While the SDS does indeed contain therapist variables, the majority of therapists opt not to answer these questions. A future direction would be well served to look closely therapist variables' effects on dropout. It is also feasible that the center policies itself can influence dropout by their center-specific session limits and other policies.

Conclusion

Dropout rates are elevated in counseling centers. From this study's large, geographically representative data-set, dropout was found to reach 40% in individual psychotherapy. Because of the numerous costs associated with premature termination, the ability to predict who may drop out of treatment can have significant benefits for the management and quality of care provided in counseling centers. Previous studies have identified several predictors of dropout, however few have specifically examined the particular demographic of the university center, and none with the breadth and dataset made possible by the practice research network of CCMH.

Through several iterations of models, many of these otherwise empirically supported variables were found to be significant in predicting dropout, along with several other previously unexamined variables with unique presentation at the university setting. These clinically derived variables reflect the distinctive nature of this demographic, and provide a sense of the complexity of dropout prediction.

The models themselves were accurate above chance, and may provide a university center with an initial tool to assess dropout risk available at the time of intake. At the very least, those individuals identified as dropouts by the model would be easy targets to direct dropout-prevention resources. There is indeed room for improvement on treatment delivery and retention of clients, and an important first step is to help clients to complete treatment, which can in turn have positive impacts on the therapists and the centers itself.

Appendix A

Tables

Table 2-1

Individuals seeking counseling services by Academic Status

Academic Status	N	Percent	Valid Percent
Freshman	14369	19.8	20.0
Sophomore	13810	19.0	19.2
Junior	16461	22.6	22.9
Senior	15818	21.8	22.0
Graduate/Prof. degree	10349	14.2	14.4
Non-student	50	.1	.1
High School	18	.0	.0
Non-degree student	189	.3	.3
Faculty or staff	58	.1	.1
Other	685	.9	1.0
Missing	888	1.2	
Totals	72695		

Table 2-2

Individuals seeking counseling services by Ethnicity and Gender

Demographic Variable	N	Percent	Valid Percent
African-American/Black	5652	7.8	8.2
American Indian/Alaskan Native	375	.5	.5
Asian American/Asian	3808	5.2	5.5
Caucasian/White	48620	66.9	70.8
Hispanic/Latino/a	5273	7.3	7.7
Native Hawaiian or Pacific Islander	172	.2	.3
Multi-racial	2580	3.5	3.8
Prefer not to answer	1088	1.5	1.6
Other	1151	1.6	1.7
Missing	3976	5.5	
Gender			
Male	25094	34.5	34.7
Female	46882	64.5	64.7
Transgender	181	.2	.2
Prefer not to answer	257	.4	.4
Missing	281	.4	
Total	72695	100.0	

Table 2-3

Therapists at counseling centers by Ethnicity and Gender

Demographic Variable	N	Percent	Valid Percent
African-American/Black	94	3.7	9.6
American Indian/Alaskan Native	4	2.7	.4
Asian American/Asian	65	.1	6.9
Caucasian/White	692	28.3	73.0
Hispanic/Latino/a	53	2.2	5.6
Native Hawaiian or Pacific Islander	3	.1	.3
Multi-racial	23	.9	2.4
Prefer not to answer	4	.2	.4
Other	11	.4	1.2
Missing	1501	61.3	
Gender			
Male	293	12.0	30.8
Female	652	26.6	68.5
Transgender	4	.2	.4
Prefer not to answer	3	.1	.3
Missing	1497	38.9	
Total	2449	100.0	

Table 2-4

Therapists at counseling centers by Degree

Degree	N	Percent	Valid Percent
B.A.	31	1.3	3.3
B.S.	16	.7	1.7
Nursing (RN, RNP, PNP)	3	.1	.3
M.S.W.	76	3.1	8.0
M.A.	155	6.3	16.4
M.S.	90	3.7	9.5
M.Ed.	30	1.2	3.2
Ed.S.	6	.2	.6
Ph.D.	378	15.4	39.9
PsyD	124	5.1	13.1
Ed.D.	15	.6	1.6
D.S.W.	0	0	0
D.O.	2	.1	.2
M.D.	4	.2	.4
Other	17	.7	1.8
Missing	1502	61.3	
Total	1449	100.0	

Table 2-5

Data Reduction

Starting- Course of therapy within 2010-2012	121698 clients 122 centers
Attended at least 1 therapy session	100831 clients 119 centers
Client's last session of therapy course was within 2010-12	94113 clients 119 centers
Defining dropout by attendance of last session: Client Cancelled, Client Rescheduled, Client No Show	Dropout = 39087 (41.5%) Completed = 55026 (58.5%)
Clients who completed both the SDS and CCAPS	**72695 clients** **107 centers**
Rechecking dropout for "complete" dataset	**Dropout = 30426 (41.9%)** **Completed = 42269 (58.1%)**

Table 3-1

Model Specifications

	Model 1		Model 2		Model 3.	
	N= 30,145		N=20,181		N=23,114	
	OR	**Std. Error**	**OR**	**Std. Error**	**OR**	**Std. Error**
Block 1- Presenting Concerns						
Hosmer-Lemeshow Test of Significance	p=.426		p=.567		p=.732	
Depression	0.92	.046	0.898	.057	N.T	
Generalized Anxiety	1.024	.044	0.949	.055	N.T	
Social Anxiety	0.873***	.018	0.861***	.023	0.865***	.017
Alcohol Use	1.042*	.019	1.053*	.024	1.066***	.021
Hostility	0.991	.028	0.975	.035	N.T	
Academic Distress	1.078**	.025	1.052	.031	N.T	
Eating Concerns	0.983	.011	0.973*	.014	0.969*	.013
Distress Index	1.296	.133	1.471*	.165	1.271***	.024
Block 2- Demographics						
Hosmer-Lemeshow Test of Significance	p=.125		p=.150		p=.429	
Race/Ethnicity						
Caucasian/White	*reference*		*reference*		*reference*	
American Indian or Alaskan Native	1.359	.214	1.362	.271	1.327	.246
Asian American/Asian	1.042	.056	1.027	.070	1.038	.065
African-American/Black	1.239***	.045	1.235***	.054	1.237***	.050
Hispanic/Latino/a	1.148**	.046	1.16**	.055	1.176**	.052
Native Hawaiian or Pacific Islander	0.899	.242	0.880	.296	0.915	.290
Multi-Racial	1.046	.062	1.075	.078	1.081	.073
Prefer not to answer	1.041	.099	1.159	.125	1.155	.117
Other	1.183	.096	1.163	.117	1.175	.109
Academic Status						
Freshman/First-year	*reference*		*reference*		*reference*	
Sophomore	0.938	.037	0.942	.046	0.970	.043
Junior	0.91**	.036	0.919	.046	0.947	.043
Senior	0.875***	.037	0.859**	.047	0.894*	.044
Graduate/professional degree student	0.71***	.042	0.676***	.056	0.666***	.052
Non-student	1.226	.682	1.504	.924	1.649	.922
High-School student taking college classes	0.797	.740	0.964	.779	0.989	.777
Non-degree student	0.701	.285	0.634	.364	0.610	.347
Faculty or staff	0.775	.935	0.494	1.262	1.102	1.018
Other	0.91	.131	0.908	.165	0.984	.153
Current financial situation						
Always Stressful	*reference*		*reference*		*reference*	
Often Stressful	0.856***	.039	0.903*	.048	0.902***	.045

Sometimes Stressful	0.786***	.038	0.808***	.047	0.806*	.044
Rarely Stressful	0.703***	.044	0.705***	.055	0.713***	.051
Never Stressful	0.678***	.060	0.698***	.074	0.720***	.069
<u>Financial situation growing up</u>						
Always Stressful	*reference*		*reference*		*reference*	
Often Stressful	0.975	.050	0.950	.062	0.942	.057
Sometimes Stressful	1.019	.047	1.040	.059	1.026	.054
Rarely Stressful	0.971	.048	1.002	.059	0.975	.054
Never Stressful	1.113*	.052	1.141*	.064	1.080*	.059
<u>Gender</u>						
Male	N/A		*reference*		*reference*	
Female			1.152***	.034	1.121***	.030
Transgender			1.121	.324	0.952	.303
Other			0.523	.392	0.591	.344
<u>Relationship Status</u>						
Single	N/A		*reference*		*reference*	
Seriously Dating/Committed Rltnship			1.159***	.032	1.179***	.030
Civil union, domestic partner, equiv.			0.864	.239	0.902	.222
Married			1.120	.083	1.097	.077
Divorced			1.045	.180	1.144	.167
Separated			1.317	.174	1.308	.164
Widowed			1.269	.830	1.854	.776
Block 3- Alcohol						
<u>Hosmer-Lemeshow Test of Significance</u>	p=.030*		p=.194		p=.071	
<u>Felt the need to reduce alcohol use</u>						
Never	*reference*		*reference*		*reference*	
Prior to college	1.181*	.071	1.304**	.087	1.272***	.071
After starting college	1.066	.039	1.108*	.048	1.108*	.041
Both	1.118	.064	1.131	.079	1.135	.065
<u>Others expressed concern re: alcohol use</u>						
Never	*reference*		*reference*		N.T	
Prior to college	1.073	.076	1.015	.094		
After starting college	1.037	.048	1.021	.058		
Both	1.058	.074	1.128	.093		
<u>How many times binge drink last two weeks</u>						
None	N/A					
Once	1.089*	.034	1.060	.041	1.067	.039
Twice	1.228***	.040	1.227***	.049	1.227***	.046
3-5 times	1.153**	.047	1.166**	.057	1.181**	.053
6-9 times	1.38***	.086	1.339**	.105	1.287*	.099
10 or more times	1.169	.138	1.310	.177	1.280	.160
Block 4- Critical Concerns						
<u>Hosmer-Lemeshow Test of Significance</u>	p=.050		p=.536		p=.186	

Seriously considered injuring other						
Never	*reference*		*reference*		N.T	
Prior to college	0.892	.070	0.864	.089		
After starting college	0.921	.099	0.985	.123		
Both	0.882	.071	0.896	.088		
Intentionally caused injury to other						
Never	*reference*	.108	*reference*		N.T	
Prior to college	1.165	.174	1.204	.134		
After starting college	1.251	.182	1.154	.209		
Both	1.647**	.062	1.350	.227		
Injured yourself without suicide intent						
Never	N/A		*reference*		N.T	
Prior to college			0.973	.049		
After starting college			1.023	.081		
Both			0.981	.061		
Seriously considered attempting suicide						
Never	N/A		*reference*		*reference*	
Prior to college			0.884*	.054	.866	.044
After starting college			0.985	.069	.965	.059
Both			0.897	.065	.858	.053
Made a suicide attempt						
Never	N/A		*reference*		N.T	
Prior to college			1.116	.075		
After starting college			1.165	.120		
Both			0.987	.172		
Experienced traumatic event						
Never	N/A		*reference*		N.T	
Prior to college			0.983	.043		
After starting college			1.000	.050		
Both			1.007	.055		
Had unwanted sexual contact						
Never	N/A		*reference*		N.T	
Prior to college			1.013	.050		
After starting college			0.976	.061		
Both			0.939	.083		
Block 5- Mental Health Hx						
Hosmer-Lemeshow Test of Significance	-		p=.572		p=.552	
Attended Counseling for mental health						
Never	N/A		*reference*		0.000***	
Prior to college			1.039	.044	0.228	.040
After starting college			0.828***	.050	0.000***	.046
Both			0.974	.057	0.455	.053
Taken prescribed mental health meds						

Never	N/A	*reference*		0.002**	
Prior to college		1.054	.060	0.232	.054
After starting college		1.125*	.051	0.000***	.047
Both		1.149*	.060	0.013*	.055
Been hospitalized for mental health reasons					
Never	N/A	*reference*		N.T	
Prior to college		0.931	.083		
After starting college		0.948	.096		
Both		1.125	.201		
Block 6- Extracurriculars					
Hosmer-Lemeshow Test of Significance	-	p=.263		p=.528	
Level of involvement in extra-curriculars					
None	N/A	*reference*		*reference*	
Occasional Participation		0.974	.041	0.978	.038
One regularly attended activity		0.920	.044	0.908*	.040
Two regularly attended activities		0.891*	.048	0.879**	.044
Three or more regularly attended activities		0.842***	.051	0.848**	.048
Athletic team participation					
No	N/A	*reference*		*reference*	
Yes		0.827***	.057	0.848**	.053
Member of ROTC					
No	N/A	*reference*		N.T	
Yes		1.162	.155		
Block 7- Social Supports					
Hosmer-Lemeshow Test of Significance	-	p=.253		p=.369	
"I get help/support I need from my family"					
Strongly Disagree	N/A	*reference*		*reference*	
Somewhat Disagree		1.050	.060	1.029	.055
Neutral		1.081	.060	1.063	.056
Somewhat Agree		1.058	.055	1.047	.051
StronglyAgree		1.121*	.058	1.067	.054
"I get help/support needed from friends"					
Strongly Disagree	N/A	*reference*		*reference*	
Somewhat Disagree		0.841**	.065	0.839**	.061
Neutral		0.894	.062	.917	.058
Somewhat Agree		0.844**	.059	0.866**	.055
Strongly Agree		0.800***	.065	0.827**	.060
			.103		.094

Note. Reference groups for categorical variables labeled as such. N/A= variables not included in Model 1.
N.T= variables removed from Model 3 due to non-significance. *p<.05. **p<.01. ***p<.001.

Table 3-2

Sensitivity, Specificity, and Correct Prediction Rate by Model

		Predicted Dropout		% Correctly IDed
		0 no	1 yes	
Model 1				
Actual Dropout	0 no	15098	2299	86.8
	1 yes	9883	2865	22.5
Individual prediction accuracy		60.44%	55.48%	59.6[a]
Model 2				
Actual Dropout	0 no	9445	2016	82.4
	1 yes	6148	2572	29.5
Individual prediction accuracy		60.57%	56.06%	59.5[a]
Model 3				
Actual Dropout	0 no	11164	2081	84.3
	1 yes	7232	2637	26.7
Individual prediction accuracy		60.69%	55.89%	59.7[a]

Note. [a] denotes overall model accuracy

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