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Using the Counseling Center Assessment of Psychological Symptoms - 34 (CCAPS-34) to Predict Premature Termination in a College Counseling Sample

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USING THE COUNSELING CENTER ASSESSMENT OF PSYCHOLOGICAL SYMPTOMS – 34 (CCAPS-34) TO PREDICT PREMATURE TERMINATION IN A COLLEGE COUNSELING SAMPLE

by

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ABSTRACT

Swift and Greenberg (2012) observed that variables influencing the decision to drop out fluctuate according to the primary presenting problem, the amount of structure in therapy, the length of treatment, and the clinical setting. Due to these reports, researchers may focus on predictors of premature termination (PT) in treatment settings where the unique situational characteristics may have an idiosyncratic influence on the decision to withdraw from services (Phillips, 1985; Swift & Greenberg, 2012). The purpose of this exploratory study was to examine client characteristics that impact dropout in University Based Clinics (UBC). Results from the logistic regression analysis indicated higher levels of social anxiety and lower levels of pretherapy functional impairment reduced the probability of PT. Findings from the Classification and Regression Tree (CART) analysis suggested higher levels of hostility and generalized anxiety may predict an increase the dropout rate even when accounting for the protective influence of social anxiety and higher levels of pretherapy functioning. Lastly, results from the Survival Analysis suggested the risk of PT was lowest during the early stages of counseling and steadily increased for clients who remained in services. These findings indicate that higher levels of social anxiety and lower levels of pretherapy functioning may partially attenuate the risk of PT as clients progress along the episode of care. Results from this analysis were triangulated against the existing PT literature and implications for teaching, practice, and future research are discussed.

Keywords: Premature Termination, Unilateral Termination, University Based Clinic, Symptom Severity, Functional Impairment

CHAPTER I

INTRODUCTION

Background

Premature Termination (PT) has been referred to as the foremost problem facing mental health providers and researchers (Pekarik, 1985b; Phillips, 1985). PT is also thought to undermine the effectiveness of psychotherapy (Gottschalk, Mayerson, and Gottleib, 1967; Ogrodniczuk, Joyce, and Piper, 2005), contribute to inflated administrative costs (Baekeland and Lundwall, 1975), negatively impact the ability to interpret and generalize research findings (Beckham, 1992; Harris, 1998; Ogrodniczuk, Joyce, and Piper, 2005), and negatively affects the confidence of therapists (Barrett, Chua, Crits-Christoph, Gibbons, Casiano, & Thompson, 2008). Despite years of research, the professional literature has been unable to establish clear correlates and predictors of PT. (Corning and Malofeeva, 2004, Corning, Malofeeva, & Bucchianeri, 2007; Barrett et al, 2008). For those variables that do emerge during data analysis, follow-up studies often fail to replicate research findings (Garfield, 1994, Harris, 1998). Swift and Greenberg (2012) reported premature termination (PT) in counseling may be affected by factors such as the treatment setting, how researchers define dropout, the amount of structure in therapy, and the type of treatments offered. Currently, there is literature examining which predictors of PT are unique to various mental health treatment settings (i.e. inpatient treatment programs, mental health centers, hospitals, etc.). Also, research activity has been focused on which correlates of PT can be associated with a variety of presenting problems (i.e. eating disorders, substance abuse, male batterers, depression, personality disorders, etc.). However, little research appears to have exclusively examined predictors of PT among college students receiving individual services within university counseling centers.

Hyun, Quinn, Madon, & Lustig, (2006) reported that college students represent a diverse clientele with unique social and psychological characteristics. Mennicke, Lent, and Burgoyne (1988), suggested the students seeking services in college counseling centers may represent a unique group that would benefit from independent investigation outside of the broader PT literature. Also, factors contributing to PT are, at least, partially moderated by the presenting problem, and the treatment setting (Swift and Greenberg, 2012). According to epidemiological findings from the American College Health Association (ACHA, 2010), college students face various factors that pose challenges to academic success. Some of the commonly observed challenges include: relationship difficulties (11%), depression (11.7%), concern for a troubled friend or family member (11.9%), anxiety (18.3%), and stress (27.4%). Additionally, the incidence rates of mental health issues observed on college campuses include: attempted suicide (1.3%), self-injury (5.3%), suicidal ideation (6.2%), debilitating depression (30.7%), overwhelming anger (38.2%), feelings of hopelessness (45%), loneliness (56.4%), and sadness (60.7%; ACHA, 2010). A growing debated within the literature concerns the question, are counseling centers observing an increasing number of students with more severe psychological problems (Benton, Robertson, Tseng, Newton, and Benton, 2003; Hoeppner, Hoeppner, and Campbell, 2009). Researchers have used a variety of strategies to measure these trends.

Historically, Stone and Archer (1990) predicted that the mental health needs among college students would steadily rise. Such reported increases have even received attention in the national media, suggesting there is a growing concern for the state of mental health services on college campuses (Shea, 2003). Although the national media reports that the increase in the mental health needs facing college students is an indisputable truth, few firm conclusions can be drawn from the discrepant evidence available in the empirical literature (Heppner, Kivlighan, Good, & Roehlke, 1994; Sharkin, 1997, Benton, Robertson, Tseng, Newton, and Benton, 2003; Sharkin, 2003, Hoeppner, Hoeppner, and Campbell, 2009).

The Counseling Center Assessment for Psychological Symptoms – 34 (CCAPS-34) is a new and emerging instrument. Initially conceived by an expert panel of clinical personnel, the CCAPS-34 provides a brief measurement tool targeting symptoms and presenting problems that most commonly affect students in university settings (Locke et al, 2009). The CCAPS-34 was developed to create a symptom checklist that provides relevant diagnostic information to clinic staff while collecting data that allows researchers to monitor trends in mental health service utilization. Because of its widespread deployment in counseling centers across the nation, unpacking the versatile measurement properties for CCAPS-34, might allow clinicians to further enhance their ability to differentiate clients who run the risk of prematurely terminating mental health services across the during the episode of care.

First, it is well documented that little convergence has emerged in the literature consistently identifying correlates and/or predictors of PT (Baekeland & Lundwall, 1975; Garfield, 1994; Corning & Malofeeva, 2004). Some authors suggest that without a standardized definition of PT, researchers will not be able to replicate results or synthesize their findings across studies (Garfield, 1994; Hatchett & Park 2003). Second, some researchers argue that the cross sectional analytic approaches, often used in the PT literature, are ill suited for measuring a dynamic construct that varies as treatment progresses (Corning & Malofeeva, 2004). Lastly, there is a dearth of literature examining the specific correlates and predictors of PT unique among clients receiving services in University Counseling Clinics (UBC). As mentioned by Bados, Balaguer, and Saldaña, (2007), correlates and predictors of PT may vary according to the primary presenting problem, the treatment setting, and the treatment type (i.e. Cognitive Behavioral Therapy; Psychoanalytic; etc.). For example, among clients receiving inpatient CBT treatment for Anorexia Nervosa, Binge-Purge (ANB) type, childhood sexual abuse, maturity fears, and low self-esteem have emerged in the literature as consistent predictors of early treatment withdrawal (Carter, Bewell, Blackmore, & Woodside, 2006; Halmi et al, 2005; Tasca,, Taylor, Bissada, Ritchie, & Balfour; 2004; Woodside, Carter, & Blackmore, 2004; Zeeck, Hartmann, Bucholz, C., & Herzog, 2005). In contrast, predictors of PT in offender treatment programs have emerged as a complex menu of demographic characteristics, indicators of criminality (i.e. presence of psychopathy, Antisocial Personality Disorder, prior violent offenses, etc.), factors related to treatment responsiveness (i.e. denial, low levels of treatment motivation, poor treatment engagement), and psychological variables (i.e. below average intelligence, presence of personality diagnoses, etc.; Olver, Stockdale, & Wormith, 2011). To date, valid and reliable predictors of PT in UBCs have yet to be identified (Mennicke, Lent, & Burgoyne, 1988).

Because of these concerns, this investigation explored how variables identified in the PT literature and clinical variables measured by the CCAPS-34 influenced early treatment withdrawal. This observational study examined archival data collected from college students receiving services in a UBC. First, this investigation used techniques from the data mining literature to model the capability and accuracy of these variables in predicting termination status. Then this study, modeled fluctuations in the risk of PT as clients progressed along the Episode of Care (EOC)

Problem Statement

After years of research investigators have been unable to derive firm conclusions from the discrepant evidence that has emerged. To date, the literature has been saturated with methodological limitations, inconsistent definitions, and inadequate analytic techniques. Moreover, the PT research also lacks a firm theoretical foundation to drive future research activity. Finally, the stream of research investigating PT in University Counseling Centers remains narrow, with few consistent predictors emerging from the existing analyses. The purpose of this investigation was to model pretherapy client variables that predicted dropout, and how the risk of PT varied as clients progressed in their treatment.

Terms

Binary Logistic Regression (LR)

Is a multivariate approach to data analysis where the dependent variable comprises two binary categories. Unlike ordinary least squares (OLS) regression, binary LR relies on maximum likelihood parameter estimation to model the influence of the predictors on the outcome variables (Field, 2009). This analysis relied on propensity scores to estimate the sensitivity and specificity of the model in predicting completion or dropout.

Classification and Regression Trees (CART)

Classification and regression tree (CART) are relatively new methods that offer an alternative approach for differentiating between groups (Finch and Schneider, 2006). CART modeling is an exploratory multivariate technique drawn from the data mining literature. It is used to identify the relationships between variables and assists researchers in deriving decision-making algorithms (Fawcett, 2006; Kiernan et al, 2002).

College/University Counseling Center

A program embedded within an accredited institution of higher education seeking to provide preventive and remedial services to students and faculty presenting with a broad range of mental health needs. Services include personal counseling, career counseling, vocational guidance, psychiatric services, and psychological testing (Whiteley, Mahaffey, and Geer, 1987).

Episode of Care (EOC)

Time-limited (12 sessions) mental health services provided to a client by the university counseling and psychological services center. The episode of care refers to the client's longitudinal progression in treatment; beginning with the initial intake evaluation and ending with the final counseling appointment (Hamilton, Moore, Crane, & Payne, 2011; Wampold & Brown, 2005)

Missed-last session criteria

Clients were classified as treatment dropouts if they failed to attend their last scheduled appointment or failed to schedule a follow-up session before achieving the treatment goals mutually agreed upon between the client and counselor.

Premature Termination (PT)

A client-initiated withdrawal from therapy prior to achieving the treatment goals mutually agreed upon between the client and counselor (this term is used interchangeably with early dropout, unilateral termination, early withdrawal, attrition, and early termination).

Receiver Operating Characteristic (ROC) Plot

The ROC plot is, "a technique for visualizing, organizing, and selecting classifiers based on their performance (Fawcett, 2006 p. 861)." The ROC curve has been used to graph the performance of medical diagnostic tests and statistic models in correctly detecting group membership.

Survival Analysis

This investigation conducted a Discrete-Time Cox Proportional Hazards (Cox PH) Regression analysis. This analytic strategy falls under a family of statistical modeling techniques called survival analysis. Sometimes referred to as an *event history analysis*, *failure time analysis*, *hazard analysis*, *transition analysis,* and *duration analysis*. This data analytic method predicts the probability or risk that an *event* (a qualitative change) will occur at a specific point in time (i.e. death). This class of techniques treats the dependent variable as a measure of the rate of event occurrence (Allison, 2010).

Treatment Completion

Occurs when client and counselor terminate the counseling relationship after achieving the treatment goals mutually agreed upon between the therapist and client (used interchangeably with mutual termination).

Research Questions

1. What combination of variables assessed by the CCAPS-34 and identified in the PT literature best differentiate between completers and dropouts among clients seeking services in a UBC?

   H_1: In a UBC sample, completers and dropouts will not differ along the dimensions measured by the CCCAPS-34 or outlined in the PT literature.

2. Do variables measured by the CCAPS-34 and identified in the PT literature increase the risk of PT along the episode of care among clients seeking services in a UBC?

   H_2: The covariates measured by the CCAPS-34 and identified in the PT literature will not increase the hazard of PT as the client progresses along the EOC

Theoretical Perspectives

As many authors have noted, the PT literature is saturated with discrepant findings, unclear operational definitions, and inadequate statistical analyses (Barrett et al, 2008; Corning and Malofeeva, 2004; Garfield, 1994; Hatchett & Park, 2003; Swift, Callahan, & Levin, 2009; Pekarik, 1985; Wierzbicki & Pekarik, 1993). Despite years of research into PT, investigators have been unable to synthesize the existing evidence into a theoretical framework capable of explaining and predicting PT. To date, three models have been used to underpin the PT literature (Barrett et al, 2008): Andersen's Behavioral Model of Health Services Use (BMHSU; Andersen,1968/1995), The Barriers to Treatment Model, 1997 (Kazdin, Holland, and Crowley, 1997; Kazdin and Wassell, 2000), and the Delay Discounting Model (Swift and Callahan, 2010). Additionally, five models have emerged in the literature describing how clients progress in treatment. These include the Decay Curve (Phillips, 1985), the Dose Effect Model of Psychotherapy

(Howard, Kopta, Krause, and Orlinsky, 1986), the Phase-Model of Psychotherapy Outcome (Howard, Luger, Maling, and Martinovich, 1993), and the good enough level model (Barkham et al, 1996).

This research project relied upon the Decay/Attrtion Curve (Phillips, 1985/1987), the Phase-Model of Psychotherapy Outcome (Howard, Luger, Maling, and Martinovich, 1993), and the good enough level model (GEL; Barkham et al, 1996). This section will review each of these models and discuss how they were used to conceptualize PT.

Andersen's behavioral model of health services use.

Originally, introduced during the 1960's to predict and explain the utilization of health services, the behavioral model provides a flexible structure for understanding the complex system of variables influencing a clients' decision to seek health care services (Andersen, 1968/1995). According to Andersen (1995), the decision to seek healthcare depends on three general domains: primary determinants of health behavior, health behavior, and health outcomes. Primary determinants of health behavior represent individual and environmental characteristics that influence one's decision to pursue healthcare services. Some examples of these determinants include: gender, age, SES, and social attitudes toward healthcare treatment. Health behavior characteristics refer to personal health practices and how clients use healthcare services. Health outcomes represent the quality of healthcare services available to clients. Factors that influence health outcomes include public confidence in healthcare services, access to services, customer satisfaction, and client improvement. For this proposed research study, the BMHSU provides the foundation for conceptualizing how different variables influence the decision to prematurely withdraw from counseling services. Under this model, the decision to prematurely terminate services is a function of complex dynamics involving individual attitudes, social norms, and the quality of health care services available to clients.

The phase-model of psychotherapy outcome.

Howard, Luger, Maling, and Martinovich (1993) introduced the phase-model of psychotherapy outcome. This model describe clients' progress in therapy as moving through a series of three sequential phases; *remoralization, remediation,* and *rehabilitation.* During the *remoralization* phase, clients may interpret their situation as helpless and perceive themselves as powerless to improve their negative emotional state. Progression through this phase can occur quickly as the client begins to restore their self-efficacy by reactivating their existing coping skills. During the *remediation* phase therapy focuses on the development and implementation of new coping skills to reduce the impact of maladaptive symptoms. Finally, during the *rehabilitation* stage clients continue in treatment to address patternistic behaviors or beliefs that prevent the client's attainment of life goals.

The phase-model of psychotherapy outcome provides conceptual tool regarding therapy as a dynamic process. As clients progress in treatment, different phases of treatment are associated with a unique set of objectives. For this proposed research study, the phase-model will be used to conceptualize dropout as occurring within different phases along the episode of care (EOC). Clients who withdraw from services during the early phases of treatment may be influenced by different factors than those who withdraw during the later phases of treatment. This model provides justification for examining how correlates and predictors of PT influence termination rates differently as clients progress in treatment.

The good enough level model.

Barkham et al (1996) observed that the improvement rates remained stable until treatment progress reached an observed cutoff point, after which the increment appeared to decelerate. Barkham et al (1996) referred this cutoff point as the "good enough level." The good enough level (GEL) model hypothesizes that improvement rates are a function of multiple influences that vary across clients. After the GEL is reached, the rate of improvement may change due to the influence of client, problem, or treatment characteristics. This model holds particular utility for clinicians and administrators, as it emphasizes that improvement rates are variable across clients, clinicians, and presenting problems (Baldwin et al, 2009).

The GEL model suggests that the rate of improvement remains stable until a cutoff point is reached. This observation suggests that clients who withdraw from treatment before reaching the cutoff point may be influenced by different factors than those dropout during later phases of treatment. For this research study, the GEL and phase-model suggest that correlates and predictors of PT may not be static indicators that remain stable across the EOC. Instead, the decision to withdraw from services may be dependent upon a number factors related to personal factors, social characteristics, the quality and accessibility of healthcare services, and progress in treatment.

Procedures

This study is observational in nature and relied on convenient sampling procedures to examine archival data collected from college students receiving services in a UBC. In this program, mental health providers offer time-limited, non-manualized counseling services for individuals, groups, and couples. These services are designed to provide students with support when facing personal, academic, or career-related issues. This researcher analyzed student protected health information (PHI) using *a priori* criteria to determine suitability for participation in the study. This sample was used to develop predictor models that explain early treatment withdrawal in UBC's.

For this investigation the dependent variable under study was treatment status (TS). TS represented a binary variable comprised of two categories: PT or Completed. PT represented (1) a conscious decision by the client to leave treatment, (2), resulting in the discontinuation of counseling against the therapist's recommendations, and (3) divergent from the originally agreed upon duration of treatment. PT was operationalized as a client-initiated, withdrawal from therapy prior to achieving the treatment goals mutually agreed upon between the client and counselor (Baekeland & Lundwall, 1975; Wierzbicki & Pekarik, 1993; Garfield, 1978/1994; Hatchett and Parks, 2003, Ogrodniczuk, Joyce, and Piper, 2005; Corning, Malofeeva & Bucchianeri, 2007). Completion of treatment was defined by one of the following criteria: (1) Client and counselor mutually agreed that treatment goals had been completed. (2) Client remained in counseling until the maximum number of sessions had been reached. (3) Client was referred to an external mental health providers following completion of the maximum 12 sessions. (4) Client and counselor agreed that no further appointments are necessary.

After receiving approval from the Institutional Review Board (IRB), data was collected through a hand search of student protected health information (PHI) securely maintained by the OCS.

Data Analysis

Classification and Regression Trees (CART)

Classification and regression tree (CART) methods were used to differentiate completers from dropouts. CART modeling is an exploratory multivariate technique drawn from the data mining literature. It is used to identify the relationships between variables and assists researchers in deriving decision-making algorithms (Fawcett, 2006). CART Modeling is also a recursive partitioning technique designed to generate rather than test hypothesis (Kiernan et al, 2002). CART methods are useful when researchers aren't clear which variables are influencing a dependent variable.

Classification and regression tree (CART) are relatively new methods that offer an alternative approach for differentiating between groups (Finch and Schneider, 2006). CART modeling is a nonparametric statistic, which uses iterative techniques to divide participants into homogenous groups based on the relationships between the IV and DV. CART modeling has been successfully applied in DNA sequencing, medicine, genetics, epidemiology, and psychological research (Stobl, Malley, and Tutz, 2009).

Binary Logistic Regression (LR)

Binary LR was selected for this analysis because both continuous and categorical variables can be included in the model (Henington, 1996). Although computationally different, Binary LR has become increasingly popular because it yields similar outputs to those produced by OLS regression (Keith, 2006). Like OLS regression, LR is informed by the general linear model and measures the relationships between a series of covariates and the target outcome. However, unlike OLS regression, the target outcome in LR is categorical and are made of two or more levels. For this analysis, treatment status was the target variable, and comprised two levels: dropout or completer. Additionally, multiple regression techniques often rely on ordinary least squares estimation. In contrast, because the outcome variables are categorical and violate the assumption of normality, LR uses maximum likelihood methods to derive parameter estimates (Field, 2009).

Because LR techniques are informed by the general linear model they offer different modeling techniques compared to those underlying the Classification and regression tree (CART) methods. According to Raubertas, Rodewald, Humiston, and Szilagi, (1994), neither technique consistently produces superior estimates of group membership in comparison studies. By comparing the predicted group membership estimates along an ROC plot, this analysis endeavored to derive a precise model capable of predicting group membership for this sample.

Receiver Operating Characteristic (ROC) Analysis

Receiver operating characteristic (ROC) analyses have become popular in the health science literature for measuring the accuracy of medical diagnostic tests and relies on Signal Detection theory (SDT) to compare the probability of correctly identifying someone with a disease against the tests' capability of identifying a patient who is healthy. (Pintea and Moldovan ,2009). SDT is an analytic technique developed by researchers studying psychophysics, cognitive psychology, engineering, and statistics (Link, 1994).

Under this approach, the signal represents a dichotomous outcome variable (i.e. Premature Terminator or Treatment completer) and detection refers to the IVs predicting group membership. Signal detection compares predicted estimates of group membership based on the statistical model to outcome events observed in the data. The statistical package calculates the model's accuracy in predicting group membership. In order to interpret the adequacy of a model in distinguishing between groups, a statistic referred to as *area under the receiver operating characteristic* (AUROC) curve is used. An AUROC ranging from .5 to .7 is regarded as having low accuracy, from .7 to .9 is considered moderately accurate, and > .9 is highly accurate (Steiner and Cairney, 2007). This analysis plotted classifier performance in the ROC space using propensity scores. More simply, the predicted probability of dropping out derived from both analytic models was compared against the observed values in the dataset (Fawcett, 2006).

Survival Analysis (SA)

SA refers to a family of sophisticated analytic techniques used to model how a series of explanatory variables impact the occurrence (conditional probability) of an event along an interval of time (Allison, 1984/2010; Kleinbaum & Klein, 2005; Muthen & Masyn, 2005; Singer & Willet, 1993; Willett & Singer, 1993).). Given the lack of convergence within the PT literature, speculation has emerged that the statistical techniques used to measure predictors of early dropout are inadequate as they assume variables occur within a single point in time (Corning and Malofeeva, 2004; Muthen & Masyn, 2005). Some authors have argued that standard statistical techniques (i.e logistic regression, ordinary least squares [OLS] regression, Analysis of Variance [ANOVA], and Analysis of Covariance [ANCOVA]) are ill equipped for analyzing time-dependent explanatory variables (i.e. age, weight, income, etc.), potentially leading to biased results or a loss of information (Allison, 1984; Willett and Singer, 1994?). As a result, Corning and Malofeeva (2004) warned that the PT literature appears to be saturated with distorted findings and misleading inferences. Corning and Malofeeva (2004) argued that SA techniques may improve the precision of research findings as they provide more information about how the target variables influence PT at various points along the EOC.

CHAPTER TWO

LITERATURE REVIEW

Introduction

This literature review examined, the mental health needs found in college counseling centers; presents the various definitions used to operationalize PT to derive a reliable and valid procedure for studying this phenomenon; surveyed the broader PT research and epidemiological studies to identify crosscutting variables that predict PT across a number of treatment settings and presenting problems; discuss the research on predictors of PT unique to UBCs; examine existing theoretical frameworks used by researchers to underpin PT research.

The literature examining PT among clients receiving services in University Based Clinics (UBC) remains a developing area of inquiry. Swift and Greenberg (2012) found evidence supporting the variability of discontinuation rates across treatment settings, client diagnosis, the length of treatment, the amount of structure in therapy, and therapist level of experience. More research is needed to identify valid and reliable predictors of PT in UBCs (Mennicke, Lent, & Burgoyne, 1988).

Mental Health in College Counseling Centers

The University of Pittsburgh, the American College Counseling Association (ACCA), and the International Association of Counseling Services (IACS) have collaboratively published the annual National Survey of Counseling Center Directors since 1981 (NSCCD; Gallager, 2010). The findings serve as an analogue for mental health trends on college campuses. Since 1995, center directors have observed increases in the number of severe and/or complex mental health cases treated in their clinics

(Gallagher, 1995; Gallagher, 2000; Gallagher, 2005; Gallagher, 2010). In 2005, it was estimated that 42.8% of service recipients were suffering from severe psychological symptoms. In 2010, this number increased to 44% with 6.3% of those students requiring more complex treatments in order to maintain their enrollment. Counseling center directors have also noted increases in crisis issues, psychiatric medication issues, learning disabilities, alcohol abuse, illicit drug abuse, self-injury, on-campus sexual assault, eating disorders, career-planning issues, and problems related to earlier sexual abuse (Gallagher, 2010). Limitations exist with this retrospective method as the results embody perceptions of college counseling center directors instead of true epidemiological trends. The NSCCD is limited to measuring the perceptions of counseling center directors over time. Some evidence in the literature suggests the level of severity in psychological symptoms has remained stable on college campuses (Sharkin, 1997; Benton, Robertson, Tseng, Newton, and Benton, 2003; Hoeppner, Hoeppner, and Campbell, 2009).

A review of the literature suggests that college students face a number of pressures impacting academic performance. According to the National College Health Assessment (ACHA, 2000, [n = 16,024]; ACHA, 2005, [n = 54,111]; ACHA, 2010, [n = 95,712]), students cite a number of stressors that disrupt academic success including: stress (28.6%), sleep difficulties (20.4%), anxiety (19.9%), cold/flu (14.8%), depression (11.9%), and concern for a troubled friend or family member (10.8%; ACHA, 2011). Benton, Robertson, Tseng, Newton, and Benton (2003), analyzed archival data gathered over a 13-year period (n=13,257) from a college counseling center housed in a large Midwestern University. Results from the analysis noted that patterns of substance abuse, eating disorders, legal problems, and chronic mental illness remained stable during the observation period. However, significant increases were observed in abuse (physical, sexual, and emotional), anxiety, depression, suicidal ideation, sexual assault, relationship problems, stress/anxiety, family issues, physical problems, and personality disorders. Sharkin (2003) urged caution when interpreting these findings and recommended that researchers need more stringent criteria to classify severe psychological phenomena. He highlighted the difficulty with classifying presenting problems as primarily developmental, or psychologically disordered. He further argued that researchers should reserve the term severity for students who present with diagnosable conditions that interfere with academic success. Sharkin concluded that if Benton et al (2003) had classified severity differently, the evidence may have suggested that mental health problems were stabilizing rather than increasing (Sharkin, 2003).

Hoeppner, Hoeppner, and Campbell (2009) also researched increased psychopathology for college students. Results from their analysis did not indicate that college counseling centers are treating students with more severe mental health needs. Hoeppner, Hoeppner, and Campbell, analyzed an archival sample of 6,675 students at a UBC between 1993 to 2005. The purpose was to analyze trends in service utilization over a span >10 years using the criteria recommended by Sharkin (2003), Results from their investigation suggested that the need for mental health services among college students and the severity of psychopathology had remained stable.

Design limitations for Hoeppner, Hoeppner, and Campbell's (2009) study mirror those reported in Sharkin's (2004) review of Benton et al (2003). Although the data collection period was extended past 10 years, investigators did not offer specific parameters for determining severe psychopathology, and limited external validity by relying on archival data gathered from a single UBC (Hoeppner, Hoeppner, and Campbell, 2009).

It remains unclear if UBC's have observed significant increases in the number of clients reporting mental health concerns, relationship problems, or psychopathology. It is clear from the evidence that college students continue to face pressures impacting their mental health and disrupting academic success. Clear evidence has yet to emerge definitively supporting an increase in the severity of symptoms and/or the prevalence of complex mental health diagnoses. The research described in this section drew from large, longitudinal datasets, but those represent a small subset of the larger population. Further research with nationally representative samples is needed to uncover true epidemiologic trends.

Counseling Center Assessment of Psychological Symptoms (CCAPS-34/CCAPS-62)

The Center for Collegiate Mental Health was established in 2005 as a large-scale national research initiative to investigate the mental health needs of college students across the nation (CCMH, 2010). Their mission was to advance the understanding of mental health in the college setting, and to improve the provision of mental health services. Three instruments were created to gather epidemiological and clinical data; the Standardized Data Set (SDS), the CCAPS-62, and its shorter version, the CCAPS 34.

The CCAPS is a data collection mechanism for conducting large-scale research while also serving as a clinically relevant psychometric tool for practicing clinicians. The test developers designed an instrument to ensure administration and scoring could be completed without compromising staff resources (CCMH, 2010; Locke et al. 2011). Two symptom checklists were created: 1) the CCAPS-62 and 2) the CCAPS-34. Although, the

CCAPS-62 takes seven to ten minutes to complete, the CCMH began receiving requests for a shorter version (CCMH, 2010). The development team used item response theory (IRT) techniques to reduce the item pool without compromising information (CCMH, 2010; Locke et al, 2012). The final version resulted in the CCAPS-34, which measures seven subscales: Depression, Eating Concerns, Substance Use, General Anxiety, Hostility, Social Anxiety, and Academic Distress.

CCAPS-34

The CCAPS-34 is a self-administered questionnaire that can be completed by paper and pencil or through a *Titanium Schedule* software system. This system operates as a web-based networking tool, collecting and aggregating data gathered from all participating UBCs. Scoring can be completed by hand, through the *Titanium Schedule* software system, or through a Microsoft Excel scoring program (CCMH, 2010). Although, the CCAPS-34 is designed to be administered at the beginning and at the end of treatment, longitudinal administration throughout the EOC can be used to provide time series data (CCMH, 2010; Locke et al, 2010; Locke et al, 2012). Items on the CCAPS-34 are scored along a 5-point, Likert-type rating scale (*Not at all like me -0, 1,2,3,4 - Extremely like me*). Neither instrument produces a composite score as each subscale is treated as a discrete construct.

The CCAPS-34 uses two scoring procedures. First, normative scores are obtained by comparing raw scores (arithmetic mean for a subscale) against the percentile tables located in the testing manual (CCMH, 2010). The CCAPS-62 and the CCAPS-34 both use percentile rankings to interpret test scores against clinical norms derived from a large sample of college students. Percentile ranks are limited in their ability to determine if the degree of change is due to the effect of the therapeutic intervention or if the degree of change can be attributed to measurement error (Jacobson & Truax, 1991; CCMH, 2010).

The CCAPS-34 measures therapeutic gains using a reliable change index (RCI). The RCI)is used as an alternative method to measuring therapeutic improvement where clinically significant change is defined as, "The level of functioning subsequent to therapy places that client closer to the mean of the functional population, than it does to the mean of the dysfunctional population (pg. 13; Jacobson and Truax, 1991)." RCI scores represent the minimum amount of change (either positive or negative) that must occur before the change can be attributed to something other than measurement error. This index represents a robust alternative to percentile rankings because it is calculated using the raw scores from each subscale at various test administrations, (Jacobson & Truax, 1991; CCMH, 2010).

The implementation of the CCAPS-34 in college counseling centers offers a practical symptom checklist specifically tailored to examine those mental health issues often treated in UBC's, and can provide clinical data for researchers to examine client variables that influence early treatment withdrawal. This study will be able to capitalize on the widespread use of this instrument to effort to examine its capability in distinguishing clients at higher risk of early treatment withdrawal.

Operationalizing Premature Termination

The literature examining premature termination (PT) often analyzes the differences between clients who prematurely withdraw from therapy against those who continue to completion. Investigators would benefit from an empirically derived definition of PT that can represent a discrete construct comparable across studies

(Hatchett & Park, 2003). PT researchers use an assortment of terms; attrition, dropout, early termination, early withdrawal, and unilateral termination (Swift, Callahan, and Levine, 2009). Researchers have also relied on intuitive but inconsistent operational definitions. This variability may have contributed to the lack of consistent findings despite decades of research into psychotherapy dropout. Failure to use a standardized construct for research may prevent the accurate comparison of research findings (Baekeland & Lundwall, 1975; Hatchett & Park, 2003; Pekarik, 1985; Sharf, Primavera, and Diener, 2010; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993).

Another constraint is the differences in how clients are categorized as completers or dropouts. The *treatment duration* method categorizes dropouts as those who failed to attend a certain number of sessions. In addition, various researchers selected different cutoff points (ranging from 3 to 10 sessions). Clients who left treatment before reaching the cutoff point were classified as terminators. Those who continued were defined as completers. Opponents of this method argued that clients who terminate counseling during the early stages of treatment may be influenced by different factors than clients who dropout later. Clients under this classification system could represent multiple groups with unique, statistically independent, characteristics and outcomes (Baekeland & Lundwall, 1975).

Another criticism suggests treatment duration is problematic because clients may withdraw prematurely after achieving positive therapeutic gains whereas others may complete treatment without improvement (Baekeland & Lundwall, 1975; Pekarik & Wierzbicki, 1993; Pekarik, 1986, Garfield, 1994). Pekarik (1985) empirically tested treatment duration as a reliable and valid construct and concluded that treatment duration is an ineffective classification system incapable of distinguishing premature terminators from mutual completers. Pekarik, urged researchers to avoid describing PT under the traditional duration-based method and suggested using therapist judgment instead.

Hatchett and Park (2003) examined the relationship between termination rates and interrater agreement across four operational definitions of PT. After calculating PT rates under each definition, they measured interrater reliability for detecting early treatment withdrawal. Results from this analysis suggest that two definitions (1. *therapist judgment* and 2. *missed-last session criteria*) produce termination rates consistent with the previous literature. Both definitions also produced considerable interrater agreement between therapeutic providers. Alternative definitions including *median-split method* or *intake only,* observed inflated estimates of PT with lower interrater reliability.

Hatchett and Park (2003) suggested that *missed last session criteria* would produce the most reliable comparisons across studies and recommended this definition as the most appropriate index. They also proposed that researchers measure the rate of clinically significant change just before termination. Under this method, clients whose scores fell within the clinically significant range are classified as dropouts while those who fall within the normal range would be considered as completers.

Swift, Callahan, & Levine (2009), examined the utility of this method against other classification systems commonly referenced in the literature. Their findings did not support using clinically significant change as an independent approach. However, the results did suggest that researchers may extend their description to include (a) clients who were classified as dropouts despite achieving recovery, or (b) clients who were classified as completers without achieving recovery.

The PT literature uses a variety of operational definitions to categorize clients as completers or dropouts. It is important for investigators to rely on empirically derived methods for categorizing early treatment withdrawal in order to increase the accuracy of research findings (Swift, Callahan, and Levine, 2009; Swift and Greenberg, 2012). This study used the term PT interchangeably with dropout, attrition, early termination, PT, early withdrawal, discontinuation, and unilateral termination According to Ogrodniczuk, Joyce, and Piper (2005), the term PT denotes (1) a conscious decision by the client to leave treatment, (2), the discontinuation of treatment that is against the therapist's recommendations, and (3) divergent from the originally agreed upon duration of treatment. For this investigation, PT was defined as a client-initiated, withdrawal from therapy prior to achieving the treatment goals mutually agreed upon between the client and counselor (Baekeland & Lundwall, 1975; Wierzbicki & Pekarik, 1993; Garfield, 1978/1994; Hatchett and Parks, 2003, Ogrodniczuk, Joyce, and Piper, 2005; Corning, Malofeeva & Bucchianeri, 2007).

Correlates and Predictors of Premature Termination

This section will expand our focus beyond college treatment centers and survey the literature across a broad range of treatment settings. The purpose is to narrow the field of variables identified in the literature down to a series of indicators that have the most consistent and robust influence on termination rates for all types of therapy. Also, this review will survey the epidemiological research to learn how PT manifests in nationally representative samples.

Baekeland and Lundwall (1975) reviewed empirical findings suggesting that a number of variables may place clients at greater risk for prematurely withdrawing from treatment. Such variables included age (<25), gender, socioeconomic status, insecure attachments to others, occupational, marital, or residential instability, aggressive or passive aggressive behavior, sociopathy, drug dependence, and the desire to seek help.

Baekeland and Lundwall (1975) also highlighted conceptual limitations that inhibited the advancement of PT research proposing that conventional wisdom failed to account for the variability among clients who unilaterally withdrew from treatment at different points along the EOC. In addition, some clients left counseling after achieving positive therapeutic gains, suggesting that PT is not a negative therapeutic outcome in all cases. They concluded that these findings suggest that motivations for dropping out of treatment may be linked to the amelioration of symptoms and/or the point during therapy at which a client withdraws. They also proposed that symptom severity should be considered an influential factor in PT. Its degree of influence was unclear as findings showed variability across treatment settings and presenting diagnoses. For example, in outpatient mental health settings, clients with lower levels of depression and anxiety were at increased risk of PT. In substance abuse programs, these same diagnoses were associated with a lower risk of PT (Baekeland and Lundwall, 1975). Although the influence of symptom severity remains unclear in the literature, recent findings reviewed by Barrett et al (2008) lent further support to its relationship with PT.

Field dependence (FD) emerged as an important variable associated with PT. FD refers to an individual's cognitive style representing one's sense of self in relation to others. As clients advance in their development, their sense of individuality moves from a dependent to differentiated sense of self. A client who is FD may look for others to guide their decision-making because their sense of self is heavily influenced by referent cues from others. Clients who rely less on the social environment and more on their own internal frame of reference are described as field independent (FI; Witkin, Goodenough, & Ottman, 1979).

Researchers hypothesized that FI clients would be more autonomous, self-reliant, and possess stronger psychological boundaries. Researchers hypothesized that these characteristics would place them at greater risk for PT (Baekeland and Lundwall, 1975). The utility of this variable remains unclear as findings from independent samples produce discrepant outcomes. Results have sometimes produced counterintuitive findings directly refuting the proposed hypothesis (Baekeland and Lundwall, 1975). Because field dependence-independence has received little attention in the recent PT research, little is known about its relationship to early treatment withdrawal.

Baekeland and Lundwall (1975) also identified treatment provider characteristics that may increase the risk of PT. The therapist variables include ethnocentrism, dislike for their clients, and aversion to medication. Therapists who exhibit such characteristics were more often male, detached, too permissive, had a tendency toward introversion, and frequently cancelled appointments. Baekeland and Lundwall (1975) also noted client-counselor relationship variables including discrepant treatment expectations and having multiple treatment options as potentially linked to early treatment withdrawal.

Garfield (1978/1994) conducted a follow-up comprehensive literature review examining the research on correlates of PT in psychotherapy. Garfield's focus differed from Baekeland and Lundwall's (1975) as he narrowed his field of literature to recipients of mental health services and appeared more cautious in formulating conclusive interpretations (Pekarik, 1985). He found that the median number of sessions attended was six. This distribution follows a negatively accelerating curve with a sizable majority of clients terminating treatment by the end of the 10th session. Garfield noted there is a lack of convergence within the scientific literature and emphasized that the research of the era made little progress in identifying reliable and stable predictors of PT.

Findings from Garfield's (1978/1994) review did emphasize that recipients of psychotherapy prefer short-term treatment approaches. He also highlighted the conceptual difference between cancellations and no-shows, reporting that no-shows tend to be correlated with higher rates of PT, and that variables commonly examined in the PT research including sex, age, occupation, income, and psychiatric diagnoses appear unreliable. Although race did emerge in the literature as a predictor of PT, few researchers attempted to partial out the variance accounted for by social class factors, producing inflated estimates of predictive utility. Garfield (1978/1994) reviewed a number of studies investigating the use of personality assessments as potential tools for identifying clients at risk of PT. Findings suggest that neither the Rorshach nor the MMPI were able to predict PT across clinical settings. According to Garfield's findings, empirical support was only obtained for SES and level of education as reliable predictors of PT. Garfield also cautioned that the effect of education on PT is small.

Pekarik (1985) focused his review on the impact of discrepant expectations among clients and service providers in terms of treatment duration. Pekarik suggests that clients expect short-term treatment approaches, to immediately begin relevant interventions, and may settle for a modest level of improvement. Pekarik emphasized that although SES appears statistically related to PT, discrepant expectations predict PT across all socioeconomic categories, and theorized that discrepant expectations for treatment duration and the failure to establish mutually agreed upon goals could inflate the risk of PT. Pekarik found that clients expect psychotherapy will last for approximately 10 sessions, whereas therapists tend to view psychotherapy as taking place over a longer time period (Garfield, 1978/1994; Koss, 1979; Pekarik, 1985).

Results from the literature reviews suggest that clients often withdraw from treatment before the 10th session. These findings suggest that clients may designate treatment length in spite of the therapist's recommendations (Garfield, 1978/1994; Pekarik, 1985). Further, these findings lend support to the hypothesis that clients only attend treatment until a crisis has abated (Baekeland and Lundwall, 1975; Pekarik, 1985). In some cases, PT is only early withdrawal from the therapist's perspective, whereas the client determines that sufficient treatment gains have been achieved to warrant the discontinuation of services. SES and level of education emerged as consistent pretreatment variables correlating to PT, although the size of their effect on early treatment withdrawal remained unclear. Interaction variables associated with the therapeutic alliance provided preliminary groundwork for the development of strategies to reduce the rate of PT. Finally, the influence of age (<25), gender, insecure attachments to others, occupational, marital, or residential instability, aggressive or passive aggressive behavior, sociopathy, drug dependence, field dependence-independence, symptom severity, and the desire to seek help remained unclear.

Meta-Analytic Evidence.

The literature reviews discussed to this point attempted to synthesize the vast network of empirical findings contributing to PT. The lack of convergence and supporting data for inferences proposed by researchers are addressed by five meta-analyses on PT (Pekarik and Wierzbicki, 1993, Sharf, Primavera, and Diener, 2010, Swift, Callahan, and Volmer, 2011, Olver, Stockdale, and Wormith, 2011, and Swift and Greenberg, 2012). This review examines four of these investigations given their relevance to PT in a UBC. The review conducted by Olver, Stockdale, and Wormith (2011) is excluded as research findings were strictly focused on variables influencing dropout in offender treatment programs.

Pekarik and Wierzbicki (1993) conducted the first meta-analysis of the PT research and found that the pooled mean dropout rate was 46.86% (95% CI=[42.9, 50.82]) across treatment settings. An analysis of variance (ANOVA) examining the rate of PT among different treatment approaches, clinical settings, and demographic groups did not produce significant mean differences. However, significant mean differences were found when different definitions of PT were used. These findings lent support to the argument that conflicting definitions in the PT literature can influence discontinuation rates. They also examined the pooled effect sizes for sex, race, age, education, SES, and marital status. Results suggested that clients who are African American, are under educated, and/or come from a low SES are at greater risk for prematurely terminating treatment. This analysis was limited to six demographic variables

Sharf, Primavera, and Diener (2010) conducted a meta-analysis on 11 studies to examine the relationship between therapeutic alliance and premature termination. Additionally, Sharf, Primavera, and Diener tested the moderating effects of age, education, ethnicity, treatment length, primary diagnosis, treatment setting, and definition of dropout on the relationship between therapeutic alliance and PT. Results suggest that clients, in dyads which had a weaker therapeutic alliance, were more likely to withdraw from treatment. Although the relationship between therapeutic alliance was statistically significant, the strength of the relationship was moderate (d=.55 95% CI [.37, 73]). Also, educational history (< 12^{th} grade; >12^{th} grade), treatment length, and setting were observed to have statistically significant moderating effects on the relationship between therapeutic alliance and premature termination. Although these results support previous empirical findings, the relationship between therapeutic alliance and PT yield moderate effect sizes. These findings suggest that while the therapeutic relationship is an important influence, there are other unexamined forces that may impact a client's decision to prematurely leave treatment.

Swift, Callahan, and Vollmer (2011) conducted a meta-analysis on 38 studies examining the influence of client preferences on therapeutic outcomes including: 1) role preferences, 2) therapist preferences, and 3) treatment preferences. Role preferences represent how clients and therapists negotiate their activity in session. Some clients may prefer the therapist to be more directive, whereas other clients prefer that the counselor assumes a more passive role. Therapist preferences comprise ideal characteristics that clients would like their therapist to possess. For example, clients may hold preferences regarding their therapists' gender, experience, or age. Treatment preferences refer to the clients desired format for the interventions used during counseling. Some clients may only be interested in pharmacotherapy but not in psychosocial treatment, whereas other clients may be interested in individual counseling but refuse group therapy. Results indicate that preference matching reduced the likelihood of PT (OR=5.59, $p < .001$ 95% CI [.44, .78])

Swift and Greenberg (2012) conducted the most recent meta-analysis on 669 studies representing nearly 84,000 participants. According to their findings the pooled dropout rate across treatment settings was 19% (95% CI [18.7%, 20.7%]). These findings represent a more conservative and precise measure of PT than the dropout rate 46.86% (95% CI=[42.9, 50.82]) published by Wierzbicki and Pekarik (1993). A number of variables relevant to this investigation were observed to increase the risk of early treatment withdrawal including younger age (d=.16; 95% CI [.07,.24], p <.008; k=52) , clients treated in a UBC (30.4%; 95% CI [26.6%,34.4%]; k=53), diagnosis (Q= 93.58, p < .001), clients receiving treatment that was not time limited (29%; 95% CI [26.6%, 31.6%]; k=131), or treatment that wasn't manualized (28.3%; 95% CI [25.9%, 30.7%]; k = 138). Termination rates were not affected by race, employment status, treatment orientation, individual or group treatment, or provider demographic characteristics (age, race, or gender). Swift and Greenberg also used meta-analytic and meta-regression techniques to examine the influence of client gender, marital status, and level of education on PT. Results from the meta-regression analysis indicated that committed relationships may serve as a protective barrier against the decision to withdraw from services. Significantly higher rates of PT were also observed in studies with a higher percentage of male subjects. Client age and diagnoses were observed as the most robust predictors of PT. Consistent with findings published by Wierzbicki and Pekarik (1993), the dropout rate was affected by the definition used to operationalize PT. Swift and Greenberg (2012) observed that more experienced therapists have lower dropout rates when compared against trainees. The authors theorize that this discrepancy is related to the greater emphasis experienced therapists place upon the therapeutic alliance. These findings are consistent with those reported by Sharf, Primavera, and Deiner (2010) suggesting that the relationship between the therapeutic alliance and PT is moderated by treatment length, setting, and therapist experience.

These findings suggest that early attempts to measure the rate of PT produced inflated estimates. The 46.86% dropout rate reported by Pekarik and Wierzbick (1993) was a function of early meta-analytic techniques. Using a random effects model, Swift and Greenberg (2012) observed an average weighted dropout rate of 19%. UBC's were observed to have the highest rate compared against other treatment settings. Empirical findings also support the hypothesis that dropout rates found are sensitive to the operational definition used by researchers. These findings suggest the need for a standardized definition of PT to guide research. Another finding suggests that therapeutic relationship has a robust but moderate effect on the decision to withdraw from treatment across treatment settings. This finding is also consistent with the psychotherapy outcomes literature suggesting that the therapeutic alliance is a consistent but moderate predictor of positive treatment outcomes (Wampold et al 1997; Fluckiger, Del Re, Wampold, Symonds, and Horvath, 2012). Variables observed to moderate the relationship between the therapeutic alliance and PT include educational history (< 12th grade; >12th grade), treatment length, and clinical setting. Findings also suggest that younger age, diagnosis, having a less experienced therapist, and receiving treatment that wasn't time limited or manualized are significant correlates of PT. In contrast to previous research dropout rates were not affected by race, employment status, treatment orientation, individual or group treatment, or provider demographic characteristics (age, race, or gender).

Epidemiological Research.

Another approach to PT research examines early treatment withdrawal from an epidemiological perspective. This targeted approach places early treatment withdrawal in the context of large-scale population patterns. Epidemiological studies also compare termination rates across medical and psychosocial treatments provided by medical and mental health professionals.

Edlund et al (2002) conducted an epidemiological study on clients who received mental health treatment in the United States and Canada to uncover patterns and identify global predictors associated with PT from pharmacotherapy, talk therapy, combined talk therapy and pharmacotherapy, and spiritual counseling. Findings from their analyses produced an unweighted dropout rate of 19% supported previous research that clients younger than 25 were at higher risk for PT (OR=1.64, $p < .05$ 95% CI [1.01–2.64]). The authors speculated that these findings could be linked with a) the greater reliance young people have on others to attend appointments or b) the greater dysfunction associated with early onset mental illness. Clients who received concurrent treatment with medication and psychosocial techniques were more likely to remain in treatment. Positive treatment outcomes remained stable if the combined treatment methods were provided by a general practitioner (pharmacotherapy) and a nonmedical professional (talk therapy). Finally, clients who do not believe in the efficacy of mental health treatments were more likely to withdraw from treatment. According to Edlund et al, when compared against respondents who felt very comfortable with mental health treatment, those who reported being very uncomfortable were around 2.46 times more likely to dropout of treatment (OR = 2.4, 95% CI=[1.4–4.1]). Respondents who reported feeling somewhat uncomfortable with mental health treatment were approximately 2.7 times more likely to dropout of treatment (OR=1.6, 95% CI=[1.1-2.2]). Finally, those respondents who felt somewhat comfortable with treatment were roughly 1.6 times more likely to dropout (OR=1.6, 95% CI=[1.1-2.2]). When compared against respondents who believe in the efficacy of mental health treatment, respondents who did not were about 1.6 times more likely to dropout (OR=1.6, 95% CI = [1.2-2.2]).

Wang (2007) conducted a follow-up to the Edlund et al (2002) study. Results from this analysis found that clients who believe mental health treatment is ineffective had a higher rate of dropout (29.3% 95% CI=[(23.5,35.1]). Clients who presented with more severe distress also had a higher rate of PT (34.1%, $p < .05$, 95% CI=[28.5,39.8]) and were roughly 1.39 times more likely to withdraw from services (OR=1.39, 95% CI=[1.0,1.92]). Wang observed that dropout rates varied among mental health treatment providers. Termination rates across provider specialty were: 1.) Family doctors/ general practitioners=11.8% (95% CI = [10.0,13.6]); 2.) Other medical doctors= 17.7% (95% CI=[9.8-25.5]); 3.) Any medical doctor=19.4% (95% CI=[17.3, 21.4]); 4.) Religious advisors=19.9% (95% CI=[14.0, 25.8]); 5.) Social Workers/Therapists = 20% (95% CI=[16.3-23.8]); 6.) Psychologists=21.9% (95% CI=[17.3, 26.4]); 7.) Any health professional=22.4% (95% CI=[20.4, 24.3]). 8.) Psychiatrists=22.7% (95% CI=[18.8, 26.7]); 9.) Alternative medicine practitioners=24.8% (95% CI=[13.9,21.4]); 10.) Nurses=29.1% (95% CI=[21.3, 36.8]). These findings show higher rates of PT among clients treated by psychiatrists and psychologists when compared against primary care physicians. The authors speculated that mental health specialists encounter more complex and chronic mental health conditions that are inherently difficult to treat. Wang also reported that dropout rates from mental health treatment may be lower than other chronic medical conditions. Reviewing findings from previous epidemiological studies Wang reasoned that the average, unweighted dropout rate from mental health treatment (22.3%) may be lower than other chronic medical conditions including: 1.) Hypertension (33%); 2.) Rheumatoid arthritis (31 – 41%). Lastly, clients between the ages of 15 – 25 (30.1%, $p < .001$, 95% CI= [24.6,35.6]), nonwhite (24.3%, 95% CI=[17.1,31.6]), and/or diagnosed with a mood (31.0%, $p < .001$, 95% CI= [27.2, 34.8]), anxiety (28.2%, $p < .005$, 95% CI= [23.6, 32.6]), or substance abuse disorder (40.8%, $p < .001$, 95% CI= [33.7, 48.0]) were at increased risk of PT.

The most recent epidemiological investigation (*n*=693) conducted by Westmacott (2010) focused on identifying variables that differentiate clients who prematurely withdraw from treatment because they feel better than from those who are dissatisfied with their progress. Results from the analysis found that the most frequent reasons for withdrawing from treatment were feeling better (43.4%), belief that psychotherapy wasn't helping (14.1%), or the course of therapy had been completed (13.4%). Other results from the analysis supported previous findings that a low-income status would increase the odds of citing therapy as unhelpful as a reason for PT. Finally, the presence of substance dependency, mood, or anxiety disorders decreased the odds of reporting that improvement in therapy had contributed to their early withdrawal. A major limitation is that clients who endorsed more than one reason for PT were excluded from the final analysis although previous research shows that clients who unilaterally withdraw from treatment endorse multiple reasons contributing to their decision (Westmacott, Hunsley, Best, Rumstein-McKean, & Schindler, 2010).

These findings suggest that age (<25) is a robust predictor of PT across treatment settings, modality, provider, and clinical presentations. Other findings include clients who do not believe in the efficacy of mental health treatment are less likely to continue services whereas those who have experienced positive change are more likely to remain; mental health treatment providers appeared to have higher rates of PT when compared against primary care providers, suggesting that the complex diagnostic profiles encountered by mental health specialists could influence the decision to withdraw; and the rate of PT in psychotherapy may be lower than treatments for chronic medical conditions such as diabetes and hypertension. These findings appear to suggest that the decision to withdraw from treatment may be linked to the chronicity and complexity of the presenting problem, experiencing positive gains in treatment, and believing that mental health treatment is effective.

Premature Termination in University Based Clinics

According to Swift and Greenberg (2012), UBC's have the highest termination rates when compared against other treatment settings, and the authors speculate that these findings are due to a higher proportion of younger clients and trainee clinicians than are found in other treatment settings. PT from treatment has been investigated across a number of clinical settings (Baekeland and Lundwall, 1975), but the topic of dropout in UBC's appears to be an evolving area of inquiry.

Rodolfa, Rappaport, and Lee (1983), investigated the differences between treatment completers and dropouts using numerous therapist, client, and administrative variables. They found that clients assigned to practicum students were more likely to withdraw from treatment. Another finding was the rate of PT increased as the length of time from intake until assignment to a counselor increased. Tracey (1986) measured the influence of therapeutic alliance on PT, and used topic determination (TD) to describe the mutuality of treatment expectations between client and therapist. Tracey defined TD as, "the proportion of topic initiations that were subsequently followed by the other participant (pg. 785)." Results from the analysis showed that poor topic determination during early sessions could be used to predict lower client satisfaction ratings and PT. Implications for these findings emphasized the importance of establishing clear roles between the client and counselor while also negotiating which topics are to be discussed in counseling.

Martin, McNair, & Hight (1988), used the hypothesis that clients prematurely terminate from UBC's because they do not view their therapists as expert, attractive, or trustworthy with a survey that also asked their reasons for prematurely withdrawing from treatment. Results did not support the hypothesis that clients withdrew from treatment because they found their therapist untrustworthy or viewed them as unattractive or unskilled. Other reasons for withdrawal included that they didn't have the time, felt they no longer needed treatment, or forgot their appointments.

Hynan (1990) also investigated client reasons for prematurely withdrawing from treatment and hypothesized that early terminators would provide different reasons than late terminators for why they withdrew from treatment. Early termination was operationalized as attending five or fewer sessions, and late termination was operationalized as attending six or more sessions. Hynan, surveyed 31 student participants who had prematurely terminated counseling services for anxiety or depression. Results from the chi-square analysis suggested that late terminators reported withdrawing because they had improved and felt therapy was no longer needed. Additional findings suggested that early terminators cited situational constraints preventing them from continuing in therapy and discomfort with counseling as reasons for withdrawing from services. There are two limitations associated with this research design. First, the sampling procedure excluded subjects who sought services after the first 24 weeks of the academic calendar resulting in a restricted sample size. Also, empirical findings have demonstrated that using a median-split method to operationalize PT produces inflated dropout rates (Hatchett and Park, 2003).

Kokotovic and Tracey (1990) wanted to test if a poor working alliance would predict PT in a UBC, using Hotelling's T^2 to differentiate between dropouts and completers. The variables used to measure working alliance were client and counselor agreement on treatment plan, agreement on interventions, the bond between client and counselor, client's satisfaction with treatment, overall adjustment, educational concerns, emotional arousal, public speaking, and intimate relationships. Findings suggest that none of the variables could be used to differentiate among treatment completers and dropouts. Although such findings were unexpected, the methodological-analytic techniques used in this research may have had two constraints; one, constraint is that it used a restricted definition of PT defined as failure to attend more than four counseling sessions or failure to continue in treatment after the initial session; and second single administration of the instruments used to measure the variables during the initial session. The resulting analysis appears to reflect a cross-sectional perspective, rather than approaching data collection longitudinally. Longitudinal or time-series data have been recommended in the literature as uniquely suited for PT research (Corning and Malofeeva, 2004). The results from Koktovic and Tracey's (1990) analysis contradict recent meta-analytic evidence suggesting that a poor working alliance (Sharf, Primavera, and Diener, 2010) and failure to match the treatment to client preferences (Swift, Callahan, and Vollmer, 2011) may significantly impact rates of PT.

One problem that may hinder the understanding of PT is that many studies analyze arbitrary variables that are not informed by a theoretical framework (Mennicke et al., 1988; Longo, Lent, & Brown, 1992). One study that did use a theoretical framework was the one by Longo, Lent, and Brown (1992) that tested the applicability of self-efficacy from Bandura's social cognitive theory (Bandura, 1986) to explain and predict PT. Findings lent preliminary support for the predictive utility of self-efficacy in differentiating completers from dropouts. However, results from the analysis should be interpreted with caution as the findings yielded a small effect size which indicates that the predictors were inadequate in fully differentiating completers from early terminators.

Levy, Thompson-Leonardelli, Smith, and Coleman (2005) used a sample of 1,461 participants to measure the predictive possibilities of race, time on waiting list, presenting problem, and attrition. The logistic regression analysis results showed that African American (AA) clients were less likely than European American (EA) clients to return for counseling following the intake session regardless of presenting problem; that clients who were on a waiting list for longer than three weeks were less likely to return; and that EA clients were more likely to return than all other ethnic groups if the wait time was 3 weeks or less. Previous research suggests that SES moderates the relationship between race and treatment withdrawal, meaning that AA clients of low SES are more likely to withdraw from treatment than AA clients who fall under the middle of high SES categories (Mennicke, Lent, and Burgoyne, 1988). Researchers should be cautious when using race as a variable without accounting for the moderating effect of SES.

Westmacott, Hunsley, Best, Rumstein-McKean, and Schindler (2010), examined the divergent experiences reported by clients and therapists when reporting the reasons behind premature termination in terms of working alliance and barriers to treatment. Their findings supported the hypothesis that clients who prematurely withdrew from treatment would rate situational barriers, dislike for the therapist, and the desire to end treatment over and above the desire to accomplish treatment goals. They also found that counselors tended to assign a higher rate of psychological distress to clients who withdrew from treatment early. Other findings were that clients who prematurely withdrew from treatment cited multiple reasons for terminating treatment unilaterally, whereas treatment providers only identified a few, and that the development of a strong working alliance by the end of the third session would predict the termination type. These findings highlight the importance of the working alliance in establishing mutually agreed upon roles between the counselor and client, diagnosis, treatment planning, and interventions.

Lampropolous, Schneider, and Spengler (2009) examined predictors of early termination among college students receiving services in a training clinic under the care of graduate student interns. An archival sample was used (n=380) to develop a predictor model capable of differentiating clients who complete treatment from those who prematurely withdraw from services. Findings showed a 16% dropout rate after intake, a 57.4% dropout rate from therapy, and a 26.6% completion rate. Additional findings were that client age, income, perceived difficulty, and functional impairment were influential in classifying clients who would prematurely withdraw from treatment, and that functional impairment (measured by GAF score at intake) was identified as the only statistically significant variable in the 4-predictor model to have a large effect on the decision to withdraw. Results from this study provided evidence supporting the influence of functional impairment at intake.

Another variable that may contribute to PT in UBCs is the use of trainees as treatment providers. Swift and Greenberg (2012) found that the pooled mean termination rate in UBC's is approximately 30.4% (95% CI [26.6%, 34.4%], but that the termination rate among clients receiving services from graduate trainees is 26.6% (95% CI [22.2%, 31.5%]). Such evidence suggests that these findings may not be directly translatable to UBC's where clients receive services from experienced treatment providers. More research is needed to examine the moderating effect of therapist level of experience on the relationship between functional impairment and the decision to prematurely terminate counseling services.

Romans et al (2011) examined the influence of symptom distress at intake on premature termination. Their findings suggest that women who report higher levels of symptom distress at intake are at greater risk for PT. The authors reported that these results are novel and of concern, as prior research findings have failed to support gender differences in unilateral termination.

In summary, clients receiving services from trainee clinicians and those with higher functional impairment were more likely to drop out of treatment. The rate of PT also increased with longer waiting lists. Further, clients who withdraw during initial sessions often cite situational barriers as the reason for withdrawal. Clients who withdraw during later phases of treatment are more likely to report their presenting symptoms had improved and further therapy was unnecessary. Findings also suggest that a positive working alliance is associated with the decision to remain in treatment. Dyads with a strong working alliance and collaborative topic determination observed lower dropout rates. Clients were also at greater risk of PT if a strong working alliance was not established by the third session.

Empirical evidence also suggests that clients who withdraw from treatment cite multiple reasons for their departure. Some of these include; obtaining treatment goals and deeming further therapy unnecessary, inability to incorporate therapy into their schedule, experiencing external barriers, forgetting to attend, and dislike for the therapist or discomfort with the counseling process. Researchers also examined how therapists conceptualized PT. Findings suggest that counselors assign a higher rate of psychological distress to dropouts and their attributions for why clients choose to withdraw from services aren't consistent with those offered by clients.

Results from the reviewed studies provide some empirical support for the importance of establishing and maintaining a positive working alliance. Consistent with reported by Swift, Callahan, and Vollmer (2011), these findings also suggest that discrepant treatment or role preferences could increase the rate of PT. These findings also highlight the influence of external barriers, therapist experience, and functional impairment on PT. Although a strong therapeutic alliance is a robust predictor of treatment completion and positive outcomes, its effect size is consistently moderate (Wampold et al 1997; Fluckiger, Del Re, Wampold, Symonds, and Horvath, 2012; Sharf, Primavera, and Deiner, 2010; Swift and Greenberg, 2012). This evidence highlights that other contributing factors have yet to be identified such as; the influence of pretreatment variables on PT and the influence of these variables controlling for covariates such as age, functional impairment, therapist experience, manualized versus non-manualized treatments, treatment length, diagnosis, and therapeutic alliance.

Theoretical Models of Premature Termination

Much of the research examining PT investigates arbitrary variables that aren't determined by a theoretical framework (Mennicke et al., 1988; Longo, Lent, & Brown, 1992), and this has led to the difficulty in synthesizing existing evidence into a theoretical framework capable of explaining and predicting PT. To date, three models have been used to underpin the PT literature: Andersen's Behavioral Model of Health Services Use (1968/1995), The Barriers to Treatment Model, 1997 (Kazdin, Holland, and Crowley, 1997; Kazdin and Wassell, 2000), and the Delay Discounting Model (Swift and Callahan, 2010). Although each of these models has been introduced in the professional literature, more research is needed to investigate the utility of each model in explaining PT. Each model is briefly discussed below.

Andersen's Behavioral Model of Health Services Use (BMHSU).

The BMHSU provides a flexible structure for understanding the complex system of variables influencing the decision to seek health care services (Andersen, 1968/1995). His model proposes that the useof health care services depends on three general domains: primary determinants of health behavior, health behavior, and health outcomes (see figure 1-1).

The primary determinants of health utilization behavior contain three subcategories: 1) population characteristics, 2) the healthcare system, and 3) the external environment. Population characteristics represent predisposing and enabling factors. Predisposing variables explain how both individual and socio-environmental characteristics influence the decision to pursue healthcare services, and are characteristics such as: demographics of race, age, and gender; social structure such as culture, social network, social interaction, education, occupation, and ethnicity;, health beliefs such as attitudes, values, and knowledge of health; genetic factors; and psychological such as, cognitive deficits, mental dysfunction, and autonomy). Enabling or inhibiting factors are variables that may improve or hinder access to healthcare services. These variables include the individual's status in the community, available resources such as . money, social networking, health insurance; and the ability to cope with problems. The health care system refers to organizational/systemic characteristics that influence health policy, the availability of health resources in the community such as adequate access to inpatient psychiatric beds, and how changes in health policy fluctuate over time. The external environment describes physical characteristics of the environment such as; rural, urban, crime rates, etc.; political influences, and economic variables.

The second general domain includes health behavior and is divided into two clusters: personal health practices and the use of health care services. Personal health practices are behaviors such as diet, exercise, and self-care. The use of healthcare services refers to the type of health care services accessed, the setting, and the reason for seeking services.

The last domain examines health seeking outcomes which is divided into three separate factors; perceived health status, evaluated health status, and consumer satisfaction. Perceived health status is the degree to which both professionals and the general public believe that current services are effectively maintaining or improving public health. Evaluated health status refers to the effective access to the selected services that are shown to improves health, and efficient access, such as when health status improves with increased utilization and consumer satisfaction. All of these serve as additional outcome measures for assessing utilization (see figure 1 for a graphical depiction).

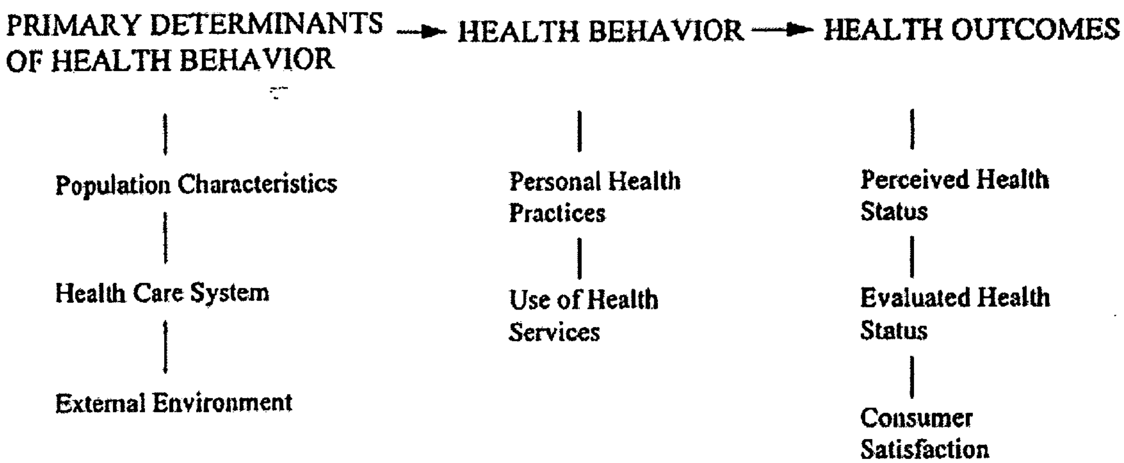


Figure 1. Andersen's Behavioral Model of Health Services Use. from, "Revisiting the behavioral model and access to medical care: Does it matter? " by R. Andersen, 1995, *Journal of Health and Social Behavior*, 36, p.2. Copyright by SAGE publications, Inc. Reprinted with permission (see Appendix J).

Barriers-to-Treatment Model.

The barriers-to-treatment model was originally developed to provide researchers with a conceptual tool to aid in understanding and predicting PT. This model proposes that therapy may be viewed as an inconvenient and demanding task (Kazdin and Wassell, 2000). Kazdin, Holland, and Crowley (1997) write that clients encounter barriers that interfere with treatment progress and inhibit motivation to continue receiving services. Kazdin (1996) found that clients who encounter multiple treatment obstacles are at greater risk for prematurely terminating treatment. The *barriers-to-treatment* model lists three general barriers: structural barriers, perceptions about mental health problems, and obstructive perceptions about mental health services (Owens et al, 2002). Structural barriers refer to external obstacles preventing access to treatment; such as a lack of health insurance, inadequate coverage, a lack of qualified providers, transportation difficulties, unreasonable service costs, and difficulties in accessing services. The perceptions about mental health problems barrier refer to internally held attitudes by the individual that may limit or prevent access to treatment services. Such perceptions may include minimization of the mental health problem, failing to recognize the existence of a mental health diagnosis, and inadequate perceptions about the ability to control mental health symptoms. Obstructive perceptions about mental health services describe negative beliefs about treatment that may inhibit the decision to initiate or remain in therapy. These may include negative experiences with previous treatment providers and social stigma surrounding mental health treatment (See Figure 2; Owens et al, 2002).

Structural	Perceptions about mental health problems	Perceptions about mental health services
• Lack of health insurance • Inadequate coverage • Lack of qualified providers • Transportation difficulties • Unreasonable service costs • Difficulties in accessing services	• Minimization of the mental health problem • Failing to recognize the existence of a mental health diagnosis • Inadequate perceptions about the ability to control mental health symptoms	• Negative experiences with previous treatment providers • Social stigma surrounding mental health treatment

Figure 2. Barriers-to-Treatment model

Delay Discounting Model.

The delay discounting model seeks to explains how the value of a reward decreases as the time until its received increases (Green & Myerson, 2004; Swift & Callahan, 2010). When faced with two potential outcomes, delay discounting represents the decision to choose between a small- but received sooner reward versus a larger- but received later reward (Madden & Johnson, 2010). For example, when presented the choice to accept a $5.00 payment today versus a $10.00 payment in two weeks, delay discounting represents the individual's decision to discount the value of the larger-later reward ($10.00) in favor of the smaller-sooner reward ($5.00).

The delay discounting model uses an individually determined decision-making process that depends upon an individual's needs and unique situational contexts. As the delayed time until receipt is extended, observers may notice fewer and fewer people choosing to wait for the larger - later reward. The individual discounts the value of receiving the $10.00 reward in approximately 3-months versus accepting the $5.00 payment today.

The delay discounting model has been introduced as a potential framework to understand PT (Swift & Callahan, 2010). Evidence in the literature suggests that the median number sessions attended are near six and as the length of treatment increases, the number of clients who continue in therapy falls. Garfield (1995) reports that the majority of clients withdraw from treatment by the tenth session. The delay discounting model appears to warrant further investigation as a potential conceptual framework to underpin research into PT. A delay discounting measure of treatment expectancy could allow clinicians to determine a client's desired recovery rate and how many sessions a client will tolerate before dropping out. The utility of this model in predicting PT has yet to be examined empirically. More research is needed before firm conclusions can be made about the role of delay discounting in early treatment withdrawal

Dose-Effect Literature.

This section will discuss four models discussed in the professional literature including: the decay curve, the dose-effect model, the phase model of psychotherapy outcomes, and the good enough level model.

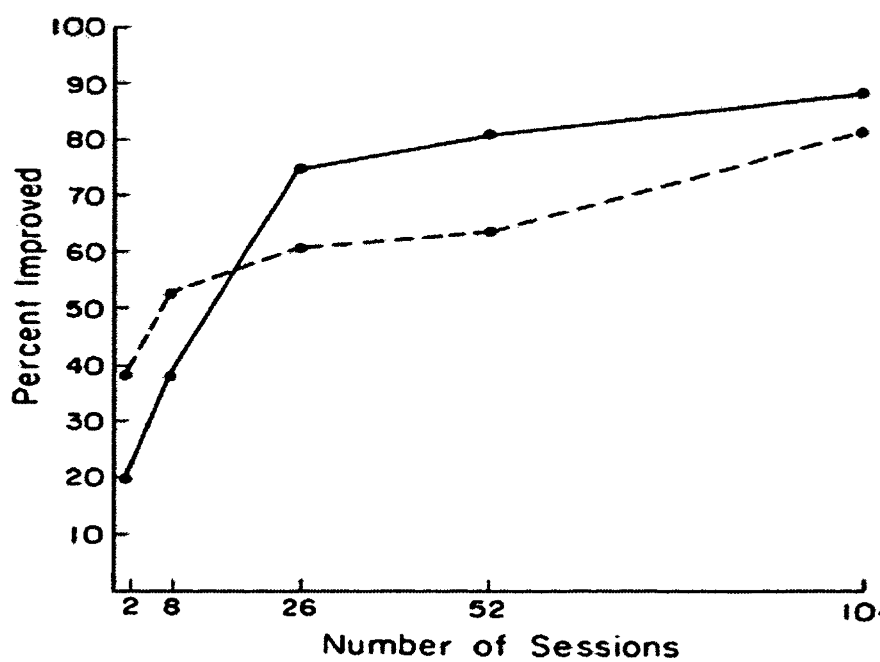
Garfield (1978/1994) reported that the median number of counseling sessions attended is six. This distribution follows a negatively accelerating curve with most clients terminating services after the 10th session, and the findings emphasize that short-term treatment approaches are preferred (Garfield, 1978/1994; Koss, 1979; Pekarik, 1985). Pekarik (1985) also suggests that clients may settle for a modest level of improvement and may designate treatment length in spite of the therapist's recommendations (Garfield, 1978/1994; Pekarik, 1985). These findings suggest that the decision to withdraw from treatment may be due to clients feeling that they have achieved acceptable gains in treatment and deem further therapy unnecessary.

Examining how termination rates vary at different points along the course of treatment would permit a better understanding of what motivates clients to prematurely withdraw from services based upon their level of improvement in therapy, and the number of sessions attended.

Decay curve. Baekeland and Lundwall's (1975) found that approximately 20 – 57% of clients drop out after the initial session and 31 – 56% withdraw before completing 4 visits. Phillips (1985) reported evidence from the literature suggesting that the mean number of sessions attended is 4.7. Phillips also reported that 27 – 70% of clients show marked improvements between 1 and 3 months of treatment and another 18% improve between 4 – 6 months of treatment. Phillips (1985) concluded that the termination rate was an unstable construct that appeared to vary along the course of treatment. He also believed such findings provided evidence for the existence of a decay curve.

Phillips (1985/1987) proposed that, as the length of treatment increases, the number of clients participating in therapy and the degree of marked improvement appears to steadily decline creating a negatively accelerating, decline curve. Phillips argued that focusing on the attrition curve could allow identification of therapist, client, and policy variables that are affecting continuation in treatment. He also proposed that attrition research needs to focus on how the therapeutic encounter adapts to the client's needs and how unique characteristics within the delivery system interact to increase the risk of premature termination.

The dose-effect model of psychotherapy. Howard, Kopta, Krause, and Orlinsky (1986), introduced the dose-effect model of psychotherapy to describe that positive therapeutic gains progress along a negatively accelerating function of treatment length. Early research into this model suggested that positive therapeutic gains (effect) increase as the numbers of sessions (dose) accumulate. Preliminary findings illustrated that 10-18% of clients improve prior to the first session, 48-58% of clients improve after 8 sessions, 75% improve after 6-months, and 85% of clients can be expected to show improvements after a year of treatment (Howard, Kopta, Krause, & Orlinsky, 1986). Also, as the numbers of sessions rise, the rate of improvement contracts leading to larger therapeutic gains during the earlier stages of treatment and smaller incremental gains at later stages, and that the dose-effect relationship varies according to the presenting problem. The findings reported by Howard, Kopta, Krause, and Orlinksy (1986) showed that 50% clients suffering from depressive disorders or anxiety symptoms showed improvement between 8 and 13 sessions. In contrast, 50% of clients who fell on the borderline-psychotic diagnostic continuum, reported that they had improved between 13 and 26 sessions, whereas treatment providers documented improvement occurring between 26 and 52 sessions. Follow-up research lent further support to the dose-effect hypothesis, demonstrating that clients experiencing distress symptoms such as anxiety, depression, and obsessive-compulsive disorder, recover at a faster rate when compared against clients presenting with characterological symptoms, such as hostility, paranoid ideation, psychoticism, sleep disturbances, and overeating (Kopta, Howard, Lowry, and Beutler, 1994).



Note. Objective ratings at termination are shown by the solid line; subjective ratings during therapy are shown by the broken line.

Figure 3. Dose-Effect Response to Psychotherapy

Phase-model of psychotherapy outcome. Howard, Luger, Maling, and Martinovich (1993) introduced the phase-model of psychotherapy outcome. This model describe clients' progress in therapy as moving through a series of three sequential phases; *remoralization, remediation,* and *rehabilitation. Remoralization* refers to the enhancement of the client's subjective well-being. Prior to treatment, clients may interpret their situation as helpless and perceive themselves as powerless to improve their negative emotional state. Progression through this phase can occur quickly when the clinician and/or client engage in activities that increase the client's sense of hope and locus of control such as setting up an appointment, taking steps to improve one's situation. The *remoralization* phase can restore hope which provides clients with the motivation and self-efficacy to reactivate their existing coping skills. The *remediation* phase refers to the middle stage of psychotherapy that focuses on the development and implementation of new coping skills to reduce the impact of negative symptomatology. The *rehabilitation* stage describes what is popularly viewed as psychotherapy (Howard, Luger, Maling, and Martinovich, 1993). Clients in this stage choose to continue in treatment to address patternistic behaviors or beliefs that prevent the client's attainment of life goals. This model is consistent with empirical findings reported by Kopta, Howard, Lowry, and Beutler, (1994), showing that distress symptoms achieve a faster rate of recovery than characterological symptoms. Also, the dose-effect and phase models of psychotherapy have each received empirical support in the literature (Lutz, Lowry, Kopta, Einstein, and Krause, 2001; see Figure 4 for a graphical depiction).

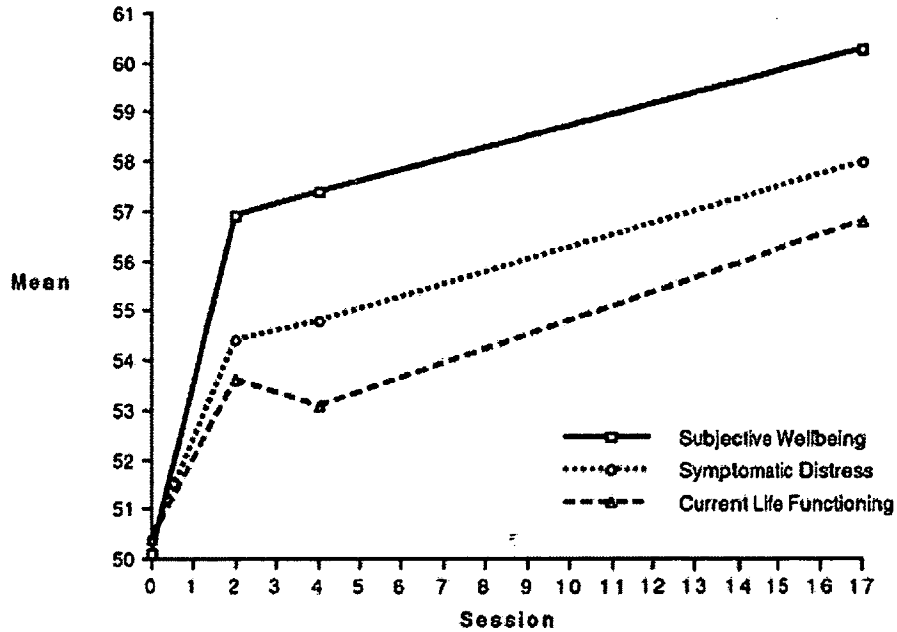


Figure 4. Phase Model of Psychotherapy Outcome

The good enough level model. Barkham et al (1996) cautioned that previous methods used to measure the dose-response curve assume that the rate of improvement remains constant across all participants, but this assumption unintentionally excludes those participants who experienced rapid improvement and discontinue treatment after reaching their target goals (see Figure 5). Barkham et al (1996) conducted a randomized controlled trial to investigate both the pattern of negative acceleration and the hypothesis that different symptoms respond variably to the number of treatment sessions. Their analysis was unable to replicate the standardized negative acceleration documented by Howard et al (1986) until after session 16. This result showed that the improvement rate remained stable until treatment progress reached an observed cutoff point, after which the increment appeared to decelerate. Barkham et al (1996) referred this cutoff point as the "good enough level." The good enough level (GEL) model hypothesizes that improvement rates are a function of multiple influences that vary across clients, for example, after the GEL is reached, "the rate of improvement might vary depending on the characteristics of the problem, characteristics of the client, or characteristics of the treatment, and as a consequence, different problems would take a different numbers of sessions to reach their GEL (p. 161)."

This model holds particular utility for clinicians and administrators, as it emphasizes that improvement rates are variable across clients, clinicians, and presenting problems (Baldwin et al, 2009). Programs seeking to limit the number of treatment sessions may unintentionally favor clients who show rapid improvement while obstructing therapeutic gains for those who progress at a slower rate and require a higher dosage of sessions.

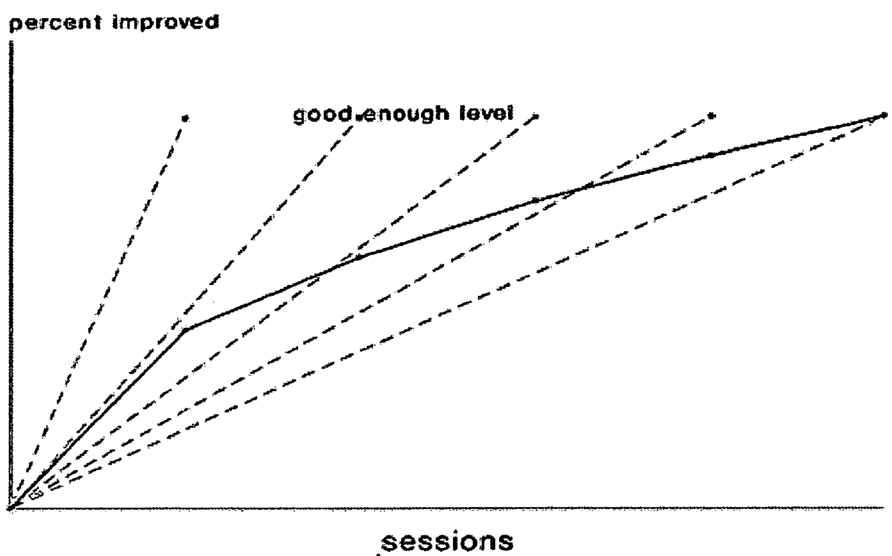


Figure 5. The Good Enough Level Model

In summary, the median number of counseling sessions attended were six, and this distribution followed a negatively accelerating curve with most clients terminating services after the 10^{th} session. Researchers have observed that clients may settle for a modest level of improvement and may place limits on the length of therapy in spite of treatment recommendations (Garfield, 1978/1994; Pekarik, 1985). These findings seem to suggest that recipients of psychotherapy prefer short-term treatment approaches and attend treatment until a crisis has receded (Baekeland and Lundwall, 1975; Garfield, 1978/1994; Koss, 1979; Pekarik, 1985). Swift and Greenberg (2012) found evidence suggesting the long-term treatments are associated with a higher risk of PT, which is consistent with earlier findings.

Phillips (1985/1987) found that as the length of treatment increases, the number of clients participating in therapy and the degree of marked improvement appears to steadily decline. Howard, Kopta, Krause, and Orlinsky (1986) found that 10-18% of clients improve prior to the first session, 48-58% of clients improve after 8 sessions, 75% improve after 6-months, and 85% of clients can be expected to show improvements after a year of treatment. Kopta, Howard, Lowry, and Beutler, (1994) found that clients presenting with characterological symptoms must stay longer in treatment before achieving marked improvement. Barkham et al (1996) showed that the rate of improvement differs across participants and is a function of treatment characteristics, the clinical setting, and client characteristics. They also suggested that the rate of improvement increases steadily until a cutoff point, referred to as the "good enough level", was reached. These findings appear consistent with those offered by Swift and Greenberg (2012). In their analysis, those presenting with eating disorders or personality disorders were higher risk for PT when compared against clients presenting with mood, psychotic, or anxiety disorders. This finding could have implications for PT researchers by accounting for clients receiving long-term treatment are also at higher risk of PT. Results from this vein of research also suggests that as clients pass through the stages of treatment (remediation, remoralization, and rehabilitation), therapeutic gains are affected by the nature of the problem, unique characteristics of the client, and characteristics of the treatment. Once therapeutic gains advance to a good enough level, the rate of improvement will begin to decelerate. These findings are also consistent with prior research reporting that clients may withdraw from treatment once the crisis has been resolved or they have achieved a level of recovery sufficient for them to decide that no further treatment is necessary (Baekeland and Lundwall, 1975; Garfield, 1978/1994; Koss, 1979; Pekarik, 1985; Phillips. 1985). An examination of these findings appears to suggest that the decision to withdraw from treatment may be due to clients achieving acceptable gains and deeming further therapy unnecessary, and that the decision to remain in treatment is impacted by different variables dispersed along the EOC. The purpose of this investigation is to determine how client variables impact the decision to withdraw from services as treatment progresses.

CHAPTER THREE

Methodology

Chapter three provides a detailed account of the methodological procedures used to conduct this analysis. This study is descriptive in nature to illustrate the clinical utility of the CCAPS-34 in predicting PT among service recipients in a college counseling center. This section will document the purpose of this study, the research questions and hypotheses, research design and rationale, participants, sampling procedures, data analysis procedures, variables, instrumentation, threats to internal and external validity, limitations, and delimitations.

Purpose

This study investigated the capability of the CCAPS-34 and variables identified in the PT literature for differentiating between completers and dropouts. This study also analyzed the risk of PT in a UBC as treatment progresses along the EOC. Finally, this study investigated the development of a practically useful model capable of helping clinicians identify clients at the greatest risk of PT.

Research Questions

Research Question 1

What combination of variables assessed by the CCAPS-34 and identified in the PT literature will best differentiate between completers and dropouts among clients seeking services in a UBC?

Hypothesis

In a UBC sample, completers and dropouts will not differ along the dimensions measured by the CCCAPS-34 or outlined in the PT literature.

Research Question 2

Do variables measured by the CCAPS-34 and identified in the PT literature increase the risk of PT along the episode of care among clients seeking services in a UBC?

Hypothesis

The covariates measured by the CCAPS-34 and identified in the PT literature will not increase the hazard of PT as the client progresses along the EOC.

Participants

This analysis relied upon archival data, gathered since 2009, from the counseling and psychological services (CAPS) center housed within Old Dominion University. The researcher analyzed student protected health information (PHI) using *a priori* criteria to determine suitability for participation in the study. The inclusionary criteria required that: 1) All participants must have been enrolled as either undergraduate or graduate students while receiving services or be employed through the university in a staff or faculty position; 2) All participants must have received mental health counseling services in the UBC clinic where investigators will collect and analyze the data; 3.) All participants must have signed a written consent form agreeing that their records may be used for future research prior to initiating counseling services; 4.) Service recipients must have begun services after the CCAPS-34 was implemented in daily practice by clinic staff. 5.) Clients who receive an intake but do not meet criteria for counseling services will be excluded. 6.) Participants receiving couple or group counseling services will also be excluded.

Data Collection

All data was collected from Old Dominion University's (ODU) Office of Counseling Services (OCS). The OCS program is located in the Webb Center on ODU's main campus. Therapeutic providers offer time-limited, non-manualized counseling services for individuals, groups, and couples. These services are designed to provide students with support when facing personal, academic, or career-related issues. This study drew from a sample of undergraduate and graduate students enrolled in ODU who have received counseling services in the OCS program. This sample was used to develop predictor models that explain early treatment withdrawal in UBC's. This investigation relied on archival data collected during routine treatment services. The principal investigator did not have direct contact with participants and no experimental manipulation was applied. A data collection research assistant (employed by the OCS program) examined electronic health records under supervision from the counseling center director. All data was recorded using a codebook developed for this investigation.

Precautions were developed to ensure client information is protected. All data was anonymized and secured to protect participants from violations of privacy and/or breaches of confidentiality. No identifying information was used in the analysis such as, employer names, relatives names, university identification numbers, home addresses, e-mail addresses, social security numbers, emergency contact information, or telephone/fax numbers.

After receiving approval from the Institutional Review Board (IRB), data was be collected through a search of student protected health information (PHI) securely maintained by the OCS. The following guidelines were used to prevent any inappropriate or unintended disclosure of student PHI: 1.) All data collection was conducted onsite by a research assistant employed by the principal investigator; 2.) All identifiable information was removed from the codebook and subsequently mailed to the principle investigator for analysis. All data was anonymized prior to leaving the clinic and direct access to student files was prohibited for anyone other than OCS employees.

Instrumentation

Counseling Center Assessment of Psychological Symptoms - 34

The CCAPS-34 is 34-item, multi-factorial symptom checklist designed to gather data describing the mental health needs of college students, while still maintaining functional clinical utility for practitioners (Locke et al, 2012). According to the CCMH (2010), the CCAPS-34 uses scores measured along a 5-point Likert-type rating scale (*not at all like me* to *extremely like me*).

The CCAPS-34 is the short form version of the Counseling Center Assessment for Psychological Symptoms – 62 (CCAPS-62). Researchers began receiving requests for a shortened version that would allow for multiple administrations (Locke et al, 2012). Using classical test theory (CTT) and item response theory (IRT) methods, researchers measured the performance of each item as it related to the target construct (for a detailed description of the procedures see Locke et al, 2012). This narrowing process allowed researchers to remove items without reducing the measurement properties of each subscale.

During a large-scale validation study, researchers used Cronbach's α to assess for internal consistency. Reliability estimates ranged from.822 to .915 on the CCAPS-62 and from .824 to .876 on the CCAPS-34 (CCMH, 2010). The following table depicts: 1) the internal consistency values for each subscale on the CCAPS - 34, 2) the number of items contained in each subscale, and 3) the range of internal consistency values identified by Ponterotto and Ruckdeshel (2007) representing the adequacy of reliability estimates.

Table 1

Internal Consistency of the CCAPS-34

Subscale		# of Items	Adequacy Estimates*	
Depression	.876	6	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70
Generalized Anxiety	.825	6	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70
Social Anxiety	.824	5	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70
Academic Distress	.824	4	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70
Eating Concerns	.890	3	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70
Hostility	.843	6	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70
Substance/Alcohol Use	.826	4	Excellent	.85
(*N*=19,247)			Good	.80
			Moderate	.75
			Fair	.70

Test – retest reliability estimates after 1 week (*n*=86) ranged from .792 to .866 and from .742 to .864 after 2 weeks (*n*=47; Locke et al, 2012). Construct validity was assessed using a Confirmatory Factor Analysis (CFA). The reported model fit statistics lent support to the hypothesized factor structure ($S \square B \square^{2} (506) = 1096.05 P < .001$; CFI=.98; NNFI=.98;RMSEA=.49 [CI 90% (.045, .053)];SRMR=.063).

Convergent validity was examined by comparing the performance on each subscale of CCAPS-34 to an established psychometric measure including: The Alcohol Use Disorders Identification Test (AUDIT, Saunders, Aasland, Babor, de la Fuente, and Grant, 1993), Beck's Depression Inventory (BDI; Beck, Ward, Mendelson, Mock, and Erbaugh, 1961), the Beck Anxiety Inventory (BAI; Beck, Epstein, Brown, Steer, 1988), Social Phobia Diagnostic Questionnaire (SPDQ; Newman, Kachin, Zuellig, Constantino, & Cashman-McGrath, 2003), the Student Adaptation to College Questionnaire (SACQ; Baker, & Siryk, 1984; Baker, & Siryk, 1986) , the Eating Attitudes Test (EAT-26; Garner & Garfinkel, 1979, Garner, Olmstead, Bohr, & Garfinkel, 1982; Mintz & O'halloran, 2000), State-Trait, Anger Expression Inventory-2 (STAXI-2; Spielberger, 1999), Self-report Family Inventory (SRFI; Beavers, Hampson, & Hulgus, 1985; Beavers, Hampson, & Hulgus, 1990).

Table 2

Comparison of CCAPS-34 Subscales to existing assessment tools

CCAPS – 34 Subscale	Corresponding Psychometric Instrument
Alcohol Abuse	Alcohol Use Disorders Identification Test (AUDIT)
Depression	Beck's Depression Inventory (BDI)
Generalized Anxiety	Beck Anxiety Inventory (BAI)
Social Anxiety	Social Phobia Diagnostic Questionnaire (SPDQ)
Academic Distress	Adaptation to College Questionnaire (SACQ)
Eating Concerns	Eating Attitudes Test (EAT-26)
Hostility	State-Trait Anger Expression Inventory (STAXI-2)

A non-clinical sample of 483 undergraduate students (mean age of 18.49) who received course credit for participation was used for the analysis. The Pearson product moment correlations between the corresponding instruments ranged from .520 (the Eating Concerns subscale with he EAT-26) to .77 (the Alcohol Abuse subscale and the AUDIT; Locke et al 2012). The measurement properties for the CCAPS-34 reported by Locke et al (2012) suggest that this instrument will be suitable for this investigation. The performance for each subscale of the CCAPS-34 will be assessed prior to the data analysis and compared against the psychometric properties discussed above.

Procedures

Outcome Variable

For this investigation the dependent variable under study was treatment status (TS). TS represented a binary variable comprised of two categories: PT or Completed.

Dummy coding was used to categorize clients into either group. Completer will be dummy coded as 0 and PT will be coded as 1.

PT represents (1) a conscious decision by the client to leave treatment, (2), resulting in the discontinuation of counseling against the therapist's recommendations, and (3) divergent from the originally agreed upon duration of treatment. PT was defined as a client-initiated, withdrawal from therapy prior to achieving the treatment goals mutually agreed upon between the client and counselor (Baekeland & Lundwall, 1975; Wierzbicki & Pekarik, 1993; Garfield, 1978/1994; Hatchett and Parks, 2003, Ogrodniczuk, Joyce, and Piper, 2005; Corning, Malofeeva & Bucchianeri, 2007). As recommended by Swift and Greenberg (2012), this investigation used two methods for categorizing clients as completers or dropouts: missed last session criteria and therapist judgment. Using these procedures PT was characterized by one who (1) fails to schedule or attend any subsequent appointments, and (2) the counselor determines that treatment was discontinued. Withdrawal from treatment must occur before treatment goals have been achieved and before reaching the mutually agreed upon number of sessions.

Completion of treatment was defined by one of the following criteria: (1) Client and counselor mutually agreed that treatment goals have been completed. (2) Client remained in counseling until the maximum number of sessions had been reached. (3) Client was referred to an external mental health provider following completion of the maximum 12 sessions. (4) Client and counselor agree that no further appointments are necessary.

Design

A non-experimental design methodology was selected as this investigation seeks to observe naturalistic events without the manipulation of an independent variable (Johnson, 2001; Wiersma and Jur 2009). This study is observational in nature and will rely on convenient sampling procedures to examine archival data collected from college students receiving services in a UBC. According to findings reported by Swift and Greenberg (2012), the rate of PT in UBC's was approximately 30.4% (95% CI [26.6%, 34.4%]). The base termination rate reported by Swfit and Greenberg (2012) was used to compare results from this analysis against an empirically derived benchmark.

Data Analysis

As mentioned above, these analyses modeled the capability of the CCAPS-34 and variables identified in the PT literature in differentiating between completers and dropouts. To overcome concerns cited in the literature regarding inadequate analytic techniques, this investigation implemented various statistical procedures commonly used in medical research. The analytic strategy for research question 1 drew from the methodological procedures introduced by Lampropolous, Schneider, and Spengler (2009), while the analytic strategy for research question 2 drew from the techniques used by Corning and Malofeeva (2004). Analyses were conducted using EQS, SAS 9.3, and the Statistical Package for the Social Sciences (SPSS) version 20.0.0.

For this analysis, variables identified in the PT literature and the subscales measured by the CCAPS-34 were used to derive a model capable of predicting group membership. All data was collected through a search of electronic client records and recorded using the coding sheet listed under Appendix A.

This analysis examined the following predictor variables drawn from the PT literature age, gender, marital status, academic status, race/ethnicity, and functional impairment. Functional impairment is a continuous independent variable measured by client scores on the Global Assessment of Functioning (GAF) scale obtained during intake (APA, 2000; Endicott, Spitzer, Fleiss, and Cohen, 1976). To measure the influence of symptom severity on PT, the following clinical variables measured by the CCAPS-34 were evaluated: GA, Depression, Social Anxiety, Academic Distress, Eating Concerns, Hostility, and Substance/Alcohol Use. Treatment status serveed as the criterion/grouping variable and comprised two levels: completers and dropouts (see Appendix B for the list of variables included in the analysis and a detailed codebook).

Research question 1. This analysis took place in 4 phases: 1) Building the Logistic Regression Model (Hosmer and Lemeshow, 2004), 2) Fitting the Logistic regression model to the data, 2) Growing a classification and regression tree (CART), and 3) Comparing the predictive accuracy for each model along the Receiver Operating Characteristic (ROC) Curve.

Logistic regression analysis. First, the data was modeled using a binary logistic regression (LR) analysis. Because LR techniques are informed by the general linear model they offer different modeling techniques compared to those underlying the Classification and regression tree (CART) methods. According to Raubertas, Rodewald, Humiston, and Szilagi, (1994), neither technique consistently produces superior estimates of group membership in comparison studies. By comparing the predicted probability of group membership (propensity scores) along an ROC plot, this analysis attempted to determine which model is more accurate in predicting group membership for this sample. Odds ratios, the log-likelihood, standard errors, the Wald statistic, the Hesmer-Lemeshow goodness of fit index, and the chi-square goodness of fit indexes from the LR analysis will be examined to determine which covariates can be removed to derive an optimal but parsimonious model.

To obtain the best fitting model, the purposeful selection macro written for SAS 9.3 was used to systematically narrow the field of covariates (Bursac, Gauss, Williams, & Hosmer, 2007; Hosmer and Lemeshow, 2002). Results from the model-building procedure identified SA, GA, and GAF as important contributors. The purposeful selection procedure entered all explanatory variables (e.g. age, gender, marital status, academic status, race/ethnicity, functional impairment, Depression, Generalized Anxiety, Social Anxiety, Academic Distress, Eating Concerns, Hostility, and Alcohol Abuse) into a series of univariable logistic regression models. Explanatory variables with a p value $< .25$ were retained for the analysis. Using the remaining variables, a series of multiple logistic regression models were fitted to the data. The purpose of this step was to examine each variable's influence on overall model fit when other covariates are included in the analysis. Because Generalized Anxiety, Social Anxiety, and Functional Impairment were shown to alter model fit when removed, these variables were retained. Finally, all covariates are analyzed for interactions effects and entered into the model. No interaction effects were noted. Propensity scores were calculated to compare specificity and sensitivity estimates between the LR and CART models.

Classification and regression tree (CART) analysis. The classification and regression tree (CART) methods were used to differentiate completers from dropouts. Because predictive discriminant analysis (PDA) assumes that the independent variables operate on a continuous scale (Henington, 1994; Keith, 2006), CART methods were selected in order to account for categorical independent variables. CART modeling is an exploratory multivariate technique drawn from the data mining literature. It is used to identify the relationships between variables and assists researchers in deriving decision-making algorithms (Fawcett, 2006). The goal of this analysis was to provide identify common characteristics shared by clients who prematurely terminate services.

CART Modeling is a recursive partitioning technique (Kiernan et al, 2002). CART methods are appropriate in this investigation for two reasons. First, recursive partitioning methods are exploratory techniques useful for generating new hypotheses as opposed to hypothesis testing strategies often employed in counseling research (Kiernan et al, 2000). Because there is no theoretical foundation or firm empirical conclusions available in the literature, a systematic approach is needed to inform the variables included in the hazard model. Also, recursive partitioning models are sensitive to misclassification (i.e. false positives, false negatives; Kiernan et al, 2000).

Classification and regression tree (CART) are relatively new methods that offer an alternative approach for differentiating between groups (Finch and Schneider, 2006). CART modeling is a nonparametric statistic, which uses iterative techniques to divide participants into homogenous groups based on the relationships between the IV and DV. The groups are divided even further, with subsequent iterations, until a stopping point criterion is reached (Kiernan, Kraemer, Winkleby, King, and Barr, 2001; Finch and Schneider, 2007). The stopping point is achieved when there aren't enough participants in each node to warrant further partitioning, or if all participants in the node fall under one homogenous group (Raubertas, Rodewald, Humiston, and Szilagyi, 1994).

The analysis began with all participants in a primary node. The modeling package then mathematically divided the initial node into two homogenous groups. This analysis used a *Gini* splitting procedure wherein the variable with the strongest relationship to the DV was targeted for further partitioning (Raubertas, Rodewald, Humiston, and Szilagyi, 1994). With each step during the analysis, more nodes were created until no additional improvements to the model could be made through subsequent partitioning.

CART modeling has been successfully applied in DNA sequencing, medicine, genetics, epidemiology, and psychological research (Stobl, Malley, and Tutz, 2009). CART modeling produces a decision tree referred to as a dendogram (Lampropoulous, Schneider, and Spengler, 2009). The resulting dendogram can be used to understand how various deviations among the independent variables relate to the outcome variables. For example, Lampropopolous, Schneider, and Spengler (2009) investigated predictors of PT in graduate training clinics. Results from their analysis produced the following CART dendogram. Interpretation of the model suggests that clients younger than 40.5, with an annual income below $20,000, and a GAF score < 49 at intake are not likely to remain in treatment. However, those who were most likely to complete treatment, presented with an annual income < $20,000, were younger than 23.5 years old, and received an intake GAF falling between 72.5 and 83.5. These findings suggest that functional impairment was an important factor discriminating between the completer and dropout groups.

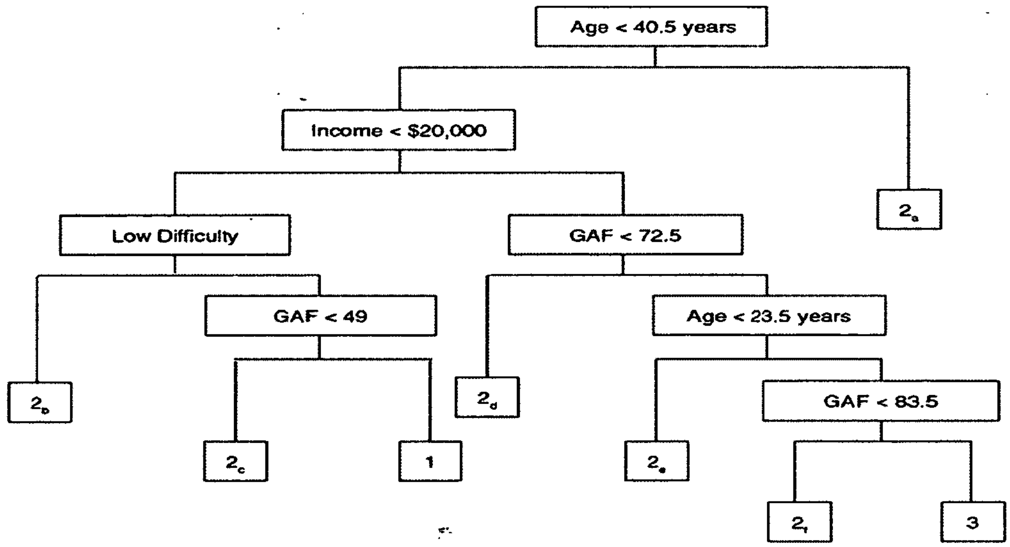


Figure 6. Sample Dendogram. From, "Predictors of early termination in a university counseling training clinic" by G. Lampropolous, M. Schneider, and P. Spengler, 2009, *Journal of Counseling and Development.* 87, p. 41. Copyright by John Wiley & Sons, Inc. Reprinted with permission (see Appendix K).

Practical decision-making algorithms can be produced by analyzing the dendogram outputs. The final step will use propensity scores derived from the logistic regression analysis to make comparisons with propensity scores derived from the CART model. The ROC analysis was used to compare the model characteristics between the Binary logistic regression model and CART model.

Receiver operating characteristic (ROC) analysis. Receiver operating characteristic (ROC) analyses have become popular in the health science literature for measuring the accuracy of medical diagnostic tests and relies on Signal Detection theory (SDT) to compare the probability of correctly identifying someone with a disease against the tests' capability of identifying a patient who is healthy. (Pintea and Moldovan ,2009). SDT is an analytic technique developed by researchers studying psychophysics, cognitive psychology, engineering, and statistics (Link, 1994). According to Agras et al (2000)

Signal Detection (SD) is also well-established procedure in epidemiology and medical research.

For this analysis, the signal was represented by a dichotomous outcome variable (i.e. dropout or completer) and detection refers to the IVs predicting group membership. Signal detection compares propensity scores based on the statistical model to outcome events observed in the data (see figure 3.2 below). Because PT is the target variable under investigation *Dropout* will be identified as a positive result and *Completed* will be identified as a negative result.

Table 3

2X2 Confusion Matrix (Fawcett, 2005)

		Results		
		Dropout	Completed	Total
Predicted	Dropout	*Hit* True Positive [TP]	*Miss* False Positive [FP]	T+
	Completed	*Miss* False Negative [FN]	*Hit* True Negative [TN]	T-
	Total	D+	D-	

The statistical package calculated the model's accuracy in predicting the probability of group membership. Metrics required to plot the accuracy of a diagnostic test along an ROC curve are specificity, sensitivity, positive predictive value (PPV), and the negative predictive value (NPV). Sensitivity and specificity measure the predictive capability of the model while the PPV and NPV represent the probability that the outcome will occur (Linden, 2005). Sensitivity is the probability for correctly predicting treatment dropouts, and Specificity refers to the probability of correctly predicting that clients will complete treatment (Raubertas et al, 1994). PPV is the probability that a client will drop out when they are classified as dropouts, and NPV refers to the probability that a client will remain in treatment when classified as completers (Pintea and Moldovan, 2009).

The ROC curve provides a visual representation for the number of "hits" or "misses," observed between the predicted estimates and the sample data (see figure 3.3). The ROC is divided in half by a reference line representing a test whose capability for discriminating between groups is no better than chance. Because the reference line represents the null hypothesis, for a test to be meaningful the plots should fall well toward the northwest corner of the ROC space (Pintea and Moldovan, 2009). ROC curves have a lower bound of 0 and have an upper bound of 1 meaning that the areas above and below the reference line are equal to .50 (Swets, 1988). In order to interpret the adequacy of a model in distinguishing between groups, a statistic referred to as *area under the curve* (AUC) is used. An AUROC ranging from .5 to .7 is regarded as having low accuracy, from .7 to .9 is considered moderately accurate, and > .9 is highly accurate (Steiner and Cairney, 2007). This analysis will plot classifier performance in the ROC space. More simply, the predicted group membership derived from the logistic regression analysis and CART models were compared against the observed values in the dataset (Fawcett, 2006).

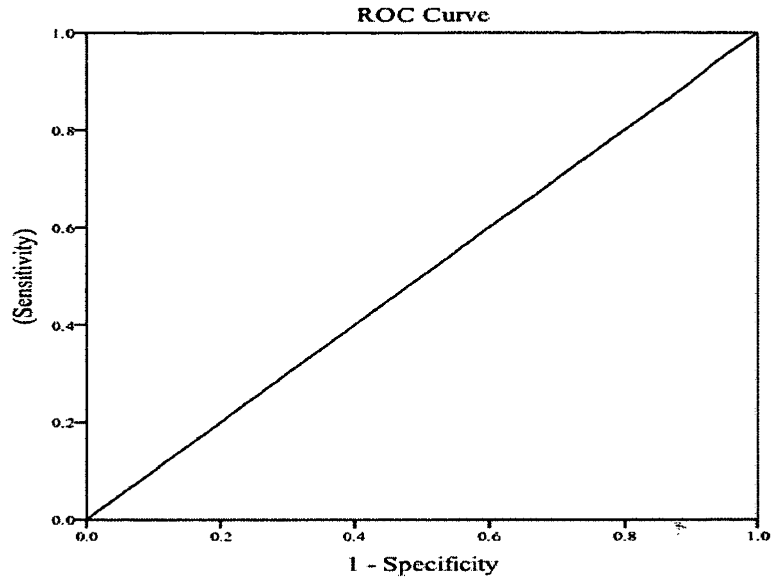


Figure 7. ROC space example

Research question 2. This analysis modeled the influence of the predictor variables on PT. A Discrete-Time Cox Proportional Hazards (PH) model was used to estimate the influence of the model on the risk of PT as an individual progressed along the EOC. Cox PH modeling falls under the family of survival analytic techniques often used in the medical and health sciences. In the analysis discussed above, treatment status (TS) was the target DV and comprised two levels: dropout and completer. Under this statistical model, the DV represented the time until a client drops out of treatment. The analysis measured the effect of the predictor variables on the time until a client either completed or withdrew from treatment. This section will describe the observation period and a brief summary of survival analytic techniques.

Observation period. This analysis measured the risk of PT as treatment progressed along the EOC. Treatment began during the initial intake and proceeded until the maximum number of 12 allotted sessions has been reached. Time represents a discrete variable measured at one-week intervals. Dummy coding was used to represent each session.

The data was drawn from archival data set collected since 2009. Because entry participation in the study was not dependent upon a designated observation period clients who entered treatment at different times were analyzed as one group. This strategy eliminated left censoring within the data as all clients had either completed or withdrew from treatment prior to analysis. Censoring is a unique feature in survival analysis that refers to cases where researchers are missing the exact time when the event occurred (Kleinbaum and Klein, 2010). Missing event data on the right side of the observation period is called right censored whereas data missing on the left side of the observation period is known as left censored (Allison, 1984). Kleinbaum and Klein (2010) suggest that right censoring is the most common. Some examples of right censoring occur when participants remain alive at the end of the data collection period or withdraw prematurely from the research study. Left censoring refers to instances where, the true survival time is less than or equal to the observed survival time (Kleinbaum and Klein, 2010). This may occur when researchers observe a positive diagnostic test during data collection but are unsure when individual was truly infected with a disease. Survival analysis uses special corrections to address different censoring issues within the dataset (Allison, 1984).

Survival analysis. Corning and Malofeeva (2004) advocated for the use Survival Analysis (SA) techniques when researching premature termination as such procedures may improve the precision and interpretability of the research findings. They propose this because psychotherapy is a longitudinal process (i.e. occurring over a period of 6 – 12 sessions), data analysis procedures must account for changes, trends, and patterns observed across the episode of care. SA techniques appear to offer a potential resolution, as these analytic methods statistically model the time until the occurrence of an event (Allison, 1984/2010; Kleinbaum & Klein, 2005).

SA techniques are referred to by various names throughout the literature including: event-history analysis, survival analysis, hazard analysis, failure time analysis, transition analysis, and duration analysis (Allison, 2010). For example, biostatisticians employ SA procedures to model the progression of a disease, from initial onset until the occurrence of death (Mapp, Hardcastle, Moss, & Robinson, 1999). Additionally, engineers may conduct a *failure-time analysis* to measure the log time until mechanical failure when machinery is exposed to environmental stress (Joyce, Gaffney, Kher, & Wilson, 2009). Readers can reference additional examples of these techniques across the literature as applied to medicine (Hakemi et al, 2010), education (Scarborough, Hebbeler, Spiker, & Simeonsson, 2011), economics (Mehmet, 2011), and psychology (Krebs, Strom, Koetse, & Lattimore, 2009). A number of studies implementing SA procedures to examine the topic of PT have emerged in the existing professional literature (Corning, & Malofeeva, 2004; Corning, Malofeeva, & Bucchianeri, 2007; Giese-Bloo et al, 2006; Jiménez-Murcia et al, 2007; Woodside, Carter, & Blackmore, 2004). A number of doctoral dissertations introduce SA techniques for research examining PT (Chasson, 2008; Ozanian, 2003; Patra, 2007; Sim, 2007; Wolfson, 2007). Despite broad application across various scientific disciplines, few studies are found in the professional literature where SA procedures are used to specifically examine PT among students seeking services in a UBC.

SA is a family of sophisticated analytic techniques used to model how a series of explanatory variables impact the occurrence of an event along an interval of time (Allison, 1984/2010; Kleinbaum & Klein, 2005; Muthen & Masyn, 2005). SA attempts to model the time until the occurrence of an event by treating time as either discrete or continuous (Allison, 2010; Singer & Willet, 1993; Willett & Singer, 1993). According to Allison (1984), although time is always measured in discrete units (i.e. milliseconds, seconds, minutes, hours, days, weeks, years, decades etc.), when time intervals are narrow and precise, they can be treated as continuous. In contrast, discrete units represent cases wherein the measurement of time is broad, and narrow intervals are unavailable. It can be difficult to measure time along continuous intervals in the social and behavioral sciences and researchers have underscored the utility of discrete-time SA for research in both educational and clinical settings (Lesick, 2007; Muthen & Masyn, 2005; Singer and Willett, 1995; Willett & Singer, 1993). Using discrete versus continuous-time methods yield similar findings and the selection between approaches depends more upon convenience and cost rather than statistical precision. (Allison, 1984).

Associated with SA are the Cox PH models used to measure the risk that an event will occur within the observation period (Allison, 2010). Cox PH modeling is a popular approach to statistical analysis that yields findings interpreted similarly to Ordinary Least Squares (OLS; Kleinbaum and Klein, 2005). Output statistics are interpreted using regression coefficients, standard errors, p values, and the hazard ratio, and relies on maximum likelihood (ML) estimation to calculate model coefficients. Because of this the Wald Statistic and log likelihood ratio (LR) are used in place of the unstandardized regression coefficients *(b)* and R^2 respectively (Field, 2009; Kleinbaum and Klein, 20005). Simulation studies suggest that the LR analysis produces more accurate estimates when compared against the Wald statistic (Kleinbaum and Klein, 2005).

Chapter 4

Results

This study explored how variables identified in the PT literature and clinical variables measured by the CCAPS-34 influenced early treatment withdrawal in a University Based Clinic (UBC). This investigation used binomial logistic regression to build a model capable of differentiating completers from dropouts; Classification and Regression Trees (CART) were used to examine how the variables under study interact to differentiate completers from dropouts; and survival analysis techniques were used to model how the risk of PT fluctuates as clients progress along the Episode of Care (EOC). The purpose of this chapter is to present the findings from these analyses.

Data Preparation

Sample Characteristics. Table 4 presents the demographic characteristics for gender, race/ethnicity, residency, and academic status of this sample (n=285). The majority of participants (62.5%; n=178) were female and 54.4% (n=155) were Caucasian. Ages ranged from 18 – 56 (n = 282; 3 missing values), with a mean age of 22 (Range= 18 – 25 y/o, SD= 4.53, Variance= 20.525, Median = 21, Mode = 21). Ninety-four percent (n = 269) of participants were domestic students and 2.4% (n = 7) of participants were international students (9 cases missing from the analysis). The majority of the students (56.8%; n=162) were single and 38.6% (n=110) were seriously dating/in a committed relationship. Most participants were upper classmen with 27.7% (n=79) juniors and 23.2% (n=66) were seniors. Approximately 35 % were either sophomores (n=53) or freshmen (n=49). The remaining participants were graduate/professional students (11.9%) or non-degree seeking students (n=2). Most of the sample (57.9%) lived off-campus in an apartment/house, 40.7% lived on campus, 1.1% (n=3) shared a house on/off campus with other students, and .4% (n=1) lived in a fraternity/sorority house.

Table 4

Demographic Characteristics

Variable	*N*	%
Gender (N=285)		
Male	107	37.5%
Female	178	62.5%
Race/Ethnicity (N=284)		
Caucasian	155	54.4%
African American/Black	80	28.1%
Multi-Racial	18	6.3%
Asian-American/Asian	14	4.9%
Latino(a)/Hispanic	11	3.9%
Other	3	1.1%
Hawaiian/Pacific Islander	2	.7%
Alaskan Native	1	.4%
Residency Status (N=276)		
Domestic	269	94.4%
International	7	2.4%
Academic Status (N=283)		
Freshman	49	17.2%
Sophomore	53	18.6%
Junior	79	27.7%
Senior	66	23.2%
Graduate/Professional Student	34	11.9%
Non-Degree Seeking	2	.7%

For this investigation PT was characterized by one who (1) fails to schedule or attend any subsequent appointments, or (2) the counselor determines that treatment was discontinued. Withdrawal from treatment must occur before treatment goals have been achieved and before reaching the mutually agreed upon number of sessions. Completion of treatment was defined by one of the following criteria: (1) Client and counselor mutually agreed that treatment goals have been completed. (2) Client remained in counseling until the maximum number of sessions had been reached. (3) Client was referred to an external mental health provider following completion of the maximum 12 sessions. (4) Client and counselor agree that no further appointments are necessary.

Students in the sample completed a mean of 2.46 sessions (Median=2, Mode=0, SD=3.1). A one-way analysis of variance (ANOVA) was conducted in SPSS 20.0 to determine if the average number of completed sessions differed between completers and dropouts ($F[1,281]=34.440$, $p < .05$,   =.11). Results indicated that clients who completed treatment (n= 116) attended an average of 3.71 sessions (SD= 3.753, SE= .275; 95% CI [3.17, 4.25]), whereas clients who prematurely withdrew (n=167) from services attended an average of 1.61 sessions (SD= 2.26, SE= .23; 95% CI [1.16, 2.06]). An examination of the confidence intervals suggests that the mean difference is statistically significant. Hansen, Lambert, and Forman (2002) reported that the mean number of sessions attended by clients in UBCs was 5.8 (Median= 4; SD-5.2). Because the results for this sample deviated from Hansen et al.'s findings, the rate of treatment withdrawal was examined. Figure 8 presents the decay curve observed in this sample. The *x*-axis depicts the session number while the *y*-axis represents the percentage of clients withdrawing from treatment. The results indicated that the percentage of clients withdrawing from treatment at each session appeared to follow a negatively accelerating attrition curve with 61.97% of clients terminating after the initial visit, 34.51% after the 3^{rd} session, and 13% withdrew after the 6^{th} session.

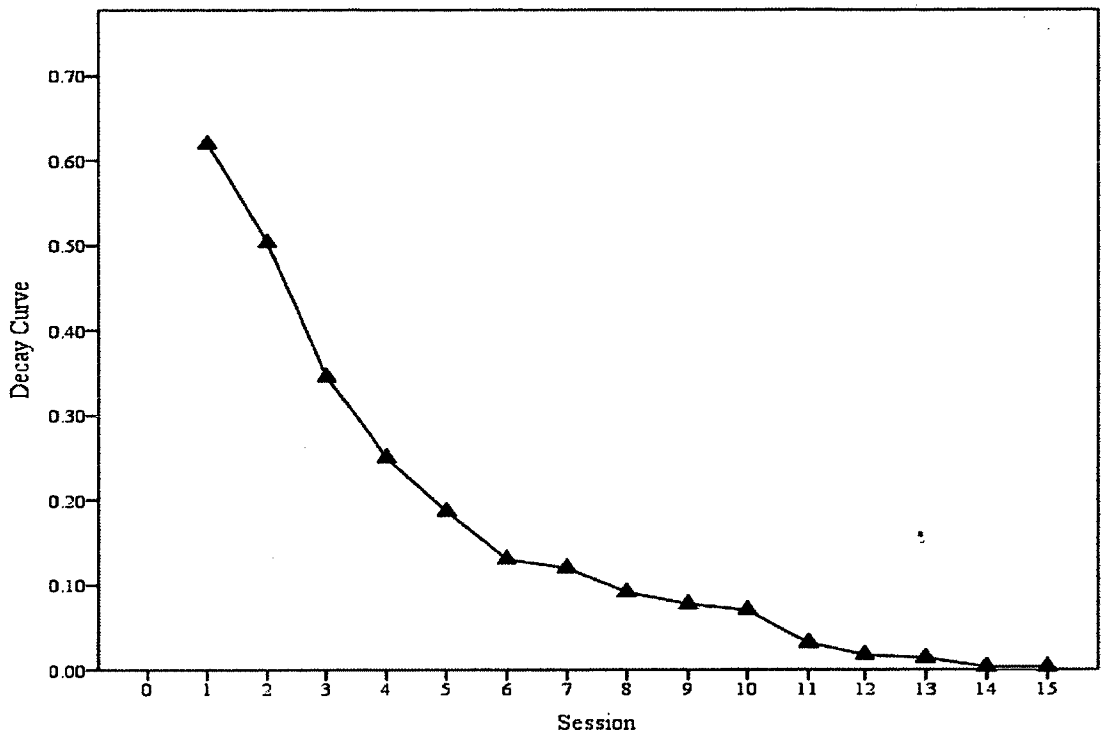


Figure 8. Decay/Attrition Curve

Participant scores on the GAF had a mean of 63.77 (Median=64, Mode = 60, SD=6.284) and a range of 42 (Max=84 [.4%], Min=42[.4%]). These findings appear consistent with Kettman et al (2007) who conducted a 7 – year longitudinal study (n=827) documenting trends in the severity of mental health issues treated in UBC's. Results from their analysis produced a mean GAF score of 63.95 (SD=6.81). The dispersion of GAF scores were normally distributed across this sample (Skewness=.020, Kurtosis=.409). The modal number of psychiatric diagnoses was 2 (Median=2.04) with a range of 5 (Max=5, Min=0), and the dispersion was also normally distributed for this sample (Skewness= .491, Kurtosis=-.296). The treatment status variable indicated that 58.9% (n=168) of participants prematurely withdrew from treatment (dropout) and 40.7% (n=116) completed services (Completion; 1 missing case). The rate of PT in this sample approached findings reported by Pekarik and Wierzbicki (1993; 46.86%; 95% CI=[42.9, 50.82]) while surpassing the average termination rate (30.4%; 95% CI [26.6, 34.4]) reported by Swift and Greenberg (2012). These divergent findings suggest a need for replication studies to examine predictors of PT using large-scale, multi-site samples specifically targeting termination rates in UBC's.

CCAPS-34 Calibration. A series of Confirmatory Factor Analyses (CFA) were conducted on the study sample (n = 285) using EQS 6.2 software (Bentler and Wu, 2012). Each scale measured by the CCAPS-34 was examined to ensure the measurement properties were performing adequately with this dataset (Dimitrov, 2010). Because the CCAPS-34 is not designed to produce a total score, individual CFA's were examined for each subscale. Also, a multi-factorial CFA was used to examine a 7-factor model (comprising 7 subscales measured by the CCAPS-34) for comparison with the validation study published by Locke et al (2011).

Maximum likelihood (ML) methods were used to estimate model parameters. The robust estimation function in EQS 6.2 was used to accommodate for deviations from multivariate normality (Bentler, 2006). All missing data were corrected using the ML estimation function in EQS 6.2. Additionally, all factor loadings were scaled to 1 and error terms were not permitted to correlate with one another (Byrne, 2006; Kline, 2010; Locke et al, 2011). Finally, to achieve an acceptable balance between Type I and Type II error rates, Hu and Bentler (1999) recommended that researchers use .6 as the minimum cutoff for RMSEA and .95 as the minimum cutoff for NFI, NNFI, CFI, and IFI. The following fit indices are referenced in this analysis: the Satorra-Bentler (S-B) ^{2} (Satorra and Bentler, 2010), the Bentler-Bonnett Normed Fit Index (NFI; Bentler & Bonnett, 1980), the Bentler-Bonnett Nonnormed Fit Index (NNFI; Bentler & Bonett, 1980), the

Comparative Fit Index (CFI; Bentler, 1990), Bollen's Incremental Fit Index (IFI; Bonnett, 1989), and McDonald's Fit Index (MFI; McDonald, 1989), and the Root-Mean-square Error of Approximation (RMSEA; Steiger & Lind, 1980). Table 5 depicts the results from the confirmatory factor analyses. Using the minimum cut off criteria recommended by Hu and Bentler (1999), Depression, Academic Distress, and Alcohol Abuse exhibited adequate model fit where as Generalized Anxiety, Social Anxiety, and Hostility fell below the recommended values.

Table 5

CCAPS – 34 Subscale fit indices

	df	*S-B* ^{2}	*NFI*	*NNFI*	*CFI*	*IFI*	*MFI*	*RMSEA*	
DEP	9	47.70**	.941	.918	.951	.951	.934	.123	.869
GA	9	76.99**	.857	.784	.870	.872	.888	.163	.805
SA	9	88.32**	.808	.629	.815	.817	.864	.242	.775
AD	2	12.95**	.974	.934	.978	.978	.981	.139	.816
EC*	0	-	-	-	-	-	-	-	.877
HOS	9	61.09**	.830	.748	.849	.852	.912	.143	.763
AA	2	7.18**	.969	.931	.977	.978	.991	.096	.846

*The EC subscale produced a just-identified model that fully explained the variance in the data. No model fit indices could be derived from the analysis.
**p < 01

A 7-factor model was examined to test the performance of the CCAPS-34 with this sample. Table 6 compares model fit statistics derived from this analysis against those reported by Locke et al (2011). The normalized Mardia's coefficient was 35.549, suggesting that the robust function in EQS would be necessary to adequately estimate model parameters. Results from this analysis were S-B ^{2}(506) =1168.613 p < .001, NFI= .762, NNFI= .831, CFI = .841, IFI=.849, MFI=.310, and RMSEA= .068 (90% CI [.063, .073]). Cronbach's alpha for the CCAPS-34 was .898. Using the minimum cut off criteria recommended by Hu and Bentler (1999), these results suggest that the CCAPS-34 underperformed with this sample and results from this investigation might be an artifact of instrument bias.

Table 6

Comparing fit indices to Locke et al (2011)

	Current Sample	*Locke et el (2011)*
S-B ^{2}(506)	1168.613*	1096.05*
NNFI	.762	.98
CFI	.841	.98
IFI	.849	.98
MFI	.310	--
RMSEA	.068	.049

*p < .01

Research Question 1

1. What combination of variables assessed by the CCAPS-34 and identified in the PT literature will best differentiate between completers and dropouts among clients seeking services in a UBC?

   H_1: In a UBC sample, completers and dropouts will not differ along the dimensions measured by the CCCAPS-34 or outlined in the PT literature.

Logistic Regression Analysis. The logistic regression analysis was conducted using SPSS 20.0. Raw scores were calculated for each subscale and converted to normalized scores using procedures outlined in the CCAPS manual (CCMH, 2012). Results from the model-building procedure (outlined in Chapter 3) identified SA, GA, and GAF as potentially important contributors. Using these variables, a three-parameter (3-P) binomial logistic regression (BLR) model was fitted to the data. Results from the analysis indicated that the 3-P BLR for this sample was significantly different from the baseline model (LR ^{2}(3)=15.358, p < .002; Additionally, an examination of the Hosmer-Lemeshow goodness of fit index (GFI) was non-significant (HL ^{2}[8]= 4.508, p > .809) suggesting that predicted values derived from the model were not significantly different from the observed values. These findings suggest that the omnibus model was a significant predictor of PT. Because regression coefficients are difficult to interpret when using logistic regression (Osborne, 2012), the following formula offered by King (2008):

$$\text{Percent change} = 100\ (\text{OR} - 1) \tag{1}$$

was used to calculate the percentage of change in odds ratios (OR; Osborne, 2006). Table 7 depicts the regression coefficients derived from the logistic regression model. These findings suggest that for each one-unit increase in GA (OR=1.252; $p > .05$, 95% CI [.951, 1.649]) at intake, we can predict rates of dropout to increase by multiplicative constant of 25.23%. Further, for each one-unit increase in SA (OR=.688; $p < .05$, 95% CI [.528, .897]) at intake, we can predict rates of dropout to decrease by 31.20%. Finally, for each one-unit increase in the GAF score (OR=.948; $p < .05$, 95% CI [.907, .991]) at intake, we can predict rates of dropout to decrease by 5.16%. Finally, although these findings suggest that the BLR model was statistically significant, its practical predictive utility in this setting is small (-2 log L= 363.091; *C-S* Pseudo R^2= .053; Nagelkerke Pseudo R^2 =.072).

Table 7

Regression coefficients and Odds Ratios

	B	*S.E*	*df*	Exp(B)
GAF	-.053*	.022	1	.948
GA	.225	.140	1	1.252
SA	-0.374*	.135	1	.688

* $p < .05$

Classification and Regression Tree (CART) Analysis. The purpose of this analysis is to profile interactions between predictor variables that can be used to differentiate between those participants who completed treatment from those who unilaterally terminated. CART methods were used to model clusters of variables that collaboratively influence the decision to prematurely terminate from counseling services (Kitsantas, Moore, & Sly, 2006).

Because percentile rankings can be used to streamline interpretation in clinical settings, each subscale was transformed using percentile tables available in the CCAPS manual (CCMH, 2012). Percentile rankings simplify the interpretation of the model allowing these findings to translate into clinical practice. Tree induction was performed using SPSS 20.0 software. All study variables were entered into the model simultaneously (e.g. Age, Race/Ethnicity, International Status, Relationship Status, Current housing status [on campus or off campus], academic status, GAF, DEP, GA, SA, AD, EC, HOS, and AA).

The primary root node (node 0) was partitioned to create two subsets based on scores derived from the SA subscale (Improvement = .014; see figure 5 for a visual depiction of this summary). The following child nodes were identified: 1.) Participants with scores below the 25th percentile (n=69; node 1); 2) Participants with subscale scores above the 25th percentile (n=215; node 2). A stopping criterion prevented any further partitioning in node 1. Results indicated that 73.9% (n=51) of participants in this node prematurely withdrew from treatment and 26.1% (n=18) successfully completed services. These findings suggest that if clients score below 1.00 on the SA subscale, they may be more likely to drop out of treatment. Of the 215 participants who scored above the 25th percentile, node 2 was further partitioned into two subsets (Improvement = .020). A score of 73.5 on the GAF was identified as the cutoff point dividing the subsample into: 1.) GAF < 73.5 (node 3); 2.) GAF > 73.5 (node 4). A stopping point criterion produced a terminal node for participants in node 4 (n=12). Results indicate that 91.7% (n=11) of participants in this node completed treatment and 8.3% (n=1) unilaterally withdrew from services. An examination of this pathway (e.g. root to node) suggests that clients who scored above 1.00 on the SA subscale and above 73.5 on the GAF, were more likely to complete treatment. Participants who scored below 73.5 on the GAF scale were partitioned into two additional child nodes based on scores derived from the HOS subscale (Improvement = .018). The recursive partitioning algorithm identified the 16.5th percentile as a decision rule. A terminal node was observed for participants who scored below the 16.5th percentile (n=34; node 5). Within node 5, 32.4% (n=11) discontinued treatment, and 67.6% (n=23) completed. An examination of this decision pathway suggests that if clients score above 1.00 on the SA subscale, below 73.5 on the GAF, and deny any items on the HOS scale, they were more likely to be classified as completers. Additionally, participants with HOS scores above the 16.5th percentile (n=169; node 6) were again partitioned into two additional nodes based on GA scores (Improvement = .014). The decision rule identified the 46th percentile on the GA subscale as the cutoff point. A terminal node was observed among participants with GA scores above the 46th percentile (n=117; node 8). Within this terminal node, 69.2% (n=81) of participants prematurely terminated services and 30.8% (n=36) of participants successfully completed treatment. An examination of this pathway suggests that if clients scored above 1.00 on the SA subscale, below 73.4 on the GAF, above 0.00 on HOS, and above 1.5 on the GA subscale, they were more likely to prematurely withdraw from services. Lastly, clients with GA subscales below the 46th percentile (node 7) were partitioned into two terminal nodes based upon GAF Scores (Improvement = .010). Participants with GAF Scores above 61.5 (n=37; node 10), 56.8% (n=21) of clients discontinued services and 43.2% (n=16) completed treatment. This decision rule suggests if clients score above 1.00 on the SA subscale, below 73.4 on the GAF, above 0.00 on HOS, below 1.5 on GA, and below 61.5 on the GAF, they were more likely to discontinue treatment. Among those participants whose GAF scores fell below 61.5 (n=15; node 9), 20% (n=3) were identified as dropouts and 80% (n=12) as completers. An examination of this alternative pathway suggests if clients score above 1.00 on the SA subscale, above 73.4 on the GAF, above 0.00 on HOS, above 1.5 on GA, and score above 61.5 on the GAF, they were more likely to discontinue treatment.

An examination of these results suggest that participant scores derived from the GAF, SA, GA, and HOS subscales may be useful in classifying clients as completers and dropouts. Additionally, the majority of clients who scored below 1.00 on the SA subscale withdrew from treatment prematurely. However, a summary of these findings suggests that most participants in the sample who scored above 1.00 on the SA subscale, were influenced by additional variables. Using participant scores on the SA subscale as a baseline, classification profiles emerged for each group (completers, dropouts). This profile suggests that completers were more likely to score above 73.5 on the GAF. However, for those completers who received GAF score below 73.5, they also endorsed 0 items on the HOS subscale. In contrast, participants who dropped out of treatment often scored below 73.4 on the GAF, above 0.00 on HOS, and above 1.5 on the GA subscale.

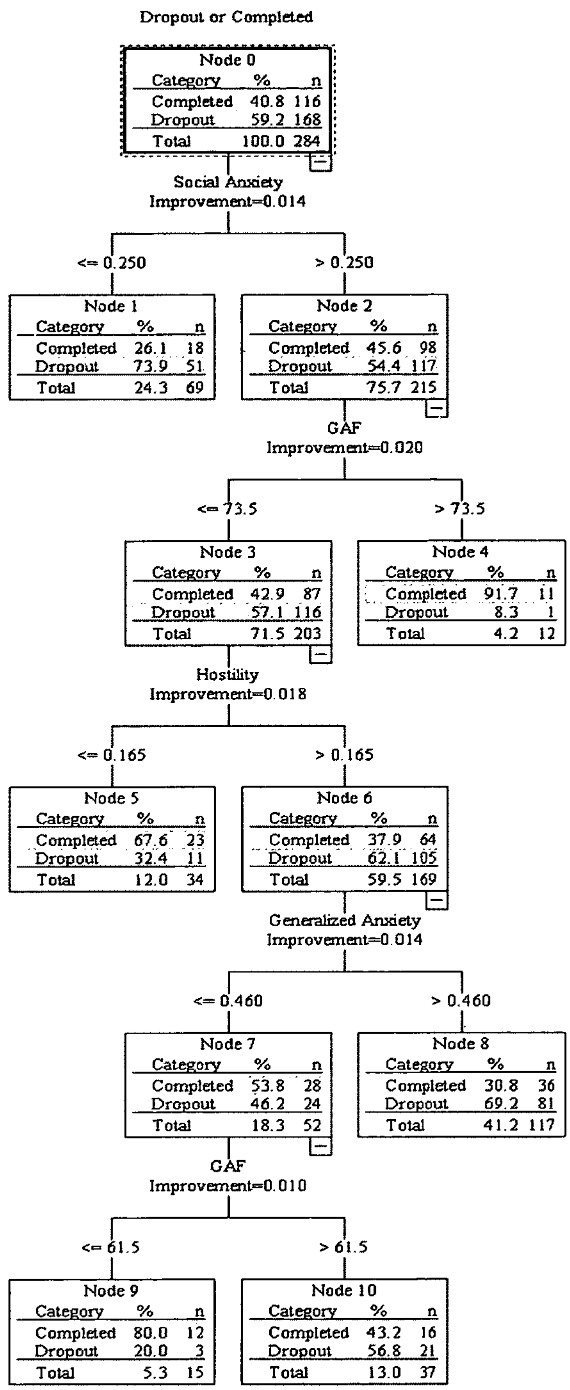


Figure 9: CART Dendogram

Area under the Receiver Operating Characteristic Curve (AUROC). The purpose of the AUROC analysis was to examine the model's accuracy to distinguish between groups. This analysis plotted propensity scores from the logistic regression model and the Classification Tree against the observed values in the dataset (Fawcett, 2006). Figure 10 depicts the AUROC for the logistic regression model (AUROC=.638, SE=.033, 95% CI [.572, .703]).

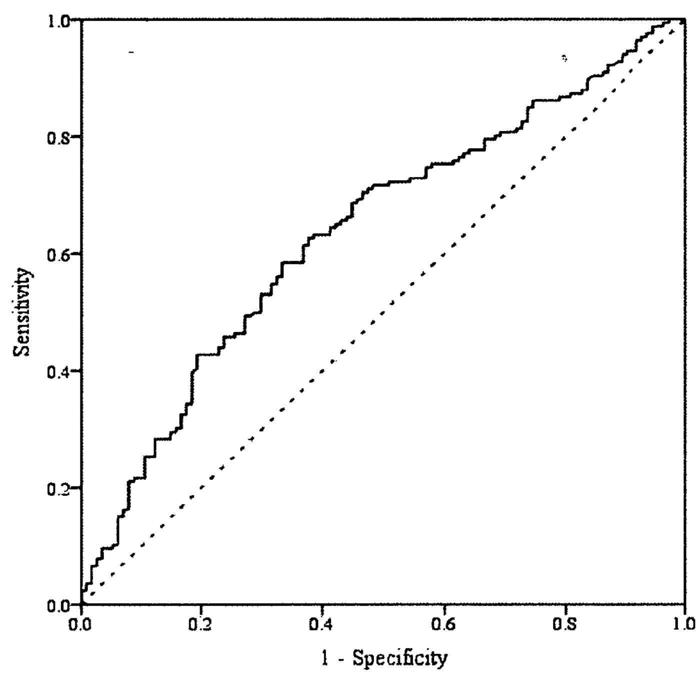


Figure 10: AUROC analysis for the Logistic Regression model

Additionally, Figure 11 depicts the AUROC analysis for the CART model (AUROC= .693, SE=.033, 95% CI [.629, .757]). Using the estimates offered by Steiner and Cairney (2007), AUROC values ranging from .5 to .7 are regarded as having low accuracy, from .7 to .9 are considered moderately accurate, and > .9 is highly accurate. Results from this analysis suggest that while both models predicted group membership better than chance, neither model offered enough accuracy to be practically useful in clinical settings. Additionally, an examination of the confidence intervals suggests that the difference between the LR and CART models is not statistically significant.

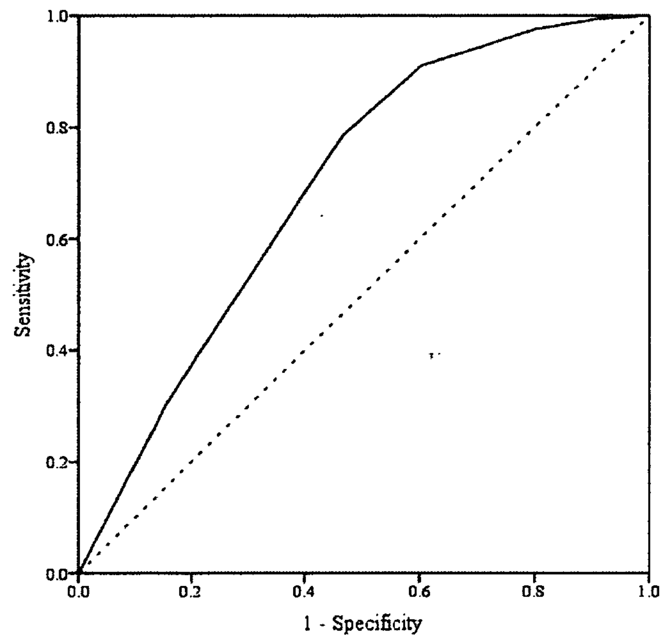


Figure 11: AUROC analysis for the CART model

Research Question 2

Q_2: Do variables measured by the CCAPS-34 and identified in the PT literature increase the risk of PT along the episode of care among clients seeking services in a UBC?

H_2: The covariates measured by the CCAPS-34 and identified in the PT literature will not increase the hazard of PT as the client progresses along the EOC.

Survival Analysis.

Baseline Model. Figure 8 depicts the *baseline hazard function* demonstrating the risk of PT at each session without including any covariates in the model. The *x*-axis represents the number of sessions attended and the y-axis represents the hazard probabilities. A visual inspection of the baseline hazard function suggests that the risk of PT is lowest during the early stages of treatment and appears to steadily increase along the EOC. The rate of acceleration appeared to reach a plateau between sessions 6 and 11, after which the hazard rate appeared to accelerate rapidly.

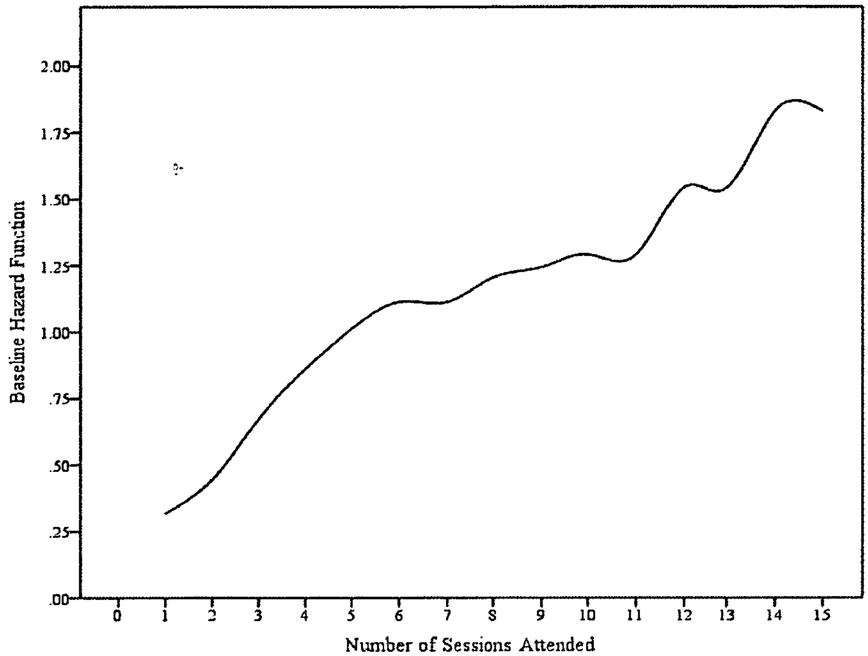


Figure 12: The Baseline Hazard Function

Testing covariates. A Discrete-Time Cox PH Regression analysis was selected to test covariates. The PHREG function in SAS 9.3 was used to estimate the best fitting model. The DISCRETE function was also used to account for ties. Allison (2010) suggests that the DISCRETE method is suitable for applications where target events occur simultaneously. This method of analyzing ties was selected because dropout is a discrete-time variable that is evaluated by session attendance/absence. A determination of treatment status can only be made after appointments operating on a weekly interval schedule (Corning and Malofeeva, 2004). Initially, a 3 – parameter (e.g. SA, GA, and

GAF) model was fitted to the data (LR $^{2}(3)=9.644$, $p < .022$; -2 Log L=782.63; AIC=787.63). Results from this model suggested that the time until PT was significantly different between completers and dropouts. However, participant scores on the GA subscale (=.084, $p > .38$; SE=.095, HR=1.087) were not statistically significant, suggesting that the time until PT did not differ between completers and dropouts based on GA symptoms. To test if GA modified the effect of the Cox PH Model, a 2 parameter (2-P) model (e.g. GAF, SA) was fitted to the data. Results from the analysis indicated that the 2-P PH model was significantly different from the baseline model (LR $^{2}(2)=8.46$, $p < .015$; -2 Log L= 782.812; AIC=786.812), These findings suggest that the 2-P Cox PH model may also be useful in predicting the risk of PT as clients progress along the EOC. The removal of GA from the model did not improve model fit. These findings are consistent with Allison (2010), who indicates that model fit is negatively influenced by the omission of important covariates rather than the inclusion of statistically non-significant predictors. Because the numerical magnitude of regression coefficients are difficult to interpret when examining Cox PH models, these values were converted to Hazard Ratios (HR; Allison, 2010b). The estimated percent of change in the Hazard Ratio for every one-unit increase in the covariate was evaluated using the following formula by Allison (2010a):

$$\text{Percent change} = 100\,(\text{HR} - 1) \qquad (2)$$

Table 8 depicts the regression coefficients for Cox PH model. These findings suggest that GAF scores appear to be approaching significance (=-.294, SE=.306, $p > .052$, HR=.971). After adjusting for other variables in the model, for every one-unit increase in GAF scores, the risk of PT decreases by an estimated 2.9%. Additional findings suggest that scores on the SA subscale were statistically significant (=-.786, SE=.015, $p <.010$, HR=.456), and that for every 1-unit increase in SA, the risk of PT decreases by 54.4%. In other words, higher scores on the GAF and SA subscale may protect clients from early treatment withdrawal in UBC's.

Table 8

Regression coefficients and Hazard Ratios

		SE	*df*		Exp(
GAF	-.294	.306	1	.052	.971
SA	-.786	.015	1	.010	.456

Hazard Function. Figure 13 presents the Hazard probabilities derived from the Cox PH model plotted for each session to compare how the model covariates influenced the rate of PT along the EOC. A visual inspection shows that the risk of PT is lowest during early sessions and increases throughout treatment. Also, the rate of acceleration appears to vary along the EOC for each group. These findings indicate that the Cox PH model was able to differentially map the probability of PT for each group along the EOC, with the largest discrepancy between completers and dropouts observed during session 7. The 2-P Cox PH model may have some utility in modeling the probability of drop out at various points along the EOC in UBC's.

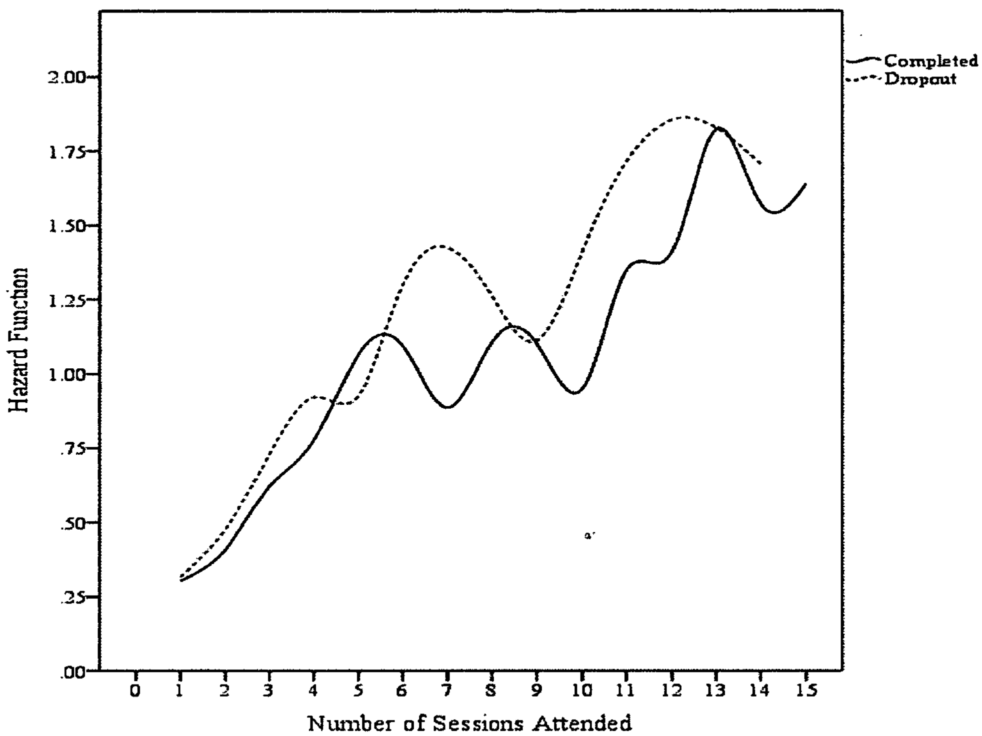


Figure 13: Hazard Function

CHAPTER 5

DISCUSSION

Although University Based Clinics (UBC) are uniquely positioned to impact the mental health of college students, little is known about the scope or consequences of PT within this clinical setting. Given the broad spectrum of influential covariates, more awareness is needed to address this fundamental problem facing clinical providers. The purpose of this exploratory study was to examine client characteristics that impact dropout in UBCs. First, we tested if completers and dropouts differed along demographic characteristics including age, gender, marital status, academic status, and race/ethnicity. Then, we examined if dropouts and completers differ along clinical characteristics including depression, generalized anxiety (GA), social anxiety (SA), academic distress (AD), eating concerns (EC), hostility, alcohol abuse (AA), and functional impairment (FI). Finally, we tested if the risk of PT remains stable as clients progress along the episode of care (EOC). This section will review the findings that emerged from the analysis and triangulate the results against the existing PT literature.

Research Question 1

What combination of variables assessed by the CCAPS-34 and identified in the PT literature will best differentiate between completers and dropouts among clients seeking services in a UBC?

Hypothesis 1

In a UBC sample, completers and dropouts will not differ along the dimensions measured by the CCCAPS-34 or outlined in the PT literature.

Findings

The results from the analysis partially supported the hypothesis that completers and dropouts would not differ along the dimensions measured by the CCAPS-34 or outlined in the PT literature. Results from the purposeful selection procedure indicated that age, gender, marital status, academic status, race/ethnicity, depression, AD, EC, hostility, and AA did not significantly influence the conditional probability of PT.

Age (< 25) is a robust but moderate predictor of PT across various clinical settings and client problems (Baekeland and Lundwall, 1975; Edlund et al, 2002; Lampropolous, Schneider, and Spengler, 2009; Swift and Greenberg, 2012; Wang, 2007). In the current investigation, client age did not significantly alter the likelihood of PT among completers or dropouts. As mentioned in chapter 4, the age distribution in this sample favored clients younger than 25 (22; Median=21; Mode=21; Range=38, SD= 4.53, Variance= 20.525; Skewness= 3.105, Kurtosis = 14.462). These findings may indicate that the unique features of the clinical setting influenced the effect of age in this sample. These results were consistent with recent meta-analytic evidence suggesting that race and marital status did not significantly influence the decision to leave treatment (Swift and Greenberg, 2012).

Among the clinical dimensions measured by the CCAPS-34, SA and GA emerged as influential covariates; as SA increases, the probability of PT drops by 31% and as scores on the GA subscale increase, the likelihood of PT increases by 25.32%. The effect size estimates for the Logistic Regression (LR) model (*C-S* Pseudo R^2= .053; Nagelkerke Pseudo R^2 =.072) indicate the omnibus model only accounts for a small amount of variance in the data. The results also indicated that the level of FI influences the conditional probability of PT. These findings appear to indicate that as level of functioning decreases the probability of PT increases by 5.16%.

CART methods were used as a hypothesis generating technique and are designed to detect the latent interactive structure among variables (Kitsantas Moore, & Sly, 2006). Given this unique design characteristic, CART methods were used to develop a preliminary decision-making model capable of identifying clinical characteristics that differentiate between completers and dropouts. The logistic regression and CART models were then compared for accuracy in classifying clients by treatment status. Although both models displayed low accuracy in predicting group membership, a number of findings emerged. Findings from the CART analysis indicated that SA,FI, hostility, and GA may form a dynamic network of interacting variables that collectively influence termination rates in UBCs. Results suggest that even when accounting for the protective influence of SA and lower levels of FI, higher levels of hostility appear to increase the percentage of clients who unilaterally withdrew from services. Lastly, the CART model observed higher completion rates among clients with elevated hostility scores, who also presented with lower levels of GA and higher levels of FI.

Conclusion

Results from the logistic regression analysis indicated that dropouts did not differ according to demographic variables including age, gender, marital status, academic status, and race/ethnicity. Also, clinical variables including depression, AD, GA, academic concerns, EC, and AA did not significantly impact the probability of PT. The results did appear to indicate that pretherapy SA and FI did influence the probability of PT. This suggests that the likelihood of PT increases with lower levels of SA, whereas the probability of PT increases with higher levels of FI.

These findings were consistent with the CART analysis, which reported that pretherapy FI and the severity of SA at intake were capable of differentiating dropouts from completers. Further examination of these findings also suggested that higher levels of FI and hostility might indirectly suppress the protective influence of SA. Still this investigation provides exploratory findings and the underlying mechanisms driving these relationships are unclear. Findings from the CART analysis were consistent with previous research suggesting that higher levels of hostility were associated with a greater probability of PT in an urban training clinic (Greenfield, 2008). Because hostility negatively impacts the client's perception of the therapeutic relationship, these findings may suggest that hostility inhibits the formation of a collaborative working alliance (Burns, Higdon, Mullen, Lansky, and Wei, 1999).

Research Question 2

Do variables measured by the CCAPS-34 and identified in the PT literature increase the risk of PT along the EOC among clients seeking services in a UBC?

Hypothesis 2

The covariates measured by the CCAPS-34 and identified in the PT literature will not increase the hazard of PT as the client progresses along the EOC.

Findings

Results from this analysis partially supported the hypothesis that covariates measured by the CCAPS-34 and in the PT literature would not increase the hazard of PT as clients progress along the EOC. Neither the logistic regression or CART analyses accounted for time as factor in the decision to unilaterally terminate from services. An examination of the baseline hazard function indicates that the risk of PT is lowest during early sessions and steadily increases as clients move along the EOC. Findings also suggest that the level of SA and FI partially influenced the probability of PT as clients progressed in their treatment. An inspection of the Hazard plot suggests the risk of PT is lowest during early sessions and continues to increase over time. The 7th session appeared to mark the largest point of deviation between each group, as the rate of acceleration increased for the dropout group and temporarily declined for the completion group.

Conclusion

The baseline Hazard function (Figure 8.) observed in this investigation appeared inconsistent with findings reported by Corning and Malofeeva (2004). According to their results, the risk of PT is highest during early sessions and appears to steadily decline over time. In contrast, the baseline Hazard function emerging from this analysis indicated that the risk of PT was lowest during the early stages of treatment and steadily grew with each subsequent session. The failure to replicate the baseline Hazard function may be due to the different methods for defining the outcome variable. The Corning and Malofeeva (2004) investigation analyzed a multinomial logistic regression model measuring mutual termination, premature termination, and censored cases. In contrast, because the current study examined a dichotomous outcome variable (e.g. dropout and completion). However, because both research analyses explored predictors of PT in a UBC and achieved opposing results, replication studies may compare how different methods for subdividing the outcome variable influence the Hazard function. Findings from the Hazard plot indicate that pretherapy FI and scores on the SA subscale may be a useful starting point when examining clinical predictors that may identify clients at risk of PT.

Summary of Findings and Conclusions

The rate of PT observed in this study exceeded the average termination rate recorded for UBC's in other studies. (Swift and Greenberg, 2012). However, this elevated dropout rate could be due to the erratic variability of dropout rates inherent to this body of literature and our use of therapist determination to dichotomize treatment status (Swift and Greenberg, 2012). Also, results from this investigation indicated that 61.9% of the sample withdrew following the initial visit, 34.5% withdrew after the third visit, and 13% withdrew after the 6th visit. These findings are consistent with Phillips (1985/1987) and Baekeland and Lundwall, (1975) who reported that client attrition in treatment appears to follow a negatively accelerating decay curve (See Figure 8). The dropout rate from this investigation indicated that 58.9% (n=168) of participants prematurely withdrew from treatment (dropout) and 40.7% (n=116) completed services. The rate of withdrawal observed in this study observed a large proportion of clients terminating services after the initial session. These findings suggest that the highest proportion of clients withdrew from treatment when the risk of PT was at its lowest point.

It was observed that when SA increases, the likelihood of PT drops by 31% for this sample. As FI decreases, the probability of PT drops by 5.16% and as scores on the GA subscale increase, the likelihood of PT increases by 25.32%. These findings support the notion that symptom severity at intake may influence the decision to unilaterally withdraw from services. The findings also suggest that SA, GA, and FI may have clinical utility in predicting the probability of PT in UBC's. These results appear consistent with earlier findings suggesting that higher levels of SA may act as a protective factor against PT (Chisholm, Crowther, & Ben-Porath, 1997; Baekeland & Lundwall, 1975; Conte, Plutchik, Picard, and Karasu, 1988) whereas higher levels of FI at intake may increase the risk of early termination (Lampropolous, Schneider, and Spengler, 2009; Lewis, 2007; Romans et al, 2011; Wang, 2007). Although the protective influence of SA has previously emerged in the literature, little is known about its relationship to PT. Social fears influence role performance across a wide range of functional domains (Kessler, Stein, and Berglund, 1998). According to Olfson et al (2000) respondents with SA were more likely to avoid treatment for fear of what others may say or think. Stein and Gorman (2001) suggest that social fears are linked to missed opportunities, as educational, career, and interpersonal decisions are influenced by the desire to avoid anxiety-producing roles. Also, according to epidemiological findings from Ruscio et al (2008), the likelihood of seeking treatment decreases as the degree of FI and the number of social fears increase. Perceived self-efficacy (Bandura, 1989) may provide a potential lens to aid in the interpretation of these findings (Hoffman, 2006). This model suggests that because clients with social phobia tend to evaluate their social skills unfavorably, increasing mastery over their fear of social rejection may reinforce continuation in treatment. Longo, Lent, and Brown (1992) observed that perceived self-efficacy showed a small, but statistically significant effect on dropout.

Lastly, this investigation examined the influence of hostility and academic concerns on the decision to unilaterally withdraw from services. Results from the BLR and Cox PH modeling strategies indicated that these variables have little influence on the decision to prematurely terminate services. In contrast, results from the CART model indicate that hostility and generalized anxiety may influence the termination rate in UBCs.

Applications to University Based Clinics

In the broader literature, PT impacts 1 in 5 clients (Swift and Greenberg, 2012;

Swift, Greenberg, Whipple, and Kominiak, 2012). In UBCs, 3 out of 10 clients withdraw prematurely (Swift and Greenberg, 2012). Although 15 sessions are needed for 50% of clients to show improvement, the median number of sessions in UBCs is 4 (M=5.8, SD=5.2; Hansen, Lambert, and Forman, 2002). These findings suggest that a substantial proportion of service recipients may be discontinuing treatment before achieving measurable improvement (Swift, Greenberg, Whipple, and Kominiak, 2012). These findings suggest a need for further research to profile thostilitye client characteristics that elevate or attenuate the risk of PT. Identifying clients at an elevated risk of PT and then implementing empirically supported interventions to increase the likelihood of treatment completion may offer a useful model for translating PT research into clinical practice.

Results from this investigation suggest that within a UBC, SA, FI, hostility, and GA may (directly or indirectly) influence the probability of PT. While the preliminary findings from this analysis may identify clients at a higher risk of dropout, they do not offer recommendations for preventing PT. Recently, Swift, Greenberg, Whipple, and Kominiak (2012) published a series of empirically supported practice recommendations developed to reduce PT across a wide range of clinical settings. According to their findings, duration and patterns of change education,.role induction, preference matching, strengthening early hope, fostering the therapeutic alliance, and comparing client expectations against the observed trajectory of change can all be used to reduce the rate of PT.

Applications and suggestions for training

Investigators from psychology, epidemiology, and medicine have generated a significant amount of the PT literature. Although few empirical studies have emerged in the professional counseling literature, the impact of PT on clients, clinicians, and administrative costs continue to impact all mental health providers. PT is a significant problem that receives little attention in the professional counseling literature. Additionally, the 2009 standards published by the Council for the Accreditation of Counseling and Related Programs (CACREP) failed to provide competency standards for preventing client attrition. This gap in the professional counseling curriculum renders graduates of counselor training programs unprepared to both identify and intervene when working with clients at high risk for PT. Although the topic of PT is broad and multifaceted, counselor-training programs may train graduate students to identify risk/protective factors that influence PT and then review interventions that may increase the likelihood of remaining in treatment. Results from this investigation may help training programs narrow the field of covariates that potentially influence the rate of PT in UBC's.

Limitations of the study

First, a clear distinction must be made between the influence of covariates linked to the probability of PT and the internal decision-making processes driving early treatment withdrawal (Swift, Greenberg, Whipple, and Kominiak, 2012). Although findings from the current investigation may narrow the field of influential covariates, these findings should be regarded as preliminary as the underlying causal mechanisms have yet to be identified or explored.

Because this analysis implemented a retrospective research design from a single UBC, the generalizability of these findings cannot be extended to other institutions (Horn, Snyder, Coverdale, Louie, & Roberts, 2009). The geographic region, size of the institution, SES characteristics of the student population, and class size may have influenced the findings. Without further research into how these institutional and demographic variables affect PT in a UBC setting, these findings must be interpreted cautiously.

According to Pintea and Moldovan (2009), CART methods risk "over fitting" the model to the data under study. Because of this risk, independent validation samples are recommended to evaluate the model characteristics. Without cross-validating the CART model against an independent sample, these findings must be interpreted with caution. For this investigation, the statistical cross-validation procedure in SPSS 20.0 failed and could not be used to evaluate the dendogram output.

The operational definition of PT used in this study combined various definitions of PT according to recommendations offered by Swift and Greenberg (2012). However, an empirically valid definition of PT has not yet been fully operationalized. More research is needed for investigators to be certain that comparisons across studies are measuring the same construct.

Finally, using the minimum cut-off criteria for model fit indices recommended by Hu and Bentler (1999), results from the initial series of confirmatory factor analyses suggest that the CCAPS-34 exhibited inadequate model fit when triangulated against data reported in the validation study (Locke et al, 2012). This result may indicate that the statistically significant findings emerging from this analysis may be explained as an artifact of instrument bias.

Recommendations for future studies

The decision to prematurely withdraw from counseling services is an important topic for practitioners, researchers, and educators. After decades of research, PT is still regarded as a significant problem facing mental health treatment providers (Swift, Greenberg, Whipple, and Kominiak, 2012). Given the findings that emerged from the CART analysis, the effect of hostility on PT warrants further development. Future research may examine how hostility influences the relationship between clients' perceptions of the therapeutic alliance and PT. Next, results from this investigation indicated that SA may offer a protective factor that attenuates the risk of PT. Future research may seek to disentangle the effect of perceived self-efficacy on the relationship between SA and the decision to withdraw from services.

Traditionally, the broad scope of research examining PT has focused on nomothetic indicators derived from quantitative techniques. As mentioned above, the PT literature is saturated with inconsistent and distorted findings (Barrettt et al, 2009; Corning and Malofeeva, 2004; Garfield, 1994; Hatchett & Park, 2003; Swift, Callahan, & Levin, 2009; Pekarik, 1985; Wierzbicki & Pekarik, 1993). Although, researchers are adapting research designs to overcome these challenges (i.e. Corning and Malofeeva, 2004; Swift and Greenberg, 2012; Lampropolous, Schneider, and Spengler, 2009), few conclusions can be made about the decision to prematurely terminate counseling services. In response to the inconsistent findings reported in the PT literature, future research may instead focus on idiographic indicators of PT using qualitative research methods. This wide gap in the PT literature represents an integral stream of unexamined data. Also, a number of administrative, client, therapist, and interpersonal dyadic variables have been found to influence unilateral termination (Reis and Brown, 1999; Barrettt et al, 2008).

However, the relationship among these variables has not been fully explored. Future research may look to modeling the structural relationships between these variables to better understand the dynamic factors that influence the decision to withdraw from services.

CHAPTER 6

MANUSCRIPT

THE IMPACT OF SYMPTOM SEVERITY AND FUNCTIONAL IMPAIRMENT ON PREMATURE TERMINATION IN A UNIVERSITY BASED COUNSELING CENTER

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Keywords: Premature Termination, Unilateral Termination, University Based Clinic, Symptom Severity, Functional Impairment

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ABSTRACT

Swift and Greenberg (2012) observed that variables influencing the decision to drop out fluctuate according to the primary presenting problem, the amount of structure in therapy, the length of treatment, and the clinical setting. Due to these reports, researchers may focus on predictors of premature termination (PT) in treatment settings where the unique situational characteristics may have an idiosyncratic influence on the decision to withdraw from services (Phillips, 1985; Swift & Greenberg, 2012). The purpose of this exploratory study was to examine client characteristics that impact dropout in University Based Clinics (UBC). Results from the logistic regression analysis indicated that higher levels of social anxiety and lower levels of pretherapy functional impairment reduced the probability of PT. Findings from the Classification and Regression Tree (CART) analysis suggested that higher levels of hostility may increase the dropout rate even when accounting for the protective influence of social anxiety and higher levels of functioning. This effect may be also intensified as the severity of generalized anxiety increases. Results from the Survival Analysis suggest that the risk of PT was lowest during the early stages of counseling and steadily increased for clients who remained in services. These findings also indicate that higher levels of social anxiety and lower levels of pretherapy functioning may partially attenuate the risk of PT as clients progress along the episode of care. Results from this analysis are triangulated against the existing PT literature and implications for teaching, practice, and future research are discussed.

Keywords: Premature Termination, Unilateral Termination, University Based Clinic, Symptom Severity, Functional Impairment

INTRODUCTION

Premature Termination (PT) has been referred to as the foremost problem facing mental health providers (Pekarik, 1985; Phillips, 1985). PT is also thought to undermine the effectiveness of psychotherapy (Gottschalk, Mayerson, and Gottleib, 1967; Ogrodniczuk, Joyce, and Piper, 2005), contribute to inflated administrative costs (Baekeland and Lundwall, 1975), negatively impact the ability to interpret and generalize research findings (Beckham, 1992; Harris, 1998; Ogrodniczuk, Joyce, and Piper, 2005), and negatively affects the confidence of therapists (Barrett et al, 2008). Because the PT literature is saturated with discrepant findings (Barrettt et al, 2009; Wierzbicki & Pekarik, 1993), unclear operational definitions (Hatchett & Park, 2003; Swift, Callahan, & Levin, 2009), and inadequate statistical analyses (Corning and Malofeeva, 2004), follow-up studies using independent samples often fail to replicate earlier findings (Garfield, 1994, Harris, 1998).

Partially influenced by methodological limitations, the stream of generalizable PT research in university-based clinics (UBC) remains narrow. Hyun, Quinn, Madon, & Lustig, (2006) reported that college students represent a diverse clientele with unique social and psychological characteristics. Mennicke, Lent, and Burgoyne (1988), suggested the students seeking services in college counseling centers may represent a unique group that would benefit from independent investigation outside of the broader PT literature. Swift and Greenberg (2012) observed that variables influencing the decision to dropout vary according to the primary presenting problem, the amount of structure in therapy, the length of treatment, and the clinical setting. Due to these reports, researchers may focus on predictors of PT in clinical settings where the unique environmental characteristics may have an idiosyncratic influence on the decision to withdraw from services (Phillips, 1985; Swift & Greenberg, 2012).

Historically, Stone and Archer (1990) predicted that the mental health needs of college students would continue to rise steadily. Epidemiological findings from the American College Health Association (ACHA, 2010) show that college students face a number of mental health issues including suicide (1.3%), self-injury (5.3%), suicidal ideation (6.2%), debilitating depression (30.7%), overwhelming anger (38.2%), feelings of hopelessness (45%), loneliness (56.4%), and sadness (60.7%; ACHA, 2010). In 2010, 91% of counseling center directors perceived that clients were presenting with more complex mental health needs (Gallagher, 2010). Benton, Robertson, Tseng, Newton, and Benton (2003), tracked the mental health trends among college students over a 13-year observation period (n=13,257). The authors noted that patterns of substance abuse, eating disorders, legal problems, and chronic mental illness remained stable while significant increases were observed in abuse (physical, sexual, and emotional), anxiety, depression, suicidal ideation, sexual assault, relationship problems, stress/anxiety, family issues, physical problems, and personality disorders.

Although, UBCs are uniquely positioned to impact the mental health of college students, little is known about the scope or consequences of PT within this clinical setting. In the broader literature, PT impacts 1 in 5 clients (Swift and Greenberg, 2012; Swift, Greenberg, Whipple, and Kominiak, 2012). In UBCs, 3 out of 10 clients withdraw prematurely (Swift and Greenberg, 2012). Although 15 sessions are needed for 50% of clients to show improvement, the median number of sessions in UBCs is 4 (M=5.8, SD=5.2; Hansen, Lambert, and Forman, 2002). These findings suggest that a substantial proportion of service recipients may be discontinuing treatment before achieving measurable improvement (Swift, Greenberg, Whipple, and Kominiak, 2012).

Research into those clinical characteristics that influence PT allows clinicians, counselors, and educators to tailor their services to client needs. Given the broad spectrum of influential covariates, more awareness is needed to address this fundamental problem facing clinical providers. The purpose of this exploratory study was to examine client characteristics that impact dropout in UBCs. First, we tested if completers and dropouts differed along the dimensions of age, functional impairment, or symptom severity. Then, we examined if the risk of PT remains stable as clients progress along the episode of care (EOC).

METHODS

Data Collection

A number of client characteristics have emerged in the literature as influencing the decision to unilaterally withdraw from counseling. According to Barrettt, Chua, Crits-Christoph , Gibbons, Casiano, and Thompson (2008) variables influencing PT can be categorized into six components including: client characteristics, enabling factors/barriers, need-related factors, environmental factors, perceptions of mental health, and perceptions of treatment. For this investigation, we restricted our analysis to examine how client characteristics commonly encountered in UBC's predict the likelihood of PT. After selecting influential explanatory variables from the broader PT literature, we tested the impact of these covariates on dropout within a UBC setting. Variables included in our analyses were: younger age (< 25; Edlund et al, 2002; Swift and Greenberg, 2012, Wang, 2007), symptom severity (Baekeland and Lundwall, 1975; Romans et al, 2010; Wang, 2007), and functional impairment (Lampropolous, Schneider, and Spengler, 2009). This investigation relied on archival data collected during routine practice at a UBC housed within large Southeastern University. Within this setting, treatment providers offer time-limited (sessions), non-manualized mental health counseling services for individuals, groups, and couples. Clinic staff consisted of 4 Ph.D. level practitioner's and 6 Master's level providers. Practicum or internship students did not provide counseling services in this UBC during the period of data collection.

Instrumentation

Counseling Center Assessment of Psychological Symptoms – 34

The Center for Collegiate Mental Health (CCMH) was established in 2005 as a large-scale national research initiative investigating the mental health needs of college students (CCMH, 2012). Its goal is to advance the understanding of mental health in the college setting, and to improve the provision of mental health services. The CCAPS-34 is 34-item, multi-factorial symptom checklist designed to gather data describing the mental health trends facing college students, while still maintaining clinical utility for applied practice (Locke et al, 2012). According to the CCMH (2012), the CCAPS-34 uses scores measured along a 5-point likert-type rating scale (*not at all like me* to *extremely like me*). Reliability estimates (N=482) ranged from.824 to .876 (CCMH, 2012). Test – retest reliability estimates after 1 week (n=86) ranged from .792 to .866 and from .742 to .864 after 2 weeks (n=47; Locke et al, 2012). Construct validity was assessed using a Confirmatory Factor Analysis (CFA). The reported model fit statistics lent support to the hypothesized factor structure (*S-B*   (506)=1096.05, p<.001, CFI=.98; NNFI=.98;RMSEA=.49 [CI 90% (.045, 053)];SRMR=.063). The CCAPS-34, measures seven independent subscales: Depression, Eating Concerns, Substance Use, General Anxiety, Hostility, Social Anxiety, and Academic Distress (CCMH, 2012; Locke et al, 2010; Locke et al, 2012). The CCAP's deployment in counseling centers across the nation offers a unique tool specifically tailored to examine those mental health issues often treated in UBC's.

Global Assessment of Functioning Scale

Pretherapy functional impairment is a continuous independent variable measured by client scores on the Global Assessment of Functioning (GAF) scale (APA, 2000; Endicott, Spitzer, Fleiss, and Cohen, 1976).

Procedures

Outcome Variable

For this investigation the dependent variable was treatment status (TS) comprised of two dichotomous outcomes: Dropout or Completed. PT was defined as a client-initiated, withdrawal from therapy prior to achieving the treatment goals mutually agreed upon between client and counselor (Baekeland & Lundwall, 1975; Wierzbicki & Pekarik, 1993; Hatchett and Parks, 2003; Corning, Malofeeva & Bucchianeri, 2007). Completion was defined by one (or more) of the following criteria: (1) Client and counselor mutually agree that treatment goals have been completed. (2) Client remains in counseling until the maximum number of sessions has been reached. (3) Client is referred to an external mental health provider following completion of the maximum 12 sessions. (4) Client and counselor agree that no further appointments are necessary.

Data Analysis

This investigation examined the influence of symptom severity (measured by the CCAPS-34), functional impairment (GAF), and age in differentiating completers from dropouts. The analytic procedure implemented during this investigation was inspired by Lampropolous, Schneider, and Spengler (2009) and Corning and Malofeeva (2004). Analyses were conducted using EQS 6.2, SAS 9.3, and the Statistical Package for the Social Sciences (SPSS) version 20.0.0.

RESULTS

Data Preparation

Sample Characteristics. Results from the descriptive analysis were examined to obtain demographic characteristics for the study participants (n=285). For this sample, 62.5% (n=178) were female and 37.5% (n = 107) were male. According to the racial/ethnic data 54.4% (n=155) were Caucasian, 28.1% (n = 80) were African American/Black, 6.3% (n=18) were multi-racial, 4.9% (n=14) were Asian American/Asian, 3.9% (n = 11) were Latino(a)/Hispanic, 1.1% (n=3) self-identified as "other," 7% (n =2) were Hawaiian or Pacific Islander, and .4% (n =1) were Alaskan Natives. The age of participants ranged from 18 – 56 (n = 282; 3 missing values). The mean age was 22 (Range=38, SD= 4.53, Variance= 20.525). The age distribution was positively skewed and leptokurtic (Skewness= 3.105, Kurtosis = 14.462) with most cases clustering between the ages of 18 – 25 (Median = 21.00, Mode=21). Additionally, 94.4% (n = 269) of participants were domestic students and 2.4% (n = 7) of participants were international students (9 cases missing from the analysis). The academic status variable indicated that 27.7% (n=79) of participants were juniors, 23.2% (n=66) were seniors, 18.6% (n=53) were sophomores, 17.2% (n=49) were freshman, 11.9% (n=34) were graduate/professional students, and .7% (n=2) were non-degree seeking (see table 4).

Table 4

Demographic Characteristics

Variable	*N*	%
Sex (N=285)		
Male	107	37.5%
Female	178	62.5%
Race/Ethnicity (N=284)		
Caucasian	155	54.4%
African American/Black	80	28.1%
Multi-Racial	18	6.3%
Asian-American/Asian	14	4.9%
Latino(a)/Hispanic	11	3.9%
Other	3	1.1%
Hawaiian/Pacific Islander	2	.7%
Alaskan Native	1	.4%
Residency Status (N=276)		
Domestic	269	94.4%
International	7	2.4%
Academic Status (N=283)		
Freshman	49	17.2%
Sophomore	53	18.6%
Junior	79	27.7%
Senior	66	23.2%
Graduate/Professional Student	34	11.9%
Non-Degree Seeking	2	.7%

On average, participants completed 2.46 sessions (Median=2, Mode=0, SD=3.1) with a range of 14 (Min=0 [37.9%], Max=14 [.4%]). A one-way analysis of variance (ANOVA) was conducted in SPSS 20.0 to determine if the average number of completed sessions differed between completers and dropouts ($F[1,281]=34.440$, $p < .05$, $=.11$). Results indicated that clients who completed treatment (n= 116) attended an average of 3.71 sessions (SD= 3.753, SE= .275; 95% CI [3.17, 4.25]) whereas; clients who prematurely withdrew (n=167) from services attended an average of 1.61 sessions (SD= 2.26, SE= .23; 95% CI [1.16, 2.06]). An examination of the overlapping confidence intervals suggests that the mean difference is statistically significant. According to Hansen, Lambert, and Forman (2002), the mean number of sessions attended by clients receiving services in UBCs was 5.8 (Median= 4; SD-5.2). Because these results deviated from findings reported in the literature, the rate of treatment withdrawal was examined. Consistent with previous research (Phillips, 1987), the percentage of clients withdrawing from treatment at each session appeared to follow a negatively accelerating decay curve with 61.97% terminating after the initial visit, 34.51% after the 3rd session, and 13% withdrawing after the 6th session (see figure 8).

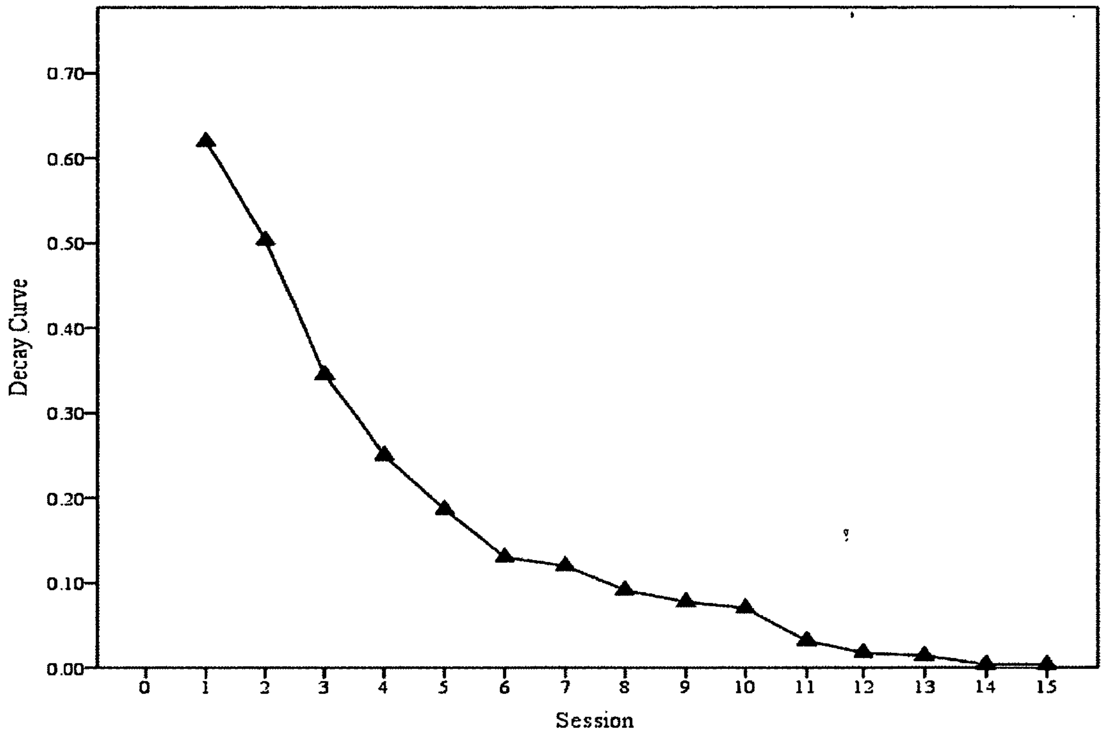

Figure 8. Decay/Attrition Curve

Participant scores observed on the GAF produced a mean of 63.77 (Median=64, Mode = 60, SD=6.284) and a range of 42 (Max=84 [.4%], Min=42[.4%]) and were normally distributed across this sample (Skewness=.020, Kurtosis=.409). The modal number of psychiatric diagnoses was 2 (39.6%, Median=2.04) with a range of 5 (Max=5 [.4%], Min=0 [1.1%]). The dispersion of psychiatric diagnoses was normally distributed (Skewness= .491, Kurtosis=-.296). The treatment status variable indicated that 58.9% (n=168) of participants prematurely withdrew from treatment and 40.7% (n=116) completed services (1 missing case). The rate PT in this sample trended toward findings reported by Pekarik and Wierzbicki (1993; 46.86%; 95% CI=[42.9, 50.82]) while surpassing the average termination rate (30.4%; 95% CI [26.6, 34.4]) reported by Swift and Greenberg (2012)..

CCAPS-34 Calibration. A Confirmatory Factor Analysis (CFA) was conducted on the study sample (n = 285) using EQS 6.2 software (Bentler and Wu, 2012) to ensure the measurement properties were performing adequately with this dataset (Dimitrov, 2010). A multi-factorial CFA was used to examine a 7-factor model (comprising 7 subscales measured by the CCAPS-34) for comparison with the validation study published by Locke et al (2011). Maximum likelihood (ML) methods and robust statistics were used to estimate model parameters (Bentler, 2006). All missing data was corrected using the ML estimation function in EQS 6.2. Factor loadings were scaled to 1 and error terms were not permitted to correlate with one another (Byrne, 2006; Kline, 2010; Locke et al, 2011). Results from this analysis were S-B ^{2}(506) =1168.613 $p < .001$, NFI= .762, NNFI= .831, CFI = .841, IFI=.849, MFI=.310, and RMSEA= .068 (90% CI [.063, .073]). Cronbach's alpha for the CCAPS-34 was .898. Using the minimum cut off criteria recommended by Hu and Bentler (1999), these results suggest that the CCAPS-34 didn't perform adequately with this sample (see Table 4 for a comparison of model fit statistics between the current sample and Locke et al [2011]).

Table 5

A comparison of fit indices between the current sample and Locke et al (2011)

	Current Sample	Locke et el (2011)
S-B ^{2}(506)	1168.613*	1096.05*
NNFI	.762	.98
CFI	.841	.98
IFI	.849	.98
MFI	.310	--
RMSEA	.068	.049

*p < .01

Logistic Regression Analysis

Raw scores were calculated for each subscale and converted to normalized scores using procedures outlined in the CCAPS manual (CCMH, 2012). To obtain the best fitting model, a purposeful selection procedure was used to systematically narrow the field of covariates (Bursac, Gauss, Williams, & Hosmer, 2007; Hosmer and Lemeshow, 2002). Results from the model-building procedure identified SA, GA, and GAF as important contributors. Using these variables, a three-parameter binomial logistic regression (LR) model was fitted to the data. Results from the analysis indicated that the LR model was significantly different from the baseline model (LR $^2(3)=15.358$, $p < .002$; Additionally, an examination of the Hosmer-Lemeshow goodness of fit index (GFI) was non-significant (HL $^2[8]= 4.508$, $p > .809$) suggesting that predicted values derived from the model were not significantly different from the observed values. These findings suggest that the omnibus model was capable of differentiating completers from dropouts. An examination of the regression coefficients were: GA (OR=1.252; 95% CI [.951, 1.649]), SA (OR=.688; 95% CI [.528, .897]), and GAF (OR=.948; 95% CI [.907, .991]). These findings suggest that for each one-unit increase in GA at intake we can predict rates of dropout to increase by multiplicative constant of 25.23%. Further, for each one-unit increase in SA at intake we can predict rates of dropout to decrease by 31.20%. Finally, for each one-unit increase in the GAF score at intake, we can predict rates of dropout to decrease by 5.16%. Finally, although these findings suggest that the LR model was statistically significant, it's practical predictive utility in applied settings is small (-2 log L= 363.091; *C-S* Pseudo R^2= .053; Nagelkerke Pseudo R^2 =.072).

Classification and Regression Tree. The purpose of this analysis is to profile interactions between predictor variables that can be used to differentiate between those participants who completed treatment from those who unilaterally terminated. CART methods will be used to model clusters of variables that collaboratively influence the decision to prematurely terminate from counseling services (Kitsantas, Moore, & Sly, 2006). Because percentile rankings can be calculated to streamline interpretation in clinical settings, each subscale was transformed using percentile tables available in the CCAPS manual (CCMH, 2012). Percentile rankings simplify the interpretation of the model allowing these findings to translate into clinical practice. Tree induction was performed using SPSS 20.0 software. All study variables were entered into the model simultaneously (e.g. Age, GAF, DEP, GA, SA, AD, EC, HOS, and AA).

The primary root node (node 0) was divided to create two subsets based on scores derived from the SA subscale (Improvement = .014; see figure 1 for a visual depiction of this summary). The following child nodes were identified: 1.) Participants with scores below the 25th percentile (n=69; node 1); 2) Participants with subscale scores above the 25th percentile (n=215; node 2). A stopping criterion prevented any further partitioning in node 1. Results indicated that 73.9% (n=51) of participants in this node prematurely withdrew from treatment and 26.1% (n=18) successfully completed services. These findings suggest that if clients score below 1.00 on the SA subscale, they may be more likely to dropout of treatment.

Of the 215 participants who scored above the 25th percentile, node 2 was further partitioned into two subsets (Improvement = .020). A score of 73.5 on the GAF was identified as the cutoff point dividing the subsample into: 1.) GAF < 73.5 (node 3); 2.)

GAF > 73.5 (node 4). A stopping point criterion produced a terminal node for participants in node 4 (n=12). Results indicate that 91.7% (n=11) of participants in this node completed treatment and 8.3% (n=1) unilaterally withdrew from services. An examination of this pathway (e.g. root to node) suggests that if clients score above 1.00 on the SA subscale and score above 73.5 on the GAF, they may be more likely to complete treatment.

Participants, who scored below 73.5 on the GAF scale, were partitioned into two additional child nodes based on scores derived from the HOS subscale (Improvement = .018). The recursive partitioning algorithm identified the 16.5th percentile as a decision rule. A terminal node was observed for participants who scored below the 16.5th percentile (n=34; node 5). Within node 5, 32.4% (n=11) discontinued treatment, and 67.6% (n=23) completed. An examination of this decision pathway suggests that if clients score above 1.00 on the SA subscale, below 73.5 on the GAF, and deny any items on the HOS scale, they were more likely to be classified as completers.

Participants with HOS scores above the 16.5th percentile (n=169; node 6) were again partitioned into two additional nodes based on GA scores (Improvement = .014). The decision rule identified the 46th percentile on the GA subscale as the cutoff point. A terminal node was observed among participants with GA scores above the 46th percentile (n=117; node 8). Within this terminal node, 69.2% (n=81) of participants prematurely terminated services and 30.8% (n=36) of participants successfully completed treatment. An examination of this pathway suggests that if clients scored above 1.00 on the SA subscale, below 73.4 on the GAF, above 0.00 on HOS, and above 1.5 on the GA subscale, they were more likely to prematurely withdraw from services.

Clients with GA subscales below the 46th percentile (node 7) were partitioned into two terminal nodes based upon GAF Scores (Improvement = .010). Of participants with GAF Scores above 61.5 (n=37; node 10), 56.8% (n=21) of clients discontinued services and 43.2% (n=16) completed treatment. This decision rule suggests if clients score above 1.00 on the SA subscale, below 73.4 on the GAF, above 0.00 on HOS, below 1.5 on GA, and below 61.5 on the GAF, they were more likely to discontinue treatment. Among those participants whose GAF scores fell below 61.5 (n=15; node 9), 20% (n=3) were identified as dropouts and 80% (n=12) as completers. An examination of this alternative pathway suggests if clients score above 1.00 on the SA subscale, above 73.4 on the GAF, above 0.00 on HOS, above 1.5 on GA, and score above 61.5 on the GAF, they were more likely to discontinue treatment.

These results indicate that participant scores derived from the GAF, SA, GA, and HOS subscales may be useful in classifying clients as completers and dropouts. A summary of these findings suggests that most participants in the sample who scored above 1.00 on the SA subscale, were influenced by additional variables. Using participant scores on SA as a baseline, classification profiles emerged for each group (completers, dropouts). This profile suggests that completers were more likely to score above 73.5 on the GAF. However, for those completers who received GAF score below 73.5, they also endorsed 0 items on the HOS subscale. Participants who dropped out of treatment often scored below 73.4 on the GAF, above 0.00 on HOS, and above 1.5 on the GA subscale.

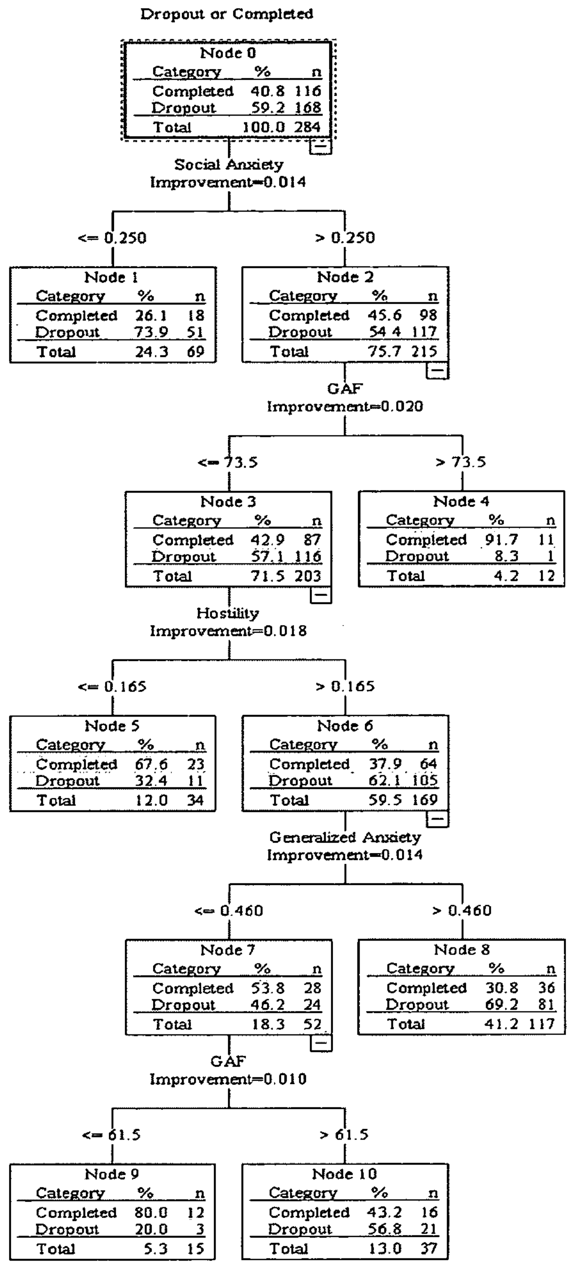

Figure 1: CART Dendogram

Area under the Receiver Operating Characteristic Curve (AUROC). This analysis compared the accuracy of the BLR model to the CART model in predicting PT. This analysis plotted propensity scores derived from the logistic regression model and the Classification Tree against the observed values in the dataset (Fawcett, 2006). An examination of the results produced an AUROC of .638 (SE=.033, 95% CI [.572, .703]) for the logistic model and an AUROC of .693 (SE=.033, 95% CI [.629, .757] for the Classification Tree. Using the rule of thumb estimates offered by Streiner and Cairney (2007), AUROC values ranging from .5 to .7 are regarded as having low accuracy, from .7 to .9 are considered moderately accurate, and > .9 is highly accurate. Results from this analysis suggest that while both models predicted group membership better than chance, neither model offered enough accuracy to be practically useful in clinical settings. Additionally, an examination of the confidence intervals suggests that difference between the LR and CART models is not statistically significant.

Survival Analysis

A *baseline hazard function* was plotted to determine the risk of PT at each session without including any covariates in the model. A visual inspection of the hazard plot indicates that the risk of PT is lowest during early stages of treatment and appears to steadily increase as clients progress along the EOC. A Discrete-Time Cox Proportional Hazards (PH) Regression analysis was conducted to examine the influence of symptom severity and pretherapy functional impairment on PT. The PHREG and DISCRETE functions in SAS 9.3 were used to estimate the model. Allison (2010) suggests that the DISCRETE method is suitable for applications where target events occur simultaneously. This method was selected because dropout is discrete-time variable evaluated by session attendance/absence on a weekly interval schedule (Corning and Malofeeva, 2004). Using covariates identified during the logistic regression analysis, a 2 parameter Cox PH model (e.g. GAF, SA) was fitted to the data. Results from the analysis indicated that the Cox PH model was significantly different from the baseline model (LR ^{2}(2)=8.46, $p < .015$; -2 Log L= 782.812; AIC=786.812), These findings suggest that our model may be useful in predicting the risk of PT as clients progress along the EOC. An analysis of the regression coefficients observed: GAF (=-.294, SE=.306, $p > .052$, HR=.971) and SA (=-.786, SE=.015, $p < .010$, HR=.456). These findings suggest that GAF scores appear to be trending toward significance. After adjusting for other variables in the model, for every one-unit increase in GAF scores, the risk of PT decreases by an estimated 2.9%. Additional findings suggest that scores on the SA subscale were statistically significant. These findings suggest that for every 1-unit increase in SA, the risk of PT decreases by 54.4%. In other words, higher levels of pretherapy functioning and social anxiety subscale may protect clients from PT in UBC's. Hazard probabilities derived from the Cox PH model were plotted for each session to compare how the model covariates influenced the rate of PT along the EOC. A smoothing spline function was fitted to the data. Figure 2 depicts the unique hazard functions for completer and dropout groups. A visual inspection shows that the risk of PT is lowest during early sessions and increases throughout treatment. Also, the rate of acceleration appears to vary along the EOC for each group. These findings indicate that the Cox PH model was able to differentially map the probability of PT for each group along the EOC. The 2-P Cox PH model may have some utility in modeling the probability of drop out at various points along the EOC in UBC's.

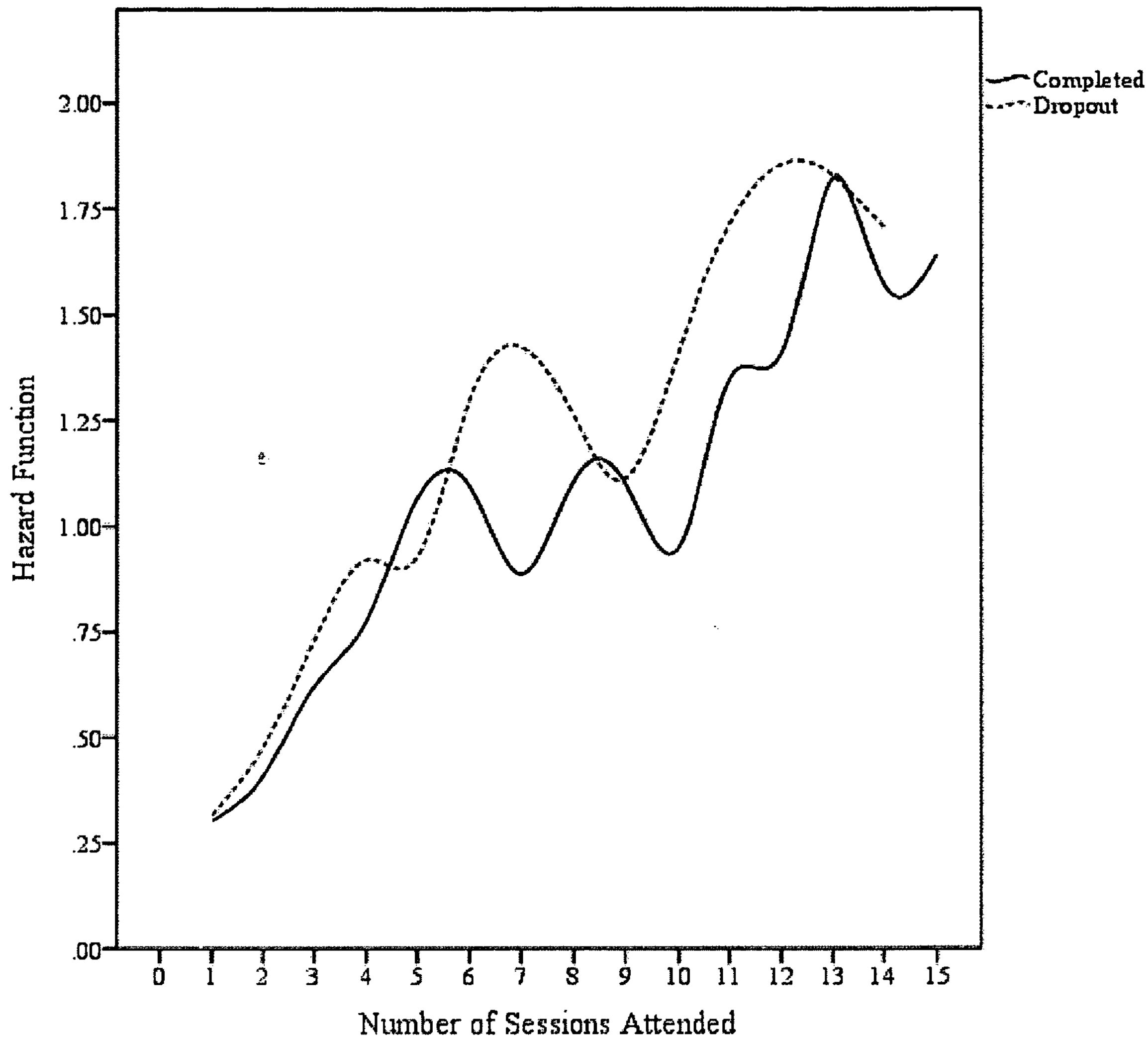

Figure 2: Hazard Function

DISCUSSION

The dropout rate from this investigation indicated that 58.9% (n=168) of participants prematurely withdrew from treatment (dropout) and 40.7% (n=116) completed services (Completion; 1 missing case). The rate of PT observed in this study exceeded the average termination rate recorded for UBC's (Swift and Greenberg, 2012; 30.4%; 95% CI [26.6, 34.4]). However, Swift and Greenberg also noted substantial variation in the rate of PT across studies (range=0% -74.23%) and observed higher rates of dropout in studies using therapist determination. The elevated dropout rate observed in this investigation could be due the natural variability in termination rates inherent to this body of literature and our use of therapist determination to dichotomize treatment status.

Across the PT literature age (< 25) emerged as a robust but moderate predictor of PT across various clinical settings and client problems (Baekeland and Lundwall, 1975; Edlund et al, 2002; Lampropolous, Schneider, and Spengler, 2009; Swift and Greenberg, 2012; Wang, 2007). In the current investigation age was not significantly different between completers or dropouts. As mentioned above, the age distribution in this sample strongly favored clients younger than 25 (22; Median=21; Mode=21; Range=38, SD= 4.53, Variance= 20.525; Skewness= 3.105, Kurtosis = 14.462). These findings may lend support to Swift and Greenberg (2012) who observed that dropout rates vary according to the treatment setting. These results may indicate that the unique demographic profile of the UBC suppressed the influence of age on PT.

During this investigation it was observed that when SA increases, the likelihood of PT drops by 31%, as functional impairment decreases the probability of PT drops by 5.16%, and as scores on the GA subscale increase the likelihood of PT increases by

25.32%. These findings support the notion that symptom severity at intake may influence the decision to unilaterally withdraw from services. This finding also suggests that the Social Anxiety, Generalized Anxiety, and pretherapy functional impairment may have clinical utility in predicting the probability of PT in UBC's. According to the effect size estimates, GAF, GA, and SA accounted for approximately 7.2% of the variance in the sample. Due to the small amount of variance explained in the data, GAF, GA, and SA may reflect lower order facets of a broader latent structural model that unifies the above-mentioned dimensions into a hierarchical conceptual framework

Results from this investigation appear consistent with earlier findings suggesting that higher levels of SA may act as a protective factor against PT (Chisholm, Crowther, & Ben-Porath, 1997; Baekeland & Lundwall, 1975; Conte, Plutchik, Picard, and Karasu, 1988) whereas higher levels of functional impairment at intake may increase the risk of early termination (Lampropolous, Schneider, and Spengler, 2009; Romans et al, 2011; Wang, 2007). Although the protective influence of SA has previously emerged in the literature, little is known about its relationship to PT. Social fears are a common and debilitating clinical state that influence role performance across a wide range of functional domains (Kessler, Stein, and Berglund, 1998). Stein and Gorman (2001) suggest that social fears are linked to missed opportunities, as educational, career, and interpersonal decisions are influenced by the desire to avoid anxiety producing roles. Perceived self-efficacy (Bandura, 1989) may provide a potential lens to aid in the interpretation of these findings (Hoffman, 2006). This model suggests that because clients with social phobia tend to evaluate their social skills unfavorably, increasing mastery over their fear of social rejection may reinforce continuation in treatment. Longo, Lent, and Brown (1992) observed that perceived self-efficacy showed a small, but statistically significant effect on dropout. Further research may seek to examine the potential effect of perceived self-efficacy on the relationship between social anxiety and PT.

These results did not support findings in the literature suggesting that disordered eating and depression influence the risk of PT (Swift and Greenberg, 2012). Results from the LR and Cox PH regression analyses failed to reject the null hypothesis, indicating that Hostility and Academic Concerns had little, if any, influence of the decision to remain in treatment. In contrast to LR and Cox PH models, CART method offer a hypothesis generating technique and are designed to detect the latent interactive structure between variables (Kitsantas Moore, & Sly, 2006). Given this unique design characteristic, findings from the CART model indicate that Hostility may be an influential variable in discriminating between dropouts and completers.

The baseline hazard function observed in this investigation appeared inconsistent with findings reported by Corning and Malofeeva (2004). According to their results, the risk of PT is highest during early sessions and appears to steadily decline over time. In contrast, our baseline hazard function indicated that the risk of PT was lowest during the early stages of treatment and steadily grew with each subsequent session. The failure to replicate the baseline hazard function may be due to the different methods for defining the outcome variable. The Corning and Malofeeva (2004) investigation analyzed a multinomial logistic regression model measuring Mutual Termination, Premature Termination, and Censored Cases. These findings are consistent with Phillips (1985/1987) and Baekeland and Lundwall, (1975) who reported that client attrition in treatment appears to follow a negatively accelerating decay curve (See Figure 8). Results from this investigation indicated that 61.9% of the sample withdrew following the initial visit, 34.5% withdrew after the third visit, and 13% withdrew after the 6th visit.

Limitations of the study

Because this analysis implemented a retrospective research design from a single UBC, the generalizability of these findings cannot be extended to other institutions (Horn, Snyder, Coverdale, Louie, & Roberts, 2009). The geographic region, size of the institution, SES characteristics of the student population, and class size may have influenced the findings. Without further research into how these institutional and demographic variables affect PT in a UBC setting, these findings must be interpreted cautiously.

Studies using tree induction techniques risk "over fitting" the model to the sample (Pintea and Moldovan, 2009). Given this risk, independent validation samples are recommended to evaluate model characteristics. For this investigation, the statistical cross-validation procedure in SPSS 20.0 failed and could not be used to evaluate the model. Without cross-validating the CART model against an independent sample, these findings must be interpreted with caution.

The operational definition of PT used in this study combined various definitions of PT according to recommendations offered by Swift and Greenberg (2012). However, an empirically valid definition of PT has not yet been fully operationalized. More research is needed for investigators to be certain that comparisons across studies are measuring the same construct.

Finally, using the minimum cut off criteria for model fit indices recommended by

Hu and Bentler (1999), results from the initial CFA suggest that the CCAPS-34 exhibited inadequate model fit when triangulated against data reported in the validation study (Locke et al, 2012). This result may indicate that the statistically significant findings emerging from this analysis may be explained as an artifact of instrument bias.

Implications

The decision to prematurely withdraw from counseling services is an important topic for practitioners, researchers, and educators. After decades of research, PT is still regarded as significant problem facing mental health treatment providers (Swift, Greenberg, Whipple, and Kominiak, 2012). Traditionally, the broad scope of research examining client characteristics that influence PT have focused on nomothetic indicators derived from quantitative techniques. As mentioned above, the PT literature is saturated with inconsistent and distorted findings (Barrettt et al, 2009; Corning and Malofeeva, 2004; Garfield, 1994; Hatchett & Park, 2003; Swift, Callahan, & Levin, 2009; Pekarik, 1985; Wierzbicki & Pekarik, 1993). Although, researchers are adapting research designs to overcome these challenges (i.e. Corning and Malofeeva, 2004; Swift and Greenberg, 2012; Lampropolous, Schneider, and Spengler, 2009), few conclusions can be made about the decision to prematurely terminate counseling services. In response to the inconsistent findings reported in the PT literature, future research may instead focus on idiographic indicators of PT using qualitative research methods. This wide gap in the PT literature represents an important stream of unexamined data. Also, a number of administrative, client, therapist, and interpersonal dyadic variables have been found to influence unilateral termination (Reis and Brown, 1999; Barrettt et al, 2008). However, the relationship among these variables has not been fully explored. Future research may look to modeling the structural relationships between these variables to better understand the dynamic factors that influence the decision to withdrawal from services.

Conclusions

Because of it's widespread deployment in UBCs across the nation, this investigation sought to examine if variables measured by the CCAPS-34 are capable of differentiating between completers and dropouts. This analysis also examined the risk of PT as clients progress along the EOC. Results partially supported findings previously discussed within the literature. For example, the results from the logistic regression analysis, the CART model, and the Cox PH regression model appeared to indicate that higher levels of social anxiety at intake appeared to be a protective factor against PT. Additionally, findings indicate that clients with higher levels of functional impairment were at increased risk of PT. Lastly, the rate of withdrawal observed in this study appeared to follow a negatively accelerating decay curve with a large proportion of clients terminating services after the initial session. Results also showed that the risk of PT is lowest during the early stages of treatment. These findings suggest that the highest proportion of clients withdrew from treatment when the risk of PT was at its lowest point. This result appears to indicate a large number of clients in the current sample are achieving therapeutic gains at an unusually rapid rate and mutually terminating services after achieving a good enough level (Baekeland and Lundwall, 1975; Barkham et al, 1996; Garfield, 1994; Hansen, Lambert, and Forman, 2002; Howard et al, 1986; Pekarik, 1985; Phillips. 1985). This investigation also examined the influence of hostility and academic concerns on the decision to unilaterally withdraw from services. Results from the BLR and Cox PH modeling strategies indicated that these variables have little influence on the decision to prematurely terminate services. In contrast, results from the CART model indicate that hostility may be an influential variable for PT in UBCs. These findings suggest the effect of hostility needs further development and future research may examine its moderating or mediating influence on the decision to unilaterally withdraw from services.

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APPENDIX A

DATA CODING SHEET

	Demographic Information for descriptive sample statistics	
1.	Client Age*	
2.	Client Gender	0 = Male 1 = Female
3.	Race/Ethnicity	0 = African-American / Black American 1 = Indian or Alaskan Native 2 = Asian American / Asian 3 = Caucasian / White 4 = Hispanic / Latino/a 5 = Native Hawaiian or Pacific Islander 6 = Multi-racial 7= Other/Unknown
4.	International student	0 = Yes 1 = No
5.	Country of Origin	
6.	Relationship Status	0 = Single 1 = Serious dating or committed relationship 2 = Civil union 3 = Domestic partnership equivalent 4 = Married 5 = Separated 6 = Divorced 7 = Widowed
7.	Current academic status:	0 = Freshman / First-year 1 = Sophomore 2 = Junior 3 = Senior 4 = Graduate / professional degree student 5 = Non-student 6 = High-school student taking college classes 7 = Non-degree student 8 = Faculty (Full-time/Adjunct/Instructor) 9 = Staff
8.	Housing Status	0 = On-campus residence hall/apartment 1 = On/off campus fraternity/sorority house 2 = On/off campus co-operative house 3 = Off-campus apartment/house 4 = Other (please specify)
	Variables Indentified in the Premature Termination Literature	
9.	Diagnosis	1 = Adjustment Disorders 2 = Anxiety Disorders 3 = Delirium, Dementia, and Amnestic and Other Cognitive

Disorders
4 = Attention Deficit/Hyperactivity Disorder
5 = Dissociative Disorders
6 = Eating Disorders
7 = Factitious Disorders
8 = Impulse-Control Disorders
9 = Mental Disorders Due to a General Medical Condition
10 = Mood Disorders
11 = Other Conditions That May Be a Focus of Clinical Attention (receiving a V code diagnosis)
12 = Personality Disorders
13 = Schizophrenia and Other Psychotic Disorders
14 = Sexual and Gender Identity Disorders
15 = Sleep Disorders | Somatoform Disorders
16 = Substance-Related Disorders

11. Functional impairment (GAF Score) at intake

Treatment Status:

12. Treatment Status — 0 = Dropout; 1= Completed

13. Number of sessions attended

- Will also be analyzed in the research questions.

Clinical Variables Measured by the CCAPS-34

			Time 1	Time 2	Time 3
12.	**Depression Scale**	**Total Score**			
Item 4	I don't enjoy being around people as much as I used to				
Item 5	I feel isolated and alone				
Item 11	I feel worthless				
Item 12	I feel helpless				
Item 21	I feel sad all the time				
Item 25	I have thoughts of ending my life				
13.	**General Anxiety**	**Total Score:**			
Item 2	My heart races for no good reason				
Item 7	I'm anxious that I might have a panic attack in public				
Item 9	I have sleep difficulties				
Item 10	My thoughts are racing				
Item 15	I have spells of terror or panic				
Item 17	I feel tense				
14.	**Social Anxiety**	**Total Score:**			
Item 1	I am shy around others				
Item 19	I make friends easily				
Item 22	I am concerned that other people do not like me				
Item 24	I feel uncomfortable around people I don't know				
Item 26	I feel self-conscious around others				
15.	**Academic Distress**	**Total Score:**			
Item 8	I feel confident I can succeed academically				
Item 28	I am not able to concentrate as well as usual				
Item 30	It's hard to stay motivated for my classes				
Item 33	I am unable to keep up with my schoolwork				
16.	**Eating Concerns**	**Total Score**			
Item 3	I feel out of control when I eat				
Item 6	I think about food more than I would like to				
Item 13	I eat too much				
17.	**Hostility**	**Total Score**			
Item 18	I have difficulty controlling my temper				

Item 20	I sometimes feel like breaking or smashing things	
Item 23	I get angry easily	
Item 29	I am afraid I may lose control and act violently	
Item 32	I frequently get into arguments	
Item 34	I have thoughts of hurting others	
18.	**Alcohol Use**	**Total Score**
Item 14	I drink alcohol frequently	
Item 16	When I drink alcohol I can't remember what happened	
Item 27	I drink more than I should	
Item 31	I have done something I have regretted because of drinking	

APPENDIX B

VARIABLE CODEBOOK

Variable Label	Description	Measurement Level
Age	Participant age (in years)	Scale
Gender	Participant Gender (dummy coding)	Nominal
Race_Ethni	Race/Ethnicity (eight levels; simple coding)	Nominal
Inter_Stu	International Status (dummy coding)	Nominal
Rela_Stat	Relationship status (8 levels; simple coding)	Nominal
Aca_Stat	Academic Status (10 levels; simple coding)	Nominal
House_Stat	Housing Status (5 levels; simple coding)	Nominal
Diagn	DSM Diagnosis (17 levels; simple coding)	Nominal
Experien	Therapist yrs of experience	Ordinal
GAF	Functional Impairment at intake	Scale
TxStatus	DV -Treatment status (2 levels; dummy coding)	Nominal
Session	Number of Sessions attended – measures time until target event (Termination or Completion; 1 - 12)	Ordinal
	CCAPS	
	Depression	
T1DTotal	Total score for CCAPS-34 Depression subscale at first measurement point (intake).	Scale
T2DTotal	Total score for CCAPS-34 Depression subscale at second measurement point (midpoint).	Scale
T3DTotal	Total score for CCAPS-34 Depression subscale at third measurement point (final).	Scale
	General Anxiety	
T1GATotal	Total score for CCAPS-34 Generalized Anxiety subscale at first measurement point (intake).	Scale
T2GATotal	Total score for CCAPS-34 Generalized Anxiety subscale at second measurement point (midpoint).	Scale
T3GATotal	Total score for CCAPS-34 Generalized Anxiety subscale at third measurement point (final).	Scale
	Social Anxiety	
T1SATotal	Total scores for the CCAPS-34 Social Anxiety subscale at first measurement point (intake)	Scale
T2SATotal	Total scores for the CCAPS-34 Social Anxiety subscale at second measurment point (midpoint)	Scale
T3SATotal	Total scores for the CCAPS-34 Social Anxiety subscale at third measurement point (final)	Scale
	Academic Distress	
T1ADTotal	Total Scores for the CCAPS-34 Academic Distress subscale at first measurement point (intake)	Scale
T2ADTotal	Total Scores for the CCAPS-34 Academic Distress subscale at	Scale

	second measurement point (midpoint)	
T3ADTotal	Total Scores for the CCAPS-34 Academic Distress subscale at final measurement point (final)	Scale
	Eating Concerns	
T1ECTotal	Total Scores for the CCAPS-34 Eating Concerns subscale at first measurement point (intake)	Scale
T2ECTotal	Total Scores for the CCAPS-34 Eating Concerns subscale at second measurement point (midpoint)	Scale
T3ECTotal	Total Scores for the CCAPS-34 Eating Concerns subscale at final measurement point (final)	Scale
	Hostility	
T1HTotal	Total Scores for the CCAPS-34 Hostility subscale at first measurement point (intake)	Scale
T2HTotal	Total Scores for the CCAPS-34 Hostility subscale at second measurement point (midpoint)	Scale
T3HTotal	Total Scores for the CCAPS-34 Hostility Subscale at final measurement point (final)	Scale
	Alcohol Abuse	
T1AATotal	Total Scores for the CCAPS-34 Alcohol Abuse Subscale at first measurement point (intake)	Scale
T2AATotal	Total Scores for the CCAPS-34 Alcohol Abuse Subscale at second measurement point (midpoint)	Scale
T3AATotal	Total Scores for the CCAPS-34 Alcohol Abuse Subscale at final measurement point (final)	Scale
	CCAPS-34 Subscale Item Scores at 3 Time Points	
	Depression Factor (6 items; 5 point Likert scale 0-4)	
T1_D4	I don't enjoy being around people as much as I used to (Intake)	Scale
T2_D4	I don't enjoy being around people as much as I used to (Time 2)	Scale
T3_D4	I don't enjoy being around people as much as I used to (Time 3)	Scale
T1_D5	I feel isolated and alone (Intake)	Scale
T2_D5	I feel isolated and alone (Time 2)	Scale
T3_D5	I feel isolated and alone (Time 3)	Scale
T1_D11	I feel worthless (Intake)	Scale
T2_D11	I feel worthless (Time 2)	Scale
T3_D11	I feel worthless (Time 3)	Scale
T1_D12	I feel helpless (Intake)	Scale
T2_D12	I feel helpless (Time 2)	Scale
T3_D12	I feel helpless (Time 3)	Scale
T1_D21	I feel sad all the time (Intake)	Scale
T2_D21	I feel sad all the time (Time 2)	Scale
T3_D21	I feel sad all the time (Time 3)	Scale
T1_D25	I have thoughts of ending my life (Intake)	Scale

T2_D25	I have thoughts of ending my life (Time 2)	Scale
T3_D25	I have thoughts of ending my life (Time 3)	Scale
	Generalized Anxiety Factor (6 items; 5 point Likert scale 0-4)	
T1_GA2	My heart races for no good reason (Intake)	Scale
T2_GA2	My heart races for no good reason (Time 2)	Scale
T3_GA2	My heart races for no good reason (Time 3)	Scale
T1_GA7	I'm anxious that I might have a panic attack in public (Intake)	Scale
T2_GA7	I'm anxious that I might have a panic attack in public (Time 2)	Scale
T3_GA7	I'm anxious that I might have a panic attack in public (Time 3)	Scale
T1_GA9	I have sleep difficulties (Intake)	Scale
T2_GA9	I have sleep difficulties (Time 2)	Scale
T3_GA9	I have sleep difficulties (Time 3)	Scale
T1_GA10	My thoughts are racing (Intake)	Scale
T2_GA10	My thoughts are racing (Time 2)	Scale
T3_GA10	My thoughts are racing (Time 3)	Scale
T1_GA15	I have spells of terror or panic (Intake)	Scale
T2_GA15	I have spells of terror or panic (Time 2)	Scale
T3_GA15	I have spells of terror or panic (Time 3)	Scale
T1_GA17	I feel tense (Intake)	Scale
T2_GA17	I feel tense (Time 2)	Scale
T3_GA17	I feel tense (Time 3)	Scale
	Social Anxiety Factor (5 items; 5 point Likert scale 0-4)	
T1_SA1	I am shy around others (Intake)	Scale
T2_SA1	I am shy around others (Time 2)	Scale
T3_SA1	I am shy around others (Time 3)	Scale
T1_SA19	I make friends easily (Intake)	Scale
T2_SA19	I make friends easily (Time 2)	Scale
T3_SA19	I make friends easily (Time 3)	Scale
T1_SA22	I am concerned that other people do not like me (Intake)	Scale
T2_SA22	I am concerned that other people do not like me (Time 2)	Scale
T3_SA22	I am concerned that other people do not like me (Time 3)	Scale
T1_SA24	I feel uncomfortable around people I don't know (Intake)	Scale
T2_SA24	I feel uncomfortable around people I don't know (Time 2)	Scale
T3_SA24	I feel uncomfortable around people I don't know (Time 3)	Scale
T1_SA26	I feel self-conscious around others (Intake)	Scale
T2_SA26	I feel self-conscious around others (Time 2)	Scale
T3_SA26	I feel self-conscious around others (Time 3)	Scale
	Academic Distress Factor (4 items; 5 point Likert scale 0-4)	
T1_AD8	I feel confident I can succeed academically (Intake)	Scale
T2_AD8	I feel confident I can succeed academically (Time 2)	Scale
T3_AD8	I feel confident I can succeed academically (Time 3)	Scale
T1_AD28	I am not able to concentrate as well as usual (Intake)	Scale
T2_AD28	I am not able to concentrate as well as usual (Time 2)	Scale
T3_AD28	I am not able to concentrate as well as usual (Time 3)	Scale
T1_AD30	It's hard to stay motivated for my classes (Intake)	Scale

T2_AD30	It's hard to stay motivated for my classes (Time 2)	Scale
T3_AD30	It's hard to stay motivated for my classes (Time 3)	Scale
T1_AD33	I am unable to keep up with my schoolwork (Intake)	Scale
T2_AD33	I am unable to keep up with my schoolwork (Time 2)	Scale
T3_AD33	I am unable to keep up with my schoolwork (Time 3)	Scale
	Eating Concerns Factor (3 items; 5 point Likert scale 0-4)	
T1_EC3	I feel out of control when I eat (Intake)	Scale
T2_EC3	I feel out of control when I eat (Time 2)	Scale
T3_EC3	I feel out of control when I eat (Time 3)	Scale
T1_EC6	I think about food more than I would like to (Intake)	Scale
T2_EC6	I think about food more than I would like to (Time 2)	Scale
T3_EC6	I think about food more than I would like to (Time 3)	Scale
T1_EC13	I eat too much (Intake)	Scale
T2_EC13	I eat too much (Time 2)	Scale
T3_EC13	I eat too much (Time 3)	Scale
	Hostility Factor (6 items; 5 point Likert scale 0-4)	
T1_H18	I have difficulty controlling my temper (Intake)	Scale
T2_H18	I have difficulty controlling my temper (Time 2)	Scale
T3_H18	I have difficulty controlling my temper (Time 3)	Scale
T1_H20	I sometimes feel like breaking or smashing things (Intake)	Scale
T2_H20	I sometimes feel like breaking or smashing things (Time 2)	Scale
T3_H20	I sometimes feel like breaking or smashing things (Time 3)	Scale
T1_H23	I get angry easily (Intake)	Scale
T2_H23	I get angry easily (Time 2)	Scale
T3_H23	I get angry easily (Time 3)	Scale
T1_H29	I am afraid I may lose control and act violently (Intake)	Scale
T2_H29	I am afraid I may lose control and act violently (Time 2)	Scale
T3_H29	I am afraid I may lose control and act violently (Time 3)	Scale
T1_H32	I frequently get into arguments (Intake)	Scale
T2_H32	I frequently get into arguments (Time 2)	Scale
T3_H32	I frequently get into arguments (Time 3)	Scale
T1_H34	I have thoughts of hurting others (Intake)	Scale
T2_H34	I have thoughts of hurting others (Time 2)	Scale
T3_H34	I have thoughts of hurting others (Time 3)	Scale
	Alcohol Use Factor (5 items; 5 point Likert scale 0-4)	
T1AU14	I drink alcohol frequently (Intake)	Scale
T2_AU14	I drink alcohol frequently (Time 2)	Scale
T3_AU14	I drink alcohol frequently (Time 3)	Scale
T1_AU16	When I drink alcohol I can't remember what happened (Intake)	Scale
T2_AU16	When I drink alcohol I can't remember what happened (Time 2)	Scale
T3_AU16	When I drink alcohol I can't remember what happened (Time 3)	Scale
T1_AU27	I drink more than I should (Intake)	Scale
T2_AU27	I drink more than I should (Time 2)	Scale

T3_AU27	I drink more than I should (Time 3)	Scale
T1_AU31	I have done something I have regretted because of drinking (Intake)	Scale
T2_AU31	I have done something I have regretted because of drinking (Time 2)	Scale
T3_AU31	I have done something I have regretted because of drinking (Time 3)	Scale

Key:

- CCAPS-34 Subscale Total Scores at 3 Time Points
- T1=Data Collected at administration 1
- T2=Data Collected at administration 2
- T3=Data Collected at administration 3
- D=Depression
- GA=Generalized Anxiety
- SA=Social Anxiety
- AD=Academic Distress
- EC=Eating Concerns
- H=Hostility
- AA=Alcohol Abuse
- Total = Composite score (mean score of the items)

APPENDIX C

DEPRESSION SUBSCALE

PAIRWISE SAMPLE COVARIANCE MATRIX

CCAPS-34 Depression Subscale

	Item 4	Item 5	Item 11	Item 12	Item 21	Item 25
Item 4	1.927					
Item 5	0.959	1.979				
Item 11	0.669	1.145	1.944			
Item 12	0.773	1.255	1.362	1.897		
Item 21	0.928	1.291	1.086	1.094	1.725	
Item 25	0.297	0.541	0.710	0.569	0.561	1.066

APPENDIX D

GENERALIZED ANXIETY SUBSCALE

PAIRWISE SAMPLE COVARIANCE MATRIX

CCAPS-34 Generalized Anxiety Subscale

	Item 2	Item 7	Item 9	Item 10	Item 15	Item 17
Item 2	2.115					
Item 7	1.021	2.011				
Item 9	0.678	0.455	2.025			
Item 10	1.054	0.566	0.765	2.025		
Item 15	1.067	1.336	0.634	0.649	2.016	
Item 17	0.994	0.828	.609	1.022	0.875	2.143

APPENDIX E

SOCIAL ANXIETY SUBSCALE

PAIRWISE SAMPLE COVARIANCE MATRIX

CCAPS-34 Social Anxiety Subscale

	Item 1	Item 19	Item 22	Item 24	Item 26
Item 1	1.483				
Item 19	0.892	1.591			
Item 22	0.360	0.316	2.081		
Item 24	0.019	0.665	0.698	1.771	
Item 26	0.758	0.465	1.192	0.922	1.870

APPENDIX F

ACADEMIC DISTRESS SUBSCALE

PAIRWISE SAMPLE COVARIANCE MATRIX

CCAPS-34 Academic Distress Subscale

	Item 8	Item 28	Item 30	Item 33
Item 8	1.446			
Item 28	0.469	1.899		
Item 30	0.775	1.323	2.169	
Item 33	0.846	1.026	1.564	2.100

APPENDIX G

EATING CONCERNS SUBSCALE

CCAPS-34 Eating Concerns Subscale

	Item 3	Item 6	Item 13
Item 3	1.396		
Item 6	0.917	1.412	
Item 13	1.000	1.138	1.534

APPENDIX H

HOSTILITY SUBSCALE

PAIRWISE SAMPLE COVARIANCE MATRIX

CCAPS-34 Hostility Subscale

	Item 18	Item 20	Item 23	Item 29	Item 32	Item 34
Item 18	1.504					
Item 20	0.889	1.897				
Item 23	1.123	0.910	1.685			
Item 29	0.445	0.678	0.447	0.937		
Item 32	0.748	0.423	0.768	0.243	2.565	
Item 34	0.207	0.385	0.181	0.368	0.136	0.524

APPENDIX I

ALCOHOL ABUSE SUBSCALE

PAIRWISE SAMPLE COVARIANCE MATRIX

CCAPS-34 Alcohol Abuse Subscale

	Item 14	Item 16	Item 27	Item 31
Item 14	1.133			
Item 16	0.519	0.711		
Item 27	0.847	0.503	0.940	
Item 31	0.629	0.550	0.631	1.450

APPENDIX J
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APPENDIX K
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APPENDIX L
CURRICULUM VITAE

Sean Hall earned a Bachelor of Arts Degree in Psychology and a Master of Arts in Counseling from Florida Gulf Coast University in Fort Myers, Fl. His clinical interests focus on mental health issues facing underserved populations. Sean has worked in a number of diverse clinical settings including grief/bereavement support, community mental health centers, psychiatric emergency services/crisis stabilization, and outpatient therapy clinics. His administrative experience includes overseeing an outpatient/inpatient utilization review program and directing graduate training clinics for Old Dominion University and the University of Alabama at Birmingham. Sean's primary research interests focus on psychotherapy processes and outcomes, measurement, and evaluation in clinical mental health counseling. He is currently a Visiting Assistant Professor and Clinic Director at the University of Alabama at Birmingham. Sean has presented and co-presented at local, regional, and national conferences on topics related to cognitive complexity, suicide prevention and intervention, clinical assessment techniques, mental health diagnosis, behavioral health systems, male recruitment and retention, mental health diagnosis, toxic training groups, and constructivist education.