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**Should I stay or should I go – predicting psychotherapy
dropout in a university training clinic**

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Psychotherapy dropout has adverse effects on patients, therapists and mental health care organizations. Research has found demographic variables, therapist experience, diagnosis and treatment setting to be related to dropout. Other variables, for instance symptom severity and interpersonal problems have been sparsely studied. The present study aimed to examine and predict psychotherapy dropout from a university training clinic sample of 350 patients. Patients of Psychodynamic Therapy displayed greater dropout rates than Brief Dynamic Therapy patients (71.2% vs 44.5%). Two binary logistic regressions were conducted, indicating that being older, being a student and being more socially avoidant predicted dropout from Brief Dynamic Therapy. Psychodynamic Therapy dropout could not be predicted. Results are discussed and recommendations for future research are made.

Premature discontinuation of treatment, also known as psychotherapy attrition or dropout, has long been regarded as a significant impediment to the effective delivery of mental health services (Swift & Greenberg, 2012; Hatchett & Park, 2003; Wierzbicki & Pekarik, 1993; Barrett, Chua, Crits-Cristoph, Gibbons & Thompson, 2008; Baekeland & Lundwall, 1975). Psychotherapy dropout has been known to cause complications with outcome research (Howard, Krause & Orlinsky, 1986) and adversely affect patients, treatment providers and society as a whole. Patients who drop out of therapy experience greater treatment dissatisfaction and worse outcomes (Björk, Björck, Clinton, Sohlberg & Norring, 2009; Klein, Stone, Hicks, & Pritchard, 2003). Other consequences, such as a decreased propensity to seek mental health treatment in the future, are also conceivable. Early dropout is especially disquieting, considering some research which suggests the need for a minimum of 11 sessions for the majority of patients to improve (Lambert, 2007). Therapists, upon losing a client to dropout, might experience a sense of failure or rejection (Sledge, Moras, Hartley & Levine, 1990; Barrett et al., 2008; Klein et al., 2003). In fact, some research suggests patient dropout to be the third greatest source of stress for mental health professionals (Farber, 1983). Dropout may also impact health care organizations and society as a whole by wasting resources and restricting the number of people that can be effectively helped (Barrett et al., 2008). Given the negative impact of psychotherapy dropout, it is no wonder that it has been a widely studied subject. However, for all the research and urgency, conflicting results leave our understanding of dropout little better than 50 years ago (Baekeland & Lundwall, 1975).

Psychotherapy dropout can be conceptually defined as premature unilateral discontinuation of treatment, meaning the patient in question decided, against the explicit or implicit advice of the therapist, to discontinue therapy before any significant change had been brought about. Although there is disagreement on the operational definitions of dropout, most agree on this conceptual definition (Hatchett & Park, 2003; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993).

Among the varying methods by which one can operationalize dropout, four are widely recognized as the most common. One prevalent method is to classify all clients who attend less than a given number of sessions, as dropouts. An example of this is the

median-split procedure, whereby if a patient attends less than the median number of sessions attended by the sample, that person is classified as a dropout. Indeed, this method is easy to calculate but is linked to needlessly normative statements about the appropriate length of treatment. As a result, it runs the risk of misclassifying early recoverees and late non-recoverees. Another method of operationalization is failure to complete a full treatment protocol. It resembles the above method and has similar drawbacks regarding operational validity. A third method is based on whether or not the patient failed to attend the last scheduled appointment. This method assumes that patients who let their therapists know ahead of time about their decision to discontinue treatment, have not actually dropped out, irrespective of having improved or not. A fourth method is based on therapist judgment. At the end of treatment, the therapists answer the question of whether or not the client dropped out. While this method is the one with the most operational validity, it has potential reliability issues, as different therapists might have differing ideas about what constitutes an inappropriate discontinuation (Hatchett & Park, 2003; Swift & Greenberg, 2012). Therapist judgment has, despite its' flaws, long been considered the best operationalization (Pekarik, 1985), however, recently a fifth method has emerged. This method determines clients to be dropouts based on whether or not they attain clinically significant change before dropping out. The benefit of this method is increased validity over length based classifications and reliability exceeding that of therapist judgment (Swift, Callahan & Levine, 2009; Hatchett & Park, 2003).

To empirically demonstrate the effects of methodological divergence, Hatchett and Park (2003) compared four operational definitions using the same sample and found dropout rates ranging from 17.6% to 53.1%. Therapist judgment and "missed last scheduled appointment" showed acceptable agreement (both produced 40.8% dropout rates) whereas the median-split procedure and failure to return after the intake interview produced a rate of 53.1% and 17.6% respectively. Apart from methodological issues, the field of dropout research has been plagued by an atheoretical approach, simplistic analyses and inconsistent findings.

Despite a long history of investigating psychotherapy dropout that has resulted in, among other things, three meta-analyses reviewing a combined total of 1154 studies spanning the years of 1949-2010 (Baekeland & Lundwall, 1975; Wierzbicki & Pekarik, 1993; Swift & Greenberg, 2012), some note that there has yet to emerge any specific theoretical framework to guide future investigative efforts. Harris (1998) makes this point as well as notes that research has been focused mainly on studying isolated variables and their correlations to dropout without clarifying interactions or potential confounding effects. Moreover, Harris notes the lack of replication in the field and as an example cites the meta-analysis by Wierzbicki and Pekarik (1993), in which, out of 32 studied variables only three had significant effect sizes. Similarly, out of 21 variables examined in the latest comprehensive meta-analysis by Swift and Greenberg (2012), 10 variables were found to be statistically significant, indicating some improvement. All variables studied were treatment, client, provider or study variables with no reported interactions between groups of variables.

Past research on psychotherapy dropout

Despite methodological inconsistencies and difficulties replicating findings, past research has found several variables to be associated with treatment dropout.

Client variables. Among client variables, the most robust finding has been socioeconomic status (SES), showing that patients with lower SES tend to drop out more, ostensibly due to difficulties in accessing and prioritizing mental health care (Baekeland & Lundwall, 1975; Wierzbicki & Pekarik, 1993; Self, Oates, Pinnock-Hamilton & Leach, 2005; Olfson et al., 2009; de Haan, Boon, Vermeiren, Hoeve & Jong, 2015). The findings on client age as related to dropout have been less decisive. While some comprehensive studies have shown that younger patients are more likely to drop out (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993; Werbart & Wang, 2012; Fenger, Mortensen, Poulsen & Lau, 2011; Baekeland & Lundwall, 1975; White et al., 2010), others show no such correlations (Kegel & Flückiger, 2015; Affleck & Garfield, 1961; Baekeland & Lundwall, 1975) and yet again others show slightly more complex interactions. For instance, Olfson et al. (2009) found in their study that younger patients indeed drop out more frequently, however only when treated by psychiatrists. Patient gender has in some reports been found to significantly correlate with dropout, with women dropping out more frequently (Wierzbicki & Pekarik, 1993; Baekeland & Lundwall, 1975; de Haan et al., 2015). In other reports, the correlation has been missing (Olfson et al., 2009; Swift & Greenberg, 2012; Kegel & Flückiger, 2015; Fenger et al., 2011; Werbart & Wang, 2012; Affleck & Garfield, 1961). Addressing gender differences in dropout propensity, one review and one naturalistic study have presented support for the notion that a therapist-patient gender mismatch may lead the patient to dropout following sexist or otherwise insensitive remarks made by a male therapist (Vasquez, 2007; Nysæter, Nordahl & Havik, 2010). In the same review, similar explanations were presented to explain high numbers of dropouts and general underutilization of mental health services among ethnic minorities and people of color (Baekeland & Lundwall, 1975; Reis & Brown, 1999; Wierzbicki & Pekarik, 1993; Olfson et al., 2009; Barrett et al., 2008; de Haan et al., 2015). Maramba and Nagayama Hall (2002) found in their meta-analysis that therapist-patient ethnic matching indeed does improve retention rates among ethnic minorities but with negligible overall effect sizes the findings were deemed to be of no clinical significance. The conclusion, instead, is that cultural sensitivity can be practiced in the therapy room regardless of ethnic matching. Further demographic variables of note are education, employment and marital status with some studies identifying lesser education level, unemployment and being unmarried as risk factors for dropout (Baekeland & Lundwall, 1975; see also Wierzbicki & Pekarik, 1993; Roos & Werbart, 2013; McCabe, 2002; Olfson, 2009; Fenger et al., 2011; Barrett et al., 2008; Richmond, 1992) while others find no such links (Swift & Greenberg, 2012; see also Fenger et al., 2011; Werbart & Wang, 2012; Affleck & Garfield, 1961).

Scarce research has been done on psychotherapy dropout using qualitative methods. One such study, by Khazaie, Rezaie, Shahdipour and Weaver (2016), investigated patients' own reasons for dropping out of therapy in Iran and found dissatisfaction with the quality of psychotherapy, financial problems, stigmatization of psychological disorders and psychotherapy being a time consuming and non-user friendly treatment as stated reasons for dropping out. To be sure, it is conceivable that these reasons, to some degree, would pose obstacles to finishing a treatment course in contexts other than Iran.

Problem type, severity and interpersonal style. The field of psychotherapy dropout research, being atheoretical and centered on demographics (Harris, 1998), has seen limited research on other variables of interest. Given the inconsistent findings regarding treatment moderators and demographics, there is widespread agreement that future research should direct its' efforts towards finding other, more robust and conclusive,

correlates of dropout (Harris, 1998; Wierzbicki & Pekarik, 1993; Swift & Greenberg, 2012). To this end, symptom severity has been studied with mixed results. While some findings dispute the existence of a correlation between symptom severity and dropout (Keijsers, Kampman & Hoogduin, 2001; White et al., 2010; Hoyer et al., 2016), others present a more nuanced picture. At least one study has found that non-responsiveness to pharmacotherapy for major depressive disorder increases the risk of dropout (Power et al., 2012) and some evidence suggests that symptom severity measured just before dropout is associated with dropout but not symptom severity measured at pretreatment (Chasson, Vincent & Harris, 2008). Among studies that have found links, some evidence indicates that lesser disorder severity predisposes one for dropout (Issakidis & Andrews, 2004; Simon & Ludman, 2010; Glombiewski, Hartwich-Tersek & Rief, 2010). This is hardly surprising, as it is likely that those with less severe problems might achieve symptom relief faster than anticipated. However, these findings beg the question of how dropout has been operationalized: on the surface, it might look like early recoverees are dropouts but these patients, having been adequately helped, are relatively unproblematic and thus trivial to study.

Dropout rates have been found to be linked to patient diagnosis, with depression, substance abuse and other addictions resulting in mean dropout rates of 36.4% for each of the diagnostic groups. The lowest dropout rates are recorded for anxiety and psychotic disorders with dropout rates of 19.6% and 20.1% respectively. Eating disorders and post-traumatic stress disorder (PTSD) record mean dropout rates of 31.0% and 27.2% respectively (Fernandez, Salem, Swift & Ramtahal, 2015). Not surprisingly, perhaps, seeing as PTSD tends to get worse before it gets better when treated with Prolonged Exposure (PE) and eating disorders, often being ego syntonic, are notoriously difficult to treat.

To my knowledge there is sparse research relating interpersonal problems to risk of dropout. Personality, which can be argued to be an extension of interpersonal style, has come up short showing no correlations between the facets of personality in the Five Factor Model (FFM) and dropout for a sample of patients with PTSD (van Emmerik, Kamphuis, Noordhof & Emmelkamp, 2011). One study, investigating risk factors for dropout in a psychodynamic group therapy unit, found poor social functioning and antisocial behavior on the Millon Clinical Multiaxial Inventory-II (MCMI-II) to predispose patients to dropout (Jensen, Mortensen & Lotz, 2014). Given that psychotherapy is an intensely interpersonal process, it is perhaps no wonder that problems in this domain better distinguish dropouts than personality alone. Furthermore, hostility and social isolation/introversion, variables closely related to interpersonal problems, have been associated with dropout in previous studies (Baekeland & Lundwall, 1975; MacNair & Corazzini, 1994). Moreover, having previously attended individual counseling is in one study predictive of remaining in treatment (MacNair & Corazzini, 1994).

Therapist variables. Therapist variables, like client variables, have centered on studying isolated characteristics but in contrast to client variables, they are far less studied. As with previous findings, these too are inconclusive. Although some studies report findings indicating that therapist experience level affects dropout rates, with trainees experiencing greater dropout rates than experienced therapists (Swift & Greenberg, 2012; Roos & Werbart, 2013; O'Brien, Fahmy, & Singh, 2009), others fail to find such links (Fernandez et al., 2015). Among licensed treatment providers, one large study found psychologists less likely to experience dropout compared to MDs and nurses but more likely when compared to social workers and marriage and family therapists (Hamilton, Moore,

Crane & Payne, 2011). Not surprisingly, therapists who are perceived as judgmental, rejecting or hostile experience greater dropout rates than others (Roos & Werbart, 2013; Baekeland & Lundwall, 1975). Furthermore, discrepancies between therapists' and patients' expectations for treatment and having a younger therapist seems to be related to dropout (Baekeland & Lundwall, 1975; Werbart & Wang, 2012). Therapist gender or ethnicity seems to have no bearing on dropout rates (Wierzbicki & Pekarik, 1993).

Results for alliance as it relates to dropout are less ambiguous. In one meta-analytic review on the subject, Sharf, Primavera and Diener (2010) found alliance to have a moderately strong correlation to dropout ($d=.55$). Furthermore, they found client education, length of treatment and treatment setting to moderate this relationship. For clients with less education, in long treatments and in an inpatient setting, alliance had a greater impact on dropout rates than compared with shorter outpatient treatments with highly educated clients. Other studies have also confirmed the importance of alliance in mediating dropout rates (Barrett et al., 2008; Johansson & Eklund, 2006).

Treatment variables. Research on treatment variables has produced ample results. A meta-analysis conducted by Swift and Greenberg (2014) investigated, among other variables, the effect of treatment type on patient dropout. Treatment types ranged from Cognitive Behavior Therapy (CBT), and variations thereof, to Dialectal Behavior Therapy (DBT), integrative approaches, Interpersonal Therapy (IPT) and Psychodynamic approaches. For nine out of 12 disorders, no effect of treatment type on dropout was found. In contrast, for depression, PTSD and eating disorders there were significant differences between treatment types with integrative approaches producing the least amount of dropout for depression (10.9% compared to an average of 19.2%) and PTSD (8.8% compared to an average of 21.0%) and DBT resulting in the least amount of dropout for eating disorders (5.9% compared to an average of 24.2%). As for other treatments, psychodynamic therapies display dropout rates on par with averages of other treatments: 26.2% for bereavement, 30.5% for borderline personality disorder, 15.2% for depression, 27.1% for eating disorders and 11.3% for generalized anxiety disorder. No distinctions are made, however, between short and long term dynamic therapy.

One study, more closely examining predictors of dropout from a university training clinic found differential predictors depending on what phase of treatment patients were in when they dropped out. Patients who dropped out after intake interview or during the evaluation phase were less educated, held high expectations regarding therapy, were more hostile and less satisfied with the therapy. Patients who dropped out during the therapy phase were less cooperative in exploring inner issues, more grandiose and displayed lower levels of guilt (Richmond, 1992). Further studies investigating training clinic dropout have implicated predictors with varying degrees of interactions and complexity. Findings by Lampropoulos, Schneider and Spengler (2009) indicate that older patients, with lesser income, higher perceived difficulty and more functional impairment were more likely to drop out. In another study, reporting an overall dropout rate of 77%, it was found that high client expectations on the effectiveness of therapy predicted dropout but was somewhat mediated by high role expectations on the therapist (Callahan, Aubuchon-Endsley, Borja & Swift, 2009). In a similar study, with a somewhat simpler design, it was found that clients outside of normative reference ranges for the Psychotherapy Expectancy Inventory-Revised (PEI-R: a scale measuring expectations on the effectiveness of psychotherapy) were 7 times more likely to drop out compared to patients who obtained results within the normative reference ranges (Aubuchon-Endsley

& Callahan, 2009). The authors conclude the study with recommendations for other training clinics to employ the use of the PEI-R in order to identify at-risk clients.

Furthermore, treatment format has been linked to divergent dropout rates, with e-therapy resulting in an average of 24.2% pretreatment dropout compared with individual and group therapy resulting in averages of 9.7% and 14.5% dropout respectively. Treatment setting also plays a role, with inpatients dropping out least frequently (18.9%) compared to outpatient (26.0%) and other settings (29.5%) (Fernandez et al., 2015). When compared to other settings, university training clinics experience the greatest frequency of dropout at 30.4% (Swift & Greenberg, 2012). Additionally, manualized therapies and those with low time limits produce less dropouts when compared to non-manualized treatments and those with no time limits (Swift & Greenberg, 2012; Sledge et al., 1990).

Study variables. Study variables have been hypothesized by some to influence the reported dropout rates. Swift and Greenberg (2012), for instance, suggest that their meta-analysis might have recorded lower dropout rates than Wierzbicki and Pekariki (1993) due to including more efficacy studies which are notably selective about their patients. It is likely that the stringent inclusion criteria of research clinics manage to weed out would-be-dropouts before even commencing treatment. However, results in a meta-analysis conducted by Fernandez et al. (2015) seem to dispute this, showing no differences in dropout rate between randomized controlled trials (RCTs) compared to other study designs.

In conclusion, previous research has implicated numerous variables as correlates of dropout. Studies have been simplistic in design and findings have been contradictory across studies. No studies seem to have included demographic variables in conjunction with symptom severity and interpersonal problems in one composite predictive model. This study aims to change that. The purpose of the present study is therefore to examine the rate of dropout and to explore whether or not interpersonal problems, problem severity and demographic variables are able to accurately predict dropout from psychodynamic psychotherapy in a university training clinic. In order to fulfill this purpose, three research questions are posed:

1. Do differences exist for rate of dropout between Psychodynamic Therapy and Brief Dynamic Therapy?
2. What variables, if any, predict dropout from Brief Dynamic Therapy?
3. What variables, if any, predict dropout from Psychodynamic Therapy?

Method

Sample

The original dataset was extracted from the database on September 9th, 2016 and consisted of 587 patients, admitted between August 23rd, 2013 and September 1st 2016. One duplicate case and two patients, having been assigned to Cognitive Behavioral Therapy (CBT)¹, were excluded from the data. Several patients did not specify which type of therapy they were interested in, but rather requested either Brief Dynamic Therapy (BDT) or Psychodynamic Therapy (PDT). However, 25 of these failed to complete therapy and

¹ CBT was not included in the present study owing to difficulties in distinguishing completers from dropouts.

fill out what therapy they ended up undergoing. Consequently, they were excluded from the study. 31 patients, assigned to BDT, were excluded on the basis of not having had enough time to finish their therapy before September 9th, 2016. The same was done for 178 patients assigned to PDT, leaving a total sample of $N=350$. Of these, 218 (62.3%) patients received BDT and 132 (37.7%) received PDT. There were no statistical differences between treatment conditions regarding age, gender, place of birth, occupation, living situation or education level (see Table 1 for details).

Table 1
Background/demographic variables. Data is presented as percent with absolute values in parentheses, alternatively as a mean \pm standard deviation.

	Total sample (N=350) % (N)
Gender	
<i>Women</i>	75.1 (263)
<i>Men</i>	24.9 (87)
Age (N=349)	30 \pm 7.4
Place of birth	
<i>Sweden</i>	92.6 (324)
<i>Other</i>	7.4 (26)
Current living conditions	
<i>With a partner</i>	29.1 (102)
<i>With a partner and child(ren)</i>	17.1 (60)
<i>Single with child(ren)</i>	5.4 (19)
<i>With a parent</i>	5.1 (18)
<i>With another relative</i>	1.1 (4)
<i>With friend(s)</i>	8.9 (31)
<i>Alone</i>	30.9 (108)
<i>Other</i>	2.3 (8)
Highest education	
<i>Elementary school</i>	1.7 (6)
<i>High school</i>	20.6 (72)
<i>College/University</i>	72.9 (255)
<i>Other</i>	4.9 (17)
Occupation	
<i>Employed</i>	55.4 (194)
<i>Studying</i>	33.7 (118)
<i>Unemployed</i>	5.1 (18)
<i>Sick leave/Early retirement</i>	1.1 (4)
<i>Retirement</i>	.3 (1)
<i>Other</i>	4.3 (15)

Description of treatment conditions and procedure

Patients who wish to enroll in therapy are given a choice of CBT, PDT or BDT, the last two of which are described below. On occasion, the patient has no preference, or signs up for one type of therapy but is recommended another by the interviewing clinician. Furthermore, if the presenting problem is deemed too severe for a therapist in training or if the presenting problem is an active substance abuse, personality disorder or psychotic disorder, the patient is directed to seek treatment elsewhere. PDT is administered once-weekly, for three semesters, in 45-50 minute sessions. The student therapist is supervised roughly once every two weeks by a senior clinician in a group of no more than four students. The theoretical basis of PDT, while basically psychoanalytical, varies between supervisors. The patient is given the opportunity to freely explore reasons for and solutions to psychological issues, past and present. BDT is mainly administered once-weekly, for 14 weeks, in 45-50 minute sessions. The student therapist is supervised roughly once every two weeks by an experienced clinician in a group of no more than four students. The theoretical basis of BDT also varies slightly between supervisors but the general guidelines are a limited scope, focus on experiencing affects and working on current difficulties and their solutions, with less attention being paid to childhood experiences. For both types of therapy, there are on occasion slight deviations from the above described guidelines.

The university training clinic at Gothenburg University routinely collects data on all patients for research and quality control purposes. All patients are informed that data may be used for research, theses or quality control. All data is anonymous and each patient is represented only by an ID-code in the datafile. After an initial intake interview with a senior clinician, patients are directed to a computer where they fill out pretreatment measurements. After a period of time, between one week and up to three months, patients are assigned a student therapist. Following their last session, patients are again directed to a computer, this time by the student therapist, to fill out posttreatment measurements. Dates for pre- and posttreatment measurements are automatically filled out.

Operational definitions of dropout

As stated, the present study conceptually defined dropout as premature, unilateral discontinuation of treatment, against the implicit or explicit advice of the therapist. However, in the operationalization of this definition, methodological concerns arise.

As there was no direct registration of dropouts in the data, proxy variables were used to distinguish dropouts from completers. To assist in this, patients were divided into four conceptual groups, as demonstrated in Table 2. Distinguishing group A from C was done using a cutoff based on the expected length of treatment. BDT patients attend approximately 14 sessions, at a rate of one session per week, resulting in a cutoff of 98 days of treatment or more to be classified a completer. For PDT, since there is no agreed upon number of sessions to be completed (PDT patients, instead, attend therapy for three semesters), a senior clinician and supervisor was consulted on approximately what dates patients begin and end therapy for each semester (C. Gunnarsson, personal communication, 23d of February 2017). From there, a cutoff of 473 days was derived for PDT patients. As previously stated, dates for pre- and posttreatment measurements are automatically filled out with the amount of days between the dates calculated in a separate variable. Since the first date is the date of the intake interview with a senior clinician, the days-variable also accounts for the delay between intake interview and start of therapy. This

delay is in general 1-4 weeks but can on occasion reach up to three months. The cutoffs for both treatment conditions, however, do not account for this delay: this was done deliberately in an attempt to reduce the number of false positives in the dropout group.

Distinguishing group B from D proved impossible with the existing dataset. In discussion with a supervisor, it was estimated that group B is of negligible size. Furthermore, excluding groups B and D from the study in order to increase validity, would entail excluding patients who discontinue therapy without prior notice, which is indeed an interesting group to examine. It was therefore decided to classify both groups B and D as dropouts. The constraints that this inevitably puts upon the study are discussed under study limitations.

Table 2

Dividing patients into four conceptual groups to aide classification of dropout.

A: Patients who have finished therapy and registered posttreatment measurements.	B: Patients who have finished therapy but have not registered posttreatment measurements.
C: Patients who have dropped out of therapy and registered posttreatment measurements.	D: Patients who have dropped out of therapy but have not registered posttreatment measurements.

Measures

Data on several background variables are collected during pre- and posttreatment measurements. Variables include gender, age, country of birth, living situation, education, occupation and a number of questions about motivation and presenting problems. Furthermore, patients fill out baseline measurements on, amongst others, Clinical Outcomes in Routine Evaluation – Outcome Measure (CORE-OM) and Inventory of Interpersonal Problems (IIP).

Clinical Outcomes in Routine Evaluation – Outcome Measure (CORE-OM; Elfström & Carlsson, 2013) is an outcome measure intended for clinical use by therapists in different settings, utilizing varying psychotherapeutic methods. It is a 34-item self-report questionnaire covering four domains: 1) Well-being (four questions), 2) Social functioning (12 questions), 3) Problems/symptoms (12 questions), 4) Risk (six questions): a) to self (harm/suicide), b) to others (harm) (Elfström & Carlsson, 2013). An example statement from the well-being subscale is “I have felt overwhelmed by my problems.”. An example from the social functioning subscale is “I have felt terribly alone and isolated.”. An example from the problems/symptoms subscale is “I have felt tense, anxious or nervous.”. Examples from the risk subscales are “I have thought of hurting myself.” or “I have threatened or intimidated another person.”. There are two ways to obtain an aggregate of the subscale scores. One is to combine all subscale means and the other is to combine all subscale means excluding the two risk subscales. In accordance with the directions in the Swedish manual, the second method was utilized (Elfström & Carlsson, 2013). In the present study, this scale is termed CORE total scale. All items have five response levels, scored 0 to 4 on a Likert scale (Evans et al., 2000). CORE-OM has been translated and validated in Sweden. Spearman’s ρ indicated a correlation of .78 between the English and Swedish versions. Chronbach’s α of .93 and .94 for non-clinical and clinical groups respectively indicated acceptable internal consistency. The test-retest stability, calculated using Spearman’s ρ , showed adequate values at .85 for the entire scale. Looking at the

effect size of the mean score differences, the ability to distinguish clinical from non-clinical groups was deemed satisfactory at $d=1.30$. Given that the total scale performs considerably better than any subscale in test-retests, correlations with referential measures and tests of internal consistency, it was decided to only use the total scale and none of the subscales for the present study (Elfström et al., 2012).

Inventory of Interpersonal Problems (IIP; Horowitz, Alden, Wiggins, & Pincus, 2000) is a 64-item self-report questionnaire, measuring interpersonal problems, on a five-point Likert scale ranging from 0 to 4, over eight domains: 1) Domineering, 2) Vindictive, 3) Cold, 4) Socially avoidant, 5) Nonassertive, 6) Exploitable, 7) Overly nurturant and 8) Intrusive. Sample items are as follows: “I am too aggressive toward other people.” (domineering), “I want to get revenge against people too much.” (vindictive), “It is hard for me to feel close to other people.” (cold), “I feel embarrassed in front of other people too much.” (socially avoidant), “It is hard for me to be assertive with another person.” (nonassertive), “I let other people take advantage of me too much.” (exploitable), “I try to please other people too much.” (overly nurturant), “I want to be noticed too much.” (intrusive). Following directions in the Swedish manual of the IIP, raw scores were transformed into normal t values (Horowitz et al., 2000). Internal consistency, measured using Chronbach’s α , for the eight scales ranges from .70 to .85. The IIP has been shown to correlate well with other measures of personality, namely Karolinska Scales of Personality (KSP; Ortet, Ibáñez, Llerena & Torrubia, 2002), Toronto Alexithymia Scale (TAS; Bagby, Parker & Taylor, 1994) and Schalling-Sifneos Personality Scale (SSPS; Bagby, Taylor & Ryan, 1986), however there is no data on test-retest reliability for the Swedish version (Weinryb et al., 1996).

Statistical analyses

Data was analyzed using SPSS 24 for Windows. Independent sample t -tests were run to examine differences in age, CORE-OM and IIP between treatment conditions. This was done in order to further elucidate potential differences that might appear in the regression analyses. Chi-square tests for independence were run for demographic variables on the nominal level of data, as well as to analyze differences in dropout frequency. The main analyses were two binary logistic regressions, exploring potential predictors of dropout, with a mix of nominal and scale data. Cohen’s (1988) guidelines were used in estimating effect sizes and a customary α of .05 was used. The exceptions to this were the multiple t -tests conducted for the IIP, exploring potential differences for the two treatment conditions: using a Bonferroni correction, the p value was adjusted to .006 for the eight tests conducted.

When running binary logistic regressions, one needs to consider the number of events per predictor variable (EPV). Events refers to the amount of observations in the smallest of the two groups in a binary dependent variable. In the case of the present study, this pertains to the amount of people that either dropped out or completed treatment depending on which group is smaller. Having too many predictors increases the risk of overfitting of the model and type I error. Based on the results of simulation studies, the rule of thumb was long considered to be 10 EPVs or more for binary logistic regressions (Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996). A more recent simulation study, however, found this rule to be unnecessarily strict and aimed to revise it to 5-9 EPVs (Vittinghoff & McCulloch, 2007). The present study has relied on the less conservative

guidelines. Furthermore, when running binary logistic regressions, strong correlations between predictor variables might inflate the results resulting in false positives. Therefore, collinearity diagnostics for all included variables were run, demonstrating tolerance and VIF values within satisfactory ranges (Pallant, 2013).

Decisions regarding which variables to include in the binary logistic regressions were made partly on the basis of the indications of previous research and partly using an inductive approach. The background variables in each analysis as well as the CORE-OM total scale were chosen based on previous research. Decisions regarding which of the eight IIP subscales to use for each analysis were made by isolating each subscale in turn using binary logistic regressions, thereby assessing individual performance in a predictive model. When five of the best performing IIP subscales had been identified, they were input in the final regression model, along with the demographic variables as well as the CORE-OM total scale.

Results

The purpose of the present study was (a) to examine the rate of dropout from psychodynamic therapy and (b) to explore potential predictors of psychodynamic psychotherapy dropout in a university training clinic.

Sample characteristics

Demographics are presented in Table 1, above. There were no statistically significant differences between treatment conditions on any demographic variable. Several *t*-tests were conducted to explore potential differences between treatment conditions on CORE-OM total scale and the IIP subscales. Results are presented in Table 3. Making a Bonferroni adjustment to the *p* value for the eight tests run on the IIP subscales, the α for these tests was set to .006. Statistically significant differences between BDT and PDT conditions were detected at the $p < .05$ level for the CORE total scale and at the $p < .006$ level for the IIP Socially avoidant and IIP Nonassertive subscales. However, the effect size was deemed small at $d = .03$ (Cohen, 1988). Mean scores on remaining subscales showed no significant differences between conditions.

Table 3

Differences in means on CORE total scale and IIP subscales between conditions

Measure	Mean	SD	<i>t</i>	df	<i>p</i>	<i>d</i>
CORE total scale						
BDT (N=216)	1.7	.6	-2.60	346	.011*	.03
PDT (N=132)	1.9	.6				
IIP Domineering						
BDT (N=214)	52.1	16.6	-.10	342	.924	.001
PDT (N=130)	52.3	16.2				
IIP Vindictive						
BDT (N=214)	53.2	12.1	-1.933	342	.054	.02
PDT (N=130)	55.9	14.0				
IIP Cold						
BDT (N=214)	53.1	16.4	-1.15	342	.251	.01

Table 3 continues.

Table 3 continuation.

PDT (N=130)	55.3	17.6				
IIP Socially avoidant						
BDT (N=214)	54.5	16.6	-2.82	342	.005**	.03
PDT (N=130)	59.7	17.0				
IIP Nonassertive						
BDT (N=214)	54.6	13.3	-3.15	342	.002**	.03
PDT (N=130)	59.2	13.0				
IIP Exploitable						
BDT (N=214)	54	12.7	-2.04	342	.042	.02
PDT (N=130)	56.9	12.7				
IIP Overly nurturant						
BDT (N=214)	53.6	11.7	-2.10	342	.041	.02
PDT (N=130)	56.3	12.2				
IIP Intrusive						
BDT (N=214)	55.1	12.3	-.78	342	.438	.009
PDT (N=130)	56.1	10.8				

* Statistically significant at the $p < .05$ level.

** Statistically significant at the $p < .006$ level.

Rate of dropout

Dropout rates are presented in Table 4. The overall dropout rate was 54.6%. There was a significant difference in dropout rate between BDT and PDT conditions, $\chi^2(1) = 23.672$, $p < .05$. However, using Cohen's (1988) guidelines, the effectsize was deemed small, approaching medium, at $phi = -.260$.

Table 4

Dropout rates

Condition	Dropout rate	p value	phi
Total sample ($N=350$)	54.6%	.000001	-.260
BDT ($n=218$)	44.5%		
PDT ($n=132$)	71.2%		

Predictors of psychotherapy dropout

Two binary logistic regressions were conducted in order to assess the impact of a number of variables on the likelihood that patients would drop out of therapy. Per the guidelines of Vittinghoff & McCulloch (2007), which state that a logistic regression should have a minimum of 5-9 EPVs, ten predictor variables were chosen for the BDT patients. To check for multicollinearity, diagnostics for all included variables were run which demonstrated tolerance and VIF values within acceptable ranges (Pallant, 2013). Results are presented in Table 5. The full model containing all predictors for BDT patients was statistically significant, $\chi^2(11, N = 212) = 21.630$, $p < .05$, indicating that the model was able to distinguish between dropouts and completers. The model explained between 9.7% (Cox and Snell R square) and 13% (Nagelkerke R Square) of the variance in dropout status and correctly classified 62.7% (percentage accuracy in classification: PAC) of

cases. As shown in Table 5, only three of the variables made a unique statistically significant contribution to the model. The strongest predictor was the score on the IIP Socially avoidant subscale, recording an odds ratio of 1.035. This indicated that for every unit increase on the IIP Socially avoidant subscale, patients were 1.035 times more likely to drop out of therapy, controlling for all other factors in the model. Patients who are students were 2.305 times more likely to drop out of therapy than non-students, controlling for all other factors in the model.

Table 5

Unique contributions to the model predicting dropout for BDT patients.

Variable	B	S.E	Wald	df	<i>p</i>	Exp(B)	95% C.I. for Exp(B)
Age	.050	.022	4.885	1	.027*	1.051	1.006-1.098
Previous therapy	-.179	.301	.356	1	.551	.836	.464-1.506
Education	-.420	.346	1.472	1	.225	.657	.333-1.295
Occupation: studying	.835	.363	5.287	1	.021*	2.305	1.131-4.696
CORE-OM total scale	-.341	.287	1.415	1	.234	.711	.405-1.247
IIP Socially avoidant	.035	.013	7.696	1	.006*	1.035	1.010-1.061
IIP Nonassertive	-.009	.018	.240	1	.624	.991	.957-1.027
IIP Exploitable	-.032	.021	2.358	1	.125	.969	.930-1.009
IIP Overly nurturant	-.010	.020	.219	1	.640	.990	.952-1.031
IIP Intrusive	.011	.013	.728	1	.394	1.012	.985-1.039

Due to small group sizes for PDT patients and following the guidelines of Vittinghoff & McCulloch (2007), the number of predictor variables for the second logistic regression was reduced to seven (age, previous therapy, CORE-OM total scale, IIP Domineering, IIP Cold, IIP Exploitable, IIP Intrusive). The overall model, containing all predictors, was not statistically significant, $\chi^2(7, N = 130) = 5.242, p = .630$, indicating that the model was not able to distinguish between dropouts and completers for the PDT condition. Furthermore, utilizing a Hosmer and Lemeshow test, the model exhibited poor goodness of fit, $\chi^2(8, N = 130) = 19.409, p = .013$.

Discussion

The purpose of the present study was first to examine the rate of dropout and second to explore potential predictors of psychotherapy dropout in a university training clinic sample of 350 patients. In summary, the present study found the mean dropout rate to be 54.6% for the total sample, with a statistically significant difference between therapy conditions (44.5% for BDT and 71.2% for PDT). Additionally, for BDT, the present study found a statistically significant model for predicting dropout which was able to accurately classify 62.7% of cases. Three out of ten predictor variables made unique contributions to the overall model: age, occupation and the IIP Socially avoidant subscale. For PDT, no such statistically significant model was found. In sum, the present study generated sufficient answers for two of three research questions: (1) Do differences exist for rate of dropout between Psychodynamic Therapy and Brief Dynamic Therapy? and (2) What variables, if any, predict dropout from Brief Dynamic Therapy? The third question, regarding dropout prediction for Psychodynamic Therapy, could not be adequately addressed.

Rate of dropout

Due to considerable heterogeneity in previous reports of dropout, the overall rate of dropout found in the present study can be considered on par with or notably higher than previous reports. A meta-analysis conducted by Wierzbicki and Pekarik (1993) examined 125 studies and found a mean dropout rate of 46.86%, whereas a more recent meta-analysis by Swift and Greenberg (2012) found a lower mean dropout rate of 19.7% across 669 studies. However, dropout rates in the studies reviewed by Swift and Greenberg (2012) ranged from 0% to 74.23%, indicating a high degree of variability in the field. Indeed, one of the earliest reviews on treatment dropout paints a similar picture. In their review, Baekeland and Lundwall (1975) cite studies that report up to 79% dropout. Therefore, while the present studies' high of 71.2% dropout for the PDT-patients is certainly a substantial amount, it is not entirely unheard of.

Previous research has found significantly higher dropout percentages in university training clinics (30.4% compared to 17.3-23.4% in other settings) which might further account for the inflated dropout frequency in the present study. This difference coincides with the fact that trainee therapists tend to have more dropouts than experienced therapists and that younger patients, who are more likely to drop out than older patients, more frequently visit university training clinics (Swift & Greenberg, 2012). The significant differences between university training clinics and other settings render generalizations from this study to other settings speculative at best. Such generalizations, if they are made at all, should be interpreted with caution.

Accounting for the difference in dropout frequency between BDT and PDT, research has shown that high time limits result in more dropouts than low time limits (Sledge et al., 1990; Swift & Greenberg, 2012). Additionally, previous studies have indicated that manualized treatments have less dropouts than non-manualized ones. Whether this is due to an inherent benefit to manualized treatments or due to manualized treatments more often being associated with efficacy studies, which are notoriously selective about their patients, is as of yet unclear (Swift & Greenberg, 2012). Still one can make the case that the gap between theory and practice is smaller for BDT than for PDT. Couple that with a narrower focus and increased attention being paid to affects and defenses, and one can argue that BDT is, if not manualized in the traditional sense, then at least more structured than PDT. This might influence patients to more often complete treatment, as structured therapy with clear goals and a narrow focus makes it easier to evaluate progress and thus decide if it is worthwhile to continue treatment. Moreover, it is important to note that student therapists receiving BDT-patients do so in their third and last semester of clinical training while the PDT-patients are treated in the students' first, second and third semesters. Thus, the PDT-patients are the first clinical encounter for many student therapists. As such, one can hypothesize that two semesters worth of clinical training and supervision makes student therapists of BDT-patients slightly more equipped to handle the relationship and ruptures in the alliance. This may be supported in research which has found that more experienced therapists attain better treatment outcomes, ostensibly because of their increased responsiveness to fluctuations in the therapy relationship (Swift & Greenberg, 2012; Hardy, Stiles, Barkham & Startup, 1998; Stiles, Honos-Webb & Surko, 1998).

Predictors of dropout

The main analyses were two binary logistic regressions run on hypothesized predictors of dropout for BDT and PDT separately. For BDT, the overall model had a relatively low percentage accuracy in classification (PAC): 62.7%. While statistically significant, the model exhibited modest *r* square values, explaining only between 9.7-13% of the variance. This may be due to any number of factors, amongst them being poor operational validity and poor predictive power by the data. These factors are discussed further under study limitations. Nevertheless, statistically significant contributions were made by three variables: age, occupation and the IIP Socially avoidant subscale. The contribution of age, while statistically significant, was small, recording an odds ratio of 1.051. Further interpreted, this means that for every unit increase in age, a patient becomes 1/20th more likely to drop out, indeed a negligible number. This was a surprising finding, as it is contrary to previous research, which, albeit contradicting at least has never shown that younger patients drop out less frequently than their older counterparts (Swift & Greenberg, 2012; Olfson et al., 2009; Fenger et al., 2011; Werbart & Wang, 2012). Why this is, exactly, is hard to say with any confidence. One explanation might be that the younger patients in this sample did not have as many obligations, such as families and children, as the older patients, leaving them free to prioritize treatment to a higher degree. If this were the case, however, it should hold true for other studies as well which it does not seem to do. The simpler explanation could then be that the present studies' results happened by chance and further studies on this population may well point in a different direction.

As previously mentioned, a BDT patient being a student made them 2.305 times more likely to dropout compared to patients who were either employed or unemployed/retired/on sick leave. Previous reports have indeed found dropouts to be on average less educated than completers (Swift & Greenberg, 2012; Baekeland & Lundwall, 1975; Fenger et al., 2011; Olfson et al., 2009; Wierzbicki & Pekarik, 1993). This, however, seems unrelated to the present study's findings as the variable specifically asking for educational history was independent of dropout. One possible explanation for this is that patients that have completed no more than high school were merged with the patients that have completed no more than elementary school and then compared to patients with college- or university degrees. This was made necessary by small group sizes and it remains possible that the merging of groups masked some differences.

The IIP Socially avoidant scale demonstrated a statistically significant, albeit weak, impact on the likelihood of dropout. With an odds ratio of 1.035, this means that for every unit increase in the IIP Socially avoidant scale, a BDT patient becomes roughly 1/28th more likely to drop out. Much like the contribution of age, this too seems a trivial number. However, with one standard deviation increase in the scale (*SD*=16.61, see Table 3), a patient becomes roughly 1.6 times more likely to drop out. Thus, some clinical applicability might remain, despite the initially low odds ratio. Social avoidance, in this case, means elevated levels of social anxiety, difficulties with initiating social interactions and expressing emotions with others. Indeed, high levels of this trait might pose a substantial obstruction to forming a positive therapy relationship and in the end cause patients to rather drop out than face their problems. To my knowledge, there is scarce research connecting the IIP to risk of treatment dropout. Nevertheless, one such study investigated the possibility of predicting dropout from a substance misuse treatment using six items from the IIP. In this study, Lovaglia and Matano (1994) found the six IIP items to be able to predict treatment dropout, however, out of the six items used, only one was retained for the version of IIP utilized in the present study (Horowitz, Alden, Wiggins, & Pincus,

2000). The mutually used item was from the IIP Intrusive subscale which in the present study did not significantly contribute to the regression model.

The logistic regression attempting to predict dropout status for PDT patients produced no results of statistical significance and indeed even displayed a poor goodness of fit. Any number of factors might be responsible for this, poor predictive power by the variables and poor operational validity being the most likely reasons. It is, however, interesting to note that the proportion of dropout was much higher for PDT patients (71.2%) than for BDT patients (44.5%). In order to achieve best performance from a binary logistic regression, the two groups of the binary outcome variable (in this case dropout) need to be roughly the same size. This is due to the significance of a regression model being determined by how well the computer can improve its' purely conjectural percentage accuracy in classification (PAC) after having input the predictor variables. As the frequency of dropout for PDT was high, the computer correctly classified a high number of dropouts by just guessing everyone dropped out, leaving little room for improvement after inputting the predictor variables.

Clinical relevance

Certainly, in order to effectively remedy high dropout rates in mental health care, one first needs to be able to distinguish dropouts from completers. Being able to accurately predict who has an increased risk of dropping out enables the therapist to choose and enact appropriate interventions to discourage dropout which in the long run might allow therapists to help greater quantities of patients. While technically a model for the prediction of dropout was found in the case of BDT patients, the PAC and r square values remain of such negligible size as to make the clinical applicability of the model virtually insubstantial. Future models must strive for better predictive power, in order for them to be of clinical use.

Study limitations

The primary limitation of the present study is the operationalization of dropout. Previous studies of treatment dropout have utilized a variety of operational definitions and it has been convincingly argued that different definitions are not interchangeable but are in fact separate constructs. As a result of this, it has been reasoned that some definitions are more valid and reliable than others (Hatchett & Park, 2003; Wierzbicki & Pekarik, 1993; Harris, 1998). Extensive criticism has been directed at "length-of-treatment"-based definitions since these do not take into account the fact that some patients recover after very few sessions and some do not recover after any given number of sessions. Length-based operationalizations would erroneously classify the first as an inappropriate dropout and the second as an appropriate completer. To combat these issues of validity, some have proposed to use a classification based on whether or not a dropout attained clinically significant change on a given measure before dropping out (Hatchett & Park, 2003; Swift et al., 2009). While the author agrees with this reasoning, the present data did not allow for this method: patients at the training clinic only fill out pre- and posttreatment measurements and nothing in between is registered in the database. As a posttreatment measurement is needed to assess clinically significant change, excluding all the patients that did not register a posttreatment measurement from the study would leave the sample size too small to run meaningful analyses.

Instead, patients without posttreatment measurements, were retained in the dataset and classified as dropouts in the present study, following discussion with a supervisor (see Figure 1 above). In retrospect, this decision might have artificially inflated the rate of dropout recorded. There are a number of reasons for posttreatment measurements to be missing: one is, to be sure, that the patient dropped out without prior notice. Others include technical malfunctions, inability or disinterest by the patient to complete the measures or perhaps even an error on behalf of the student therapist. Regrettably, with the current dataset there is no way to accurately estimate the size of this error or to distinguish “true” dropouts from “false” dropouts. What is more, even among the “true” dropouts (i.e. those who did not finish their course of therapy as scheduled), there is no way to know what the reason was for dropping out. Indeed, some patients drop out as a result of an unplanned relocation, changes in employment, having to manage sudden illness (for themselves or a relative) or other external reasons (Kazdin, Holland, Crowley & Breton, 1997). Given that these reasons are unrelated to therapy and some are impossible to remedy through therapy, they are not the primary focus of this, or other studies, investigating dropout. However, as it is impossible to weed these patients out, this remains a measurement error of unknown impact.

Moreover, the present study did not include CBT patients owing to difficulties in distinguishing dropouts from completers. It would certainly be interesting and worthwhile to study potential differences between PDT/BDT and CBT, as previous research has indicated an association between higher numbers of completers on the one hand and shorter and manualized treatments on the other (Swift & Greenberg, 2012).

Small sample sizes necessitated a restriction on the number of predictor variables for the binary logistic regressions. This led to the study having to omit some measures and background variables. While decisions of what to include were made based on previous research and qualified conjecture, including other variables might have resulted in stronger predictive models.

Being a university training clinic, the present studies’ setting excluded severely disordered patients and patients with an ongoing substance abuse, personality disorder or psychotic disorder. As such, generalizations to other settings must be made with caution, as mainly other primary care settings and especially university training clinics are comparable.

Recommendations for future research and the clinic

Future research on psychotherapy dropout needs to include bigger samples and utilize a sample selection procedure that will produce equal group sizes for the binary outcome variable in logistic regressions. This will enable greater predictive accuracy and increase the number of predictive variables that one can input into the regression model. Furthermore, excluding CBT from a study greatly diminishes the ecological validity of the results, something that should be avoided whenever possible.

Moreover, since the PAC and r square values remained negligible even when combining demographic variables with symptom severity and interpersonal problems, future research should direct its’ efforts towards finding new variables with better predictive power. One measure, that might be of use is the PEI-R, which has previously shown promising results in predicting dropout from university training clinics (Callahan, Aubuchon-Endsley, Borja & Swift, 2009; Aubuchon-Endsley & Callahan, 2009). Furthermore, seeing as previous research has implicated less therapist experience as a cause

of dropout and seeing as patients themselves state dissatisfaction with quality of therapy to be a cause of dropout, it seems fitting to more closely examine therapist variables. Further studying interaction effects between client and therapist variables might also produce useful results. The present study did not include a measure of working alliance due to the fact that the measure is only filled out after the last visit, making it unable to predict a dropout. One recommendation for the training clinic is for it to introduce measurement points during therapy, to better track progress and how it relates to the risk of dropout. This would include measuring the alliance at a midway point in therapy and perhaps that data would enable an accurate risk assessment of dropout. Introducing such a procedure, however, depends on all students rigorously adhering to it to reduce incomplete data.

The main limitation of the present study was the operationalization of dropout. Future studies should utilize other operationalizations, preferably therapist judgment or a classification based on whether or not the patient attained clinically significant change before dropping out. As of the fall semester of 2016, the training clinic has introduced a quality control questionnaire for students to fill out after concluding each course of therapy. Amongst other variables in the measure, students fill out whether or not the patient dropped out of therapy. As previously stated, therapist judgment has proven to be a valid measure of dropout and once data using this method has sufficiently accumulated, further studies can be conducted with new operationalizations, hopefully gaining more insight into the elusive but vitally important phenomenon of psychotherapy dropout.

References

- Affleck, D. C., & Garfield, S. L. (1961). Predictive judgments of therapists and duration of stay in psychotherapy. *Journal of Clinical Psychology, 17*, 134-137. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1002/1097-4679(196104)17:2<134::AID-JCLP2270170208>3.0.CO;2-3
- Aubuchon-Endsley, N., & Callahan, J. L. (2009). The hour of departure: Predicting attrition in the training clinic from role expectancies. *Training and Education in Professional Psychology, 3*, 120-126. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/a0014455
- Baekeland, F., & Lundwall, L. (1975). Dropping out of treatment: A critical review. *Psychological Bulletin, 82*, 738-783. doi:10.1037/h0077132
- Bagby, R. M., Taylor, G. J., & Ryan, D. P. (1986). The measurement of alexithymia: Psychometric properties of the schalling-sifneos personality scale. *Comprehensive Psychiatry, 27*, 287-294. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1016/0010-440X(86)90004-0
- Bagby, R. M., Parker, J. D. A., & Taylor, G. J. (1994). The twenty-item toronto alexithymia scale: I. item selection and cross-validation of the factor structure. *Journal of Psychosomatic Research, 38*, 23-32. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1016/0022-3999(94)90005-1
- Barrett, M. S., Chua, W.-J., Crits-Cristoph, P., Gibbons, M.-B., & Thompson, D. (2008). Early withdrawal from mental health treatment: implications for psychotherapy practice. *Psychotherapy Theory, Research, Practice, Training, 45*, 247-267. doi:10.1037/0033-3204.45.2.247
- Björk, T., Björck, C., Clinton, D., Sohlberg, S., & Norring, C. (2009). What happened to the ones who dropped out? outcome in eating disorder patients who complete or prematurely terminate treatment. *European Eating Disorders Review, 17*, 109-119. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1002/erv.911
- Callahan, J. L., Aubuchon-Endsley, N., Borja, S. E., & Swift, J. K. (2009). Pretreatment expectancies and premature termination in a training clinic environment. *Training and Education in Professional Psychology, 3*, 111-119. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/a0012901
- Chasson, G. S., Vincent, J. P., & Harris, G. E. (2008). The use of symptom severity measured just before termination to predict child treatment dropout. *Journal of Clinical Psychology, 64*, 891-904. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1002/jclp.20494
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd edition). Hillsdale, NJ: Erlbaum.
- de Haan, A. M., Boon, A. E., Vermeiren, R. R. J. M., Hoeve, M., & Jong, J. T. V. M. (2015). Ethnic background, socioeconomic status, and problem severity as dropout risk factors in psychotherapy with youth. *Child & Youth Care Forum, 44*, 1-16. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1007/s10566-014-9266-x
- Elfström, M. L. & Carlsson, S. G. (2013). CORE-OM, svensk version: Preliminär manual.
- Elfström, M. L., Evans, C., Lundgren, J., Johansson, B., Hakeberg, M., & Carlsson, S.G. (2012). Validation of the Swedish version of the clinical outcomes in routine evaluation outcome measure (CORE-OM). *Clinical Psychology and Psychotherapy, 20*, 447-455. doi:10.1002/cpp.1788

- Evans, C., Mellor-Clark, J., Margison, F., Barkham, M., Audin, K., Connell, J., & McGrath, G. (2000). CORE: Clinical outcomes in routine evaluation. *Journal of Mental Health, 9*, 247-255. doi:2000/030247-09
- Farber, B. A. (1983). Psychotherapists' perceptions of stressful patient behavior. *Professional Psychology: Research and Practice, 14*, 697-705. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/0735-7028.14.5.697
- Fenger, M., Mortensen, E. L., Poulsen, S., & Lau, M. (2011). No-shows, drop-outs and completers in psychotherapeutic treatment: Demographic and clinical predictors in a large sample of non-psychotic patients. *Nordic Journal of Psychiatry, 65*, 183-191. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.3109/08039488.2010.515687
- Fernandez, E., Salem, D., Swift, J. K., & Ramtahal, N. (2015). Meta-analysis of dropout from cognitive behavioral therapy: Magnitude, timing, and moderators. *Journal of Consulting and Clinical Psychology, 83*, 1108-1122. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/ccp0000044
- Glombiewski, J. A., Hartwich-Tersek, J., & Rief, W. (2010). Attrition in cognitive-behavioral treatment of chronic back pain. *The Clinical Journal of Pain, 26*, 593-601. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1097/AJP.0b013e3181e37611
- Hamilton, S., Moore, A. M., Crane, D. R., & Payne, S. H. (2011). Psychotherapy dropouts: Differences by modality, license and DSM-IV diagnosis. *Journal of Marital and Family Therapy, 37*, 333-43. doi:https://search-proquest-com.ezproxy.ub.gu.se/docview/881055488?accountid=11162
- Hardy, G. E., Stiles, W. B., Barkham, M., & Startup, M. (1998). Therapist responsiveness to client interpersonal styles during time-limited treatments for depression. *Journal of Consulting and Clinical Psychology, 66*, 304-312. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/0022-006X.66.2.304
- Harris, P. M. (1998). Attrition revisited. *American Journal of Evaluation, 19*, 293-305. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1016/S1098-2140(99)80213-6
- Hatchett, G. T., & Park, H. L. (2003). Comparison of four operational definitions of premature termination. *Psychotherapy Theory, Research, Practice, Training, 40*, 226-331. doi:10.1037/0033-3204.40.3.226
- Horowitz, L. M., Alden, L. E., Wiggins, J. S., & Pincus, A. L. (2000). *IIP: Inventory of interpersonal problems*. Umeå, Sverige: Psykologiförlaget AB.
- Howard, K. I., Krause, M. S., & Orlinsky, D. E. (1986). The attrition dilemma: Toward a new strategy for psychotherapy research. *Journal of Consulting and Clinical Psychology, 54*, 106-110. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/0022-006X.54.1.106
- Hoyer, J., Wiltink, J., Hiller, W., Miller, R., Salzer, S., Sarnowsky, S., Stangier, U., Strauss, B., Willutzki, U., & Leibing, E. (2016). Baseline patient characteristics predicting outcome and attrition in cognitive therapy for social phobia: Results from a large multicentre trial. *Clinical Psychology & Psychotherapy, 23*, 35-46. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1002/cpp.1936
- Issakidis, C., & Andrews, G. (2004). Pretreatment attrition and dropout in an outpatient clinic for anxiety disorders. *Acta Psychiatrica Scandinavica, 109*, 426-433. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1111/j.1600-0047.2004.00264.x
- Jensen, H. H., Mortensen, E. L., & Lotz, M. (2014). Drop-out from a psychodynamic group psychotherapy outpatient unit. *Nordic Journal of Psychiatry, 68*, 594-604. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.3109/08039488.2014.902499

- Johansson, H., & Eklund, M. (2006). Helping alliance and early dropout from psychiatric out-patient care: The influence of patient factors. *Social Psychiatry and Psychiatric Epidemiology*, *41*, 140-147. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1007/s00127-005-0009-z
- Kazdin, A. E., Holland, L., Crowley, M., & Breton, S. (1997). Barriers to treatment participation scale: Evaluation and validation in the context of child outpatient treatment. *Child Psychology & Psychiatry & Allied Disciplines*, *38*, 1051-1062. doi: http://dx.doi.org.ezproxy.ub.gu.se/10.1111/j.1469-7610.1997.tb01621.x
- Kegel, A. F., & Flückiger, C. (2015). Predicting psychotherapy dropouts: A multilevel approach. *Clinical Psychology & Psychotherapy*, *22*, 377-386. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1002/cpp.1899
- Keijsers, G. P. J., Kampman, M., & Hoogduin, C. A. L. (2001). Dropout prediction in cognitive behavior therapy for panic disorder. *Behavior Therapy*, *32*, 739-749. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1016/S0005-7894(01)80018-6
- Khazaie, H., Rezaie, L., Shahdipour, N., & Weaver, P. (2016). Exploration of the reasons for dropping out of psychotherapy: a qualitative study. *Evaluation and Program Planning*, *56*, 23-30. doi:S0149718915300495
- Klein, E. B., Stone, W. N., Hicks, M. W., & Pritchard, I. L. (2003). Understanding dropouts. *Journal of Mental Health Counseling*, *25*, 89-100. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.17744/mehc.25.2.xhyreggxdc0q4ny
- Lambert, M. (2007). Presidential address: What we have learned from a decade of research aimed at improving psychotherapy outcome in routine care. *Psychotherapy Research*, *17*, 1-14. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1080/10503300601032506
- Lampropoulos, G. K., Schneider, M. K., & Spengler, P. M. (2009). Predictors of early termination in a university counseling training clinic. *Journal of Counseling & Development*, *87*, 36-46. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1002/j.1556-6678.2009.tb00547.x
- Lovaglia, M. J., & Matano, R. (1994). Predicting attrition from substance misuse treatment using the inventory of interpersonal problems. *International Journal of the Addictions*, *29*, 105-113. doi:10.3109/10826089409047371
- Maramba, G. G., & Nagayama Hall, G. C. (2002). Meta-analyses of ethnic match as a predictor of dropout, utilization and level of functioning. *Cultural diversity and ethnic minority psychology*, *8*, 290-297. doi:10.1037//1099-9809.8.3.290
- MacNair, R. R., & Corazzini, J. G. (1994). Client factors influencing group therapy dropout. *Psychotherapy: Theory, Research, Practice, Training*, *31*, 352-362. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/h0090226
- McCabe, K. M. (2002). Factors that predict premature termination among mexican-american children in outpatient psychotherapy. *Journal of Child and Family Studies*, *11*, 347-359. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1023/A:1016876224388
- Nysæter, T. E., Nordahl, H. M., & Havik, O. E. (2010). A preliminary study of the naturalistic course of non-manualized psychotherapy for outpatients with borderline personality disorder: Patient characteristics, attrition and outcome. *Nordic Journal of Psychiatry*, *64*, 87-93. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.3109/08039480903406731

- O'Brien, A., Fahmy, R., & Singh, S. P. (2009). Disengagement from mental health services: A literature review. *Social Psychiatry and Psychiatric Epidemiology*, *44*, 558-568. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1007/s00127-008-0476-0
- Olfson, M., Mojtabai, R., Sampson, N. A., Hwang, I., Druss, B., Wang, P. S., & Kessler, R. C. (2009). Dropout from outpatient mental health care in the united states. *Psychiatric Services*, *60*, 898-907. doi:10.1176/appi.ps.60.7.898
- Ortet, G., Ibáñez, M. I., Llerena, A., & Torrubia, R. (2002). The underlying traits of the karolinska scales of personality (KSP). *European Journal of Psychological Assessment*, *18*, 139-148. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1027/1015-5759.18.2.139
- Pallant, J. (2013). *SPSS survival manual*. New York, NY: McGraw-Hill Education.
- Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of clinical epidemiology*, *49*, 1373-1379. doi: 10.1016/S0895-4356(96)00236-3
- Pekarik, G. (1985). The effects of employing different termination classification criteria in dropout research. *Psychotherapy: Theory, Research, Practice, Training*, *22*, 86-91. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/h0088531
- Power, R. A., Muthén, B., Henigsberg, N., Mors, O., Placentino, A., Mendlewicz, J., Maier, W., McGuffin, P., Lewis, C. M., & Uher, R. (2012). Non-random dropout and the relative efficacy of escitalopram and nortriptyline in treating major depressive disorder. *Journal of Psychiatric Research*, *46*, 1333-1338. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1016/j.jpsychires.2012.06.014
- Reis, B. F., & Brown, L. G. (1999). Reducing psychotherapy dropouts: Maximizing perspective convergence in the psychotherapy dyad. *Psychotherapy: Theory, Research, Practice, Training*, *36*, 123-136. doi: http://dx.doi.org.ezproxy.ub.gu.se/10.1037/h0087822
- Richmond, R. (1992). Discriminating variables among psychotherapy dropouts from a psychological training clinic. *Professional Psychology: Research and Practice*, *23*, 123-130. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1037/0735-7028.23.2.123
- Roos, J., & Werbart, A. (2013). Therapist and relationship factors influencing dropout from individual psychotherapy: a literature review. *Psychotherapy Research*, *23*, 394-418. doi:10.1080/10503307.2013.775528
- Self, R., Oates, P., Pinnock-Hamilton, T., & Leach, C. (2005). The relationship between social deprivation and unilateral termination (attrition) from psychotherapy at various stages of the health care pathway. *Psychology and Psychotherapy: Theory, Research and Practice*, *78*, 95-111. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1348/147608305X39491
- Sharf, J., Primavera, L. H., & Diener, M. J. (2010). Dropout and therapeutic alliance: a meta-analysis of adult individual psychotherapy. *Psychotherapy, Theory, Research, Practice, Training*, *47*, 637-645. doi:10.1037/a0021175
- Simon, G. E., & Ludman, E. J. (2010). Predictors of early dropout from psychotherapy for depression in community practice. *Psychiatric Services*, *61*, 684-689. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1176/appi.ps.61.7.684
- Sledge, W. H., Moras, K., Hartley, D., & Levine, M. (1990). Effect of time-limited psychotherapy on patient dropout rates. *The American Journal of Psychiatry*, *147*, 1341-1347. doi:147.10.134

- Stiles, W. B., Honos-Webb, L., & Surko, M. (1998). Responsiveness in psychotherapy. *Clinical Psychology: Science and Practice*, 5, 439-458. doi:10.1111/j.1468-2850.1998.tb00166.x
- Swift, J. K., Callahan, J., & Levine, J. C. (2009). Using clinically significant change to identify premature termination. *Psychotherapy Theory, Research, Practice, Training*, 46, 328-335. doi:10.1037/a0017003
- Swift, J.K., & Greenberg, R. P. (2012). Premature discontinuation in adult psychotherapy: a meta-analysis. *Journal of Consulting and Clinical Psychology*, 80, 547-559. doi:10.1037/a0028226
- Swift, J. K., & Greenberg, R. P. (2014). A treatment by disorder meta-analysis of dropout from psychotherapy. *Journal of Psychotherapy Integration*, 24, 193-207. doi:10.1037/a0037512
- van Emmerik, A. A. P., Kamphuis, J. H., Noordhof, A., & Emmelkamp, P. M. G. (2011). Catch me if you can: Do the five-factor model personality traits moderate dropout and acute treatment response in post-traumatic stress disorder patients? *Psychotherapy and Psychosomatics*, 80, 386-388. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1159/000329111
- Vasquez, M. J. (2007). Cultural difference and the therapeutic alliance: An evidence-based analysis. *American Psychologist*, 62, 878-885. doi:https://search-proquest-com.ezproxy.ub.gu.se/docview/62055494?accountid=11162
- Vittinghoff, E., & McCulloch, C. E. (2007). Relaxing the rule of ten events per variable in logistic and Cox regression. *American journal of epidemiology*, 165, 710-718. doi:10.1093/aje/kwk052
- Weinryb, R. M., Gustavsson, J. P., Hellström, C., Andersson, E., Broberg, A., & Rylander, G., (1996). Interpersonal problems and personality characteristics: psychometric studies of the swedish version of the IIP. *Personality and Individual Differences*, 20, 13-23. doi:0191-8869196 %15.00+0.00
- Werbart, A., & Wang, M. (2012). Predictors of not starting and dropping out from psychotherapy in Swedish public service settings. *Nordic Psychology*, 64, 128-146. doi:http://dx.doi.org/10.1080/19012276.2012.726817
- Wierzbicki, M., & Pekarik, G. (1993). A meta-analysis of psychotherapy dropout. *Professional Psychology: Research and Practice*, 24, 190-195. doi:0735-7028/93/S3.00
- White, K. S., Allen, L. B., Barlow, D. H., Gorman, J. M., Shear, M. K., & Woods, S. W. (2010). Attrition in a multicenter clinical trial for panic disorder. *Journal of Nervous and Mental Disease*, 198, 665-671. doi:http://dx.doi.org.ezproxy.ub.gu.se/10.1097/NMD.0b013e3181ef3627