5-2022

# The Impact of COVID-19 and Telehealth Services on Attrition Rates in Psychotherapy

Rylan B. Hellstern
*Utah State University*

THE IMPACT OF COVID-19 AND TELEHEALTH SERVICES ON

ATTRITION RATES IN PSYCHOTHERAPY

by

Rylan B. Hellstern

A thesis submitted in partial fulfillment

of the requirements for the degree

of

MASTER OF SCIENCE

in

Marriage and Family Therapy

Approved:

| | |
|---|---|
| W. David Robinson<br>Major Professor | Ryan Seedall<br>Committee Member |
| Sarah Schwartz<br>Committee Member | D. Richard Cutler, Ph.D.<br>Interim Vice Provost<br>of Graduate Studies |

UTAH STATE UNIVERSITY
Logan, Utah

2022

ABSTRACT

The Impact of COVID-19 and Telehealth Services on Attrition Rates in Psychotherapy

by

Rylan B. Hellstern, Master of Science

Utah State University, 2022

Major Professor: Dr. W. David Robinson, LMFT
Program: Marriage and Family Therapy

Clinicians in psychotherapy are constantly looking at their outcomes in order to identify and remove barriers that may inhibit treatment effectiveness. Attrition in psychotherapy has been identified as a significant obstacle in the productive delivery of mental health services. Defined generally as the ending of a treatment prior to proper optimal benefit, attrition both hinders treatment efficacy and cost-effectiveness in therapy. With the demands for quality mental health services continually increasing, resources must be identified to reduce barriers to such services. While most attrition literature focuses on the contributing factors to such premature termination, little to no research is available that discusses potential resources for attrition rates. The COVID-19 pandemic has resulted in the emergence of one of these potential resources: telehealth services. The current study aims to identify how COVID-19 and telehealth services have influenced attrition by analyzing attrition rates from both before and during the pandemic in a community health center where a transition to telehealth was made at the start of the pandemic. In addition, the variables of age, gender, socioeconomic status, and insurance coverage were also tested as potential predictors of attrition. Using a sample of deidentified patient information that identified patients who had participated in therapy services within a six-month period at a community health center (N = 329), a survival analysis was used to assess the time taken from initial appointment to the point of attrition. Results indicated that those who attended therapy via telehealth were less likely to stop attending treatment than those who participated in therapy in person. Individuals who used both in-person and telehealth visits were the least likely to terminate treatment prematurely. Clinical implications include the need for therapists to offer both telehealth and in-person services in order to give clients more resources to reduce a large barrier to needed mental healthcare treatment.

(52 pages)

PUBLIC ABSTRACT

The Influence of COVID-19 and Telehealth Services on

Attrition Rates in Psychotherapy

Rylan B. Hellstern

Clinicians in psychotherapy are constantly looking at their outcomes in order to identify and remove barriers that may inhibit effective treatment. Defined generally as the ending of a treatment prior to proper optimal benefit, attrition has been found to both hinder treatment efficacy and cost-effectiveness in therapy. While most attrition literature focuses on the contributing factors to such premature termination, little to no research is available that discusses potential resources for attrition rates. The COVID-19 pandemic has resulted in the use of telehealth services which may serve as a resource to combat attrition. The current study aims to identify how COVID-19 and telehealth services have influenced attrition by analyzing attrition rates from both before and during the pandemic in a community health center where a transition to telehealth was made at the start of the pandemic. In addition, the variables of age, gender, socioeconomic status, and insurance coverage were also tested as potential predictors of attrition. Using a sample of 329 patients who had participated in therapy services within a six-month period at a community health center, I analyzed the time taken from initial appointment to the point of attrition. Results indicated that those who attended therapy via telehealth were less likely to stop attending treatment than those who participated in therapy in person. Individuals who used both in-person and telehealth visits were the least likely to terminate treatment prematurely. Clinical implications include the need for therapists to

offer both telehealth and in-person services in order to give clients more resources to reduce a large barrier to needed mental healthcare treatment.

ACKNOWLEDGMENTS

I would like to thank Dr. Dave Robinson for his constant support and guidance throughout the development of this project. His mentorship and encouragement throughout the program have continually given me the motivation I needed to press forward and reach my goals. I would also like to thank Dr. Ryan Seedall and Sarah Schwartz for their time and willingness to help teach me both how to compile the appropriate literature and how to perform the analytic strategy used in this study.

In addition, I want to especially thank Bear Lake Community Health Centers for their collaboration in my research. Without the data they provided, this study would not have been possible.

Lastly, I would like to thank my family and my wife, Emily, in particular. She has been incredibly supportive throughout this process and has always been my cheerleader, helping me believe in my potential. I could not have done any of this without my great support network.

Rylan Hellstern

CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Page

# Chapter I

## Introduction

Therapeutic outcomes are crucial for understanding the process of therapy and whether it creates change. In psychotherapy, clinicians are constantly focused on therapeutic outcomes and the change process as it allows them to assess their own effectiveness as therapists (Wampold, 2019). Currently, various models and methods of therapy exist with their distinct processes, views, and interventions, yet each aims to promote change in clients (Wampold, 2019). While research focused on change has shown general indications that clients do benefit from therapy (Erekson et al., 2018), studies comparing psychotherapy methods have not found any particular model to be more effective in the change process than another (Shadish & Baldwin 2002, 2009; Wampold et al., 2017). With change being so important in therapy services, clinicians should look at all factors that may serve as barriers to the change process. One common barrier that has been identified among mental health service providers is attrition.

Attrition in psychotherapy is a significant obstacle in the productive delivery of mental health services as it hinders treatment efficacy and cost-effectiveness (Wierzbicki & Pekarik, 1993). While there are many names and definitions available in the literature (e.g., dropout, premature termination, early termination, and premature discontinuation), the term attrition has been defined generally as the ending of a treatment prior to proper optimal benefit (Roseborough et al., 2017). A meta-analysis looking at general studies with various definitions of attrition in therapy conducted by Swift and Greenberg (2012), found that the average rate of dropout was found to be 19.7%, implying that about one in five clients would terminate treatment prematurely. It is important that researchers and clinicians work to mitigate this issue as attrition greatly influences the individual client's ability to change and client's access to mental health services in general.

**Effects of Attrition**

For the client, it can be assumed that prematurely ending therapy essentially interrupts therapeutic treatment which consequently diminishes the client's rate of change (Xio et al., 2017). While Lopes et al. (2017) states that attrition does not necessarily indicate clinical failure, he does note that in the long run, change will take much longer to occur in individuals who abandon treatment than those who complete it. Attrition and no-show rates also affect the service provider as they contribute to a loss of revenue, underutilization of time, and long waitlists (Barrett et al., 2008). Barrett et al. (2008) comments that the larger community may be impacted by nonattendance of therapy as it tends to drain limited mental health resources for the public. With there already being a lack of mental health professionals, attrition rates only increase the need for service providers. It is because of these vast effects that much of the research on this topic focuses on the factors that may predict attrition.

With that being said, in general, there is a lack of literature on the topic of attrition in regards to psychotherapy. Much of the research that has been done is filled with confounding findings, replication failures, and relatively small differences between those who continue therapy and those who terminate prematurely (Wierzbicki & Pekarik, 1993). It is only through more examinations of attrition that such issues can be resolved. With many behavioral health organizations seeing as much as a 52% increase in the public need for services (Majlessi, 2020), it is imperative that more be done to understand the attendance of clients and reduce attrition rates so such resources can effectively meet such demands. The purpose of this research is not only to identify possible factors that predict attrition but also to understand a specific resource (i.e., telehealth) that can increase access to meet the demand of mental health services.

## Theoretical Framework

Defining theory as a set of related ideas that help to understand the world, I utilized a theoretical framework to provide descriptive, explanatory, and integrative functions of the phenomenon being studied (Knapp, 2009). Seeing as attrition rates consequently lead to a lack of access to mental healthcare, I have implemented Andersen's Behavioral Model of Health Services Use (1995) to serve as a guide as I explore ways to reduce attrition and increase accessibility. In his model, Andersen suggests that an individual's use of health services is dependent on factors that enable or impede use and their need for care. In particular, Andersen looks at predisposing demographic characteristics, social structures, environmental factors, health beliefs, and resources that allow individuals to access healthcare. Building from his theory, Penchansky and Thomas (1981) defined access as the best fit between clients and the system and divided it into to the dimensions of availability, accommodation, affordability, and acceptability. Because the purpose of this study is not to understand the predisposing characteristics of attrition, Penchansky and Thomas' model will be used more prominently while still relying on Andersen's model as a foundation. Utilizing such models will provide a lens that will help guide reasoning as to why attrition may take place and supply domains of focus to reduce attrition and increase access as well.

**Coronavirus Pandemic and Mental Health Accessibility**

Access to treatment and quality care was made increasingly difficult when the coronavirus (SARS CoV 2) was declared a pandemic in March 2020 and created havoc as it spread across the globe (Malathesh et al., 2020). Since that time, nations around the world have reported elevated rates of anxiety, depression, stress, suicide risk, and post-traumatic stress as fears of contamination and quarantining have become a part of everyday life (Cook et al., 2020; O'Connor et al., 2020; Wang et al., 2020). The pandemic has both increased the demand of mental health services as well as disrupted and halted many mental health organizations and the delivery of face-to-face mental health services in general (World Health Organization, 2020). During such a period where therapy services are critical, attrition poses an even greater danger to therapists trying to meet the growing mental health needs of their communities.

While it is difficult to identify specific causes behind attrition, therapists can utilize resources that may allow them to be more accommodating to clients and potentially increase rates of attendance. Telehealth is one such resource that is on the rise with the widespread availability and popularity of technology (Vockley, 2015). With the recent global pandemic, many clinicians have been forced to transition therapy sessions to be done via telehealth allowing them to continue to meet their client's needs while ensuring medical safety and keeping physical-distancing requirements (Taylor et. al, 2020). Such a dramatic shift in modality raises the question of how the pandemic and the availability of telehealth as a resource has influenced psychotherapy attrition rates. In this study, I explore the rates of attrition from both before and during the pandemic in a community health center where a transition to telehealth was made at the start of COVID-19. The following sections will incorporate the theoretical framework mentioned above while addressing previous literature on the effects and variables associated with attrition as well as potential solutions (specifically teletherapy) to this problem. Doing so will shed more light on the outcomes of utilizing telehealth services as a resource for the reduction of attrition rates.

# Chapter II

## Literature Review

As I seek to analyze the impact of telehealth on attrition rates, I will review the current literature addressing attrition as well as the literature regarding telehealth. While the introduction presented the problem that attrition brings to psychotherapy, the literature in the following sections will focus primarily on what has been done to mitigate the problem. I will first address how defining attrition has proven difficult as well as the factors that have been expected to impact attrition rates. As in Andersen's Model of Health Services Use, such factors including demographic, therapist, and environmental variables are mentioned below to illustrate how they may inhibit or enable access to mental health care. Finally, I discuss the important resource that telehealth services provide to psychotherapy and the potential they have to reduce rates of attrition.

**Measuring Attrition**

Throughout the literature, synonymous terms to attrition have been used such as early termination (Bohart & Wade, 2013), premature discontinuation (Swift & Greenburg, 2012), and most popular, dropout (Barrett et al., 2008; Baruch et al., 1998; Fenger et al., 2010; Khazaie et al., 2016; Lopes et al., 2017). While each term is essentially examining the same thing, the difference often lies in how each study measures attrition. For example, Baruch et al. (1998) considered anything after the first session and before the sixth session while Longo et al. (1992) defined it as failure to return after an intake assessment. Hatchett et al. (2002) counted attrition as failure to attend the last session that had been scheduled. Although it should be acknowledged that each method of measurement is valid and has benefits, such variance causes concerns that each definition used essentially measures a different construct that in turn influences its findings (Hatchett & Park, 2003).

In their meta-analysis, Swift and Greenberg (2012) mention that the labels used to describe attrition in their studies were not all consistent in measurement leading to a fluctuation in dropout rates dependent upon what operationalization was used. Upon examination they found five common methods for operationalizing attrition: attending less than a specified number of sessions, failure to complete treatment protocol, failure to attend a session or schedule future appointments, failure to reach clinically significant change in an outcome measure, and according to the therapist's judgement. Attrition classified by the therapist's clinical judgement has historically been found to be a preferable operationalization as the concept of dropout in and of itself stems from the clinician's judgment that clients terminate inappropriately from therapy (Hatchett & Park, 2003; Pekarik, 1985; Swift & Greenberg, 2012).

## Associated Variables and Factors for Attrition

The potential negative effects that attrition can have on both clients and mental health services have caused many researchers to question what common factors contribute to the sudden premature termination of therapy. In a review of the literature, it was found that most studies considered demographic variables (Barrett et al., 2008; Baruch et al., 1998; Bohart & Wade, 2013; Fenger et al., 2011; Khazaie et al., 2016; Roseborough et al, 2016) and environmental and life factors (Barrett et al., 2008; Defife et al., 2012) when looking at attrition. The following sections will give a brief summary of the general findings for both demographic and environmental and life factors.

### *Demographic Variables*

As per Andersen's model (1995), it is important that demographic factors are considered when looking at healthcare utilization, or in this case, barriers to healthcare. However, in general, demographic variables across studies have not been particularly consistent in the literature on attrition (Bohart & Wade, 2013). In the case of gender, while it is known that men are less likely to attend therapy in the first place, it is not clear whether or not a certain sex was more likely to terminate prematurely (Bohart & Wade, 2013). A longitudinal study in a community clinic conducted by Roseborough et al. (2016) found that those identifying as Pacific Islanders were the only statistically significant finding of dropout when considering ethnicity, yet Barrett et al. (2008) found that most ethnic minorities had a higher risk of dropping out.

The demographic variables of education, age, and socioeconomic status did show some consistent results across multiple studies. Clients reporting higher education (college degree) were more likely to remain in treatment when compared to those who reported only a high school or vocational schooling as their highest level of education (Barrett et al., 2008; Fenger et al., 2011; Roseborough et al., 2016). High attrition rates were found among younger, adolescent clients (under the age of 18) whereas those in the age group 30-45 or older were more likely to continue treatment (Barrett et al., 2008; Baruch et al, 1998; Fenger et al., 2011; Roseborough et al., 2016). Attrition was also common among those who had a lack of insurance coverage, financial problems, or were of a lower socioeconomic status (Barrett et al., 2008; Khazaie et al., 2016).

### *Environmental and Life Factors*

In multiple studies, results indicated that many clients unexpectedly miss appointments or drop out entirely due to circumstances of life such as physical illness, work conflicts, lack of transportation, and difficulty locating childcare (Barrett et al., 2008; Defife et al., 2012). When applied to the healthcare utilization model it is clear that these environmental factors essentially remove client's resources and become barriers of accessibility (Andersen, 1995; Penchansky & Thomas, 1981). Clinicians and agencies must keep these barriers in mind and search for strategies that can be applied in order to provide better, easier access, even when faced with these confounding factors.

## Teletherapy as an Attrition Reduction Strategy

The COVID-19 pandemic has impacted in-person services significantly as stay-at-home orders and social distancing guidelines have been put in place to reduce spread

(Taylor et al., 2020). As a result of the pandemic and the steady increase in technology, teletherapy is becoming increasingly popular and useful (Pickens et al., 2020). Skeptical clinicians initially thought teletherapy to be ineffective and unethical, however, evidence currently suggests that providing therapy through this modality has the same, and occasionally higher, levels of efficacy as face-to-face therapy (Twist & Hertlein, 2017).

In a systematic review, Turgoose et al. (2017) found that teletherapy methods were just as effective in reducing symptoms of PTSD in veterans than in-person methods. Both telephone-delivered and videoconferencing technology have been identified as supported treatments for psychologists treating clients with depression, anxiety, PTSD, or adjustment disorders (Varker et al., 2019). Burgoyne and Cohn (2020) found that telehealth can also serve as viable resource when seeing relational clients as it allows for more members of the system to participate in treatment. When surveying their clients, Burgoyne and Cohn found that 86% of clients and 80% of staff found teletherapy to provide good quality of care.

Teletherapy serves as a resource as it helps to improve access to mental health treatment by increasing availability, accommodation, affordability, and acceptability (Penchansky & Thomas, 1981)**.** While issues such as service errors or other technical issues can affect a therapist's ability to join or establish a relationship with the client electronically (Twist & Hertlein, 2017), teletherapy gives clients the opportunity to overcome many of the obstacles mentioned above (Wrape & Mcginn, 2018). The dimension of *availability* is increased as it enables clients to do it from home. *Accommodation* is enhanced as clinicians are more flexible with doing therapy in person or via telehealth depending on the client's needs. Telehealth services can capture the domain of *acceptability* as they give clients more options of therapists across the country that may be more comfortable with their immutable characteristics (i.e., ethnicity, sex, social status). *Affordability* is even increased as it does not cost the client any extra to do so and potentially saves money in travel fees. It should be noted that such a resource is dependent upon having the necessary equipment. Although widespread technological advances make telehealth appointments possible for many communities, telehealth programs require adequate broadband access which may not be available for many rural and underserved populations (Hirko et al., 2020). With teletherapy being a relatively new resource, more research is needed in order to gain a broader comprehension of its benefits and explore how such services can reach more underprivileged communities.

**Purpose of the Study**

Attrition in psychotherapy is problematic as it negatively impacts therapy clients, clinicians, and those awaiting mental health services in communities (Barrett et al., 2008). Attrition virtually stands as a barrier to the rising demands of mental health services. In order to effectively reduce such effects, appropriate resources need to be implemented in mental health organizations to increase availability, accommodation, affordability, and acceptability for clients**.** The purpose of the present study was to investigate the influence of the COVID-19 pandemic and teletherapy use on the rates of attrition in mental health services.

## Research Hypotheses

- Hypothesis 1: Rates of attrition will have decreased since COVID-19 and the switch to teletherapy. This will indicate that the risk of drop out is lower for teletherapy than in-person.
- Hypothesis 2: In accordance with previous literature (Barrett et al., 2008; Khazaie et al., 2016), variables such as insurance coverage and SES will be significant indicators of dropout risk while variables of age and gender will not predict significant risk.

Confirming these hypotheses will provide needed information to the literature on attrition as it will indicate that telehealth can serve as a resource. Knowledge of such a resource could benefit access to mental healthcare as clinicians utilize it to reduce attrition rates. Examining specific predictor variables could indicate which demographics in particular might need such resources as they may be more likely to drop out of treatment prematurely.

# Chapter III

# Methods

In this study, existing data from previously scheduled psychotherapy appointments at a community health center was investigated. Sections will elaborate more on the setting where the data was collected, the participants included, and the procedure used in acquiring the data prior to analysis. In addition, the analytic strategy will be detailed along with figures to explicitly illustrate what was done to yield the acquired results.

## Setting

Data in this study were collected from a Federally Qualified Health Center (FQHC) with seven locations across the western United States. This community health center provides medical, behavioral health, dental, and pharmaceutical services to the community, particularly to those of lower socioeconomic status as they offer a sliding fee scale for payment. The sliding fee scale is based off of household size and income and is divided into four levels: Level 1 (up to 100% of federal poverty level), Level 2 (up to 133% of federal poverty level), Level 3 (up to 150% of federal poverty level), and Level 4 (up to 200% of federal poverty level). This sliding fee scale system was used as a method of measuring income and socioeconomic status (SES) in this study as it utilizes client's tax returns, pay stubs, and bank statements to accurately compute discount qualification. The federal poverty levels used for the time of the study can be found in Table 1 in the Appendix.

Mental health providers across all of the clinics consisted of three Licensed Clinical Social Workers (LCSW) and one Licensed Marriage and Family Therapist (LMFT). Providers offer therapy services to individuals, couples, and families in 45-minute sessions. Therapy services were offered via face-to-face and telehealth until April 1, 2020 when the organization transitioned to telehealth services as their primary modality due to the COVID-19 pandemic.

**Participants**

The sample of this study consisted of 329 patients receiving mental health services at a FQHC in the Western United States. By nature, patients attending FQHC's often experience higher levels of stress due to their financial situation, cultural barriers, or other life circumstances. Many of the individuals included in the sample of this study suffered from mental health issues of higher severity due to their inability to receive services elsewhere. Participants were selected if they had been seen for therapy between the dates of January 1 and June 30, 2020, in order to examine the attrition rates both before and during the COVID-19 pandemic. In cases where a family or a couple was being treated for therapy, not every individual was tracked for attrition, only the identified patient (the individual whose name is on the schedule). Patients were excluded if they were already participating in teletherapy prior to the health center's transition to exclusive telehealth services.

Demographics of the sample varied with 135 (41%) being male, 193 (58.7%) being female and 1 (.3%) transgender male. Race of participants consisted of 302 (91.8%) White, 14 (4.3%) Hispanic, 3 (.9%) Black, 2 (.6%) American Indian, 1 (.3%) Asian, and 7 (2.1%) not reported. Average age of the participants was 32 with 266 (81%) being adults and 69 (19%) being minors (below the age of 18). Between January 1 and March 31, 2020, 75 patients attended therapy and were considered in the "in-person" group. Between April 1 and June 30, 2020, 64 patients attended therapy solely via telehealth, placing them in the "telehealth" group. From January 1 to June 30, 2020, there were 190 patients that attended therapy through both "in-person" and "telehealth" platforms. Full descriptive statistics are presented in Table 2.

**Table 2**

*Demographic Summary of Sample by Modality of Therapy*

| | In-Person N = 75 | Both N = 190 | Telehealth N = 64 | |
|---|---|---|---|---|
| | *M (SD)* | *M (SD)* | *M (SD)* | $p^*$ |
| Age | 30.17 (17.14) | 32.58 (15.74) | 36.27 (14.69) | .078 |
| | n (%) | n (%) | n (%) | |
| Gender | | | | .026 |
| Male | 41 (12%) | 70 (21%) | 24 (7%) | |
| Female | 34 (10%) | 119 (36%) | 40 (12%) | |
| Insurance | | | | .035 |
| Government | 21 (6%) | 50 (15%) | 16 (5%) | |
| Private Insurance | 40 (12%) | 123 (37%) | 35 (11%) | |
| Slide | 12 (4%) | 12 (4%) | 13 (4%) | |
| Out of Pocket | 2 (.6%) | 3 (.9%) | 0 (0%) | |
| Income | | | | .231 |
| Level 1 | 21 (13%) | 60 (36%) | 16 (10%) | |
| Level 2 | 7 (4%) | 10 (6%) | 8 (5%) | |
| Level 3 | 1 (.6%) | 8 (5%) | 4 (2%) | |
| Level 4 | 4 (2%) | 22 (13%) | 6 (5%) | |

Note. Income level 1 is the lowest and 4 is the highest based on Table 1 in the Appendix.

* Significance (*p*) is indicative of an analysis of variance (ANOVA) for age and Chi-squared test of independence for each categorical variables with therapy modality.

**Procedure**

Patients participated in therapy as usual and typically attended therapy once a week. On April 1, 2020, the community health center changed their therapeutic delivery exclusively to telehealth services in response to the COVID-19 pandemic. Patients were automatically considered as having terminated prematurely if they only attended an intake and had no future appointments scheduled. Attrition was defined by the therapists and patient charts signed by the therapy provider were utilized to verify premature termination. Participants whose clinical notes stated that a follow up was recommended but stopped attending were considered dropouts. Deidentified patient information was used so no consent was required by patients.

## Variables

The main variable of interest in this study was the delivery of therapy: in-person, telehealth, or both. Other potential confounding factors examined included age, gender, socioeconomic status (SES) via sliding fee scale brackets, and insurance coverage (private insurance, federal health programs, sliding fee scale, out-of-pocket). While race and ethnicity were originally thought to be a confounding factors, a lack of diversity in the sample inhibited such factors from being taken into consideration.

## Analytic Strategy

Survival analysis, also called time-to-event analysis, was used as the primary strategy of analysis. Survival analysis focuses on the expected duration of time until occurrence of an event of interest (Kleinbaum & Klein, 2010). In this case, such an event was attrition in psychotherapy. Such a strategy can assess the time taken from the client's initial appointment to point of premature termination. Survival analysis allows for the analysis of staggered entries by moding each individual's time since entry, meaning that although each client's initial appointments were all at different calendar dates, they can still be interpreted in regard to the same context. A visual example of this is portrayed in Figures 1 and 2.

Figure 1 illustrates the different groups of therapy participants in calendar date format while Figure 2 models how the analysis essentially shifts the staggered entries to all be considered from initial appointment within the same context. Since attrition is not experienced by every client, those whom the event did not occur during the observation period were considered “censored”. Right censoring takes place when the time of the event is known to be greater than some value but the time it took for attrition to occur after the observation period is unspecified/unknown. This was important as it allowed for the inclusion of data for clients who were still continuing in therapy, those who graduated, and those who were referred out after the designated observation period.

**Figure 1**

*Hypothetical Attrition Timeline in Calendar Format*

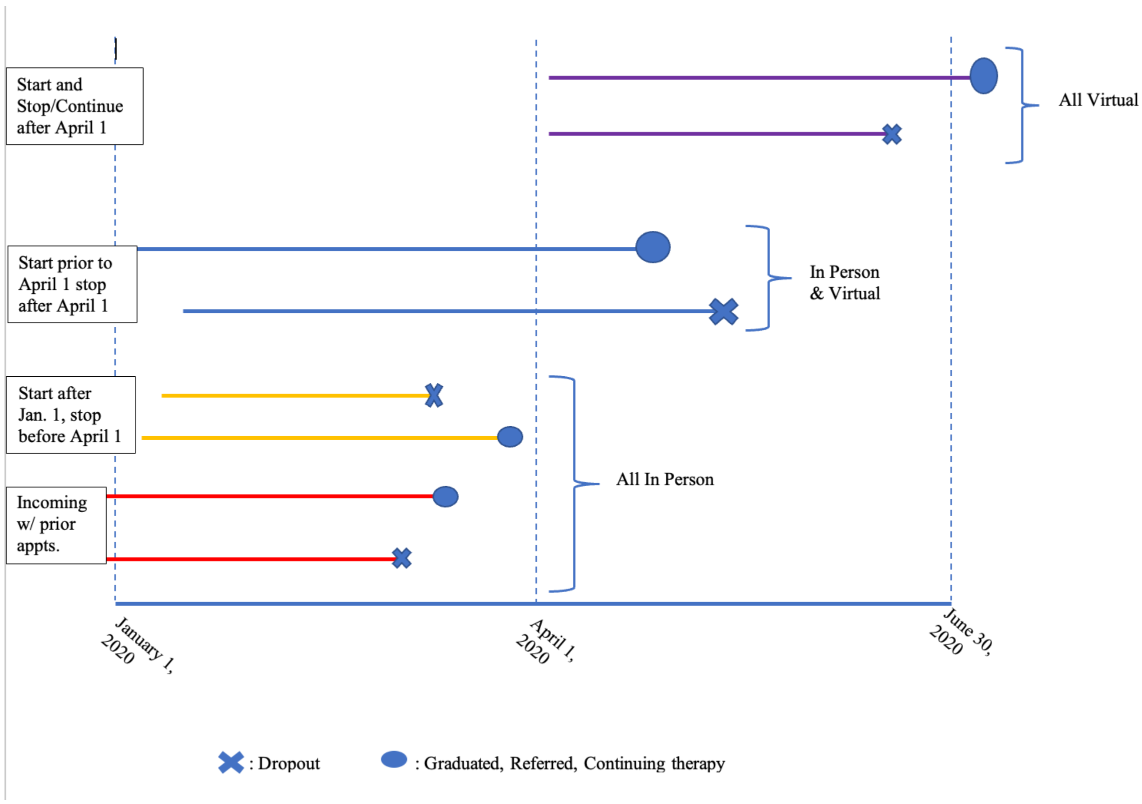
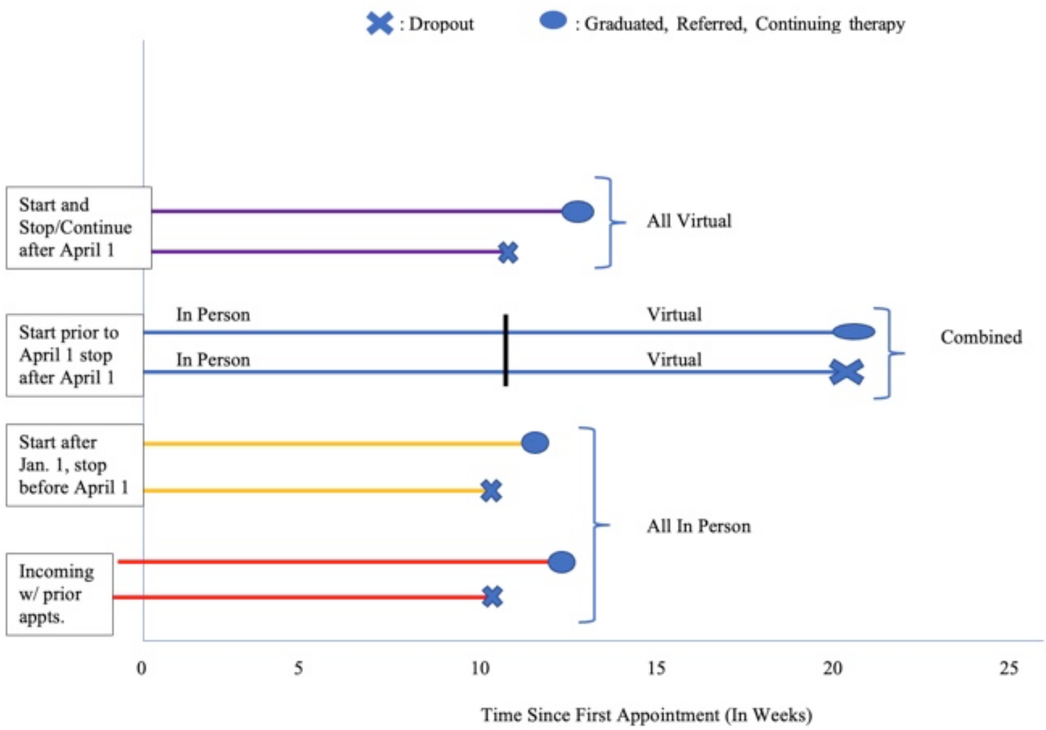


**Figure 2**

*Hypothetical Attrition Timeline in Shifted Format*

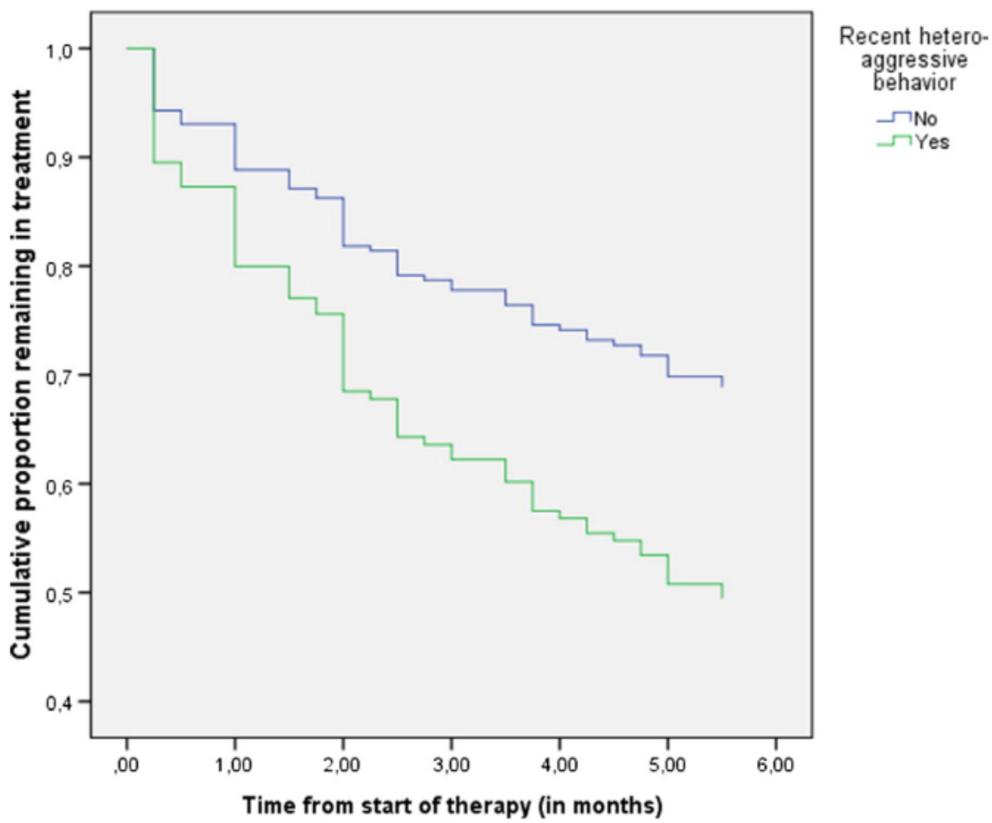



Implementation of Kaplan-Meier (KM) plots provided a descriptive graphical presentation to compare the different populations (all in-person, in person and telehealth, all virtual) and illustrate the attrition rate of each group. This non-parametric curve visually represents the survival rate across time where the survival probability drops vertically whenever one or more events of interest (attrition) occurs within the time interval (Kleinbaum & Klein, 2010). Figure 3 shows an example of a KM plot from

Gamache et. al (2018) looking specifically at attrition rates and hetero-aggressive behavior. In this study, KM plots were constructed for both the main variable of interest (delivery of therapy: in-person, telehealth, or both), as well as the other potential confounding factors (age, gender, SES, health insurance coverage, and health condition).

**Figure 3**

*Kaplan-Meyer Plot Example by Gamache et al. (2018)*




Note: Kaplan-Meier curves illustrating time to treatment dropout stratified by presence/absence of recent hetero-aggressive behavior.

In conjunction with each KM plot, a log rank test compared the population groups to see if a statistically significant difference exists between them. Specifically, this tests the null hypothesis that the survival curves from the KM plot are identical over time. The log rank test, however, does not allow for comparisons across continuous variables such as age unless they are first discretized (age in years converted to categorize such as under 18, 19-30, and over 30), resulting in loss of information. Another drawback is that KM plots and log-rank test lack estimates of effect size (Kleinbaum & Klein, 2010).

The Cox proportional hazards regression (Cox Regression) allows for quantification of differential risk across both categorical and continuous variables. Such a model provides a hazard ratio, which explains the probability of the event (i.e., attrition) occurring at any point in time for therapy type (in-person, telehealth, or both), while simultaneously controlling for any number of covariates (potential confounding factors). This directly answers the research question of how each type of therapy will influence the risk of attrition. All analyses were conducted in SPSS 27.0 (IBM Corp, 2020).

# Chapter IV

# Results

In total, one-hundred and twenty-five patients from the total sample (N = 329) dropped out of therapy during the six-month period, equaling 37.9% of the total sample. Within each individual group approximately 89.3% of the in-person group, 20% of those in the both group, and 31.2% of those in the telehealth group had terminated prematurely at the end of six months. Means, medians, and standard deviations for the groups can be found in Table 3. Overall, the mean survival time for the entire sample was about 17.8 weeks. The average survival rates for each individual modality group were 5.16 weeks for in-person, 23.14 weeks for both, and 8.13 weeks for telehealth.

## Hypothesis 1

A KM plot was used to illustrate the survival function of each therapy modality. The curve, shown in Figure 4, illustrates that the 'both' group maintained a higher survival (non-attrition) rate in comparison to the telehealth and in-person groups. At 12.5 weeks the rate of survival was 59% for the telehealth group, 3% for the in-person group and approximately 95% for the 'both'. A log rank test determined there were significant differences in the survival distribution for the different therapy modalities: in-person, telehealth, or both. The difference in the survival distributions were found to be statistically significant, $\chi^2(2) = 268.62$, $p < .001$.

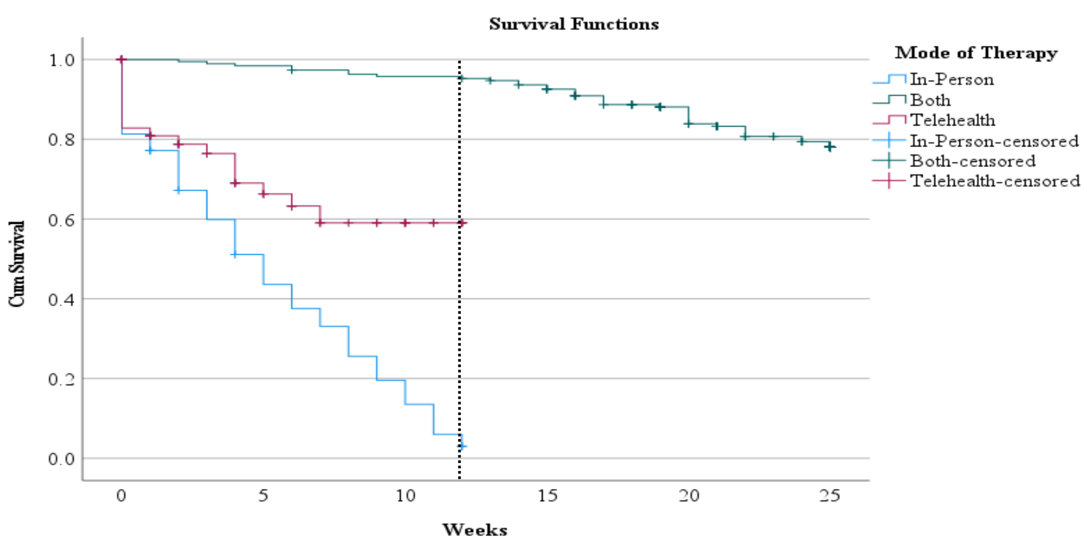
**Table 3**

*Means and Medians for Survival Time, Weeks by Modality*

| Therapy Modality | Mean | | | | Median | | | |
|---|---|---|---|---|---|---|---|---|
| | | | 95% CI | | | | 95% CI | |
| | Estimate | SE | Lower Bound | Upper Bound | Estimate | SE | Lower Bound | Upper Bound |
| In Person | 5.157 | 0.472 | 4.231 | 6.082 | 5.000 | 0.731 | 3.567 | 6.433 |
| Both | 23.143 | 0.339 | 22.479 | 23.807 | - | - | - | - |
| Telehealth | 8.128 | 0.697 | 6.761 | 9.494 | - | - | - | - |
| Overall | 17.809 | 0.551 | 16.729 | 18.889 | - | - | - | - |

**Figure 4**

*Kaplan-Meier Plot for Therapy Modality*



**Hypothesis 2**

The Cox Regression model (See Table 4) found none of the predictors (age, gender, insurance coverage, income) to be statistically significant with therapy modality. However, even when controlling for such covariates, the model showed the therapy modality groups to be statistically significant from one another. The hazards ratio (HR) or exponentiated parameter estimate, compares both the in-person and the both groups to the telehealth group as SPSS defaults to using the last variable as the indicator variable. The in-person only participants were more than twice as likely to drop out of therapy than those in the telehealth only group, $HR = 2.22$, $p = .050$. Participants who attended both modalities of therapy, were at a 99% lower risk of dropping out compared to the telehealth only group, $HR = .011$, $p < .001$.

**Table 4**

*Cox Regression of Time to Dropout (Weeks)*

| Variable | *Est.* | *SE* | *t* | *df* | *p* | *HR* |
|---|---|---|---|---|---|---|
| Age, years | -0.002 | 0.011 | 0.033 | 1 | .856 | .998 |
| Gender, male | -0.230 | 0.316 | 0.529 | 1 | .467 | .795 |
| Insurance | | | | | | |
| Out of Pocket | | | 3.250 | 3 | .355 | |
| Government | -0.870 | 1.090 | 0.637 | 1 | .425 | .419 |
| Private Ins. | -0.503 | 1.058 | 0.226 | 1 | .635 | .605 |
| Slide | -0.189 | 1.094 | 0.030 | 1 | .863 | .828 |
| Income | | | | | | |
| Level 4 | | | 4.593 | 3 | .204 | |
| Level 1 | 0.039 | 0.383 | 0.010 | 1 | .919 | 1.040 |
| Level 2 | 0.747 | 0.462 | 2.617 | 1 | .106 | 2.110 |
| Level 3 | 0.560 | 0.578 | 0.937 | 1 | .333 | 1.750 |
| Therapy Modality | | | | | | |
| Telehealth | | | 28.376 | 2 | <.001 | |
| In-Person | 0.799 | 0.408 | 3.838 | 1 | .050 | 2.223 |
| Both | -4.543 | 1.073 | 17.913 | 1 | <.001 | .011 |

Note. The reference category for gender is female. Est. = estimated beta parameter. HR = hazard ratio. Income level 1 is the lowest and 4 is the highest based on Table 1 in the Appendix.

# Chapter V

# Discussion

The main objective of the current investigation was to add to the current literature of attrition rates in psychotherapy. More specifically, this study aimed to explore telehealth as a resource for accessibility and analyze its influence on attrition rates during the COVID-19 pandemic.

## Treatment Modalities

Analyses revealed that the three modalities of therapy resulted in statistically different rates of attrition. The total attrition rate of the entire sample was approximately 38% which varies greatly from Swift and Greenberg's (2012) metanalysis which estimated a rate of 19.7%. In other words, these results indicate that about two out of every five patients in our sample ended treatment prematurely. While this is a comparatively higher rate, the fact that the data were collected from a lower income population at an FQHC does reflect the previous literatures claims of attrition being higher among those of lower socioeconomic status (Barrett et al., 2008; Khazaie et al., 2016). The COVID-19 pandemic could have also played a major part in this increased attrition rate. Sickness from and fear of the pandemic could have served as a major barrier that inhibited therapy retention.

Comparing the different groups, the participants that had received psychotherapy both in person and via telehealth showed 99% lower odds of attrition when compared to the groups of just telehealth. Through Penchansky and Thomas' model (1981), we can imply that having both telehealth and in-person therapy as options allows clients to find the "best fit" for each of the domains of availability, affordability, accommodation, and acceptability. By having both options available, clients may also be more likely to attend their appointments as they can adapt their delivery of therapy based on their current situations or potential barriers.

When looking strictly between the in-person and telehealth groups, results confirmed that those who were just in-person were over twice as likely to drop out than those who purely saw their therapists via telehealth. Such results supported my hypothesis that when teletherapy was offered as an option, attrition rates were reduced. In addition, while this study did not explicitly examine the treatment efficacy of telehealth services, these results strengthen the literature that shows teletherapy as an effective treatment option (Burgoyne & Cohn, 2020; Turgoose et al., 2017; Twist & Hertlein, 2017)

It can be inferred that participants attending in-person visits are more likely to stop attending treatment because such visits do not have as much flexibility when compared to the telehealth or both in-person and telehealth options. As noted in the literature review, unexpected life circumstances (e.g., illness, work conflicts, childcare) are often barriers to accessing mental health treatment (Barrett et al., 2008; Defife et al., 2012). When such circumstances arise, attending services at a mental health service provider is often not a possibility, whereas telehealth services provide a way for clients to still receive services from various locations, even with such confounding factors.

**Demographic Variables as Predictors**

The analyses run did not indicate any significant association between attrition and age, gender, SES, or insurance type as predictors for attrition. While the variables of age and gender were expected to result as insignificant predictors in accordance with previous literature (Bohart & Wade, 2013), the predictors of SES status and insurance coverage differed from my hypothesized results. As with earlier studies (Barrett et al., 2008; Khazaie et al., 2016) when controlling for the other variables, I expected lower SES status and lack of insurance coverage to be significant predictors of attrition. The Cox Regression model, however, did not support this expectation.

Although the results did not reflect what was hypothesized, the insignificance of such demographic variables does not differ greatly from the literature which has found inconsistencies in these variables as predictors (Bohart & Wade, 2013). However, the fact that the sample was collected from an overall lower income population may have influenced the outcome for this hypothesis. Due to this sample's lack of variability, it cannot definitely be assumed that these demographic variables had no effect on attrition rates.

**Clinical Implications**

Knowing that attrition can greatly affect the rate of change for clients in therapy (Wierzbicki & Pekarik, 1993; Xio et al., 2017), clinicians should take preventative measures to help limit barriers to mental healthcare access. With the results in this study showing higher survival rates in the 'both' and 'telehealth' groups, mental health providers should be aware of the potential resource that telehealth services can provide to reduce attrition. While some therapists may be skeptical about teletherapy and its potential hinderance on the therapeutic relationship (Twist & Hertlein, 2017), clinicians should take into account the benefits implied from the results in this study. By providing both the options for telehealth and in-person therapy delivery to clients, therapists may decrease their daily no-show rates and the number of last-minute cancellations.

Therapists may also increase attendance for clients with specific diagnoses by having telehealth as an option. Those diagnosed with depressive disorders, panic disorder, social anxiety disorders, or other anxiety disorders could particularly feel more comfortable as they can access such services while avoiding distressing circumstances such as social interactions or the outside environment (Wiederhold, 2020). Lastly, in accordance with previous research these results provide greater reasoning for therapists in rural areas to use telehealth and reach those that they might not have been able to working strictly in-person (Wiederhold, 2020).

## Limitations

A number of limitations are present within this study and should be considered when interpreting the findings. First, because of the use of extant data, I was often constrained by what was initially collected and could not obtain further information prior to analysis. While the timeframe of six months provided significant outcomes, a longer time period (additional months prior to and after COVID) could have provided a bigger picture of the phenomenon studied. This extant data also limited which additional variables were available for consideration for this study. I initially wanted to include patient's diagnoses and health conditions (chronic vs acute), but the diagnoses of such items in the patient's charts were too inconsistent to be beneficial and thus were not taken into consideration. I also planned on utilizing race and ethnicity as another predictor variable, but the sample was predominately white. This factor inhibits my ability to generalize these findings to other populations.

An unexpected limitation was the predominance of patients who were seen both before and after the start of the pandemic ($n$ = 190) in comparison to those who only received therapy via telehealth ($n$ = 64) or in-person ($n$ = 75). The makeup of the 'both' group largely consisted of patients who had been seeing a therapist for a long period of time prior to the dates assessed. Naturally, those patients who have an established history with their therapist are more likely to continue treatment than those who just start treatment. This confounding factor could have contributed to the low attrition rate of the both group when compared to those who had only participated in therapy via telehealth. While it was beyond the scope of this study, longevity of treatment is a potential confounding factor and should be considered in future studies regarding attrition.

With this being retrospective data, I was limited in my ability to control for various confounding variables as well. Due to the fact that I was unable to interact with the patients, I could not inquire as to what influenced them to drop out of treatment, whether that be life stressors, dissatisfaction with treatment or the therapist, financial issues, believing they no longer needed treatment, etc. It is because of this inability to interact with participants that I cannot conclude that it was merely telehealth that influenced attrition in each group. Because the Coronavirus pandemic was ongoing during the telehealth group, I could not separate whether or not it was the virus's influence or that of the therapy modality that affected each group's attrition rates.

Lastly, the manner in which attrition was defined in this study is also, in and of itself, a limitation. Therapist's discretion in their clinical notes about whether or not a patient should continue treatment was chosen because of its easy accessibility with the data. However, as noted by Wierzbicki and Pekarik (1993), this judgement can often lack reliability as each therapist may use different criteria to define who is or isn't ready to terminate treatment.

**Future Directions**

A prospective study that was not limited by the given data would allow for an examination of the impact of telehealth services on attrition during a longer period of time, rather than just the six-month period that we were given. Future studies using this or similar data should analyze longevity of therapy as a potential predictor variable. Additionally, similar studies should be conducted using more diverse samples from other FQHC's across the United States in order to allow the results to become more generalizable. By doing so, ethnicity could be considered as a variable and potential results could indicate which ethnic groups may have more barriers to accessing mental healthcare treatment.

Future research in this field may also consider studying the effect of an established therapeutic relationship on attrition rates. As mentioned above, many of those that did not dropout in this study appeared to have started therapy much earlier than when the data was collected, allowing them to have a longer history with their therapist. The therapeutic alliance, or the relationship the therapist has with the client, has been found to be one of the most important therapist-influenced condition for client outcomes (Fife et al., 2013). While this study did not have the means to analyze the therapeutic relationship as a factor for attrition, prospective studies in attrition may find it to be especially influential.

To strengthen the statement that utilizing both in-person and telehealth services can serve as protective factors against attrition in therapy, I hope to perform a similar study after the COVID-19 pandemic. Doing so would eliminate the pandemic as a confounding factor and potentially provide a clearer understanding of the relationship between therapy modality and rates of attrition. With services via telehealth being a choice rather than a mandate post-pandemic, I would hope to interact with the therapy patients through surveys to see what factors influence their choice in determining how they would like therapy to be delivered. Identifying such factors could further strengthen the use of the Healthcare Utilization model and its dimensions of access.

## Conclusion

Previous research has shown attrition to interfere with access to productive mental healthcare delivery as well as diminish a client's rate of change (Wierzbicki & Pekarik, 1993; Xio et al., 2017). In exploring telehealth as a resource to reduce attrition rates, I found that having both telehealth and in-person therapy visits as an option for treatment may decrease the likelihood of clients terminating treatment prior to optimal benefit. While no significant predictor variables were identified to explain why attrition occurred, these results give insight as to how clinicians can provide clients with a resource to prevent attrition. Such findings not only confirm previous conclusions made about attrition but also enhance the current literature on the subject. Adding these results to the available literature on attrition actually provides a resourceful solution to reducing rates rather than focusing primarily on the root cause of premature termination. The implications of these findings suggest that future research should examine the benefits of telehealth resources and their possibility of providing greater mental healthcare access.

**References**


Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior*, *36*(1), 1. https://doi.org/10.2307/2137284

Barrett, M. S., Chua, W.-J., Crits-Christoph, P., Gibbons, M. B., & Thompson, D. (2008). Early withdrawal from mental health treatment: Implications for psychotherapy practice. *Psychotherapy: Theory, Research, Practice, Training*, *45*(2), 247–267. https://doi.org/10.1037/0033-3204.45.2.247

Baruch, G., Gerber, A., & Fearon, P. (1998). Adolescents who drop out of psychotherapy at a community-based psychotherapy centre: A preliminary investigation of the characteristics of early drop-outs, late drop-outs and those who continue treatment. *British Journal of Medical Psychology*, *71*(3), 233–245. https://doi.org/10.1111/j.2044-8341.1998.tb00988.x

Burgoyne, N., & Cohn, A. S. (2020). Lessons from the transition to relational teletherapy during covid-19. *Family Process*, *59*(3), 974–988. https://doi.org/10.1111/famp.12589

Bohart, A. C., & Wade, A. G. (2013). The client in psychotherapy. In M. J Lambert (Ed.), *Bergin and Garfield's handbook of psychotherapy and behavior change* (pp. 219–257). essay, John Wiley & Sons.

Cooke, J. E., Eirich, R., Racine, N., & Madigan, S. (2020). Prevalence of posttraumatic and general psychological stress during COVID-19: A rapid review and meta-analysis. *Psychiatry Research*, 292, 113347. https://doi.org/10.1016/j.psychres.2020.113347

Defife, J. A., Smith, J. M., & Conklin, C. (2012). Psychotherapy appointment no-shows: clinicians' approaches. *Journal of Contemporary Psychotherapy*, *43*(2), 107–113. https://doi.org/10.1007/s10879-012-9216-6

Erekson, D. M., Clayson, R., Park, S. Y., & Tass, S. (2018). Therapist effects on early change in psychotherapy in a naturalistic setting. *Psychotherapy Research*, *30*(1), 68–78. https://doi.org/10.1080/10503307.2018.1556824

Fenger, M., Mortensen, E. L., Poulsen, S., & Lau, M. (2010). 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*(3), 183–191. https://doi.org/10.3109/08039488.2010.515687

Fife, S. T., Whiting, J. B., Bradford, K., & Davis, S. (2013). The therapeutic pyramid: A common factors synthesis of techniques, alliance, and way of being. *Journal of Marital and Family Therapy*, *40*(1), 20–33. https://doi.org/10.1111/jmft.12041

Gamache, D., Savard, C., Lemelin, S., Côté, A., & Villeneuve, E. (2018). Premature psychotherapy termination in an outpatient treatment program for personality disorders: a survival analysis. *Comprehensive Psychiatry*, 80, 14–23. https://doi.org/10.1016/j.comppsych.2017.08.001

Hatchett, G. T., Han, K., & Cooker, P. G. (2002). Predicting premature termination from counseling using the butcher treatment planning inventory. *Assessment*, *9*(2), 156–163. https://doi.org/10.1177/10791102009002006

Hatchett, G. T., & Park, H. L. (2003). Comparison of four operational definitions of premature termination. *Psychotherapy: Theory, Research, Practice, Training*, *40*(3), 226–231. https://doi.org/10.1037/0033-3204.40.3.226

Hirko, K. A., Kerver, J. M., Ford, S., Szafranski, C., Beckett, J., Kitchen, C., & Wendling, A. L. (2020). Telehealth in response to the Covid-19 pandemic: Implications for rural health disparities. *Journal of the American Medical Informatics Association*, *27*(11), 1816–1818. https://doi.org/10.1093/jamia/ocaa156

IBM Corp. Released 2020. IBM SPSS Statistics for Windows, Version 27.0. Armonk, NY: IBM Corp.

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. https://doi.org/10.1016/j.evalprogplan.2016.03.002

Kivlighan, D. M., Jung, A.-K., Berkowitz, A. B., Hammer, J. H., & Collins, N. M. (2018). 'To show or no-show'? Therapist racial-ethnic disparities in clients' nonattendance in therapy. *Journal of College Student Psychotherapy*, *33*(1), 1–13. https://doi.org/10.1080/87568225.2018.1424597

Kleinbaum, D. G., & Klein, M. (2010). Survival analysis. Springer.

Knapp, S. J. (2009). Critical theorizing: Enhancing theoretical rigor in Family Research. *Journal of Family Theory & Review*, *1*(3), 133–145. https://doi.org/10.1111/j.1756-2589.2009.00018.x

Longo, D. A., Lent, R. W., & Brown, S. D. (1992). Social cognitive variables in the prediction of client motivation and attrition. *Journal of Counseling Psychology*, *39*(4), 447–452. https://doi.org/10.1037/0022-0167.39.4.447

Lopes, R. T., Gonçalves, M. M., Sinai, D., & Machado, P. P. (2017). Clinical outcomes of psychotherapy dropouts: does dropping out of psychotherapy necessarily mean failure? *Revista Brasileira De Psiquiatria*, *40*(2), 123–127. https://doi.org/10.1590/1516-4446-2017-2267

Majlessi, S. (2020, September 9). *Demand for Mental Health and Addiction Services Increasing as COVID-19 Pandemic Continues to Threaten Availability of Treatment Options. National Council.* https://www.thenationalcouncil.org/press-releases/demand-for-mental-health-and-addiction-services-increasing-as-covid-19-pandemic-continues-to-threaten-availability-of-treatment-options/.

Malathesh, B. C., Chatterjee, S. S., & Das, S. (2020). Overview of mental health issues of COVID-19: need of the hour. *General Psychiatry*, *33*(3). https://doi.org/10.1136/gpsych-2020-100233

Miller, S. D., Hubble, M. A., & Chow, D. (2020). *Better results: using deliberate practice to improve therapeutic effectiveness*. American Psychological Association.

O'Connor, R. C., Wetherall, K., Cleare, S., McClelland, H., Melson, A. J., Niedzwiedz, C. L., … Robb, K. A. (2020). Mental health and well-being during the COVID-19 pandemic: longitudinal analyses of adults in the UK COVID-19 Mental Health & Wellbeing study. *The British Journal of Psychiatry*, 1–8. https://doi.org/10.1192/bjp.2020.212

Pekarik, G. (1985). The effects of employing different termination classification criteria in dropout research. *Psychotherapy: Theory, Research, Practice, Training, 22,* 86–91. doi:10.1037/h0088531

Penchansky, R., & Thomas, J. W. (1981). The concept of access. *Medical Care*, *19*(2), 127–140. https://doi.org/10.1097/00005650-198102000-00001

Pickens, J. C., Morris, N., & Johnson, D. J. (2020). The digital divide: Couple and family therapy programs' integration of teletherapy training and education. *Journal of Marital and Family Therapy*, 46(2), 186–200. https://doi.org/10.1111/jmft.12417

Roseborough, D. J., McLeod, J. T., & Wright, F. I. (2016). Attrition in psychotherapy: A survival analysis. *Research on Social Work Practice*, *26*(7), 803–815. https://doi.org/10.1177/1049731515569073

Shadish, W. R., & Baldwin, S. A. (2002). Meta-analysis of MFT interventions. In D. H. Sprenkle (Ed.), *Effectiveness research in marriage and family therapy* (pp. 339–370). Alexandria, VA: American Association of Marriage and Family Therapy.

Shadish, W. R., & Baldwin, S. A. (2009). Meta-analysis of MFT interventions. *Journal of Marital and Family Therapy*,29, 547–570. doi:10.1111/j.1752-0606.2003.tb01694.x

Swift, J. K., & Greenberg, R. P. (2012). Premature discontinuation in adult psychotherapy: A meta-analysis. *Journal of Consulting and Clinical Psychology*, *80*(4), 547–559. https://doi.org/10.1037/a0028226

Taylor, C. B., Fitzsimmons-Craft, E. E., & Graham, A. K. (2020). Digital technology can revolutionize mental health services delivery: The COVID-19 crisis as a catalyst for change. *International Journal of Eating Disorders*, 53(7), 1155–1157. https://doi.org/10.1002/eat.23300

Turgoose, D., Ashwick, R., & Murphy, D. (2017). Systematic review of lessons learned from delivering tele-therapy to veterans with post-traumatic stress disorder. *Journal of Telemedicine and Telecare*, *24*(9), 575–585. https://doi.org/10.1177/1357633x17730443

Twist, M.L.C. & Hertlein, K.M. (2017). Ethical couple and family e-therapy. In M.J. Murphy & L. L. Hecker (Eds.), *Ethics and professional issues in couple and family therapy* (2nd ed., pp. 261–282). essay, Routledge/Taylor & Francis Group.

Varker, T., Brand, R. M., Ward, J., Terhaag, S., & Phelps, A. (2019). Efficacy of synchronous telepsychology interventions for people with anxiety, depression, posttraumatic stress disorder, and adjustment disorder: A rapid evidence assessment. *Psychological Services*, *16*(4), 621–635. https://doi.org/10.1037/ser0000239

Vockley, M. (2015). The rise of telehealth: ‘triple aim,’ innovative technology, and popular demand are spearheading new models of health and wellness care. *Biomedical Instrumentation & Technology*, *49*(5), 306–320. https://doi.org/10.2345/0899-8205-49.5.306

Wampold, B. E., Flückiger, C., Del Re, A. C., Yulish, N. E., Frost, N. D., Pace, B. T., Goldberg, S. B., Miller, S. D., Baardseth, T. P., Laska, K. M., & Hilsenroth, M. J. (2016). In pursuit of truth: A critical examination of meta-analyses of cognitive behavior therapy. *Psychotherapy Research*, *27*(1), 14–32. https://doi.org/10.1080/10503307.2016.1249433

Wampold, B. E. (2019). *The basics of psychotherapy: An introduction to theory and Practice*. American Psychological Association.

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., McIntyre, R. S., … Ho, C. (2020). A longitudinal study on the mental health of general population during the COVID-19 epidemic in China. Brain, Behavior, and Immunity, 87, 40–48. https://doi.org/10.1016/j.bbi.2020.04.028

Wiederhold, B. K. (2020). Teletherapy: The new norm? *Cyberpsychology, Behavior, and Social Networking*, *23*(10), 655–656. https://doi.org/10.1089/cyber.2020.29196.editorial

Wierzbicki, M., & Pekarik, G. (1993). A meta-analysis of psychotherapy dropout. *Professional Psychology: Research and Practice*, *24*(2), 190–195. https://doi.org/10.1037/0735-7028.24.2.190

World Health Organization. (2020, October 5). COVID-19 disrupting mental health services in most countries, WHO survey. World Health Organization. https://www.who.int/news/item/05-10-2020-covid-19-disrupting-mental-health-services-in-most-countries-who-survey.

Wrape, E. R., & Mcginn, M. M. (2018). Clinical and ethical considerations for delivering couple and family therapy via telehealth. *Journal of Marital and Family Therapy*, *45*(2), 296–308. https://doi.org/10.1111/jmft.12319

Xiao, H., Hayes, J. A., Castonguay, L. G., Mcaleavey, A. A., & Locke, B. D. (2017). Therapist effects and the impacts of therapy nonattendance. *Psychotherapy*, *54*(1), 58–65. https://doi.org/10.1037/pst0000103

# Appendix

**Table 1**

*2020 Federal Poverty and Sliding Fee Scale Levels*

| | Level 1 | | Level 2 | | Level 3 | | Level 4 | |
|---|---|---|---|---|---|---|---|---|
| Household Size | Up to 100% of Federal Poverty Level | | Up to 133% of Federal Poverty Level | | Up to 150% of Federal Poverty Level | | Up to 200% of Federal Poverty Level | |
| | Annual Income | | Annual Income | | Annual Income | | Annual Income | |
| 1 | - | 12,760 | 12,761 | 16,971 | 16,972 | 19,140 | 19,141 | 25,520 |
| 2 | - | 17,240 | 17,241 | 22,929 | 22,930 | 25,860 | 25,861 | 34,480 |
| 3 | - | 21,720 | 21,721 | 28,888 | 28,889 | 32,580 | 32,581 | 43,440 |
| 4 | - | 26,200 | 26,201 | 34,846 | 34,847 | 39,300 | 39,301 | 52,400 |
| 5 | - | 30,680 | 30,681 | 40,804 | 40,805 | 46,020 | 46,021 | 61,360 |
| 6 | - | 35,160 | 35,161 | 46,763 | 46,764 | 52,740 | 52,741 | 70,320 |
| 7 | - | 39,640 | 39,641 | 52,721 | 52,722 | 59,460 | 59,461 | 79,280 |
| 8 | - | 44,120 | 44,121 | 58,680 | 58,681 | 66,180 | 66,181 | 88,240 |
| 9 | - | 48,600 | 48,601 | 64,638 | 64,639 | 72,900 | 72,901 | 97,200 |
| 10 | - | 53,080 | 53,081 | 70,596 | 70,597 | 79,620 | 79,621 | 106,160 |