

## DET PSYKOLOGISKE FAKULTET

# Ψ

Client predictors of therapy dropout in a primary care setting

## HOVEDOPPGAVE

Profesjonsstudiet i psykologi

Elin Hanevik og Frida Røvik

Vår 2022

Supervisor: Tormod Bøe, University of Bergen

Co-supervisor: Robert Smith, Norwegian Institute of Public Health

#### Preface

This thesis builds on data collected as part of a research project by the Norwegian Institute of Public Health (NIPH) called "Evaluation of Prompt Mental Health Care: A Randomized Controlled Trial". Based on this trial, NIPH wanted the concept of dropout to be better understood within the service of Prompt Mental Health Care. This current study is an independent piece of work. The process of exploring existing literature on dropout and deciding on a study aim has been performed by us. Furthermore, all statistical analyses were conducted by us, under the supervision of internal and external supervisors.

#### Acknowledgments

We would like to express our gratitude to our supervisors Tormod Bøe and Robert Smith. You have been a valuable source of guidance, inspiration, and constructive discussions. We highly appreciate the opportunity to take part in this project, which has provided us with valuable research experience. The art of building helpful and effective mental health services has engaged us from the very beginning of our studies. This project has motivated us to follow our passion and continue this work as future professionals.

To our families and friends, we thank you for your support and assistance in the finalization of our work. We are especially grateful for the SPSS-guidance from Jan Ole. Many thanks to our dearest Carl and Marius for standing by our side and encouraging us.

We would also like to thank our fellow psychology students and professors at the University of Bergen for six years of insightful conversations, encouraging smiles, clumsy role plays, long lunch breaks, inspiring lectures, creative study groups, festivities, exam nerves, and extensive amounts of SiB-coffee. Finally, to the clients we have met so far, we thank you for teaching us the most valuable lessons of all.

Deichman Bjørvika, Oslo, May 2022

#### Abstract

**Background:** Therapy dropout poses a major challenge. Considerable research has been conducted on predictors of dropout, however none in the context of primary mental health services in Norway. The purpose of this study was to investigate which client characteristics can predict dropout from the service Prompt Mental Health Care (PMHC). Methods: We performed a secondary analysis of a Randomized Controlled Trial (RCT). Our sample consisted of 526 adult participants receiving PMHC-treatment in the municipalities of Sandnes and Kristiansand, from November 2015 to August 2017. Using logistic regression, we investigated the association between nine client characteristics and dropout. Results: The dropout rate was 25.3%. Older clients had a lower odds ratio (OR) of dropping out compared to younger clients (OR = 0.44, [95% CI = .27, .71]). Clients with higher education had a lower odds ratio of dropping out compared to clients with lower levels of education (OR = .57, 95% CI [.35, .92]). Clients experiencing poor social support had a higher odds ratio of dropping out compared to clients with good social support (OR = 1.90, [95% CI = 1.20, 2.99]). The characteristics of sex, immigrant background, work status, daily function, symptom severity and duration of problems did not predict dropout. *Conclusion:* The predictors found in this prospective study might help PMHC-therapists identify clients at risk of dropout. Strategies for preventing dropout are discussed.

**Keywords:** Dropout; Non-attendance; Cognitive Behavioral Therapy; Prompt Mental Health Care; Improving Access to Psychological Therapies

#### Sammendrag

**Bakgrunn:** Frafall fra terapi representerer en betydelig utfordring. Derfor har det blitt grundig studert hva som kan predikere frafall fra terapi. Dette har hittil ikke blitt undersøkt i primærhelsetjenesten i Norge. Formålet med denne studien var å undersøke hvilke karakteristikker ved klienter som kan predikere frafall fra tjenesten Rask Psykisk Helsehjelp (RPH). Metode: Vi giennomførte en sekundær analyse av en randomisert kontrollert studie (RCT). Utvalget besto av 526 voksne deltakere som mottok behandling fra Rask Psykisk Helsehjelp i kommunene Sandnes og Kristiansand fra november 2015 til august 2017. Ved bruk av logistisk regresjon undersøkte vi sammenhengen mellom ni klientkarakteristikker og frafall. **Resultater:** Frafallsraten i studien var 25.3%. Eldre klienter hadde lavere odds ratio (OR) for å falle fra sammenlignet med yngre klienter (OR = 0.44, [95% CI = .27, .71]). Klienter med høyere utdanning hadde lavere odds ratio for å falle fra sammenlignet med klienter med lavere grad av utdanning (OR = .57, 95% CI [.35, .92]). Klienter med dårlig sosial støtte hadde høyere odds ratio for å falle fra sammenlignet med klienter med god sosial støtte (OR = 1.90, [95% CI = 1.20, 2.99]). Karakteristikkene kjønn, innvandrerbakgrunn, arbeidsstatus, funksjonsnivå, symptomtrykk og problemvarighet predikerte ikke frafall. *Diskusjon:* De predikerende karakteristikkene vi fant i denne prospektive studien kan hjelpe RPH-terapeuter å identifisere klienter i risiko for frafall. Strategier for å forebygge frafall diskuteres.

Nøkkelord: Frafall; Kognitiv Atferdsterapi; Rask Psykisk Helsehjelp; Improving Access to Psychological Therapies

### Table of contents

Introduction
The mental health status in Norway9
The Norwegian mental health system10
Prompt Mental Health Care12
Conceptual clarification15
Operationalizing dropout15
Dropout rates in the literature
Consequences of dropout
Previous research on predictors of dropout
Clinical factors
Sociodemographic factors26
The aim of the study28
Method
Data collection setting
Procedure for PMHC treatment
Recruitment and participants
Measures
Outcome measure
Baseline predictors
Ethical considerations

Statistical analyses
Results
Dropout
Baseline characteristics
Baseline characteristics predicting dropout
Discussion
Predictors of dropout
Age
Level of education
Social support4
Work status42
Other findings42
Study strengths
Study limitations44
Practical implications4
Awareness and flexibility through feedback45
Expectations and motivation47
Booking and termination routines49
Focus on socioeconomic challenges in treatment50
Nuancing dropout
Scientific implications

Defining dropout51
Suggestions for future research
Monitoring53
Conclusion
References
Table 1 Sociodemographic and Clinical Characteristics of Participants at Baseline
Table 2 Logistic Regression Analysis Predicting Dropout from Sociodemograhic and Clinical
variables71
Table 3 Multivariate Logistic Regression Analysis Predicting Dropout from Therapy72

#### Introduction

#### The mental health status in Norway

In Norway, the lifetime prevalence of a mental disorder is 30-50% (Helsedirektoratet, 2015a). This indicates that almost half of the population will experience serious mental health problems during their lifetime. Anxiety, depression, and drug addiction are the most common disorders (Folkehelseinstituttet, 2018). Another estimate is the yearly prevalence, stating that about 1 in 5 adults in Norway will have a mental disorder in any year. This prevalence has remained stable over recent years (Helsedirektoratet, 2015a). Compared to other West-European countries, the prevalence of mental disorders in the population is approximately the same. A distinction is often made between the prevalence of mental disorders and mental health problems. *Mental disorders* are characterized by symptoms to such an extent that they qualify for a diagnosis. *Mental health problems* is a broader definition which additionally includes people with milder symptoms that do not necessarily qualify for a disorder. We will refer to both terms throughout this paper.

Anxiety and depression are often reported as reasons for reduced ability to work, sick leave and disability benefits in Norway (NAV, 2021). Among those who received disability benefits in 2016, 36.8% were allocated this due to a primary diagnosis of a mental or behavioral disorder. Overall, this represented the largest proportion of people receiving disability benefits (NAV, 2021). Looking at the age group of 18-39 years, mental and behavioral disorders constituted as much as 62% of the primary reason for allocating disability benefits (NAV, 2021). The prevalence of mental disorders in Norway has been relatively steady over the past years (Helsedirektoratet, 2015a; Tesli et al., 2021). However, the Norwegian Labour and Welfare Administration (NAV) (2021) reported that there was a sharp increase in the number of people with mental disorders receiving disability benefits between 2010-2016.

#### The Norwegian mental health system

The Norwegian mental health system is divided into different units called primary, secondary, and tertiary services. Primary services include mental health services situated outside institutions. They often have preventive and health promoting mandates and clients can approach the services without a referral. Treatment in secondary and tertiary mental health services requires a referral from a primary or secondary service, as they are more specialized. In order to be entitled to treatment from these services, the client's mental health problems must be at an extensive level of severity accompanied by a significant loss in function. Within 10 days after the referral is admitted, the client should get information about whether he/she is entitled to treatment from the specialized units or not (Helsedirektoratet, 2015b). If the person is considered to be entitled to help, he/she should simultaneously be informed about the legal deadline for receiving treatment and the time for attendance (Helsedirektoratet, 2015b). In 2021, the average national waiting time for this service was 47.5 days (Helsedirektoratet, 2022). There are several potential negative effects of waiting times. Firstly, the clients are at risk of worsening symptoms while waiting. Secondly, they can feel overlooked and possibly not show up for treatment when it is their turn (Marshall et al., 2016).

Besides considerable waiting times, another challenge is that the strict criteria give rise to a large group of clients considered *too healthy* to be entitled to this treatment. This group is nevertheless still in need of mental health services. For instance, a client considered to be well functioning at work, despite having considerable symptoms, might be rejected if there are others with the same symptom severity, but a lower level of function. In 2021, between 23-27% of the clients referred to secondary mental health care were rejected for various reasons (Helsedirektoratet, 2022). Negative consequences of high rejection rates could be deterioration of symptoms, negative self-image and self-worth. Additionally, clients might start to trivialize their own problems since their symptoms have been evaluated as *not severe enough*. This can give the client an impression that the only way to receive help is by getting even more ill or stop functioning at work, which doubtfully motivates the client to get better.

Norway is among the countries in Europe spending most of the national health budget on mental health services (Helsedirektoratet, 2015a). Still, the Norwegian healthcare system struggles to cover the population's need for treatment. This gap between the need for mental health services within the population and the availability of these services is referred to as the *treatment gap* or *unmet needs* in the international literature (Kohn et al., 2004). The discrepancy between those who need help and those who receive it is estimated to be more than 50% for disorders of mild to moderate severity in most of the countries in the Organization for Economic Co-operation and Development (OECD) (Kohn et al., 2004; OECD, 2014). Therefore, it is a goal both nationally and internationally to scale up easily accessible mental health services (World Health Organization, 2019).

In an effort to reduce the personal and socioeconomic consequences of mental health problems, Norway has changed its strategy from mainly focusing on secondary services to implementing more accessible mental health services in primary care (Ramsdal & Hansen, 2017). This shift was addressed for the first time in Samhandlingsreformen, "Rett behandling – på rett sted til rett tid" (Meld. St. 47 (2008–2009)). The strategy included an increased emphasis on providing mental health services in the municipalities. The Norwegian law from 2012 regulating health care services states that Norwegian municipalities are obligated to offer necessary health services for people with mental health problems (Meld. St. 16 (2010–2011)). In reality, not everyone has the access they are entitled to today. However, many municipalities are in the process of establishing local primary health services for people with mild to moderate mental health problems (Ramsdal & Hansen, 2017). A recent report on the health condition in Norway stated that around 18% of the population were in contact with the primary health care for mental health problems, compared to 6% in the secondary care (Tesli et al., 2021). While the share of people in contact with secondary care remained stable between 2010-2020, it increased for primary care. This might be an early sign of the deliberated political strategy to strengthen mental health services in the primary care system. Prompt Mental Health Care has played an important role to achieve this.

#### **Prompt Mental Health Care**

Prompt Mental Health Care (PMHC), in Norwegian called Rask Psykisk Helsehjelp (RPH), is a primary care treatment model based on Cognitive Behavioral Therapy (CBT). The service was first implemented as a trial project in 2012 (Smith et al., 2016). PMCH is based on Improving Access to Psychological Therapies (IAPT), a program implemented by the UK Government in 2008. IAPT has shown solid treatment results and has proven to give mass public benefits (Clark, 2018). Today, there are equivalent services to IAPT in Norway, Australia, Japan, and Sweden (Wakefield et al., 2021).

An important goal of PMHC is to improve access to evidence-based treatment for adults with mild to moderate anxiety and depression, sleep problems, and other disorder-specific symptoms (Smith et al., 2016). A secondary goal is to enhance work participation. PMHC is easily accessible because it is free, situated in the local community, and approachable without a referral from a general practitioner (GP). The treatment is based on a *mixed care model*, entailing

application of a mix of treatment modalities with various intensity. These modalities range from low-intensity guided self-help, courses and groups to more high-intensity individual therapy. Level of intensity is considered in collaboration with the client. Mixed care differs slightly from the IAPT model, which provides a more consistent *stepped care*. Within this structure of modalities, most clients start low-intensity treatment before potentially engaging in more highintensity treatment.

Around half of the referrals to PMHC come from clients themselves (Smith et al., 2016). GPs account for most of the additional half. Suitability for the service is considered in an initial assessment session. The decision is based on the client's mental health problems, symptom severity, situation, and resources. PMHC does not formally diagnose clients. Based on the assessment, clients are either accepted or referred to another service considered more appropriate. Short waiting times are, as the name implies, supposed to be embedded in the PMHC concept. Waiting times varied in the pilot studies, with a median of 10 days between referral and assessment and eight days between assessment and the first session (Smith et al., 2016). In a more recent process evaluation, the median waiting time from the initial contact to the first session was 27 days (Lervik et al., 2020).

Clients who are accepted engage in therapy provided by interdisciplinary teams educated in CBT (Smith et al., 2016). Clients usually receive between two and 15 sessions, not counting the initial assessment. In the pilot studies, the median treatment duration was five meetings per client over a course of 10.7 weeks (Smith et al., 2016). An important aspect of the service is collaboration with relevant partners such as GPs and other primary and secondary services. Collaboration with work-related services is relevant to enhance work participation. Evaluations have shown solid effects of PMHC (Knapstad et al., 2018, 2020; Sæther et al., 2020; Smith et al., 2016). In a cohort study carried out by Knapstad et al. (2018), it was found a recovery rate of 65% for the 12 PMHC pilot sites. The effectiveness and long-term effect of PMHC have been evaluated by Knapstad et al. (2020) and Sæther et al. (2020). Both studies were conducted as Randomized Controlled Trials, using the same sample (N = 681), with PHQ-9 and GAD-7 as primary outcome measures. Participants were randomized to the experimental group (PMCH-treatment, n = 463) or control group (treatment as usual - TAU, n = 218) with a ratio of 70:30. Knapstad et al. (2020) found a 63.5% recovery rate in the PMHC group after 6-months, compared to a 38.3% recovery rate in the TAU-group. Effects were maintained at 12 months follow-up (Sæther et al., 2020). Recovery was understood as moving from clinical caseness, defined as scoring above clinical cut-off on PHQ-9 and/or GAD-7 at referral, to no longer fulfilling the criteria at 6- and 12-months follow-up. A meta-analysis evaluating the practice of IAPT revealed a slowly increasing recovery rate over the past ten years, presently at 50% (Wakefield et al., 2021).

A report from the Ministry for Health and Care services (2017) refers to PMHC as an example of a successful primary health care service for people with mild to moderate anxiety and depression. Furthermore, the report declares that the government will prioritize more money to increase the distribution of PMHC in Norwegian municipalities. In 2021, 84 Norwegian municipalities and/or districts had PMHC sites (Ose & Kaspersen, 2021). In comparison, 207 Norwegian municipalities and/or districts did not have PMHC and 39 were planning to establish PMHC.

Despite well-documented recovery effects, it is a fact that therapy does not bring desirable results for everyone (Cuijpers et al., 2014; Flor & Kennair, 2019; Walfish et al., 2012).

A considerable proportion of clients terminate therapy prematurely for a number of reasons. This group is often referred to as dropouts (Barrett et al., 2008; Fernandez et al., 2015; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Dropout has become a field of interest within research over the past fifty years, with hopes of implications that can provide meaningful and efficient therapy courses for more people.

#### **Conceptual clarification**

#### **Operationalizing dropout**

Dropout is defined in various ways across the literature (Barrett et al., 2008; Fernandez et al., 2015; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Synonyms to dropout such as non-attendance, discontinuation, attrition, premature termination, unilateral termination, non-compliance, disengagement, and no-show are frequently used. However, some of them have different connotations. The variation in definitions is a weakness within this field of research. Without a clear definition, it is difficult to compare results and provide a holistic view of the challenges of dropout.

We found that definitions of dropout are often operationalized in a threefold manner, highlighting one or more of the following aspects: 1) The number of sessions attended, 2) Premature termination, understood as termination prior to recovery, or 3) Unilateral termination, understood as lack of therapist collaboration on the decision of termination.

*Number of sessions* is frequently used to define dropout. Operationalizations are often based on a *dose-effect* understanding, entailing that a minimum number of sessions is needed for a client to show improvement in therapy (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Therefore, some studies include a set number of sessions or a given protocol that must be fulfilled in order to be considered a completer. Using only dose-effect understanding can however falsely classify clients who recover after a few sessions as dropouts. Furthermore, it can classify those who make no progress despite attending many sessions as completers (Swift & Greenberg, 2012). Wierzbicki and Pekarik (1993) stress that dropout and completion can happen at any number of sessions. This makes duration-based definitions limited when used exclusively to define dropout. A meta-analysis completed by Hans and Hiller (2013) found that CBT does not necessarily have a dose-response effect. Their findings indicate that attending more sessions does not necessarily lead to better outcomes. They rather underline the importance of completing the treatment course, regardless of the number of sessions it takes. This is why the emphasis on *premature termination* is important to add to the definition.

Grant et al. (2012) stress that there are several stages towards receiving help. Within each stage there is a possibility of dropout. This can imply that a broader definition of dropout from the very first help-seeking behavior with the health system would increase the dropout rates substantially. A distinction should be made between non-attendance and dropout. *Non-attendance* indicates not showing up for the assessment or the first session, meaning that the person does not properly enroll in a treatment course. *Dropout* on the other hand is used to describe termination from an unfinished treatment course. Therefore, IAPT studies only classify clients as dropouts if they attended at least one session of treatment in addition to an initial assessment (Furlong-Silva, 2020). In reviewing the literature, it varies whether studies uphold this distinction. Fenger et al. (2011) sought to identify sociodemographic and clinical differences between non-attenders and dropouts in a community service setting. Among the referrals, 27% did not attend their first session, whereas 11.7% dropped out during treatment. Non-attendance was predicted by five clinical variables (personality disorder, low or high function, no previous treatment, no use of antidepressants, and substance abuse) and three sociodemographic variables

(younger age, lower levels of education, and no current sick leave). In comparison, dropout was predicted by three sociodemographic variables (younger age, lower level of education, and unemployment) and one clinical variable (substance abuse) (Fenger et al., 2011). This study underlines the importance of consistency of definition.

A distinction can also be made between *early and late dropout*. Early dropout is often considered to happen during the first three sessions, whereas late dropout refers to termination at a later stage in the therapy course. It is more common to drop out early in the therapy process (Ghaemian et al., 2020). IAPT noted that among people enrolling in treatment, a considerable number drop out between the first and the second session (NHS Digital, 2021). Fernandez et al. (2015) found that the likelihood of dropout decreased by 0.3% for each additional session attended. Nevertheless, after a certain number of sessions, there seems to be a ceiling effect. This was also illustrated by Sharf et al. (2010), who found that studies with longer treatment courses of 16 to 40 sessions had more clients who dropped out compared to studies with treatment courses of nine to 16 sessions.

Another related concept is *no-show*, which often refers to missing individual sessions in a treatment course. Mitchell and Selmer (2007) stress that 20% of all scheduled appointments are missed. This accounts for almost twice the rate of other medical specialties. No-show for appointments is not necessarily a problem. Clients can have successful treatment despite missing an occasional session. This can however be a warning sign, as it was found that up to 50% of clients who missed appointments were likely to drop out of treatment (Mitchell & Selmer, 2007).

A final emphasis in the definition of dropout is the *unilateral termination* process. This is understood as terminating against the therapist's advice or without involving the therapist in the decision (Ogrodniczuk et al., 2005; Swift et al, 2017). It is worth noting that dropout is often defined by the therapist and not by the client. Therefore, the definition is dependent on the accuracy of the therapist's clinical judgment. This can be problematic for the field of research due to weak reliability, as different therapists can have different procedures to evaluate dropout (Wierzbicki & Pekarik, 1993).

As a counterpart to the various dropout terms, the term *completer* addresses those who fulfill their therapy course, regardless of their treatment outcome. Furthermore, the term *termination* refers to the act of ending a therapy course, regardless of the circumstance of dropout or completion.

#### Dropout rates in the literature

Meta-analyses and literature reviews have found the average prevalence of dropout to vary due to differences in definitions, study designs, and service settings (Di Bona et al., 2014; Wierzbicki & Pekarik, 1993; Zieve et al., 2019). To illustrate this, a meta-analysis by Wierzbicki and Pekarik (1993) found dropout rates ranging from 36% to 48% depending on how dropout was defined in the studies. Definitions in terms of therapist judgment and number of sessions attended gave the highest dropout rates. Defining dropout as termination by failure to attend a scheduled session provided lower dropout rates. Swift and Greenberg (2012) found that dropout rates were highest when determined by therapist judgment and lowest when defined as noncompletion of a set number of sessions or a treatment protocol.

Swift and Greenberg (2012) also found variation in dropout rates between different study designs. They coded dropout studies as either efficacy studies or effectiveness studies. The efficacy studies emphasized internal validity and were undertaken in a controlled setting. Effectiveness studies emphasized external validity and took place in real-life clinical settings. The latter turned out to have a higher dropout rate (26%), compared to efficacy studies (17%). Thus, different levels of control in the study setting can explain some of the variances in therapy dropout rates in the literature (Swift & Greenberg, 2012).

Some types of therapy are considered to have a higher dropout rate, for example nonmanualized treatment compared to manualized treatment (Swift & Greenberg, 2012). Regarding treatment intensity, there have been mixed results. Some studies found no difference between groups of clients receiving high-intensity and low-intensity treatments (Chan & Adams, 2014; Swift & Greenberg, 2012). Fernandez et al. (2015) however found in their meta-analysis that internet-delivered CBT formats had higher non-attendance rates compared to outpatient formats. When comparing group settings to individual settings, some studies found no difference in dropout rates (Wierzbicki & Pekarik, 1993; Zieve et al., 2019). On the other hand, Ghaemian et al. (2020) found that aspects of group therapy can provide reasons for dropout, such as fear of being recognized or a preference for individual therapy. Regarding the theoretical approach of the therapist, no differences have been found in relation to dropout (Grant et al., 2012; Zieve et al., 2019).

For psychotherapy in general, meta-analyses have shown a mean average dropout rate of approximately 19-46% (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Between the studies included in the meta-analyses, there was a great difference in dropout rates, some ranging up to 74% (Swift & Greenberg, 2012).

Looking at CBT studies exclusively, meta-analyses and literature reviews have investigated dropout rates both with and without relation to specific diagnoses (Fernandez et al., 2015; Hans & Hiller, 2013; Linardon et al., 2018; Salmoiraghi & Sambhi, 2010). The average dropout rates reported for these meta-analyses varied from 15 to 26%. Within CBT treatment, there was also a wide range in dropout rates between the studies. Some of the studies reported rates between 19-50% and 0-68% (Hans & Hiller, 2013; Salmoiraghi & Sambhi, 2010).

Within the IAPT treatment setting, an unpublished meta-analysis found an average dropout rate of 31% across all studies (Furlong-Silva, 2020). There were notable differences between the dropout rates reported in the studies, ranging from approximately 10-50%. The review of the progress made in the first rollout year of IAPT reported the dropout average to be 21.6% across sites (Glover et al., 2010). Binnie and Bonden (2016) report a non-attendance rate of 8.9% in their IAPT study. This number is however low compared to other IAPT studies and reports, which have shown non-attendance mean rates between 42-48% (Glover et al., 2010; Murphy et al., 2013; Richards & Borglin, 2011).

#### **Consequences of dropout**

Dropout can have extensive consequences for the client, the therapist, and the service. First of all, it decreases the chances of clinical recovery for the client. This has been shown in terms of higher symptom severity for dropouts at termination, compared to completers at termination (Cahill et al., 2003; Firth et al., 2015; Schindler et al., 2013; Zieve et al., 2019). In one study, clients did not differ in their rate of symptom change in the first three sessions, implying that dropouts had higher scores at termination because of fewer sessions overall (Zieve et al., 2019). Cahill et al. (2003) found similar results when matching the number of sessions between completers and dropouts. Although 70% of the dropouts achieved some reliable change during therapy, only 13% achieved clinically significant change. This was in contrast to the completers, whereof 71% achieved clinically significant change (Cahill et al., 2003). Residual subthreshold symptoms are a risk factor for relapse, which increases the chance of long-term poor outcome and the need for health services at a later time (Cahill et al., 2003; Ogrodniczuk et al., 2005; Zieve et al., 2019).

However, Lopes et al. (2018) found in their study that 62% of dropouts from treatment of depression had reached reliable change at 31-months follow-up. Thus, the majority of dropouts reported improvement over time from their last treatment session. It should be noted that the study had a small sample size (N = 63). Ghaemian et al. (2020) found that 24% of their participants reported recovery within two months after they dropped out. When looking at follow-up studies of dropouts, it is important to remember that there might be a skewness in relation to who agrees to participate. This can create an inaccurate impression of recovery among dropouts.

Thus, taking into account the different results presented above, dropout is not always equivalent to negative client outcomes. It seems that for some clients a few sessions can be enough to feel better and subsequently drop out (Marshall et al., 2016). In these cases, dropout from therapy can be a sign of satisfaction. The client's reason for dropout is therefore crucial. It should also be added that client satisfaction *here and now* leading to dropout is not necessarily sustainable, and does not automatically buffer relapse. When termination happens unexpectedly, there is no opportunity to prepare for potential future risk situations and how to combat these.

Dropout also has serious consequences for others involved in the therapy. For instance, within a group therapy setting, dropout can disrupt the group and influence the other clients' treatment process. This can give rise to insecurity, sadness, and anger in other group members (Ogrodniczuk et al., 2005). Ghaemian et al. (2020) stress that client dropout can have negative consequences also for therapists. As an example, a feeling of demoralization and failure can influence self-esteem and self-belief in clinical skills (Ogrodniczuk et al., 2005). Furthermore,

the feeling of wasting time and resources on clients that do not show up, can give rise to stress and frustration for the therapist (Ambrose & Beech, 2006).

There are also negative consequences for the national health care system and the service in terms of lost time, lost resources, and economic loss (Di Bona et al., 2014; Marshall et al., 2016). A system where every third or fourth client does not benefit adequately is an ineffective system. Resources are not only wasted on potentially unsuccessful treatment courses as they occur. More resources are likely to be needed for treatment of the same clients in the future. Spending time on clients who drop out prohibits access for others in need, which is also an expensive affair. Long waiting times can lead to worsening of symptoms and increased risk of non-attendance for those waiting (Barrett et al., 2008; Marshall et al., 2016; Reichert & Jacobsen, 2018). Additionally, long waiting lists can give rise to negative expectations of the service itself (Hicks & Hickman, 1994; Marshall et al., 2016).

#### Previous research on predictors of dropout

A number of predictors of dropout have been identified in the literature. However, the findings have been inconsistent (Barrett et al., 2008; Salmoiraghi & Sambhi, 2010; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). A distinction is often made in the literature between therapist, therapeutic alliance, service, and client factors that can predict dropout. Studies mostly address one group of factors. It should however be noted that a clear-cut distinction between groups of factors has its limitations. More often dropout is due to a complex interplay between factors.

Integrating knowledge from studies that focus on different groups of factors can bring us closer to understanding predictors of dropout. The therapist effect has been found to account for a considerable amount of the client dropout variance, findings ranging from 5.7%-12.6% (Saxon

et al., 2017; Zimmermann et al., 2016). Studies investigating the therapeutic alliance have found it to be related to dropout (Ghaemian et al., 2020; Johansson & Eklund, 2006; Sharf et al., 2010). Some claim the therapeutic alliance is more predictive than client and therapist factors separately (Wierzbicki & Pekarik, 1993). Additionally, dropout can to some extent be predicted by differences between services. Di Bona et al. (2014) and Reneses et al. (2009) reported that belonging to different municipalities or being allocated to different services provided different non-attendance and dropout rates.

Nevertheless, the largest body of research has been done on client predictors of dropout. As we will focus on client predictors in this paper, we would like to provide an overview of previous research on client factors. We have chosen to categorize client factors into clinical and sociodemographic factors. *Clinical factors* are here understood as characteristics that provide information about the intensity, duration and impact of mental health problems, in addition to internal processes and traits of the client. *Sociodemographic factors* are here understood as various statistical and population-based characteristics. Fenger et al. (2011) found that sociodemographic variables generally were more important predictors of dropout than clinical variables within the client.

#### **Clinical factors**

**Symptom severity.** High symptom severity has been presented as a predictor of client dropout, especially high levels of depression and anxiety (Binnie & Boden, 2016; Fernandez et al., 2015; Jarrett et al., 2013; Wang, 2007). Zimmermann et al. (2016) found that clients who dropped out had greater symptom severity at intake compared to completers. Binnie and Boden (2016) agree that high symptom severity can lead to dropout as the client might be too unwell to show up for treatment. High levels of depression can lead to increased feelings of hopelessness,

also directed at treatment and possible recovery. Additionally, suicidal ideation, such as thinking "I would be better off dead", has been identified as a predictor of non-attendance (Di Bona et al., 2014). High levels of general psychological distress and low levels of daily function and wellbeing has also been found to predict dropout. In this case measured through Global Assessment of Functioning (GAF) and CORE-OM (Fenger et al., 2011; Saxon et al., 2017).

Studies have interestingly also found low symptom severity and high daily function to be a predictor of dropout (Di Bona et al., 2014; Fenger et al., 2011; Zieve et al., 2019). Low symptom severity as a predictor of early dropout might be explained by relief of distress in the waiting time. It could also be that clients with lower symptom severity experience more ambivalence towards seeking help (Zieve et al., 2019). The findings on low and high symptom severity as predictors of dropout might represent a bi-modality. The two opposites can potentially lead to clients perceiving treatment as either unmanageable because one is too ill or unnecessary because one is too well.

**Duration of current mental health problem.** Similarly to the bi-modality of symptom severity, duration has been found to be predictive either if the episode had persisted for a long time (>2 years) or quite a short time (<1 month) (Di Bona et al., 2014). Again, it might be that a shorter duration makes the client perceive treatment as redundant while a longer duration can increase the feeling of hopelessness. A previous history of psychiatric care has been associated with lower dropout rates compared to clients without such a previous treatment history (Reneses et al., 2009). This is consistent with other studies showing that previous treatment indicated a higher rate of attendance to therapy in the first place (Fenger et al., 2011). However, this did not predict completion or recovery outcome.

**Diagnosis.** Type of mental disorder is another much studied clinical factor concerning dropout. Research has shown that personality disorders, eating disorders, and drug abuse are among the strongest diagnostic predictors of client dropout (Buckman et al., 2018; Fenger et al., 2011; Reneses et al., 2009; Schindler et al., 2013; Swift & Greenberg, 2012; Zieve et al., 2019). Fenger et al. (2011) found that the degree of comorbidity is associated with higher dropout rates.

**Personality traits.** Traits such as avoidance, hostility, aggressiveness, and passive aggressiveness have been linked to higher levels of dropout (Barrett et al., 2008). Additionally, cold and distant interpersonal function has been associated with lower ratings of therapeutic alliance, which subsequently was predictive of client dropout (Johansson & Eklund, 2006). Low levels of psychological mindedness in terms of the ability to self-reflect, tolerance for frustration, and ability to control own impulses, have also been linked to higher dropout rates (Barrett et al., 2008). Low psychological mindedness is a diagnostic criteria for personality disorders. This might clarify the strong predictive relationship of personality disorders and dropout.

**Client motivation and perceptions**. Some internal processes have been investigated as potential predictors of dropout. Firstly, the client's lack of motivation has been associated with dropout (Avishai et al, 2018; Keijsers et al., 2001; Schindler et al., 2013). Contrary, positive expectations to the effect of treatment have been associated with attendance (Murphy et al., 2013). Owens et al. (2002) found that clients who view mental health treatment as relatively ineffective, unnecessary, and uncomfortable are more likely to drop out. Additionally, the clients' perception of stigma related to attending the service predicted dropout. Finally, some studies have found that expectation of the duration of therapy was a better predictor of duration than any other variable (Beck et al, 1987; Pekarik, 1991).

#### Sociodemographic factors

**Sex.** Some studies have identified being male as a predictor of dropout (Reneses et al., 2009; Zimmermann et al., 2016). Others have identified being female as a predictor of dropout (Wierzbicki & Pekarik, 1993). Most meta-analyses and literature reviews conclude with inconsistent and mixed results for sex as a predictor (Barrett et al., 2008; Swift & Greenberg, 2012; Zieve et al., 2019).

**Age.** A dominant body of research has found that younger age is predictive of dropout (Edlund et al., 2002; Fenger et al., 2011; Johansson & Eklund, 2006; Reneses et al., 2009; Saxon et al., 2017; Zieve et al., 2019). Fenger et al. (2011) found that the age effect was stronger for non-attenders than for dropouts. They explain this with less stability in personal and social life, in addition to lack of experience with therapy.

**Socioeconomic status (SES)**. SES can be understood as the social standing of the individual, often measured through income, education, and work status (American Psychological Association, n.d.b). In studies by Barrett et al. (2008) and Fenger et al. (2011), socioeconomic status (SES) was presented as the most important demographic predictor of dropout. *Economic deprivation or poverty* have been identified as predictors of dropout (Binnie & Boden, 2016; Firth et al., 2015; Wierzbicki & Pekarik, 1993). Furthermore, studies have found *lower levels of education* to be a predictor of dropout (Fenger et al., 2011; Keijsers et al., 2001; Salmoiraghi & Sambhi, 2010; Wierzbicki & Pekarik, 1993). This connection might be related to low mastery and reduced ability to structure life, including adherence to treatment (Fenger et al., 2011). These results were not found in a private clinical setting (Zieve et al., 2019).

*Unemployment* has also been identified as a predictor of dropout (Fenger et al., 2011; Firth et al., 2015). Saxon et al. (2017) found that unemployment was the strongest predictor of both dropout and deterioration. Zieve et al. (2019) did not find unemployment to be a predictor of dropout in a private clinical setting. Fenger et al. (2011) found that clients on sick leave had an increased frequency of treatment show-up. This might seem contradictory. Nevertheless, unemployment and sick leave pose different situations. On the one hand, unemployment might entail limited meaningful activities during the day, stress related to finding a job, and economic concerns. On the other hand, sick leave might involve something meaningful to come back to, feeling needed and activated. This can naturally increase motivation for treatment and decrease the chance of dropout. Sick leave can additionally decrease the chance of dropout because it opens the schedule for treatment sessions (Fenger et al., 2011). This is supported by the fact that work commitment is often mentioned as a reason for dropout (Binnie & Boden, 2016; Ghaemian et al., 2020).

**Social deprivation.** The concept of social deprivation can be defined as a reduced social experience and access to resources in society due to poverty, discrimination, or other disadvantages (American Psychological Association, n.d.a). High levels of such deprivation have been identified as a predictor of non-attendance and dropout (Grant et al., 2012; Self et al., 2005). Level of social deprivation was found to be closely related to SES (Self et al., 2005).

**Immigrant background.** Studies have provided mixed results for immigrant background as a predictor of dropout. Some studies have found an association (Barrett et al., 2008; de Haan et al., 2018; Wang, 2007; Wierzbicki & Pekarik, 1993). Barrett et al. (2008) explains how immigrant background and culture can shape the clients' perception of treatment, mental health problems, and perceived stigma. People with an immigrant background have been found to report more mental health problems than the general population (Abebe et al., 2014; Kjøllestal et al., 2019). Despite this, there is an underuse of primary mental health services in this group, and

an overuse of acute and ambulant services (Ahmed et al., 2016). Similarly, the pilot studies of PMHC reported an underuse of the service by people of immigrant background (Smith et al., 2016).

**Impracticalities.** Last but not least, impracticalities can lead to dropout, such as childcare or other responsibilities, physical health problems and moving out of the municipality (Ghaemian et al., 2020; Zieve et al., 2019). Financial reasons can also contribute to dropout, especially in private clinical settings (Zieve et al., 2019).

#### The aim of the study

As demonstrated, there exists a large body of research on dropout from psychotherapy. The findings on predictors of dropout are somewhat inconsistent, especially related to client factors. There is a growing field of research that documents and supports the effect of health prevention through primary care services (Ramsdal & Hansen, 2017). However, there is limited research on these two research fields combined, namely dropout from primary mental health services. With data provided from The Norwegian Institute of Public Health (NIPH), our study aimed to investigate whether a number of client factors could predict dropout from the service Prompt Mental Health Care (PMHC) in Norway. No research on dropout had previously been conducted in this service setting. We focused exclusively on client factors, as our dataset consisted of client baseline characteristics. Based on the literature, we selected the following nine factors from the dataset we had at hand: age, sex, level of education, work status, immigrant background, social support, symptom severity, duration of problems, and daily function.

#### Method

Data was provided by The Norwegian Institute of Public Health (NIPH). It was obtained from the PMHC treatment arm of a Randomized Controlled Trial (RCT) conducted in two Norwegian municipalities. We looked into predictors of dropout among those who received the intervention, thereby making this a prospective cohort study design. The descriptions of subjects, materials, and methods were first described in the primary evaluation of the RCT by Knapstad et al. (2020). Data from this study was selected as it contained information about a wide range of sociodemographic and clinical factors of interest.

#### **Data collection setting**

The trial was conducted within routine care of PMHC in the municipalities of Kristiansand and Sandnes. These sites are located in the southern part of Norway and were found to be relatively similar to each other. They were also found to be representative of the Norwegian population on several sociodemographic variables. These were for instance rates of immigrant background, higher education, and unemployment (Knapstad et al., 2020). The Norwegian Directorate of Health assigned establishing grants to these PMHC cities for a four-year period (2013-2017). They were dependent on local funding after the establishing phase. The sites opened for ordinary intake by the second half of 2014. Data in this study were collected between November 2015 and August 2017 (Knapstad et al., 2020).

#### **Procedure for PMHC treatment**

Psychologists had professional responsibility for the service at each sight. Employees had a minimum of three years of relevant higher education. Everyone additionally completed a mandatory one-year training in CBT based on the IAPT curriculum (Knapstad et al., 2020). Ten therapists were included in the current study. The number of clients per therapist ranged from eight to 90 clients during the trial period, with a mean of 52 clients.

The therapist and client collaborated to arrive at a matched care decision. The majority of clients started with a four-session psychoeducational course. Low-intensity self-help programs

were to a limited extent accessible throughout the trial period. Nevertheless, towards the end of the trial period, internet-based programs were gradually implemented from the site <u>www.assistertselvhjelp.no</u>. This website offers guided self-help programs, for example for depression, anxiety, sleep problems, and stress. Most clients received only low-intensity treatment in terms of group-based psychoeducation (36.5%) or a combination of low and highintensity interventions (33%). Furthermore, 29.4% primarily received high-intensity treatment. Only 1% received guided self-help (Lervik et al., 2020).

#### **Recruitment and participants**

Information about the study was conveyed both through an information letter from NIPH to all GPs in the area and directly from the services at local GP association meetings. Citizens could get information about the study through the municipality web page, local newspapers, and local radio. People who contacted PMHC in Sandnes or Kristiansand, either self-referred or referred through their GP, got an appointment for an initial assessment. This assessment consisted of a clinical interview to evaluate the client's mental health problems, resources, and motivation for treatment, in addition to providing information about the study.

There were predefined inclusion and exclusion criteria to evaluate participants' eligibility for PMHC during the trial period. The primary inclusion criterion was anxiety and/or mild to moderate depression. The Patient Health Questionnaire (PHQ-9) and Generalized Anxiety Disorder scale (GAD-7) were used as screening instruments with predetermined cut-offs (PHQ-9 > = 10 and/or GAD-7> = 8) (Knapstad et al., 2020). Further requirements were a minimum age of 18 years, place of residence in the relevant municipalities, and basic Norwegian language proficiency. People were excluded if they met the criteria of more profound mental problems such as eating disorder, severe suicidal risk, bipolar disorder, severe depression, incapacitating anxiety, psychotic symptoms, substance abuse, or personality disorder. Another exclusion criteria was two or more previous attempts at treatment in the secondary services, without satisfactory effect. People with serious physical health problems as their primary challenge were also excluded. Those not considered eligible for PMHC were referred to their GP, secondary services, or other services suitable for their main challenge.

Those who met the inclusion criteria were asked to participate, gave their written consent and registered on a secure online data portal. The portal was developed by the Norwegian Social Science Data Services (NSD) and was used to collect all data and questionnaires from clients and therapists. It was also used to randomize the clients to either PMHC treatment or treatment as usual (TAU) (Knapstad et al., 2020; Sæther et al., 2020). There were 774 participants who fulfilled the inclusion criteria, whereof 526 were randomized to PMHC treatment (Knapstad et al., 2020; Sæther et al., 2020). Participant data from the PMHC group was used for the analysis in this paper.

#### Measures

#### Outcome measure

The operationalization of *dropout* in the context of PMHC was somewhat challenging as there is no a priori number of treatment sessions that define the full course of the intervention. We decided to focus on dropout occurring before completing six treatment sessions. This was chosen as it is considered the minimum number of recommended sessions for the treatment of anxiety and depression in IAPT (National Collaborating Centre for Mental Health, 2021). Due to the chosen definition, people who terminated their treatment in PMHC and went to other services before they had fulfilled six sessions were classified as dropouts. Clients who achieved their treatment goals prior to six sessions were not classified as dropouts. Therapists reported completion or dropout, the numbers of sessions attended, and the reasons for termination.

#### **Baseline predictors**

When the clients had registered, they self-reported their answers to a variety of questions in a baseline questionnaire. The questions ranged from mental and physical health to demography and lifestyle. In the following section, we will elaborate on the relevant instruments used in this study.

**Clinical variables.** The Patient Health Questionnaire (PHQ-9) and The Generalized Anxiety Disorder Assessment (GAD-7) were applied at baseline, before every session, and at 6-, 12-, 24-, and 36-months follow-up.

PHQ-9 asks the responder to evaluate nine items describing each criterion for depression based on DSM-V. The response options vary from 0 (*not at all*) to 3 (*nearly every day*), which allows a maximum sum score of 27. Caseness was defined as a minimum score of 10. A score above 14 was defined as moderate to severe symptoms of depression. The scores were coded into three different categories, namely below cut-off (0-9), mild depression (10-14), and moderate to severe depression (15-27). The variable *below cut-off* was used as a reference category. The PHQ-9 has been tested as a reliable and valid measure for making criteria-based diagnoses for depression, assessing symptom severity, and monitoring change over time (Kroenke et al., 2001). It is used as a standard measure in a range of health care settings. The internal reliability of PHQ-9 has been measured and evaluated, showing excellent test-retest reliability and Cronbach's  $\alpha$ between 0.86-0.89 (Kroenke et al., 2001). Cronbach's  $\alpha$  based on our data was 0.80. GAD-7 measures the frequency of seven common symptoms of general anxiety. Similar to PHQ-9, the response options vary from 0 (*not at all*) to 3 (*nearly every day*). The maximum sum score is 21. Caseness was set at 8, and a score above 14 was defined as severe symptoms of anxiety. GAD scores were coded into three categories, namely below cut-off (0-7), mild-moderate anxiety (8-14), and severe anxiety (15-21). *Below cut-off* was used as a reference category. GAD-7 has been found to have good validity and reliability for measuring general anxiety. It is also specific and sensitive to detect social anxiety, PTSD, and panic disorder. The instrument can be used both to assess symptom severity and monitor change over time (Knapstad et al., 2020; Spitzer et al., 2006). It has shown excellent test-retest reliability and Cronbach's  $\alpha$  of 0.92 (Spitzer et al., 2006). Cronbach's  $\alpha$  based on our data was 0.83.

The Work and Social Adjustment Scale (WSAS) measures impairment of daily function by evaluating five items on a scale ranging from 0 (*not at all*) to 8 (*very severely*). The answers are based on function at work and in social relations during the last month (Zahra et al., 2014). The sum scores reported were converted to a binary variable. Scores within the highest tertile were coded as 1 (*low functional status*), while scores in the lowest two tertiles were coded as 0 (*high functional status*). WSAS has been used in former PMHC evaluations (Smith et al., 2016). Furthermore, WSAS has comparable reliability, sensitivity, and discriminant validity to PHQ-9 and GAD-7 (Zahra et al., 2014).

**Sociodemographic variables.** The sociodemographic questions were reported as binary. These questions included sex (*female: yes/no*), age (*above 30 years: yes/no*), higher education (*university/college: yes/no*), and immigration background (*1st or 2nd generation immigrant: yes/no*). Employment was assessed by two multiple response questions regarding current work status and source of income. Based on their answers, participants were coded into four different categories. These were in regular work/retirees/home stayers/unknown, in part-time work receiving financial support, without work receiving financial support and student. The in regular work/retirees/home stayers/unknown variable was used as a reference category.

Questions about lifestyle and social variables were also reported using binary responses. Most relevant for this analysis was the question of social support. The 3-item Oslo Social Support Scale (OSSS-3) covers the number of close confidants, the sense of concern shown by others, and perceived availability of practical help from neighbors (Koacalevent et al., 2018). A sum score ranging from 3 to 14 was calculated. Clients scoring 3 to 8 were coded as 1 (*low social support*), whereas those scoring 9 to 15 were coded as 0 (*medium to high social support*). Validity and reliability for OSSS-3 have been reported as satisfying (Koacalevent et al., 2018). Cronbach's α of the OSSS-3 was relatively low based on our data (.58).

#### **Ethical considerations**

The RCT was reported according to the CONSORT statement. No changes were made to the design after trial commencement. The regional ethics committee for western Norway (REK vest: No. 2015/885) approved the trial protocol (Knapstad et al., 2020; Sæther et al., 2020).

#### Statistical analyses

Preliminary analyses were undertaken to prepare the specific statistical techniques to address the research question. These included frequency analyses, coding into dichotomous categories, choice of regression model, and further assessments of the suitability of the model. All variables were checked for errors, outliers, normality of distribution, variance, and missing data. Within the variables higher education, duration of problems, and immigrant background, we found some missing data (<3%). Missing data were handled by listwise deletion in the regression analyses. Logistic regression was considered the most appropriate analysis as the dependent variable was dichotomous (Pallant, 2013). In order to assess the suitability of the logistic regression model, we looked for violation of assumptions for a logistic regression. This was done by taking into account the sample size and multicollinearity. In our analysis, we had a sample of 526 participants and included nine independent variables. We ran a multicollinearity test between all the independent variables to determine the rate of correlation between them. We found tolerance values between .736 and .970 among our independent variables, indicating a low correlation. Thus, we could proceed with the variables we had selected based on the literature.

To examine possible relationships between dropout as a dependent variable and client factors as independent variables, we first did logistic regression analyses for nine variables of relevance according to the literature. Of sociodemographic variables, these were age, sex, immigrant background, work status, level of education, and social support. Of clinical variables, these were symptom severity, duration of problems, and daily function. By doing this, we first examined the effect each independent variable had on the dependent variable. Therapists and municipalities were included in all analyses as fixed effects.

The independent variables reaching p values < .05 in the logistic regression analyses were subsequently included in a multivariate logistic regression model. Multivariate regression allowed us to assess the strength of the relationship between dropout and several predictor variables. It also provided information about the importance of each predictor to the relationship, with the effect of other predictors statistically eliminated. This way, we discovered whether the relationships we found in the first analyses remained statistically significant. If the strength of an association changed when included in the multivariate analysis, further analyses were conducted to understand what accounted for the variation in the outcome variable. This was done by exploring different combinations of variables using logistic regression analysis, and observing possible changes. Therapists and municipalities were included in the multivariate model as fixed effects. All statistical analyses were performed using IBM SPSS Statistics, version 28.0.1.0.

#### **Results**

## Dropout

In this current study, 133 (25.3%) participants dropped out of therapy. Meanwhile, 393 (74.7%) participants completed therapy. Therapists reported the following reasons for termination of therapy for the dropout group: not being able to contact the client (36.1%), lack of motivation (19.5%), changed to other service (15.1%), unsatisfactory effect (4.5%), moving out of municipality (3%), other reasons (4.5%) and unknown (17.3%). The mean number of sessions attended for the dropout group was 2.36 (SD = 1.67). For the completers group it was 7.37 (SD = 4.5) sessions. Dropout happened most frequently between assessment and the first session (20%) and between the fourth and fifth sessions (21.8%).

# **Baseline characteristics**

Descriptive analyses of the sample can be found in Table 1. The total number of participants was 526, of whom approximately two-thirds were female. The mean age of the sample was 34.95 (SD = 12) and 60% of the sample were above 30 years of age. Within the sample, 12% had a first or second-generation immigrant background and 44.3% reported having higher education. The majority of the sample were either in regular work (32.3%) or in work receiving financial support (36.5%). The rest of the sample was either without work receiving financial support (15.2%) or students (16%). Within the sample, 32.5% reported having poor social support.

Looking at clinical characteristics, the PHQ-9 mean was 13.9 (SD = 5), while the GAD-7 mean was 11.3 (SD = 4.6). For PHQ-9, the majority (46%) of clients scored within moderate to severe symptoms of depression. For GAD-7, the majority (50.6%) of clients scored within mild to moderate symptoms of anxiety. Most of the sample had experienced their mental health problem for longer than six months (85.9%). A group of 36.1% reported experience of low daily function.

#### **INSERT TABLE 1 HERE**

\_\_\_\_\_

\_\_\_\_\_

#### **Baseline characteristics predicting dropout**

Results from the first logistic regression analyses are presented in Table 2. There were significant independent associations between dropout and younger age, poor social support, lower levels of education, and being a student (all *p*-values <.05).

#### **INSERT TABLE 2 HERE**

\_\_\_\_\_

\_\_\_\_\_

Table 2 shows that participants over 30 had a lower odds ratio (*OR*) of dropping out relative to participants under 30 (*OR* = .36, [95% CI = .23, .55]). Participants with higher education had a lower odds ratio of dropping out compared to those with lower levels of education (*OR* = .41, [95% CI = .26, .64]). Concerning work status, participants reporting to be a student had a higher odds ratio of dropping out compared to those who were in regular work, home stayers, or retirees (*OR* = 2.47, [95% CI = 1.35, 4.53]). Participants reporting poor social support were more likely to drop out compared to those who reported good social support (*OR* =

1.83, [95% CI = 1.19, 2.81]). The variables identified as significantly associated with dropout in the logistic regression analyses were subsequently included in the multivariate model.

#### **INSERT TABLE 3 HERE**

\_\_\_\_\_

Results from the multivariate analysis are presented in Table 3. Younger age, poor social support, and lower levels of education remained significant predictors of dropout (all *p*-values <.05). The multivariate analysis did not suggest that being a student was significantly associated with dropout (p = .169). This is in contrast to results presented from the logistic regression analyses in Table 2, where being a student was a significant predictor (p = .004). When age was included in the model, the association between being a student and having lower levels of education attenuated. However, lower levels of education remained a statistically significant predictor of dropout. This was evident as participants with higher education had a lower odds ratio of dropping out compared to those with lower levels of education (OR = .57, 95% CI [.35, .92]). Poor social support also remained a significant predictor of dropout, as participants reporting poor social support were more likely to drop out compared to those who reported good social support (OR = 1.90, [95% CI = 1.20, 2.99]). Finally, age under 30 was the strongest predictor of dropout in the multivariate model, as participants aged over 30 were less likely to drop out compared to those under 30 (OR = 0.44, [95% CI = .27, .71]).

#### Discussion

# **Predictors of dropout**

Our aim was to investigate whether a number of sociodemographic and clinical client factors could predict dropout from a primary care setting, based on indications from previous

literature. This had not been studied in the PMHC service context until now. Our results partly support previous findings from the literature that specific sociodemographic factors can predict dropout. These were younger age, lower levels of education, and poor social support. Other sociodemographic factors identified in the literature were not significant predictors in this context, such as sex, immigrant background, and unemployment. Contrary to our expectations, clinical factors such as symptom severity, duration of problems, and daily function were not significant predictors of dropout. The dropout rate of 25.3% was in accordance with previous rates reported in the literature, however at the lower end.

# Age

Our results showed that clients under the age of 30 had a higher risk of dropout, which is in accordance with former research (Fenger et al., 2011; Johansson & Eklund, 2006; Reneses et al., 2009; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Fenger et al. (2011) explain the link between younger age and dropout by more profound adherence problems and challenges with engagement. Problems with adherence among younger clients might be due to by the unfinished maturation process of executive functions of the brain through adolescence and into young adulthood. Less developed cognitive abilities might reduce the capacity for self-reflection and psychological mindedness. These abilities are necessary in order to take different perspectives in therapy (Barrett et al., 2008; Ogrodniczuk et al., 2005).

Young adulthood is also characterized by less stable social and personal situations (Fenger et al., 2011). An unpredictable schedule might increase the chance of no-show for therapy sessions. Furthermore, group affiliation becomes more important for self-evaluation through social development. In addition, feeling disconnected, different, or experiencing stigma can become a barrier to completing therapy. On the contrary, knowledge about mental health problems and access to treatment is more available for the younger generation today than for previous generations. This might lower the threshold for younger people to seek treatment when needed. Easy access might simultaneously lower the threshold for dropping out when experiencing that treatment does not work or is no longer needed. Finally, the described characteristics of younger clients might make it more difficult to establish a good therapeutic alliance, which in itself is a predictor of dropout (Johansson & Eklund, 2006).

#### Level of education

In accordance with previous literature, we found that level of education influenced the likelihood of dropout (Fenger et al., 2011; Wierzbicki & Pekarik, 1993). Lower levels of education might be linked to dropout on the basis of cognitive abilities, difficulties structuring life, and a low feeling of mastery (Dalgard et al., 2007; Fenger et al., 2011). Thereby, it might not be education itself that is decisive, but rather the abilities to acquire and implement therapeutic knowledge. For instance, abilities such as attention and planning are important in therapy. Low feeling of mastery can also decrease self-confidence and motivation for treatment. Sharf et al. (2010) found in their meta-analysis that the association between therapeutic alliance and dropout was stronger under the condition of lower levels of education. This might be because educated clients in some regards are more similar to their therapists. Thereby, it is easier to facilitate a good therapeutic alliance and converge expectations for treatment (Sharf et al., 2010).

Lower levels of education might additionally have secondary consequences such as lower income, which can increase perceived life stress. When struggling to meet basic needs, it can be difficult to find time for sessions and remember appointments, leading to no-show. Several instances of no-show in a row might result in a rejection from the service, thereby defining the client as a dropout. Thus, clients with lower levels of education might experience a double burden. Not receiving the necessary help adds to the stressful socioeconomic situation.

We found in our model that the strength of the relationship between lower levels of education and dropout was somewhat reduced when adding age to the model. The relationship between lower levels of education and dropout might to some extent be explained by age, as more people of younger age are yet to have an education degree.

## Social support

Poor social support was found to predict dropout, in line with former research on nonattendance and early dropout (Grant et al., 2012; Self et al., 2005). In times of difficulties, supportive networks can be an important resource. This can be in terms of having someone to seek comfort in and share the burden with, who simultaneously can motivate and hold expectations. The experience of social inclusion is crucial for self-image and identity. Social support is of special importance in a therapeutic setting because it has been identified as an enabling factor for a person's use of healthcare services (Barrett et al., 2008). Conversely, poor social support can give rise to feeling alone with one's problems. This can make it more challenging to maintain motivation and faith in oneself throughout treatment. These findings underline that the client's ability to show up to treatment is influenced by factors outside the therapist's office.

Another hypothesis of how poor social support and dropout is linked is through the therapeutic alliance. Poor social support can sometimes be caused or maintained by the client's problematic relational patterns. These patterns might be transferred to the therapeutic alliance. We know that personality traits such as avoidance, hostility, aggressiveness and passive-aggressiveness, cold and distant interpersonal functioning, and low psychological mindedness

have been found to negatively influence the therapeutic alliance (Barrett et al., 2008; Johansson & Eklund, 2006). A poor therapeutic alliance can subsequently be linked to dropout.

### Work status

We found that being a student was the only statistically significant variable for work status in our first logistic regression analysis. However, when including this variable in the multivariate regression, the significance attenuated. Exploring this further, we found that the relationship between being a student and dropout was reduced when adding age to the model. This is probably due to the fact that students tend to be younger. Based on these results, the possible explanations of the association between dropout and age also applies to the association between being a student and dropout.

We did not find an association between dropout and employment in this study. This is contrary to former research which has found unemployment and sick leave to predict dropout (Fenger et al., 2011; Firth et al., 2015; Saxon et al., 2017). The majority of our study sample were either in work without receiving benefits (32.3%) or in work receiving benefits (36.5%). A minority were out of work receiving benefits (15.2%). Our results might be explained by the nature of PMHC, which targets people with lower symptom severity and higher function.

# Other findings

We did not find an association between dropout and the remaining sociodemographic factors such as immigrant background and sex. Previous literature has provided somewhat mixed results on these predictors. Furthermore, we did not find any effects for the clinical client variables, contrary to previous research.

The lack of association between dropout and high symptom severity might be because our sample is drawn from a primary care service. This entails that the target group was clients with mild to moderate depression and/or anxiety. People with more complex and severe problems were rather referred to specialized health care after assessment. Therefore, the clients in our sample generally had a lower and homogenous symptom severity. Moreover, daily function will often naturally follow symptom severity. Therefore, clients with mild to moderate symptoms are likely to have a higher level of daily function compared to clients with more severe symptoms in other services.

The lack of association between lower symptom severity and dropout might be explained by the nature of the service and the definition of dropout in PMHC. Unlike some other services, PMHC does not follow a given protocol including a set minimum or maximum of sessions for the client. The number of sessions are rather determined by the clients' needs. Furthermore, the definition of dropout was in our study based on the therapist's evaluation of the treatment goal. Thus, some clients with low symptom severity only needed a few sessions before the treatment goal was met. These clients were not considered as dropouts in this study, even though they had less than six sessions. This is in contrast to several other studies that categorize clients who leave before a minimum of given sessions as dropped out (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Therefore, it is possible that clients with low symptom severity were more rarely defined as dropouts in this study, which might explain the lack of association with low symptom severity.

#### Study strengths

Our study has several strengths. When collecting the data, questionnaires and measurements were used to cover a wide range of baseline information regarding the clients. With limited missing data (<3%) and relatively large sample size (N = 526), we were able to make thorough analyses with relevant baseline factors identified through the literature.

Our instruments were standardized and validated with high Cronbach's alpha. The only exception was the Oslo Social Support Scale (OSSS-3) with a Cronbach's alpha of .58. This might imply that the instrument lacked some consistency across questions in this sample, and potentially underestimated the association between social support and dropout. The various instruments used in this study are applied within the PMHC service, which makes it possible to compare results from PMHC within and across countries to other similar services such as IAPT. This contributes to a strengthened external validity and generalizability of our results.

When performing the analysis, we included therapists and municipalities as fixed effects. This way, we excluded variations that could be attributed to these factors and thereby reduced the potential for Type I error.

#### **Study limitations**

The results from this study should be considered in the context of some limitations. Firstly, our study only investigates one group of factors, namely client factors. This was due to the nature of our dataset. Client factors alone cannot explain dropout, which is rather a complex interplay between the client, therapist, therapeutic alliance, and service (Wierzbicki & Pekarik, 1993). Our results should therefore be supplemented by findings from other groups of factors, and in this way provide a holistic understanding of the concept of dropout. Secondly, our study had limited data on dropout from guided self-help, only used by 1% of our sample. This is a limitation, as guided self-help is an important component of the mixed care model (Lervik et al., 2020). Thus, this study cannot provide solid information about dropout from this treatment modality.

A weakness concerning our understanding of dropout is that we only had the perspective of the therapist at hand. The clients' experience might have differed from what the therapists

reported, thereby weakening the reliability (Wierzbicki & Pekarik, 1993). Some clients could have disagreed that they were categorized as dropouts, and vice versa. The majority of reasons for dropout noted by therapists emphasized actions of the clients such as lack of response or loss of motivation. This however says nothing about the underlying reasons for their decision. Ghaemian et al. (2020) and DeJong et al. (2011) found that the majority of clients do not discuss concerns with the treatment with their therapist before they drop out. If this is generally the case, there is reason to believe that therapists often lack information to understand the individual dropout situation accurately.

#### **Practical implications**

This study has implications for the quality improvement of PMHC and other mental health services in order to reduce wasted resources as a result of dropout. Both individual therapists and services should aim to have evidence based competence and routines for how to prevent and respond to dropout.

# Awareness and flexibility through feedback

Therapists should first and foremost be aware that there is an increased risk of dropout when they meet clients of younger age, lower levels of education and low social support. Nevertheless, such awareness could potentially give rise to unconscious expectations of poorer outcomes implying that the responsibility is on these clients. As mentioned, therapists who meet clients with poor social support can sometimes struggle to establish a therapeutic alliance. In these instances, it can be tempting to conclude that the client is the problem. This can give rise to negative consequences such as the client feeling misunderstood. Thus, predictors of dropout should rather be seen as markers encouraging therapists to be more flexible in order to adapt to the client. This can however be challenging. Marshall et al. (2016) identified that clients reported limited flexibility from the therapist and lack of individual adjustments as the main reasons for dropout.

One barrier to being sensitive and flexible is that therapists struggle to identify when their interventions are not working for the client (Walfish et al., 2012). Furthermore, therapists have a tendency to overestimate their own performance. The reality is that therapists differ substantially in dropout rates among their clients, from no dropouts to 32% dropouts in one study by Binnie and Boden (2016). An even greater variance of 1.2% to 73.2% was found in a study by Saxon et al. (2017). The latter study found an interesting distribution of dropout rates among different therapists' clients. It turned out that 15.3% had significantly better dropout outcomes than the average and 23.5% had significantly poorer dropout outcomes than the average. Clients who met the below-average therapists. The remaining 61% of the therapists were not significantly different from the average. Self-assessment bias and huge variations in performance demonstrate that therapists should monitor outcomes using formal methods rather than just clinical judgment in their work to prevent dropout (Walfish et al., 2012).

Kegel and Flückiger (2015) and Wierzbicki and Pekarik (1993) stress that there is more evidence for the predictive value of client-reported process characteristics than looking at client baseline characteristics. Considering this, a highly effective way to prevent dropout is to seek the client's feedback (Ghaemian et al., 2020; Zieve et al., 2019). The concept of Feedback Informed Treatment (FIT) is to monitor the client's improvement through an Outcome Rating Scale (ORS) and the therapeutic alliance through a Session Rating scale (SRS). These are standardized digital tools that are easy to apply. They thereby allow therapists to systematically gain information to help them adapt to the individual client with regards to focus, style and relationship. The tools have been shown to be cost-effective in the context of IAPT (Delgadillo et al., 2021). A multilevel meta-analysis of feedback instruments generally found a 20% increased chance of dropout from therapy conditions that did not use feedback, compared to those that used feedback (de Jong et al., 2021). Drawing an example from our results, FIT could help adjust the focus of therapy with a client experiencing poor social support. After a session of working with rumination, SRS could reveal a preference for rather working to improve the client's social situation.

However, FIT only achieves its purpose if it is used correctly. This requires that the therapist is genuinely concerned with seeking feedback and honest responses which are further discussed with the client. One study found that only half of the therapists who used feedback systems talked to their clients about the results (Hatfield & Ogles, 2007). This is problematic, as it is the dialogue and collaboration which helps the therapist to become more flexible. Exploring the reason for these results, it was identified a need for better training on how to use feedback tools in therapy (Hatfield & Ogles, 2007). Therefore, implementation of FIT in PMHC must include thorough training on how to utilize results to discuss and adapt to the individual client. In order to maintain such an implementation over time, it is crucial to establish a *feedback culture* which should be a leader and service responsibility.

## Expectations and motivation

Solid client preparation for treatment through communicating expectations and motivation has been proven useful to prevent dropout (Ghaemian et al., 2020; Marshall et al., 2016; Ogrodniczuk et al., 2005). This is likely to be especially important for the client groups we identified to have a higher chance of dropout. Lack of communication about *expectations* is a common driver behind dissatisfaction with the service and increases the chance of dropout (Ghaemian et al., 2020; Marshall et al., 2016; Ogrodniczuk et al., 2005). People who drop out often report that expectations of treatment were not met (Barrett et al., 2008; Binnie & Boden, 2016; Marshall et al., 2016). Not being involved in the decision-making can contribute to this, and has been identified as a critical factor of dropout (Ghaemian et al., 2020).

There is reason to believe that clients often start therapy with expectations about *time limitations* that are rarely communicated. Findings that expectations of the duration of therapy were a better predictor of treatment duration than any other variable confirms this (Beck et al., 1987; Pekarik, 1991). Several studies have found higher dropout rates for non time-limited treatment (Ogrodniczuk et al., 2005; Sledge et al., 1990; Zieve et al., 2019). Providing a time perspective or an end date to therapy has proven to reduce the risk of dropout (Beck, 1987; Ogrodniczuk et al., 2005; Pekarik, 1991; Zieve et al., 2019). In this study sample, the number of sessions attended ranged from one to 25. Providing clients with an absolute time perspective is difficult. This is because the number of sessions in PMHC is based on continuous evaluations of the need in dialogue with the client. Therapists can however provide an estimate of how many sessions the client can expect. Another option is to agree to set up three to five sessions initially and subsequently evaluate the further need.

Furthermore, the value of building *motivation* has been shown to be of importance to prevent dropout (Avishai et al., 2018; Ogrodniczuk et al., 2005). Looking at our results, a large proportion (19.5%) of the dropout group was terminated due to lack of motivation, according to the therapist. This underlines the importance of building and preserving client motivation throughout treatment. This might be especially important for clients with poor social support, who might be in lack of close confidants to motivate them.

# Booking and termination routines

Another area of action to prevent dropout is for services to improve their booking routines and offer more flexible schedules for the individual session. When asking clients to report the reason for no-show, forgetting is often mentioned (Binnie & Boden, 2016; Ghaemian et al., 2020). The need to get in touch with clients was evident in our sample, seeing that 36.1% of the dropout group were terminated because they were unreachable. Binnie and Boden (2016) found that clients are rarely involved in booking therapy sessions. When actively involving clients and implementing more convenient booking systems, this reduces no-show and dropout rates. Pennington and Hudson (2012) found lower non-attendance among clients invited by telephone and with a text message reminder, compared to clients invited only by letter. Another way to improve booking is to use text message reminders (Gurol-Urganci et al., 2013) or preferably different communication channels for different groups (Fenger et al., 2011). Adapting channels might be a way to engage young people at risk of dropout.

Service routines should also address those who are about to drop out or recently dropped out. Routines for when no-show will lead to discharge by the therapist are often vague and practices vary between therapists and services (Binnie & Boden, 2016). Scheduled telephone support for people at risk of dropping out from internet-delivered CBT has shown promising results (Pihlaja et al., 2020). Calls after dropout can also be considered implemented as a routine. This in order to promote recovery, gain feedback on dissatisfactory experiences, and possibly also re-engage the client (Ghaemian et al., 2020). Follow-up is however time-consuming, which underlines the importance of service routines stating who should be provided with such followup (Pihlaja et al., 2020). Clients who drop out due to situational reasons such as consequences of low levels of education or poor social support might benefit especially from follow-up.

### Focus on socioeconomic challenges in treatment

Strong situational and social predictors of dropout should be an indication that mental health services need to address the socioeconomic aspects of the clients' troubles. If social support and low levels of education are not taken into account, this questions the ecological validity of the service. PMHC has the mandate to enhance work participation and work closely with other primary care services in the municipalities. Nevertheless, a recent evaluation report of PMHC stresses that this focus area has been neglected (Lervik et al., 2020). It could be argued that socioeconomic challenges should be emphasized more in therapy as a measure to prevent dropout. Some clients might even be more in need of social interventions than psychological interventions and should be guided to another service (Fenger et al., 2011).

# Nuancing dropout

Finally, it is important to remember that dropout is not exclusively negative (Lopes et al., 2018). Some people leave treatment because they experience improvement already in the first couple of sessions (Cahill et al., 2003; Ghaemian et al., 2020). Others might have low symptom severity to begin with and so they are more ambivalent about treatment (Zieve et al., 2019). Young people might be overrepresented in this group, as they have a lower threshold for talking about mental health and approaching therapy. Dropout due to early improvement might be especially relevant for primary care services, which try to be easily accessible and reach people at an early stage. A natural side effect of this strategy is that dropout also becomes an accessible option. Dropout due to early improvement does however not guarantee a long-time improvement (Cahill et al., 2003; Ogrodniczuk et al., 2005; Zieve et al., 2019). Therefore, we need to differentiate problematic cases of dropout from non-problematic cases. It is not realistic to expect dropout-free services. We should rather discuss what kind of dropout is tolerable.

# Scientific implications

## **Defining** dropout

Research on dropout is a complicated matter, as there is no unified operationalization of the concept (Barrett et al., 2008; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). The variation in dropout definitions has led to different dropout rates across studies and the research field is characterized by mixed and conflicting findings related to predictors.

We experienced this firsthand when comparing various definitions across the field to our own. We used the following operationalization: stopping the treatment when the therapist reported that the treatment goal had not yet been fulfilled and the client completed less than six sessions. Our definition had the benefit of including participants that terminated at an early stage. This allowed people to recover early, leave therapy, and still not be defined as dropouts. This is especially important for a primary care service. Thereby, our sample consisted of both nonattenders and dropouts. Ideally, these should be investigated as two different groups in future research as some research has found them to be different from each other (Fenger et al., 2011). An upper limit of six sessions was chosen as this was the minimum number recommended for treatment in IAPT (National Collaborating Centre for Mental Health, 2021). Some might have terminated unilaterally after this stage, nevertheless, they were still considered to have received a complete treatment course within PMHC. Another aspect of our definition was the inclusion of people who chose to leave treatment for other primary or secondary services before the sixth session. This group was categorized by the therapists as dropouts by our predefined operationalization. It was however not reported whether the decision to leave for other services was due to dissatisfaction with treatment and if it was a bilateral or unilateral decision. It is also

possible that some clients were waitlisted for other services prior to entering PMHC, and changed to the particular service upon availability.

The absence of a unified definition of dropout is problematic. Studies that claim to examine the same phenomena, but use different operationalizations, find results that might not be comparable. The priority for future research should therefore be to set a unifying definition of dropout. Going through the literature, we have identified the following criteria which are often used to define dropout: number of sessions, unilateral termination, and premature termination. These aspects should all be included in future operationalizations of dropout.

# Suggestions for future research

This paper has brought us one step closer to understanding dropout by identifying the client variables that potentially predict dropout in the PMHC context. The need remains to understand the impact of other variables such as the therapist, therapeutic alliance, and service. Future research should also ideally take into account the nested structure that therapy services often have, by applying multilevel modeling. In order to do this, data sets are needed that provide more extensive data on therapist and system variables than what we had at hand. Furthermore, research aimed at understanding predictors of dropout from guided self-help interventions is yet to be explored, as we had limited data on this modality.

Additionally, there is a need for more knowledge about client perspectives on dropout in the Norwegian context. Peers should be involved in the whole process of this research, and the further implementation of the knowledge in the services. However, those who participate in studies after they drop out might not be representative of the dropout group as a whole (Ghaemian et al., 2020; Marshall et al., 2016). In a study by Ghaemian et al. (2020), only 35% of the dropouts got engaged with dropout follow-up calls. Hypothetically, the remaining 65% might be more dissatisfied with therapy or more severely ill. Therefore it is of importance to interpret follow-up studies with precaution.

# Monitoring

PMHC partly follows a set of predefined routines and procedures. Therefore, the service has great potential to research and exchange best practices across sites (Lervik et al., 2020). IAPT routinely tracks the results of all treatment sites and reports them annually, including dropout rates (NHS Digital, 2021). This makes it possible to work systematically to reduce dropout rates within the service as a whole. PMHC could also benefit from such centrally coordinated research and guidelines for the prevention of dropout. This is however only possible if PMHC takes a stand to fully adopt the same procedures. As the sites are decentralized and each municipality is responsible for organizing their respective service, this represents a challenge.

Another way to monitor dropout would be to consequently report dropout in clinical studies. Researchers are not obligated by ethical standards to report the undesirable effects of therapy such as dropout and deterioration (Flor & Kennair, 2019). As a result, dropout does not gain much attention other than missing data reports. The dominant body of research rather focuses on the improvement clients experience when engaging in therapy (Lambert, 2013). However, dropout poses a valuable source of information. Addressing the limitations of therapy can increase our chances of making treatment more helpful and meaningful for everyone.

#### Conclusion

In conclusion, this present study provides empirical support that is partly in line with previous research on client factors that play a role in predicting dropout from other service settings. The main findings were that people of younger age, lower levels of education, and poor social

support had a higher odds ratio of dropping out compared to people of higher age, higher education, and good social support. This had never been studied in the context of PMHC before. Our study provides valuable insight into a large client group who may not get satisfactory effects of treatment. As PMHC has become a national area of investment, this knowledge is of great importance for how we can improve the service to reduce dropout. This can subsequently save both human and economical resources. It would be beneficial to work towards a unifying definition of dropout, apply multilevel models, and explore dropout from the clients' perspective in future research on dropout.

#### References

- Abebe, D. S., Lien, L., & Hjelde, K. H. (2014). What We Know and Don't Know About Mental Health Problems Among Immigrants in Norway. *Journal of Immigrant and Minority Health*, 16(1), 60–67. https://doi.org/10.1007/s10903-012-9745-9
- Ahmed, S., Shommu, N. S., Rumana, N., Barron, G. R. S., Wicklum, S., & Turin, T. C. (2016).
  Barriers to Access of Primary Healthcare by Immigrant Populations in Canada: A
  Literature Review. *Journal of Immigrant and Minority Health*, *18*(6), 1522–1540.
  https://doi.org/10.1007/s10903-015-0276-z
- Ambrose, J., & Beech, B. (2006). Tackling non-attendance for outpatient appointments. *Mental Health Practice*, 9(5), 22–25. 10.7748/mhp2006.02.9.5.22.c1900
- American Psychological Association. (n.d.a). *Social deprivation*. APA Dictionary of Psychology. https://dictionary.apa.org/social-deprivation
- American Psychological Association. (n.d.b). *Socioeconomic status*. APA Dictionary of Psychology. https://dictionary.apa.org/socioeconomic-status
- Avishai, A., Oldham, M., Kellett, S., & Sheeran, P. (2018). Sustaining attendance at a mental health service: A randomized controlled trial. *Journal of Consulting and Clinical Psychology*, 86(12), 1056–1060. https://doi.org/10.1037/ccp0000341
- 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
- Beck, C. N., Lamberti, J., Gamache, M., Lake, E. A., Fraps, C. L., McReynolds, W. T., Reaven,N., Heisler, G. H., & Dunn, J. (1987). Situational factors and behavioural self-predictions

in the identification of clients at high risk to dropout of psychotherapy. *Journal of Clinical Psychology*, 43(5), 511–520. https://doi.org/10.1002/1097-

4679(198709)43:5<511::aid-jclp2270430515>3.0.co;2-u

- Binnie, J., & Boden, Z. (2016). Non-attendance at psychological therapy appointments. *Mental Health Review Journal*, 21(3), 231–248. https://doi.org/10.1108/MHRJ-12-2015-0038
- Buckman, J. E. J., Naismith, I., Saunders, R., Morrison, T., Linke, S., Leibowitz, J., & Pilling, S. (2018). The Impact of Alcohol Use on Drop-out and Psychological Treatment Outcomes in Improving Access to Psychological Therapies Services: An Audit. *Behavioural and Cognitive psychotherapy*, 46(5), 513–527. https://doi.org/10.1017/S1352465817000819
- Cahill, J., Barkham, M., Hardy, G., Rees, A., Shapiro, D. A., Stiles, W. B., & Macaskill, N. (2003). Outcomes of patients completing and not completing cognitive therapy for depression. *British Journal of Clinical Psychology*, *42*(2), 133–143. https://doi.org/10.1348/014466503321903553
- Chan, S. W. Y., & Adams, M. (2014). Service Use, Drop-Out Rate and Clinical Outcomes: A Comparison Between High and Low Intensity Treatments in an IAPT Service. *Behavioral and cognitive psychotherapy*, 42(6), 747–759. https://doi.org/10.1017/S1352465813000544
- Clark, D. M. (2018). Realizing the Mass Public Benefit of Evidence-Based Psychological Therapies: The IAPT Program. *Annual review of clinical psychology*, 14(1), 159–183. https://doi.org/10.1146/annurev-clinpsy-050817-084833
- Cuijpers, P., Turner, E. H., Mohr, D. C., Hofmann, S. G., Andersson, G., Berking, M., & Coyne,
   J. (2014). Comparison of psychotherapies for adult depression to pill placebo control
   groups: A meta-analysis. *Psychological Medicine*, 44(4), 685–695.

https://doi.org/10.1017/S0033291713000457

- Dalgard, O. S., Mykletun, A., Rognerud, M., Johansen, R., & Zahl, P. H. (2007). Education, sense of mastery and mental health: results from a nation wide health monitoring study in Norway. *BMC Psychiatry*, 7(1), 1-9. https://doi.org/10.1186/1471-244X-7-20
- de Haan, A. M., Boon, A. E., de Jong, J. T., & Vermeiren, R. R. (2018). A review of mental health treatment dropout by ethnic minority youth. *Transcultural psychiatry*, 55(1), 3–30. https://doi.org/10.1177/1363461517731702
- de Jong, K., Conijn, J. M., Gallagher, R. A., Reshetnikova, A. S., Heij, M., & Lutz, M. C.
  (2021). Using progress feedback to improve outcomes and reduce drop-out, treatment duration, and deterioration: A multilevel meta-analysis. *Clinical Psychology Review*, 85, Article e102002. https://doi.org/10.1016/j.cpr.2021.102002
- DeJong, H. B., Broadbent, H., & Schmidt, U. (2011). A systematic review of dropout from treatment in outpatients with anorexia nervosa. *International Journal of Eating Disorders*, 45(5), 635–647. https://doi.org/10.1002/eat.20956
- Delgadillo, J., McMillan, D., Gilbody, S., de Jong, K., Lucock, M., Lutz, W., Rubel, J., Aguirre, E., & Ali, S. (2021). Cost-effectiveness of feedback-informed psychological treatment:
  Evidence from the IAPT-FIT trial. *Behaviour research and therapy*, *142*, Article e103873. https://doi.org/10.1016/j.brat.2021.103873
- Di Bona, L., Saxon, M., Dent-Brown, K., & Parry, G. (2014). Predictors of patient nonattendance at Improving Access to Psychological Therapy services demonstration sites. *Journal of Affective Disorders*, 169, 157-164. https://doi.org/10.1016/j.jad.2014.08.005
- Edlund, M. J., Wang, P. S., Berglund, P. A., Katz, S. J., Lin, E., & Kessler, R. C. (2002). Dropping Out of Mental Health Treatment: Patterns and Predictors Among

Epidemiological Survey Respondents in the United States and Ontario. *American Journal* of *Psychiatry*, 159(5), 845–851. https://doi.org/10.1176/appi.ajp.159.5.845

- 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(3), 183–191. https://doi.org/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(6), 1108–1122.
  https://doi.org/10.1027/com00000044

https://doi.org/10.1037/ccp0000044

- Firth, N., Barkham, M., Kellett, S., & Saxon, D. (2015). Therapist effects and moderators of effectiveness and efficiency in psychological wellbeing practitioners: A multilevel modelling analysis. *Behaviour Research and Therapy*, 69, 54–62. https://doi.org/10.1016/j.brat.2015.04.001
- Flor, J. A. & Kennair, L. E. O. (2019). Skadelige samtaler: Myten om bivirkningsfri terapi. Tiden Norsk Forlag.

Furlong-Silva, J. (2020). Exploring Factors Related To, and Predictors Of, Dropout in Improving Access to Psychological Therapies (IAPT) Services: A Systematic Review and Secondary Analysis of the PRaCticed Data [Unpublished doctoral dissertation]. Faculty

Folkehelseinstituttet. (2018). Folkehelserapporten – kortversjon; Helsetilstanden i Norge 2018 (Utgave 2). Retrieved 02.01.22 from https://www.fhi.no/globalassets/dokumenterfiler/rapporter/2018/helsetilstanden-i-norge-20182.pdf

of science, University of Sheffield. https://etheses.whiterose.ac.uk/27699/1/Furlong-Silva\_%20J\_%20170149293\_%20Redacted%20Thesis%20Final.pdf

- Ghaemian, A., Ghomi, M., Wrightman, M., & Elis-Nee, C. (2020). Therapy discontinuation in a primary care psychological service: Why patients drop out. *The Cognitive Behavioral Therapist*, 13. https://doi.org/10.1017/S1754470X20000240
- Glover, G., Webb, M., & Evison, F. (2010). Improving access to psychological therapies: A review of the progress made by sites in the first rollout year. North East Public Health Observatory. https://dro.dur.ac.uk/30523/1/30523.pdf?DDD45
- Grant, K., McMeekin, E., Jamieson, R., Fairfull, A., Miller, C., & White, J. (2012). Individual Therapy Attrition Rates in a Low-Intensity Service: A Comparison of Cognitive Behavioural and Person-Centred Therapies and the Impact of Deprivation. *Behavioural and Cognitive Psychotherapy*, 40(2), 245–249.
  - http://dx.doi.org/10.1017/S1352465811000476
- Gurol-Urganci, I., de Jongh, T. de, Vodopivec-Jamsek, V., Atun, R., & Car, J. (2013). Mobile
   phone messaging reminders for attendance at healthcare appointments. *Cochrane Database of Systematic Reviews*, 12. https://doi.org/10.1002/14651858.CD007458.pub3
- Hans, E., & Hiller, W. (2013). Effectiveness of and dropout from outpatient cognitive behavioral therapy for adult unipolar depression: A meta-analysis for nonrandomized effectiveness studies. *Journal of Consulting and Clinical Psychology*, *81*(1), 75–88. https://doi.org/10.1037/a0031080
- Hatfield, D. R, & Ogles, B. M. (2007). Why Some Clinicians Use Outcome Measures and Others
  Do Not. Administration and Policy in Mental Health and Mental Health Services
  Research, 34(3), 283–291. https://doi.org/10.1007/s10488-006-0110-y

Helse- og omsorgsdepartementet. (2017). Mestre hele livet- regjeringens strategi for god psykisk helse (2017-2022) Regjeringen.

https://www.regjeringen.no/contentassets/f53f98fa3d3e476b84b6e36438f5f7af/strategi\_f or god psykisk-helse 250817.pdf

Helsedirektoratet. (2015a). Internasjonalt perspektiv på psykisk helse og helsetjenester til mennesker med psykiske lidelser (IS-2314).

https://www.helsedirektoratet.no/rapporter/internasjonalt-perspektiv-pa-psykisk-helse-oghelsetjenester-til-mennesker-med-psykiske-

lidelser/Internasjonalt%20perspektiv%20p%C3%A5%20psykisk%20helse%20og%20hel setjenester%20til%20mennesker%20med%20psykiske%20lidelser.pdf/\_/attachment/inlin e/2784807c-b441-4137-a3a1-

61fff9f8836a:75040e04f7107e9eec48b8d9fada6ad1866dc7a4/Internasjonalt%20perspekti v%20p%C3%A5%20psykisk%20helse%20og%20helsetjenester%20til%20mennesker%2 0med%20psykiske%20lidelser.pdf

Helsedirektoratet. (2015b, October 6th). Aktuell informasjon om lov og forskrift for prioriteringsveilederne. Retrieved 02.15.22 from https://www.helsedirektoratet.no/veiledere/prioriteringsveiledere/aktuell-informasjonom-lov-og-forskrift-for-prioriteringsveilederne/nar-det-er-konkludert

Helsedirektoratet. (2022, May 5th). *Psykisk helse for voksne- ventetid*. Retrieved 02.02.22 from https://www.helsedirektoratet.no/statistikk/kvalitetsindikatorer/psykisk-helse-for-voksne/gjennomsnittlig-ventetid-for-voksne-i-psykisk-helsevern

Hicks, C., & Hickman, G. (1994). The impact of waiting-list times on client attendance for relationship counseling. *British Journal of Guidance & Counseling*, 22(2), 175–182.

https://doi.org/10.1080/03069889408260312

- Jarrett, R. B., Minhajuddin, A., Kangas, J. L., Friedman, E. S., Callan, J. A., & Thase, M. E. (2013). Acute Phase Cognitive Therapy for Recurrent Major Depressive Disorder: Who Drops Out and How Much do Patient Skills Influence Response? Behaviour research and therapy, 51(4-5), 221–230. https://dx.doi.org/10.1016%2Fj.brat.2013.01.006
- Johansson, H., & Eklund, M. (2006). Helping alliance and early dropout from psychiatric outpatient care: The influence of patient factors. *Social Psychiatry and Psychiatric Epidemiology*, 41(2), 140–147. https://doi.org/10.1007/s00127-005-0009-z
- Kegel, A. F., & Flückiger, C. (2015). Predicting Psychotherapy Dropouts: A Multilevel Approach: Predicting Dropouts: A Multilevel Approach. *Clinical Psychology & Psychotherapy*, 22(5), 377–386. https://doi.org/10.1002/cpp.1899
- Keijsers, G. P., Kampman, M., & Hoogduin, C. A. L. (2001). Dropout Prediction in Cognitive Behavior Therapy for Panic Disorder. Behavior Therapy, 32(4), 739–749. https://doi.org/10.1016/S0005-7894(01)80018-6
- Kjøllestal, M., Straiton, M. L., Øien-Ødegaard, C., Aambø, A., Holmboe, O., Johansen, R.,
  Grewal, N., K., & Indseth, T. (2019). *Helse blant innvandrere i Norge*. (978-82-8406-026-2) Folkehelseinstituttet.
  https://www.fhi.no/globalassets/dokumenterfiler/rapporter/2019/levekarsundersokelsenblant-innvandrere-i-norge-2016-rapport-2019-v2.pdf
- Knapstad, M., Lervik, L. V., Saether, S. M. M., Aaro, L. E., & Smith, O. R. F. (2020).
  Effectiveness of Prompt Mental Health Care, the Norwegian Version of Improving
  Access to Psychological Therapies: A Randomized Controlled Trial. *Psychotherapy and Psychosomatics*, 89(2), 90–105. https://doi.org/10.1159/000504453

- Knapstad, M., Nordgreen, T., & Smith, R. F., Otto. (2018). Prompt mental health care, the Norwegian version of IAPT: clinical outcomes and predictors of change in a multicenter cohort study. *BMC Psychiatry*, 18(1). 1-16. https://doi.org/10.1186/s12888-018-1838-0
- Koacalevent, R. D., Berg, L., Beutel, M., Zenger, M., Härter, M., Nater, U., & Brähler, E.
  (2018). Social support in the general population: standardization of the Oslo Social
  Support Scale (OSSS-3). *BMC Psychology*, 6(31). https://doi.org/10.1186/s40359-018-0249-9
- Kohn, R., Saxena, S., Levav, I., & Saraceno, B. (2004). The treatment gap in mental health care. Bulletin of the World Health Organization, 82(11), 858–866.
- Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x
- Lambert, M. J. (2013). *Bergin and Garfield's handbook of psychotherapy and behavior change* (6th ed.) John Wiley & Sons.
- Lervik, L. V., Knapstad, M. &. Smith, O. R. F. (2020). Process evaluation of Prompt Mental Health Care (PMHC): The Norwegian version of Improving Access to Psychological Therapies. *BMC Health Services Research*, 20(437). 1-17. https://doi.org/10.1186/s12913-020-05311-5
- Linardon, J., Hindle, A., & Brennan, L. (2018). Dropout from cognitive-behavioral therapy for eating disorders: A meta-analysis of randomized, controlled trials. *International Journal* of Eating Disorders, 51(5), 381–391. https://doi.org/10.1002/eat.22850
- Lopes, R. T., Gonçalves, M. M., Sinai, D., & Machado, P. P. (2018). Clinical outcomes of psychotherapy dropouts: Does dropping out of psychotherapy necessarily mean failure?

*Brazilian Journal of Psychiatry*, 40(2), 123-127. https://doi.org/10.1590/1516-4446-2017-2267

Marshall, D., Quinn, C., Child, S., Shenton, D., Pooler, J., Forber, S., & Byng, R. (2016). What IAPT services can learn from those who do not attend. *Journal of Mental Health*, 25(5), 410–415. https://doi.org/10.3109/09638237.2015.1101057
Meld. St. 16 (2010–2011). *Nasjonal helse- og omsorgsplan*. Helse- og omsorgsdepartementet. https://www.regjeringen.no/no/dokumenter/meld-st-16-20102011/id639794/
Meld. St. 47 (2008–2009). *Samhandlingsreformen - Rett behandling - på rett sted - til rett tid*. Helse-og omsorgsdepartementet.

https://www.regjeringen.no/no/dokumenter/stmeld-nr-47-2008-2009-/id567201/

- Mitchell, A. J., & Selmes, T. (2007). Why don't patients attend their appointments? Maintaining engagement with psychiatric services. *Advances in Psychiatric Treatment*, *13*(6), 423-434. https://doi.org/10.1192/apt.bp.106.003202
- Murphy, E., Mansell, W., Craven, S., Menary, J., & McEvoy, P. (2013). Pilot study of an investigation of psychological factors associated with first appointment nonattendance in a low-intensity service. Behavioural and Cognitive Psychotherapy, 41(4), 358–469. https://doi.org/10.1017/S1352465812000811

National Collaborating Centre for Mental Health. (2021). *The Improving Access to Psychological Therapies Manual* (5th ed.). National Health Service.
Hhttps://www.england.nhs.uk/wp-content/uploads/2018/06/the-iapt-manual-v5.pdf

NAV. (2021, September 3rd). *Diagnose uføretrygd*. Retrieved 02.14.22 from https://www.nav.no/no/nav-og-samfunn/statistikk/aap-nedsatt-arbeidsevne-oguforetrygd-statistikk/uforetrygd/diagnoser-uforetrygd

NHS Digital. (2021). *Psychological Therapies, Annual report on the use of IAPT services, 2020-*21 (10th ed). https://digital.nhs.uk/data-and-

information/publications/statistical/psychological-therapies-annual-reports-on-the-use-ofiapt-services/annual-report-2020-21#

- OECD. (2014). Making Mental Health Count: The Social and Economic Costs of Neglecting Mental Health Care. OECD Health Policy Studies. https://read.oecd-ilibrary.org/socialissues-migration-health/making-mental-health-count\_9789264208445-en#page1
- Ogrodniczuk, J. S., Joyce, A. S., & Piper, W. E. (2005). Strategies for Reducing Patient-Initiated Premature Termination of Psychotherapy. *Harvard Review of Psychiatry*, *13*(2), 57–70. https://doi.org/10.1080/10673220590956429
- Ose, S. O., & Kaspersen, S. L. (2021). *Kommunalt psykisk helse- og rusarbeid: Årsverk, kompetanse og innhold i tjenestene*. (IS-24/8, nr 7). SINTEF. https://www.sintef.no/globalassets/sintef-digital/helse/endeligrapport2021\_sintef.pdf
- Owens, P. L., Hoagwood, K., Horwitz, S. M., Leaf, P. J., Poduska, J. M., Kellam, S., & Ialongo, N. S. (2002). Barriers to Children's Mental Health Services. Journal of the American Academy of Child & Adolescent Psychiatry, 41(6), 731–738. https://doi.org/10.1097/00004583-200206000-00013
- Pallant, J. (2013). SPSS survival manual: A step by step guide to data analysis using IBM SPSS (5th ed.) Routledge.
- Pekarik, G. (1991). Relationship of Expected and Actual Treatment Duration for Adult and Child Clients. *Journal of Clinical Child and Adolescent Psychology*, 20(2), 121–125. https://doi.org/10.1207/s15374424jccp2002\_2

Pennington, D., & Hodgson, J. (2012). Non-attendance and invitation methods within a CBT service. *Mental Health Review Journal*, 17(3), 145–151. https://doi.org/10.1108/13619321211287256

- Pihlaja, S., Lahti, J., Lipsanen, J. O., Ritola, V., Gummerus, E. M., Stenberg, J. H., & Joffe, G. (2020). Scheduled Telephone Support for Internet Cognitive Behavioral Therapy for Depression in Patients at Risk for Dropout: Pragmatic Randomized Controlled Trial. *Journal of medical Internet research*, 22(7), 15732–15732. https://doi.org/10.2196/15732
- Ramsdal, H., & Hansen, G. V. (2017). The organisation of local mental health services in Norway: Evidence, uncertainty and policy. *Evidence & Policy: A Journal of Research*, Debate and Practice 13(4), 605–622.

http://dx.doi.org/10.1332/174426416X14715382995623

- Reichert, A., & Jacobsen, R. (2018). The impact of waiting time on patient outcomes: Evidence from early intervention in psychosis services in England. *Health economies*, 27(11), 1772–1787. https://dx.doi.org/10.1002%2Fhec.3800
- Reneses, B., Munoz, E., & opez-Ibor, J. J. (2009). Factors predicting drop-out in community mental health centres. *World Psychiatry*, 8(3), 173–177. https://doi.org/10.1002/j.2051-5545.2009.tb00246.x
- Richards, D. A., & Borglin, G. (2011). Implementation of psychological therapies for anxiety and depression in routine practice: Two year prospective cohort study. *Journal of affective disorders*, *133*(1–2), 51–60. https://doi.org/10.1016/j.jad.2011.03.024
- Sæther, S. M. M., Knapstad, M., Grey, N., Rognerud, M. A., & Smith, O. R. (2020). Long-term outcomes of Prompt Mental Health Care: A randomized controlled trial. *Behaviour Research and Therapy*, 135, 103758. https://doi.org/10.1016/j.brat.2020.103758

Salmoiraghi, A., & Sambhi, R. (2010). Early termination of cognitive-behavioural interventions: Literature review. *The Psychiatrist*, 34(12), 529–532. https://doi.org/10.1192/pb.bp.110.030775

- Saxon, D., Barkham, M., Foster, A., & Parry, G. (2017). The Contribution of Therapist Effects to Patient Dropout and Deterioration in the Psychological Therapies. *Clinical Psychology Psychotherapy*, 24(3), 575–588. https://doi.org/10.1002/cpp.2028
- Schindler, A., Hiller, W., & Witthöft, M. (2013). What predicts outcome, response, and drop-out in CBT of depressive adults? A naturalistic study. *Behavioural and Cognitive Psychotherapy*, 41(3), 365–370. https://doi.org/10.1017/S1352465812001063
- 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(1), 95–111. https://doi.org/10.1348/147608305X39491.
- Sharf, J., Primavera, L. H., & Diener, M. J. (2010). Dropout and therapeutic alliance: A metaanalysis of adult individual psychotherapy. *Psychotherapy: Theory, Research, Practice, Training*, 47(4), 637–645. https://doi.org/10.1037/a0021175
- 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(10), 1341–1347. https://doi.org/10.1176/ajp.147.10.1341
- Smith, R. F., Otto., Alves, D. E., & Knapstad, M. (2016). Rask Psykisk Helsehjelp: Evaluering av de første 12 pilotene i Norge. Folkehelseinstituttet. https://www.fhi.no/globalassets/dokumenterfiler/rapporter/2016/rask\_psykisk\_helsehjelp \_evalueringsrapp\_12\_piloter.pdf

- Spitzer, R. L., Kroenke, K., & Williams, J. B. & Löwe, B. (2006). A Brief Measure of Assessing Generalized Anxiety Disorder- The GAD-7. Archives of Internal Medicine, 166(10), 1092–1097. https://doi.org/10.1001/archinte.166.10.1092
- Swift, J. K., & Greenberg, R. P. (2012). Premature Discontinuation in Adult Psychotherapy: A Meta-Analysis. *Journal of Consulting Clinical Psychology*, 80(4), 547–559. https://doi.org/10.1037/a0028226
- Tesli, M. S., Handal, M., Torvik, F. A., Knudsen, A. K. S., Odsbu, I., Gustavson, K., Reichborn-Kjennerud, T., Nesvåg, R., Hauge, L. J., & Reneflot, A. (2021,12.03). *Psykiske lidelser hos voksne*. Folkehelseinstituttet. https://www.fhi.no/nettpub/hin/psykisk-helse/psykiskelidelser-voksne/
- Wakefield, S., Kellett, S., Simmonds-Buckley, M., Stockton, D., Bradbury, A., & Delgadillo, J. (2021). Improving Access to Psychological Therapies (IAPT) in the United Kingdom: A systematic review and meta-analysis of 10-years of practice-based evidence. *British Journal of Clinical Psychology*, 60(1), 1–37. https://doi.org/10.1111/bjc.12259
- Walfish, S., McAlister, B., O'Donnell, P., & Lambert, M. J. (2012). An Investigation of Self-Assessment Bias in Mental Health Providers. *Psychological Reports*, *110*(2), 639–644. https://doi.org/10.2466/02.07.17.PR0.110.2.639-644
- Wang, J. (2007). Mental Health Treatment Dropout and Its Correlates in a General Population Sample. *Medical Care*, 45(3), 224–229. https://doi.org/10.1097/01.mlr.0000244506.86885.a5

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. (2019). *Special initiative for mental health (2019–2023)*. Mental Health and Substance Use. https://www.who.int/publications-detail-redirect/special-initiative-for-mental-health-(2019-2023)
- Zahra, D., Qureshi, A., Henley, W., Taylor, R., Quinn, C., Pooler, J., Hardy, G., Newblod, A., & Byng, R. (2014). The work and social adjustment scale: Reliability, sensitivity and value. *International Journal of Psychiatry in Clinical Practice*, *18*(2), 131–138. https://doi.org/10.3109/13651501.2014.894072
- Zieve, G. G., Persons, J. B., & Yu, L. A. D. (2019). The relationship between dropout and outcome in naturalistic cognitive behavior therapy. *Behavior Therapy*, 50(1), 189–199. https://doi.org/10.1016/j.beth.2018.05.004
- Zimmermann, D., Rubel, J., Page, A. C., & Lutz, W. (2016). Therapist Effects on and Predictors of Non-Consensual Dropout in Psychotherapy. *Clinical Psychology & Psychotherapy*, 24(2), 312–321. https://doi.org/10.1002/cpp.2022

Baseline characteristic	Full sample $N = 526$	Dropout $n = 133$	Completer n = 393 Frequency (%)	
	Frequency (%)	Frequency (%)		
Sociodemographic				
Sex				
Female	343 (65.2%)	77 (57.9%)	266 (67.7%)	
Male	183 (34.8%)	56 (42.1%)	127 (32.3%)	
Aged 30 or higher	320 (60.8%)	56 (42.1%)	264 (67.2%)	
Poor social support	171 (32.5%)	55 (41.4%)	116 (29.5%)	
mmigrant background	63 (12.0%)	19 (14.3%)	44 (11.2%)	
Higher educated	231 (44.3%)	41 (31.1%)	190 (48.8%)	
Work status				
In regular work, retirees, home stayers or unknown	170 (32.3%)	34 (25.6%)	136 (34.6%)	
In work, receiving financial support	192 (36.5%)	47 (27.8%)	155 (39.4%)	
Without work, receiving financial support	80 (15.2%)	27 (20.3%)	53 (13.5%)	
Student	84 (16.0%)	35 (26.3%)	49 (12.5%)	
Clinical				
Symptoms of depression				
Below cut-off	109 (20.7%)	23 (17.3%)	86 (21.9%)	
Mild	175 (33.3%)	42 (31.6%)	133 (33.8%)	
Moderate-severe	242 (46.0%)	68 (51.1%)	174 (44.3%)	

# Table 1

Symptoms of anxiety			
Below cut-off	123 (23.4%)	28 (21.1%)	95 (24.2%)
Mild-moderate	266 (50.6%)	70 (52.6%)	196 (49.9%)
Severe	137 (26.0%)	35 (26.3%)	102 (26.0%)
Duration >6 months	452 (85.9%)	119 (90.2%)	333 (84.7%)
Low daily function	190 (36.1%)	52 (39.1%)	138 (35.1%)

*Note:* Mean age for this sample was 34.95 (SD = 12). Mean score for symptoms of depression (PHQ-9) was 13.9 (SD = 5). Mean score for symptoms of anxiety (GAD-7) was 11.3 (SD = 4.6).

Predictor	В	SE	Wald	df	р	OR	95% CI for <i>OR</i>	
							Lower	Upper
Sociodemographic								
Aged 30 or higher	-1.02	.22	22.10	1	<.001	.36	.23	.55
Sex: Female	31	.22	1.98	1	.159	.74	.48	1.13
Higher educated	89	.23	15.30	1	<.001	.41	.26	.64
Immigrant background	.21	.31	.45	1	.503	1.23	.67	2.26
Poor social support	.60	.22	7.49	1	.006	1.83	1.19	2.81
Work status								
In work receiving financial support	.01	.28	.00	1	.986	1.01	.59	1.73
Without work, receiving financial support	.59	.32	3.39	1	.066	1.81	.96	3.39
Student	.90	.31	8.52	1	.004	2.47	1.35	4.53
Clinical								
Symptoms of depression								
Mild	.09	.31	.09	1	.769	1.10	.60	2.00
Moderate-severe	.26	.29	.80	1	.370	1.30	.74	2.28
Symptoms of anxiety								
Mild-moderate	.08	.27	.92	1	.761	1.09	.64	1.84
Severe	08	.31	.07	1	.796	.92	.51	1.69
Symptom duration >6 months	.31	.34	.86	1	.355	1.37	.71	2.64
Low daily function	.13	.22	.34	1	.562	1.14	.74	1.74

 Table 2

 Logistic Repression Analysis Predicting Dropout from Sociodemographic and Clinical variables

*Note:* OR = odds ratio. CI = confidence interval. Municipalities and therapists were included as fixed effects. Number of participants = 526. Significance level set to p < .05.

# Table 3

Multivariate Logistic Regression Analysis Predicting Dropout from Therapy

<u> </u>	e		•	Ũ	1 0		1.	
Predictor	В	SE	Wald	df	р	OR	95% CI for <i>OR</i>	
							Lower	Upper
Age 30 or higher	833	.25	10.82	1	<.001	.44	.27	.71
Student	.47	.34	1.89	1	.169	1.60	.82	3.11
Poor social support	.64	.23	7.55	1	.006	1.90	1.20	2.99
Higher education	56	.24	5.38	1	.020	.57	.35	.92
Constant	33	.53	.40	1	.529	.72		

*Note:* OR = odds ratio. CI = confidence interval. Municipalities and therapists were included as fixed effects. Number of participants = 520. 6 missing cases. The multivariate model was statistically significant  $\chi^2(15, N = 520) = 84.79, p < .001$ . The Hosmer-Lemeshow test for goodness of fit showed a significant value of .160. Significance level set to p < .05.