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„Dropout Analysis in an Internet Based Intervention Study"

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Contents

Introduction

“The best way to guarantee a loss is to quit.” This quote by the American actor Morgan Freeman encapsulates the urging issue of people quitting or withdrawing from digital or real life health interventions at an early stage. Not only are participants who are dropping out missing out on a chance to participate from the respective programme, valuable data are lost and often cannot be used altogether, even though the dropped out participants had made a certain progress before ending the programme prematurely. This thesis aims at finding, reviewing and validating underlying factors of early dropout from psychological health interventions on the basis of a Germany-wide mental imagery behavioural activation training for a currently depressive population using behavioural activation. I aimed at identifying underlying factors of early dropout in the existing literature and reviewing them on the basis of the present study. Recognising and eventually considering such factors in the planning of future studies could initiate substantial progress in terms of reducing attrition and lead to less dropouts of participants. If it was possible to identify participants, who are at greater risk of dropping out of the respective studies, they could be subsequently attended closer during the study period or recruited with more vigour to counteract missing datasets. As discussed hereafter, dropout is especially an issue in internet based intervention studies, trainings or app based programmes as well as such programmes, where little or none human interaction at all is included (Prenkaj et al., 2021). Accurately interpreting findings and translating them to practical applications has become a growing concern in digital health research due to the low engagement and high attrition rates observed in digital mental health interventions. A recent overview on digital mental health programmes aimed at people with current depressive symptoms identified that, on average, slightly more than 50% of the participants completed the full intervention and only about 25% of the participants fully completed the respective intervention when it was delivered within routine health care settings in a naturalistic setting (Moshe et al., 2021). These dropout rates differ between intervention types and diagnoses, a more comprehensive overview will be provided in the course of this paper.

A variety of variables have been assumed to enhance the chance of a subgroup of participants to drop out from a study (Donkin et al., 2011; Kok et al., 2017; Schmidt et al., 2019). Thus far, it hasn't been possible to identify reliable and universally valid factors for dropout in online based or real life interventions. The reasons for this are manifold and will be discussed in the course of this paper.

Although this paper will mainly focus on the issue of dropouts on the basis of an online psychological intervention study, the same mechanisms may apply to a much broader range of scenarios such as *MOOCs* (massive open online courses), online taught courses of any kind in general, high schools as well as universities (Chen et al., 2019; Moreno-Marcos et al., 2020). Albeit the present study sample is rather small, the extensive diagnostic data allows for a close insight into possible factors of early dropout as well as a basis for discussing a generalisable framework for future research studies and other applications.

The idea for the present thesis emerged during the COVID pandemic, in which the importance of digital interventions grew bigger at a rapid pace, as I will further examine in the following paragraphs.

Mental Imagery as Motivational Amplifier

Depressive disorders have been found to be heterogeneous, exhibiting significant variation in the symptomatology from one individual to another (e.g. Han et al., 2022). Behavioural activity has been shown to be a stable and low-threshold method to improve depressive symptoms and elevate moods (Ekers et al., 2014). A number of studies has shown that mental imagery (i.e. mentally imagining activities, situations or emotions) can function as a strong amplifier of motivational attitudes towards rewarding behaviours (Bär et al., 2023; Heise et al., 2022; Renner et al., 2021). A certain degree of anhedonia and lack of motivation is inherent to many manifestations of depressive disorders, hence it does not surprise that many individuals with depressive disorders are experiencing difficulties with carrying out their hobbies as well as other positively perceived activities. This can lead to a vicious cycle, in that the lack of these activities can lead to intensification and manifestation of depressive symptoms. The overarching trial, this analysis is based on, tests a newly developed mental imagery protocol, targeted on facilitating people's decision-making towards positive and rewarding activities.

Definition and Role of Digital Interventions

Digital interventions, research projects and health applications play a central role in the field of modern psychological research and treatment of mental disorders. Especially since the global COVID-19 pandemic, digital solutions forced their way into many areas of the field, new start-ups, business ideas research approaches and educational formats emerged (Khan et al., 2023; van Daele et al., 2022). Digital interventions are often summoned under the term *mHealth* (Mobile Health). Mobile phones especially, despite their currently already high importance, are becoming more and more relevant in many aspects of everyday life. 67% of the European population own at least one smartphone, and the number of smartphone users is rising worldwide. There are more than 100.000 health apps available in app stores and it is estimated that 30% of Germans have at least one digital health app of any kind installed on their phones (Thranberend et al., 2016).

Developed long before the pandemic, but much accelerated by the extraordinary circumstances, digitalisation and digital applications found its way in the German healthcare system in the form *of Digital Health Applications* (DiGAs) that can be prescribed by medical doctors as well as psychological psychotherapists (Sauermann et al., 2022). Since there are numerous DiGAs still being designed and tested, this development illustrates once again the enormous importance of digital health interventions now and in the years ahead. The extensive licensing process as well as the possibility to prescribe such programmes has substantially increased the importance and relevance of digital health care applications. Moller et al. (2017) attest a wide range of digital interventions great potential for testing, refining and developing theories of behaviour change by applying and testing techniques of behavioural change in real life context and potentially by gathering a broader range of data such as physiological or real time data in the case of *ecological momentary assessment* (EMA). Internet- and mobile-based interventions offer various potential advantages such as low-threshold access, geographic independence, constant availability, and potentially much lower cost (Paganini et al., 2018). Despite such advantages, it is assumed that the potential dropout rates in solely digital interventions, trainings or online courses might be higher compared to conventional formats (Prenkaj et al., 2021). Ensuring and supporting adherence to the therapeutic programme is a particular challenge in digital interventions as there are less options to obtain these by face to face contact or other means of direct contact (Eysenbach, 2005). Such interventions demand substantially more effort by respective users compared to traditional formats. As there are usually no planned appointments included in such programmes, the offered intervention modules constantly compete with daily live events and schedules and demand varying amounts of self-discipline (Baumeister & Vohs, 2007). Taking these considerations into account, compliance and engagement remain pivotal challenges in the implementation of digital interventions (Cuijpers et al., 2019; Yardley et al., 2016).

Numerous studies have indicated that internet-based interventions can serve as viable remedies for depression, producing similar outcomes to those achieved through in-person treatments (e.g. Andrews et al., 2010). In a meta-analysis including 83 studies by Moshe et al. (2021), they report a significant medium overall effect size of digital interventions compared with all control conditions (g = .52), whilst finding high overall heterogeneity. Thus, they report significantly higher effect sizes in interventions that involved human therapeutic guidance (g = .63) compared with self-help interventions (g = .34), and significantly lower effect sizes for effectiveness trials (g = .30) compared to efficacy trials. This heterogeneity in effect sizes can be found equivalently in reported dropout rates (Moshe et al., 2021). Guth et al. (2023) are discussing current evidence of the efficacy of DiGAs and conclude that while 28 of 29 analysed RCTs use CBT-based methods, digital applications, especially in the treatment of panic disorder syndromes, produce large effect sizes and stable adherence. Considering many of the aspects discussed in this chapter, it does not surprise that feasibility of many digital interventions has been found to be higher than for real life programmes, arguably due to missing access routes, free time management or even the convenience of being able to anonymously quitting the programme altogether at any given time (Gratzer & Khalid-Khan, 2016).

Anonymity, especially in light of growing concerns for data privacy is considered a key benefit of digital interventions by many affected people (i.e. users) compared to conventional programmes where face to face contact and hence a certain form of identification is often required (Burns et al., 2010; Horgan et al., 2013; Huckvale et al., 2019). While privacy and anonymity is perceived as comfortable by many participants, effectiveness can be reduced in study contexts without any contact with mental health professionals, hence a balance need to be found (Garrido et al., 2019).

Definition of Dropout

First and foremost, the question arises how exactly we define the term *dropout*. Throughout literature, there is no consensus on the exact definition of dropout and definitions vary substantially between studies. The terms “*dropout*”, “*attrition*”, or “*premature termination*" as well as “*engagement*”, “*adherence*” respectively are used interchangeably in the literature, are defined as discharge or interruption, initiated by the patients or healthcare professionals and are usually measured either binary as completion or non-completion or as the completed percentage of the treatment programme (Fassino et al., 2009). These differences in dropout definition may also somewhat naturally arise from the variety in study designs. For instance within a therapeutic intervention it may be sufficient to attend a certain number of therapy sessions or modules to reach desired therapeutic outcomes. Hence, participants could drop out of the study and at the same time being considered *completers* (a term that is widely used in literature for participants who complete over 75% of a programme (i.e. Fassino et al., 2009). Haan et al. (2013) assume these discrepancies between definitions may lead to indifferent results as well as variation in results across dropout studies. In theory, digital health interventions have the advantage of being able to precisely measure adherence to the programme by technical means, therefore being able to analyse which participants received which part of the training. In reality, these analyses are rarely conducted thoroughly (Merchant et al., 2014).

O'Keeffe et al. (2019) conceptualise a quite insightful approach to understanding and defining dropout, however on the basis of psychotherapy attendance and quitting of psychotherapy sessions . They differentiate between three different types of dropout: “Dissatisfied” dropout (intervention failed to meet their needs), “got-what-they-needed” dropout (stopping an intervention due to symptom improvement), and “troubled” dropout (stopping an intervention due to the feeling it is not the right time to engage in it).

Consequently, numbers of dropout found in reviews, overviews and meta analyses are greatly varying and are based on different assumptions. The differences in data acquisition regarding participants and dropout data are even greater and many studies lack detailed descriptions of participant characteristics, let alone the assessment of further criteria like psychiatric diagnoses or feasibility questionnaires.

Dropout Rates in Psychological Interventions

As discussed, it remains a challenge to compare dropout rates between different forms of interventions and programmes, hence reporting an average or standard dropout rate across all kinds of digital applications proves to be difficult. Furthermore, lacking analyses and reporting of dropout data are making further analyses difficult. Moshe et al. (2021) report in a meta-analysis that only 36 of 83 digital treatments for depression (43%) provided measures of average treatment compliance. Moshe et al. (2021) found a mean dropout rate of 42.38% in 44 studies using digital interventions that reported numbers of dropout (*Note*. This average number was calculated by the author and is not reported in the original paper). They don’t provide predictive factors of dropout but elaborate on possible reasons for early dropout and highlight the importance of such analyses, postulating a “Science of Attrition” (i.e. the comprehensive engagement with the topic) to be put back on the agenda of research, especially in the field of digital interventions and app based programmes.

Kaltenthaler et al. (2008) found a mean dropout rate of 31.75% in 16 computerised cognitive behaviour therapy trials (CCBT), with a range from 0% to 75%. The reasons for dropouts were only assessed and reported in six of these 16 trials. The most common reported reasons were being too busy or experiencing changes to their daily life circumstances. The authors further discuss the difficulties in comparing dropout rates due to the commonly found low data quality. Richards and Richardson (2012) reported a mean dropout rate of 57% in 40 analysed computer-based psychological treatments for depression.

Dropout rates in face-to-face psychotherapy are difficult to compare due to varying definitions and reported reasons for the premature discontinuation of a therapy. It can be estimated though that around 13% - 20% of psychotherapy treatments in Germany end due to patients dropping out of the therapy (Albani et al., 2013; Cinkaya et al., 2011; Reuter et al., 2014).

There is evidence that a higher number of units to work through lead to higher dropout. That is, the more modules a trial includes and thus the more time participants need to spend within the study, the more participants leave the respective trial prematurely (Eysenbach, 2005; Kaltenthaler et al., 2008).

Amid their easy administration and distribution as well as other benefits mentioned earlier, a recent meta-analysis reports dropout rates as high as 48 % in smartphone apps for depressive symptoms when accounted for publication bias (Torous et al., 2020). The authors claim that such high dropout rates are posing a threat to the validity of RCTs of mental health apps.

In a study designed to evaluate an online programme for people with elevated depressive levels on a waiting list for face to face treatment, Kenter et al. (2013) reported low adherence, only 18% of participants completed the whole online programme and 65% completed at least part of the sessions, reasons for dropout were not examined.

Karyotaki et al. (2015) analysed predictors and rates of treatment dropout in self-guided web-based interventions for depression. Across the ten included randomised controlled trials, 40% of participants dropped out before the completion of 25% treatment modules, 59% dropped out before completing half of the treatment modules. Eventually, only a small percentage of 17% of all participants across studies were reported to complete all treatment modules (Karyotaki et al., 2015). While many of the studies are comparable to the WIMBA-study, evaluated in this thesis, all trials included in the analysis were self-guided web-based interventions compared to the certain extent of *support* (i.e. telephone call at the beginning of the study), participants received during the WIMBA-study.

Potential Factors of Dropout in Digital Interventions

Analogous to dropout rates discussed in previous chapters it has proven a challenge to outline and analyse general factors that determine the factors of participants dropping out of different programmes. Demographic factors as well as behavioural characteristics, perceived feasibility and appreciation of the respective study as well es motivational and psychological factors have been assumed to function as predictors in recent literature, though the evidence remains mixed. At this point I would like to refer to an essay by then Campbell Collaboration CEO Howard White who states that there is no such thing as mixed evidence but merely poorly synthesized evidence (White, 2016). Taking widespread small effect sizes into account, this assessment might explain a valid proportion of unclear evidence as to which factors specifically influence dropout rates across digital interventions. Karyotaki et al. (2015) conclude that the probability of dropout is predictable by a number of factors and not randomly distributed. Yet, the need for meta analyses with high power is prevalent and will be further discussed in following chapters.

Demographic Factors of Dropout

Some, although strongly mixed, evidence could be found that demographic factors influence the risk of dropout from internet-based interventions. It has been reported that sex, age and levels of education are associated with dropout rates (Karyotaki et al., 2015).

Concerning age as a factor there is evidence that younger participants are dropping out less (Clarke et al., 2005; Elbert et al., 2016) and that the probability of dropping out decreases with every year of age (Karyotaki et al., 2015; Lange et al., 2003). Several studies found no association between age and dropout (Andersson et al., 2005; Linardon et al., 2018; Ström et al., 2004). As discussed earlier regarding the topic of mixed evidence, it has to be said that results are difficult to compare considering small sample sizes and different qualities of samples. For instance, a significant difference in mean and median age or different ranges of age within participants between different analyses could yield different results regarding the influence of age on dropping out (see also Melville et al., 2010).

Gender has been reported to be a predictor of dropout in the literature with women being more likely to complete a certain programme than men (Kramer et al., 2014; Mackinnon et al., 2008; Neil et al., 2009; van der Zanden et al., 2012). Other studies found no association between gender and dropout probability (Andersson et al., 2005; Clarke et al., 2005). Only binary gender classifications (i.e. male and female) were found during the literature search, diverse gender identifications have not been assessed or analysed to my knowledge.

A lower educational qualification (or *educational level*) has also been identified as a possible factor of participants dropping out of online programmes (Karyotaki et al., 2015; Schmidt et al., 2019). Karyotaki et al. (2015) reported a *relative risk* (RR) of 1.23 for participants with only primary education compared to higher education in a meta-analysis comprising 10 studies. Lange et al. (2003) found no differences regarding dropout probability between different levels of completed education.

Psychological Factors of Dropout

Another line of research focussed on psychological and psychopathological factors influencing dropout rates. Thus evidence was found that depressive load at baseline measure (Christensen et al., 2009) as well as comorbid anxiety symptoms (Karyotaki et al., 2015) were associated with probability of dropout.

There is a large body of evidence that higher depressive scores at baseline measurement are associated with higher dropout rates (Clarke et al., 2002; Kenardy et al., 2006; Mackinnon et al., 2008; Ong et al., 2008; Yeung et al., 2015). These results have not only been obtained in the context of depressive samples or studies focussing on interventions for depressive disorders. Possible reasons for that link are yet to be reported in detail, but many possible factors are deductible from the depressive syndrome, such as a lack of motivation, lack of self-discipline or limited coping strategies regarding the challenges incorporated in online intervention programmes. Moreover, these results lead to a decisive question, namely, are specific subgroups more prone to dropping out of online programmes, hence at risk to not profit from offered programmes in the same way like other participants. Coexisting anxiety symptoms have been reported to especially influence dropout probabilities in online programmes (Neil et al., 2009; van der Zanden et al., 2012). Garrido et al. (2019) report no difference in dropout rates between participants severity of symptoms at baseline. Cohen and Schleider (2022) report opposite results regarding the effect of baseline anxiety levels on dropout rates in online programmes. The high comorbidity with depressive disorders and the specific components of anxiety disorders (i.e. worry and fear, hesitation in regard to starting new activities) suggest that they may play a pivotal role in the prediction of attrition and dropout rates. In cases where programmes for anxiety disorders are designed to treat anxiety disorders there is evidence that higher baseline severity of anxiety symptoms are associated with lower adherence to the intervention (Al-Asadi et al., 2014). Karyotaki et al. (2015) report co-morbid anxiety symptoms as a significant predictor of higher dropout rates in a meta-analysis comprising ten self-guided web-based interventions for depression.

Treatment Condition as a Dropout Predictor

Literature search revealed no evidence for an association between the respective intervention group, participants are allocated to, in many cases an intervention group vs a control group or waiting list group, and dropout rates in the respective programme (Ormhaug & Jensen, 2018). Requirements for participants can greatly differ between intervention groups and waiting groups, resulting in different aspects influencing possible dropout. Thus, participants might feel a sense of boredom in waiting group conditions rather that intervention groups while challenges as well as strenuousness might be much higher in intervention groups, depending on the type of tasks included in the respective study. On the other hand, research participants are often more motivated than real life users of digital interventions, so adherence could remain unaffected by treatment condition (Huckvale et al., 2019). I have included such analysis in the present work, although further (e.g. qualitative) analysis of dropouts naturally proved difficult as participants who had already dropped out of the study were hard to reach and often didn't respond to requests. Dropout rates in intervention groups vs waiting list conditions should nevertheless always be considered in the evaluation of the respective programme, e.g. to further analyse if dropout rates appear to be significantly higher in one group or the other.

Level of Guidance as a Dropout Predictor

Evidence suggests that the extent and type of guidance affects dropout rates in online programmes. A number of works report higher participant engagement with the intervention when therapeutic support is provided (Alfonsson et al., 2016; Ivanova et al., 2016). Bisby et al. (2022) report slightly lower completion in self-guided compared to clinician-guided treatments. There is further evidence that the level of provided support (i.e. phone calls, communication, therapeutic support) affects dropout rates in digital interventions (Furukawa et al., 2021). During literature review it became clear that regarding this factor, a binary classification (i.e. self-guided treatments vs clinician-guided treatments or generally guided treatments) does not suit the manifold variety of online programmes in that all kind of intermediate forms are possible. The study discussed here is a good example in that a very brief human contact is offered right at the beginning of the study but thereafter it is a completely unguided intervention. As with many other aspects of dropout prediction it proves difficult to coherently describe, measure and compare levels of guidance throughout different forms of programmes or interventions.

Different dropout rates for different levels of guidance have been reported by Richards and Richardson (2012): Levels of dropout were 74% for no support, 38.4% for administrative support and 28% for therapeutic support. The odds ratios (OR) of dropping out between the different types of support comparatively are reported: No support vs Administrative support: OR = 2.45, $z = 15.65$, $p < .001$. No support vs Therapist support: OR = 7.35, $z = 19.08$, $p < .001$. Administrative support vs Therapist support: OR = 3.0, $z = 10.21$, $p < .001$. As discussed, a number of studies cannot be assigned precisely to one of the levels of support. Noticeably, the present study as well cannot be precisely allocated to one of the discussed support levels.

Computer Self-Efficacy as a Dropout Predictor

Self-efficacy is defined as one’s belief in one’s capacity to exert actions required to achieve particular performance or other goals. Computer self-efficacy has been defined as “an individual’s judgment toward his or her own capability of computer use” (Compeau & Higgins, 1995). An extensive literature search revealed no results, indicating that technological knowledge or affinity could be a valid predictor of dropout. This seems in line with expectations, especially as nowadays technological appliances and applications have become regularly used by a huge part of global population, widespread and mundane and most of the analysed online programmes do not require high levels of technological knowledge in the use. Nonetheless, meaningful interindividual differences regarding the use of and attitude towards technology can be assumed. The concept of computer self-efficacy has been prominently brought up by Barbeite and Weiss (2004). Barbeite and Weiss (2004) developed and evaluated new and different scales, one for general or beginning activities and one for advanced activities. While it can be assumed that most participants of online based interventions would strongly agree with the items of the base level activities scale (e.g. “I feel confident using the computer to write a letter or essay”), I expect the latter scale to differentiate between participants (e.g. “I feel confident explaining why a program (software) will or will not run on a given computer”), hence it will be used in the present analysis. It has been suggested that the concept of computer self-efficacy could play a role in e-learning programmes, being associated with pupils academic success as well as satisfaction with the programme (Jun, 2005; Street, 2010).

Research Questions and Hypotheses

Demographic Factors

The first research question of the present paper focuses on possible demographic factors that are associated with higher risk of dropout.

Hypothesis 1

The probability to drop out from the programme is higher for male than for female participants.

Hypothesis 1.1

Dropouts show lower educational levels than completers.

Hypothesis 1.2

Dropouts have a lower mean age than completers.

Psychological factors

The second research question evaluates psychological measures and their association with premature termination of the study.

Hypothesis 2

Dropouts are showing higher depressive levels at baseline measurement.

Hypothesis 2.1

The relative risk of participants with comorbid anxiety symptoms to drop out from the study is higher than of those without such comorbid symptoms.

Hypothesis 2.2

Dropouts are showing lower levels of computer self-efficacy than completers.

Further factors

Which further factors determine the risk of dropping out of the online intervention?

Hypothesis 3

The probability of dropping out from the study is higher in the intervention group than in the waiting list group.

Hypothesis 3.1

Feasibility ratings are lower for dropouts than for completers.

Methods

Study Design

The study used a between-subject design with two conditions: An experimental condition, consisting of keeping an activity diary plus mental imagery instructions and a waitlist control condition, where participants had to fill in the same questionnaires as the experimental condition, but didn't receive any further instructions or tasks. The study consisted of a preliminary online questionnaire (including demographic data) to test for eligibility followed by a telephone interview in case of fulfilling preliminary inclusion criteria and four online held sessions over the course of four weeks in case of fulfilling further inclusion criteria, evaluated during the phone call. Participants who completed the waiting list control group protocol had the chance to receive the experimental group training subsequent to the finished study.

Participants

Eligibility Criteria

In order to be included in the study, participants had to be fluent in German, be aged between 18 and 65 years, scoring between 14 and 28 on the BDI-II (this criterion has been revoked on 1st May 2023, removing any upper limit for BDI-II scores) indicating mild to moderate levels of depressive symptoms as well as meeting diagnostic criteria for a major depressive episode on the Mini-DIPS. A practical inclusion criteria was being in possession of a German phone number (to conduct the telephone interview) and internet access for the subsequent study sessions. Exclusion criteria were being in medical or psychological treatment for a mental health condition at the start of the study period and fulfilling diagnostic criteria for severe mental health problems including bipolar disorder, psychotic disorders (Mini-DIPS), suicidality (Mini-DIPS, BDI-II) or substance dependence (Mini-DIPS).

Recruitment

Participants, whose data is used in this sample were recruited between January 2022 and May 2023. Participants were recruited Germany-wide using various approaches such as online platforms (e.g. “Psychologie Heute”, “Diskussionsforum Depression”, “Depressionen Selbsthilfe Forum”), mostly specifically designed for people with mental disorders such as depressive or anxiety disorders. Apart from that, we distributed physical flyers (see appendix) in numerous locations and private households, used Instagram, Facebook, *Ebay-Kleinanzeigen* (German *Gumtree* equivalent) and more specific recruitment strategies such as contacting rehabilitation facilities, psychotherapists and GP surgeries throughout Germany. Participants were reimbursed for their participation (i.e. completion of the study over the course of four weeks) in form of an Amazon voucher (25 €). Participants provided informed consent online via the study website (for additional participant information, see the appendix).

Study Sample

Power calculations with G*Power (Faul et al., 2009) yielded a total sample size of 140 participants for a small effect size (expected effect size based on a pilot study) with 95% power and $\alpha = 0.05$. To account for estimated dropout over the four week period, 192 participants are aimed to be recruited. Power calculations for subsequent dropout analysis yielded similar results, i.e. 176 participants for one sided t tests with two independent groups (88 per group). The sample of the present analysis did not meet these criteria at the time of writing.

95 participants were included in the study. 63 female, 31 male participants and one diverse attendee, mean age 33.8 years. An overview of participants sociodemographic characteristics is provided in Table 1.

Table 1

Sociodemographic Characteristics of the Study Sample

	n	%
Gender		
Female	63	66.3
Male	31	32.6
Diverse	1	1.1
Relationship status		
Single	43	45.3
Married/partnered	49	51.6
Divorced/widowed	3	3.2
Highest educational level		
Middle school	7	7.4
High school/some college	23	24.2
Completed apprenticeship	8	8.4
University or postgraduate degree	56	58.9
Age		
Mean	33.84	
SD	11.53	
Range	19-65	

Note. N = 95 (N = 46 in the active training group, N = 49 in the waitlist control group).

Measures

Dropout

Dropout in the present analysis is defined as a termination of the study by the participant, either intentionally or by inactivity. Every termination after randomisation (see procedure overview in Figure 1) is considered a dropout from the intervention. Depressive levels are operationalised as BDI sum scores, anxiety symptoms are assessed with the Mini-DIPS-OA (Margraf & Cwik, 2017). Computer Self-Efficacy and feasibility scores are reported by mean scale scores of the respective scales.

Beck's Depression Inventory

Depression levels were measured using Beck’s Depression Inventory (BDI-II) (Beck et al., 1996). The BDI-II consists of 21 statements, with each statement having four possible options on a scale value of 0 to 3. Scores can thus rank between 0 and 63. Sample statements are “I do not feel sad.” (0) – “I feel sad” (1) – “I am sad all the time and I can't snap out of it” (2) – “I am so sad and unhappy that I can't stand it” (3) or “I do not feel like a failure” (0) – “I feel I have failed more than the average person” (1) – “As I look back on my life, all I can see is a lot of failures” (2) – “I feel I am a complete failure as a person..” (3). Before 1st May 2023, only participants with BDI-II scores between 14 and 28 were allowed in the study, from 1st May 2023 onwards, the upper limit was removed and all participants with BDI-II scores of 14 or higher were accepted. Glischinski et al. (2019) evaluated BDI-II cut-off points and found scores higher than 13 to be reliable predictors of depressive syndromes for the general population.

MINI-DIPS-OA

Psychiatric diagnoses were made using the *Mini-DIPS Open Access* (Mini-DIPS-OA) (Margraf & Cwik, 2017). The Mini-DIPS-OA is an abridged and reformatted version of the DIPS-OA (Diagnostic Interview of Mental Disorders) (Margraf et al., 2017) and allows for numerous lifetime diagnoses, current and past, according to DSM-5 and ICD-10 diagnostic criteria such as depressive disorders, anxiety disorders, trauma and stress related disorders, or sleep disorders. Diagnoses were made during planned phone calls and registered in an online system. As opposed to other diagnostic instruments (e.g. Beck's Depression Inventory, providing point based results), the Mini-DIPS categorises diagnoses within a binary system (i.e. ”present” or “not present”). Using the Mini-DIPS-OA, BDI-II scores were thus verified and examined using the extensive set of questions included in the Mini-DIPS-OA. Example questions from the Mini-DIPS include: “Did your weight or appetite change?”, “Did your sleep change”, “Were you constantly feeling tired or weak?” (Depressive/mood disorders); The internal consistency was described as around 0.9, retest reliability ranged from 0.73 to 0.96 and stable construct validity was indicated by several analyses (Wang & Gorenstein, 2013).

Computer Efficacy Scale

Computer Efficacy was measured using the Computer Self-Efficacy Scale (CSE) for advanced activities (CSE-AA) (Barbeite & Weiss, 2004). The scale is measured on a 5-point Likert scale and consists of four items (see appendix), items include “I feel confident troubleshooting computer problems”, “I feel confident understanding terms/words relating to computer hardware” or “I feel confident explaining why a program (software) will or will not run on a given computer”. Mean scores can thus rank between 1 and 5. I translated the items into German and discussed comprehensibility with my colleagues. The short scale was reported to strongly correlate with years using the computer, comfort and experience using the computer as well as experience using the Internet hence indicating stable construct validity (Barbeite & Weiss, 2004). The reliability for the advanced CSE items was reported .85 using Cronbach’s alpha, indicating satisfactory internal consistency (Abdullah & Mustafa, 2019).

Feasibility

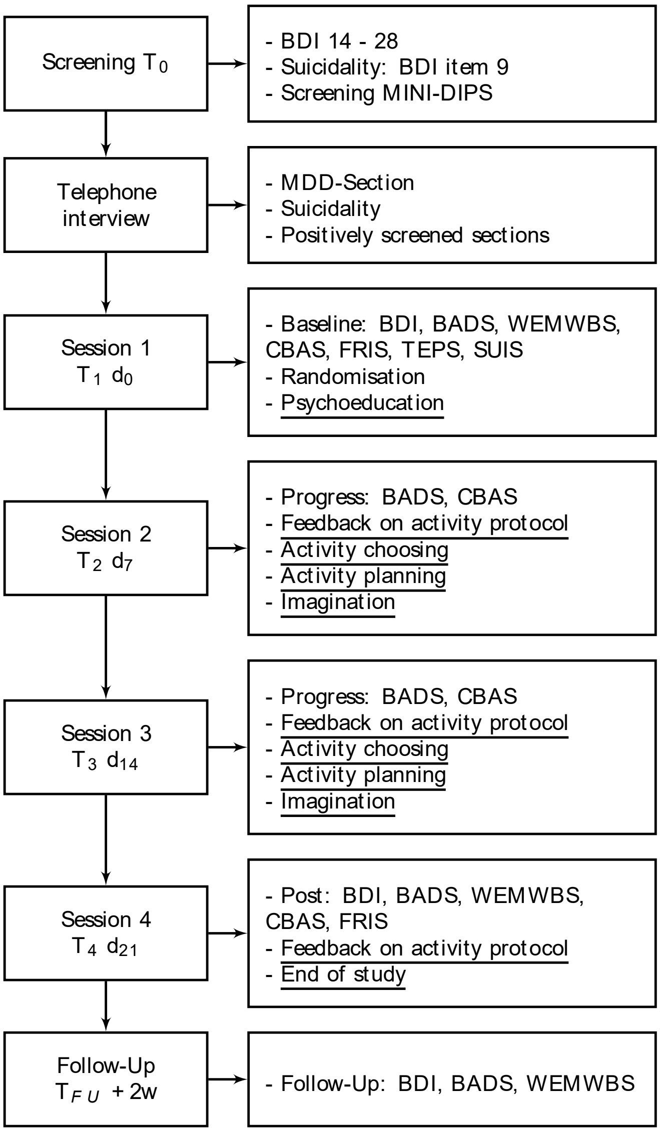
Feasibility is assessed using a self-developed feasibility-scale that is based on literature in the field (see appendix). Items include “I felt well guided during the study”, “I perceived the online format as pleasant” and “I would recommend this study to a friend”. Answers are given on a 7-point Likert scale, thus mean scores rank between 0 and 6.

Procedure

The dropout analysis is part of the “WIMBA” (Web-based Imagery Behavioural Activation) study, conducted by the PROMIND research group (Prospective Mental Imagery in Depression) located at the Department of Clinical Psychology and Psychotherapy at the Institute of Psychology of the University of Freiburg, Germany (department head Prof. Dr Tuschen-Caffier). Group leader is Dr Fritz Renner, who was leading the study with doctoral candidate Max Heise. The study was approved by the ethics committee of the German Psychological Society (DGPs). Participants took part in the study via the study website. The study used a between-subject design with two conditions: activity scheduling plus mental imagery and wait-list control. The online study consisted of 4 sessions over the course of four weeks. The study ran on the *formr* platform (Arslan et al., 2020) which was used to send out e-mails containing links to study sessions and collect questionnaire data. A two-stage screening procedure was applied: The first part was conducted online where individuals who are interested in participating in the study were asked to complete a short online screening questionnaire consisting of the BDI-II. Only participants scoring between 14-28 (before 1st May 2023) on the BDI-II, indicating mild to moderate levels of depression, were invited to the second part of the screening. Participants who scored outside of this BDI-II range or scored above “1” on the suicidal thoughts item of the BDI-II and participants who are currently in medical or psychotherapeutic treatment for a mental disorder were informed that they are not eligible to participate in the study. The online screening procedure took about five minutes to complete. The second part of the screening was conducted via telephone. A member of the research team was administering the Mini-DIPS interview. Participants who fulfilled the diagnostic criteria for a major depressive episode were included in the study. Participants who fulfilled the criteria for either bipolar disorder, psychotic disorders, suicidality, or substance dependence were excluded from the study. Participants who were excluded from the study were thanked for their interest and informed that they are not eligible to participate in the study. Following the screening, we advised individuals, irrespective of the outcome of the screening, to contact their general practitioner in case they are concerned about their mood or negative feelings or thoughts.

Figure 1

Flowchart of the Study Process



Note. Dropouts were ascertained after randomisation. Underlined elements were only shown to the experimental group or to the control group after finishing the study. BADS: Behavioral Activation for Depression Scale (Kanter et al., 2007); BDI-II: Beck Depression Inventory (Beck et al., 1996); CBAS: Cognitive Behavioural Avoidance Scale (Röthlin et al., 2010); FRIS: Freiburg Reward Imagery Scale (https://osf.io/9y64q); Mini-DIPS: Diagnostic Short-Interview for Mental Disorders (Margraf et al., 2021); SUIS: Spontaneous Use of Imagery Scale (Kosslyn et al., 2001), TEPS: Temporal Experience of Pleasure Scale (Gard et al., 2006); WEMWBS: Warwick-Edinburgh Mental Wellbeing Scales (Tennant et al., 2007).

Experimental Condition

Participants in the experimental condition were asked to monitor their activity levels and mood for two days using an activity monitoring form (Martell et al., 2010). The form was introduced in session 1 and could be completed by following a link the participant received via e-mail. Subsequent sessions all lasted between 15 and 30 minutes. Session 1 was designed as an introductory session, focusing on psychoeducational elements such as the basic components of depressive disorders or the relation between activity and mood. Baseline questionnaires were assessed (including SUIS, BADS, TEPS, FRIS, BDI-II, CBAS, BEAQ, WEMWBS). Thereafter, the training rationale was explained i.e. why and how engagement in subjectively pleasant and rewarding activities can have a positive impact on mood and hence depressive symptoms. The content was provided in an interactive manner using text, graphics and audio materials. The session concluded with the introduction of an activity and mood monitoring form, to be used on two days before the next session. During subsequent sessions 2, 3 and 4, participants continued filling out activity monitoring forms, planning positive activities combined with engaging in a two minute imagery exercise designed to rehearse a vivid and detailed imagination of the positive activity, presented via an audio script (Renner et al., 2019). During the follow-up assessment two weeks after session 4, participants received questionnaires measuring activity levels (BADS), mental well-being (WEMWBS), depression (BDI-II) and a short questionnaire on the studies' feasibility. Participants were afterwards given thanks for their participation in the study and reimbursed for their time.

Waitlist Control Condition

Participants in the waitlist control condition only completed the standard questionnaires at baseline, at 4-weeks and in the follow-up assessment. After the last assessment, waitlist condition participants had the opportunity to follow the training of the experimental condition. The decision to follow or not to follow the training of the experimental condition to the full extent (i.e. completing all sessions) had no impact on the reimbursement of participants in the control condition.

Statistics and Figures

Statistical analyses were calculated using IBM SPSS (version 29), figures were compiled using LaTeX (Figure 1) and MATLAB (version 9.14.0, R2023a) (The MathWorks Inc., 2023) (Figure 2). All comparisons between dropouts and completers were calculated using independent samples t-tests, dichotomous variables (e.g. anxiety disorder, gender) are analysed using odds ratios (ORs).

Results

Dropout from the Study

An overall 12% of participants dropped out from the study prematurely. Table 2 shows characteristics of dropouts and completers respectively.

Table 2

Overview of Dropouts and Completers

	Completers		Dropouts	
	n	%	*n*	%
Gender				
Female	57	68.7	6	50
Male	25	30.1	6	50
Diverse	1	1.2	0	0
Treatment condition				
Training group	40	48.2	6	50
Control group	43	51.8	6	50
Age				
Mean	34.58		28.75	
SD	11.96		6.18	
Range	19-65		19-39	
Total	**83**	**87.4**	**12**	**12.6**

Note. $N = 95$ ($N = 46$ in the active training group, $N = 49$ in the waitlist control group).

Hypothesis 1

The probability to drop out from the programme is higher for male than for female participants.

An odd's ratio (OR) calculation was conducted and revealed no significant difference in the probability of dropping out from the study between male and female participants (OR = 2.28, 95% CI [0.670, 7.764], $p = .187$). Male participants, although were 2.28 times likelier to terminate the study prematurely. (*Note*: The diverse gender participant ($N = 1$) was filtered out for this analysis in order to execute the OR analysis).

Hypothesis 1.1

Dropouts show lower educational levels than completers.

An ordinal distribution of educational levels is assumed with values between 1 (University or postgraduate degree) and 6 (no educational degree). The 12 participants who dropped out of the study (M = 2.08, SD = 1.31) displayed higher mean educational levels compared to the 83 participants who completed the study (M = 1.80, SD = 1.07). This difference, -0.29, 95% CI [-0.96, 0.39] was not significant, $t(93) = -0.85$, $p = .199$; it did represent a small-sized effect, $d = 0.26$.

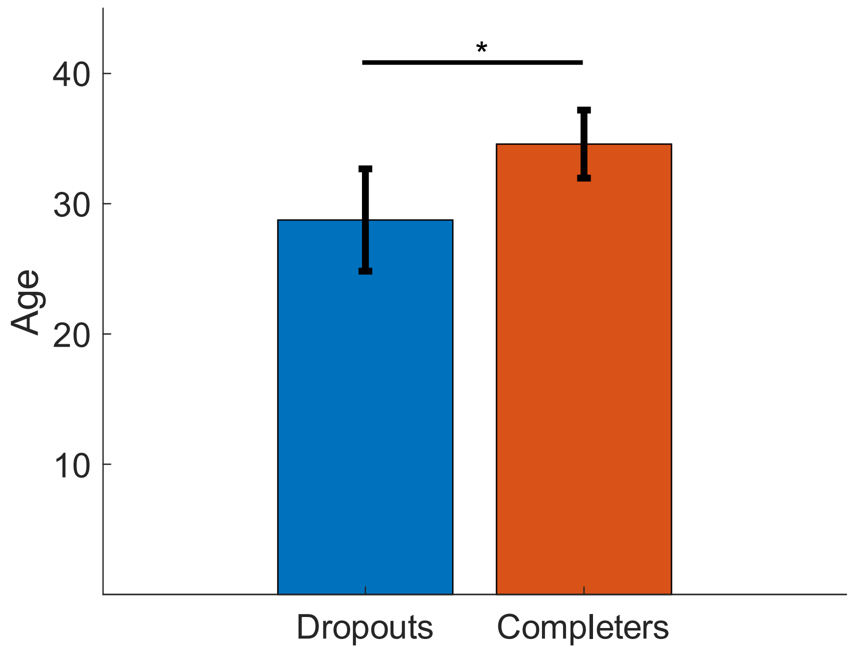
Hypothesis 1.2

Dropouts have a lower mean age than completers.

The 12 participants who dropped out of the study (M = 28.75, SD = 6.18) displayed a lower mean age compared to the 83 participants who completed the study (M = 34.58, SD = 11.96). This difference, -5.95, 95% CI [1.37, 10.51] was significant, $t(25) = 2.67$, $p = .006$; it did represent a medium-sized effect, $d = 0.52$. Levene’s test for equality of variances showed that equal variances could not be assumed and correctional factors were included in the calculation. A graph displaying the results can be seen in Figure 2.

Figure 2

Mean Age of Dropouts and Completers



Note. *N* = 95, Dropouts (N = 12), Completers (N = 83). Asterisk (*) represents a significance level below *p* = .05. Error bars show 95% confidence intervals.

Hypothesis 2

Dropouts are showing higher depressive levels at baseline measurement.

The 12 participants who dropped out of the study (*M* = 21.00, *SD* = 4.45) displayed lower depressive levels at baseline measurement compared to the 83 participants who completed the study (*M* = 22.06, *SD* = 5.90). This difference, 1.06, 95% CI [-2.46, 4.58] was not significant, *t*(93) = 0.60, *p* = .276; it did represent a small-sized effect, *d* = 0.18.

Hypothesis 2.1

The probability of participants with comorbid anxiety symptoms to drop out from the study is higher than of those without such comorbid symptoms.

Comorbid anxiety symptoms were assumed if participants were positively assessed for one of the tested anxiety disorders in the Mini-DIPS (i.e. panic disorder, agoraphobia, social anxiety disorder, specific phobia, generalised anxiety disorder). An odd's ratio calculation was conducted and revealed no significant difference in the probability of dropping out from the study between participants with and without comorbid anxiety symptoms (OR = 0.41, 95% CI [0.950, 1.777]). Participants with comorbid anxiety symptoms were by the factor 0.4 times less likely to terminate the study prematurely.

Hypothesis 2.2

Dropouts are showing lower levels of computer self-efficacy than completers.

The 11 participants who dropped out of the study (*M* = 3.58, *SD* = 0.99) displayed lower depressive levels at baseline measurement compared to the 72 participants who completed the study (*M* = 3.59, *SD* = 1.22). The observed difference, -0.015, 95% CI [-0.672, 0.643] was not significant, $t(81) = -0.044$, $p = .483$. (*Note*: For this analysis only *N* = 83 data points are reported because the respective items were added after the beginning of the study, hence the first 12 participants to start the study could not fill in the questionnaire).

Hypothesis 3

The probability of dropping out from the study is higher in the intervention group than in the waiting list group.

An odd's ratio (OR) calculation was conducted and revealed no significant difference in the probability of dropping out from the study between participants in the intervention group (N = 40) and the waiting list group (N = 43). (OR = 1.08, 95% CI [0.320, 3.608], $p = .91$). Thus, participants in the active training group were 1.08 times likelier to terminate the study prematurely.

Hypothesis 3.1

Feasibility ratings are lower for dropouts than for completers.

The three participants who dropped out of the study and filled in the feasibility questionnaire after dropping out (*M* = 3.86, *SD* = 0.48) displayed lower mean feasibility scores compared to the 66 participants who completed the study (*M* = 4.35, *SD* = 0.62). This difference, 0.49, 95% CI [-0.23, 1.22] was not significant, $t(67) = 1.36$, $p = .089$; it did represent a large-sized effect, $d = 0.81$.

(*Note*: For this analysis only N = 69 data points are reported because a number of participants did not fill in the feasibility questionnaire. Only three dropout participants could be reached to fill out the feasibility questionnaire after dropping out, hence only the data of three dropouts is reported).

Written Feedback by Participants

Participants were given the opportunity to prepare a written feedback in the course of the study. Written feedback included the following statements “Mit Hilfe der Studie habe ich eine Tätigkeit wieder aufgenommen, die mir gut tut und mich glücklich macht. Dafür bin ich sehr dankbar. [English translation] With the help of this study I have taken up an activity again that makes me feel good and brings me joy. I am very grateful for that”, “Ich persönlich fand das online Format sehr angenehm, gerade da der persönliche Kontakt mit unbekannten Menschen für mich eine Hürde darstellt. So könnte ich teilnehmen ohne mich unwohl damit zu fühlen. [English translation] Personally, I found the online format very pleasant, especially since personal contact with unfamiliar people is a hurdle for me. This way, I could participate without feeling uncomfortable about it“. Another feedback from a dropped out participant stated:

> Ich bin dankbar, dass die Teilnahme an dieser Studie mich auf Probleme, die vorher bereits da waren, aufmerksam gemacht hat und mir geholfen hat, eine Therapie zu beginnen.
>
> [English translation] I am grateful that participating in this study has made me aware of issues that were already present before and has eventually helped me to begin a therapy.

One participant further described his difficulties with completing the study modules:

> Ich fand es schwierig am Ball zu bleiben. Zum einen, da es ohnehin schwierig ist mit Depressionen, sich regelmäßig für etwas aufzuraffen. Zum anderen, weil die einzelnen Studiensitzungen zum Teil sehr lang waren,

> sodass ich es immer aufgeschoben habe, die nächste Sitzung zu bearbeiten. Leider konnte ich der Anonymität wegen nicht meine allgemeine Email-Adresse angeben, und habe so die Erinnerungen zur Aufforderung zur nächsten Sitzung nicht rechtzeitig gesehen.
>
> [English translation] I found it difficult to stay on track. On one hand, it's already challenging to motivate myself regularly for anything due to my depression. On the other hand, some of the study sessions were quite long, so I kept postponing working on the next session. Unfortunately, due to privacy reasons, I couldn't provide my regular email address and hence didn't see the reminders for the next session on time.

Overview dropout prediction factors

Only one of the assumed predictive factors of study dropout could be confirmed in the present analysis (Table 3). A *p* value of $p = .089$ in the feasibility assumption calculation indicates that there is a possible difference regarding the feasibility ratings between dropouts and completers if more participants are included in the analysis.

Table 3

Analysed Predictive Factors and their Statistical Significance

Factor	*p*	Significance
Gender	**.187**	**-**
Age	**.006**	**+**
Educational level	**.199**	**-**
Baseline Depressive levels	**.276**	**-**
Comorbid anxiety symptoms	**.234**	**-**
Computer self-efficacy	**.483**	**-**
Intervention condition	**.907**	**-**
Feasibility ratings	**.089**	**-**

Note. Significance is noted as negative (-) if respective p-values are greater than $p = .05$. Significance is noted as positive (+) if respective p-values are below $p = .05$.

Discussion

High dropout rates, especially under unclear circumstances as lacking exact numbers and possible reasons, pose a valid threat to digital and online interventions aimed at the treatment, improvement or prevention (e.g. psychoeducational programmes) of mental disorders. A great number of studies included in various meta analyses did not report dropout statistics altogether, let alone a more specific breakdown of dropout rates or potential factors facilitating dropout from the respective programmes (e.g. Christensen et al., 2009). Heterogeneous and large study samples are required to conduct meaningful analyses and comparisons, equally reaching diverse societal groups such as people from lower educational background, male participants or participants from low socioeconomic backgrounds. Only one of the suspected and analysed factors of dropout could be confirmed in this analysis (see Table 3). Age as a predictive factor of dropout is in line with literature, although mixed evidence exists (Elbert et al., 2016; Karyotaki et al., 2015; Linardon et al., 2018).

Cohen and Schleider (2022) make a very interesting point in presenting results that participant attrition was significantly higher in a paid, research-based context than in an unpaid, more naturalistic context. This could be one of the reasons why the observed dropout level is comparably low in this analysis. In a freely accessible naturalistic programme including 82,000 users, only 10% of participants completed more than one module (Batterham et al., 2008).

Concerning possible biases, Garrido et al. (2019) are discussing *attrition bias*, a bias resulting from not analysing or reporting dropouts and basing the subsequent analysis merely on the completed data sets. Thus, participants that quit a certain programme are often not included in the following analysis or resulting conclusions and recommendations.

Substantially important for large meta-analyses and further development of generally valid factors of dropout probability are high standards in measuring, analysing and reporting dropouts from online intervention programmes. The higher the data quality, the higher the chances of being able to develop precise and usable models for the prediction of dropouts, facilitating further research and eventually being able to prevent high rates of dropout from such interventions, resulting in a more economical use of research funds as well as a reduced proneness to discussed snares such as attrition bias. There is a growing need for high quality tools to define and analyse dropouts in online programmes, reducing the effort for upcoming research projects and subsequently leading to higher quality in results and conclusions. In a first step towards the goal, providing detailed and comprehensive information on dropped out participants should become common scientific standard for future publications.

If it proved to be likely that specific subgroups are not equally profiting from online intervention programmes, these findings would all the more emphasise the importance of acknowledging and implementing recent findings regarding factors leading to higher probabilities of dropout. If for instance men as a subgroup or depressive participants would structurally be more likely to dropout from online programmes, these findings would have to be taken into account when developing such programmes. Another issue that should be considered systematically is the body of people that cannot participate in and hence profit from online programmes altogether. This population includes people with no internet access or lacking cognitive capabilities to make proper use of digital technologies. Such considerations should play a role in not only designing and developing digital interventions but also in policy making processes and scientific analyses. Nevertheless, as mentioned before, a growing number of people has access to such technologies and is using it regularly. A noteworthy aspect is the case of participants or users dropping out from studies due to a significant symptom reduction. In such cases dropout would not be considered as “ negative” from the participants view, yet, if there is no specifically designed monitoring process for such cases, data on the dropouts would be lost for subsequent analyses.

It can be assumed that the dropout rate of the present study has been especially influenced by the high requirements in order to initially begin and eventually complete the study successfully. Among these requirements were not only strict exclusion criteria (no ongoing medical/psychotherapeutic treatment of any kind, BDI-2 score) but as well effortful steps in order to proceed within the study (online questionnaires, diagnostic telephone interview).

Another, more practical, yet important consideration in order to obtain high quality data on dropouts is the placement of questionnaires within the study, keeping in mind to place important measurements at the beginning of the study to have as many participants as possible, including dropouts and completers, completing them. This is especially difficult though with feasibility measures such as the one used in the present study, as it can't be presented at the beginning of the study. An alternative would be the constant presentation of smaller feasibility scales. Another option would be the method used in this analysis, to contact the dropouts after dropping out from the study. Albeit providing a very interesting opportunity to learn more about reasons for dropping out from the study, unfortunately chances are that only a small portion of dropouts will reply to the enquiry, although such participants that have ended the programme due to a symptom reduction might be more willing to participate. Participants, who are for example exasperated by either the extent or structure of the study are assumably less likely to be willing to respond to such queries. A distinctive remuneration (e.g. monetary or if applicable in form of experimental participant hours) would be an option to conquer such challenges, but could at the same time raise ethical issues or could easily be exploited by participants deliberately terminating the study.

It's noteworthy that 86.3% of all participants showed comorbid anxiety symptoms in at least one of the anxiety disorders tested for (i.e. panic disorder, agoraphobia, social anxiety disorder, specific phobia, generalised anxiety disorder). While this tendency is in line with literature results, it's a considerably higher rate than usually reported (Coplan et al., 2015; Pollack, 2005).

Another interesting explorative result is a large difference (i.e. difference representing a large effect) in Computer Self-Efficacy scores between men and women in the present sample (MD = 1.14, $t(78.5)$ = 6.38, p = <.001, d = 1.31). Even though we couldn't find a significant difference between men and women in this analysis, such structural differences in potentially dropout predicting characteristics are to be considered and further analysed.

An important direction for future research in the field is the development of a framework that allows researchers to analyse dropout rates in a simple and generalisable manner. This idea could be further developed into a standardised procedure that could be filled out by researchers to make comparisons between large groups of participants possible. With an easily applicable and extensive protocol, large comparative analysis would be possible.

All dropped put participants (*N* = 12) were contacted after terminating the study, yet only three reacted to the invitation and filled in the feasibility questionnaire. Despite the small sample size of dropped out participants, this low response rate could provide an insight into dropout participants' low willingness to interact with the study in general and after dropping out.

Strengths and Limitations

A distinctive strength of the present analysis is the extensive analysis of dropped out participants features and characteristics. Furthermore, contacting dropouts after they have terminated the study is a rarely adopted approach in scientific studies approach that buries great potential although it didn't yield desired results in this case. This thesis is distinct from other literature in the field in that it includes further variables like computer efficacy (i.e. one's self efficacy regarding computer related tasks and knowledge) in the evaluation and includes thorough psychiatric diagnostics made during a phone call with participants.

A pivotal limitation is the mere focus on participants with depression in the present study. Since lack of motivation and inactivity are commonly regarded as symptoms related to depressive disorders, this fact could have influenced results on a number of levels. A healthy (i.e. non-depressive) study population could have produced higher dropout rates, since the healthy participants are not symptom-laden and have less willingness to change. Thus motivation could have been higher in the present sample as to their intention to take measures against their depressive symptoms. On the other hand, that lack of depressive symptoms could have facilitated participation for healthy participants. A further limitation is certainly the strongly research-driven context compared to a naturalistic environment, especially due to the reimbursement being given to participants. These two factors alone or combined could have potentially influenced participants behaviour to a high degree.

A further limitation of the present study is certainly the small sample size and the unclear level of guidance (*unclear*, i.e. not usually used in other studies in the field) which makes it difficult to compare to other, larger studies and results from meta-analyses. A mere online study would have possibly yielded more dropouts but could have been more easily compared to other studies in the literature.

Written Feedback Qualitative Analysis

The statements cited in the result section illustrate the various reasons of not completing a study, one possible reason being the subjective or actual achievement of goals related to the respective study (e.g. improvement of depressive symptoms or beginning a therapy in the present intervention). Thus it can be seen as representing some of the various motives of dropping out of a study. Whilst some may just be not willing to further participate for no particular reason, some others may have more pronounced or distinct causes to not complete a certain study. If, although, we have no information about the dropouts whatsoever, all this potential information is lost.

Qualitative Feedback could be a further component of an improved dropout analysis as it gives participants a unique chance to freely express their opinions on the study in their own words as well as possible reasons for dropout. A disadvantage of written feedback is its relative high requirement towards participants. Data protection considerations could play a pivotal role in reaching out to dropped out participants, hence getting allowance from participants to contact them even in the event of prematurely the study or programme could facilitate the process of follow-up questioning.

Conclusion

In the present study I analysed dropout rates and potentially predictive factors of dropout in an online intervention based on imagery behavioural action, targeted at a depressive population. I evaluated possible predictive factors of dropout, I developed out of a literature search. Only one of these factors (lower age) could be confirmed in this analysis to be a significant predictive factor of dropout from an online study. If more such factors could be determined in future research and analyses, researchers could specifically target specific groups before or during research studies, online programmes or further (health) applications. Furthermore, contacting dropped out participants after their termination of the study as well as gathering and surveying written feedback, i.e. qualitative data, could considerably improve our knowledge of dropout motivations and eventually lead to a greater understanding of possible generalisable predictive factors of dropout.

Since it can be assumed that digital interventions, trainings and applications are only to gain significance in the coming years, the issue of people dropping out from such programmes will remain a central topic. Measures to prevent and analysis tools to closely monitor and report such dropouts should be a pivotal element of future research in the field. Only comprehensive, high quality data will allow for the determination of valid predictive factors of dropout and hence yield precisely tailored solutions to avoid premature terminations.

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List of Tables

List of Figures

Appendix

Abstract [English]

High dropout rates remain a pivotal challenge in online studies and interventions. Generalisable predictive factors of dropout remain unclear as high quality analyses are rare. In the present thesis, 95 participants within a mental imagery behavioural activation training for depression in a Germany-wide study were analysed and potentially predictive factors of early dropout were examined. The work adds new facets to the existing literature as it incorporates factors like Computer Self-Efficacy and psychiatric diagnoses as well as contacting participants after an early dropout, thus providing a new and comprehensive framework for future research and dropout analysis. Only one of the analysed factors analysed in this thesis could be statistically confirmed, finding that age, in line with previous literature, is a valid predictor of dropout in the present sample ($d = 0.52$). This thesis discusses problems of high attrition and dropout rates and aims at proposing strategies to reduce attrition and enhance participant engagement.

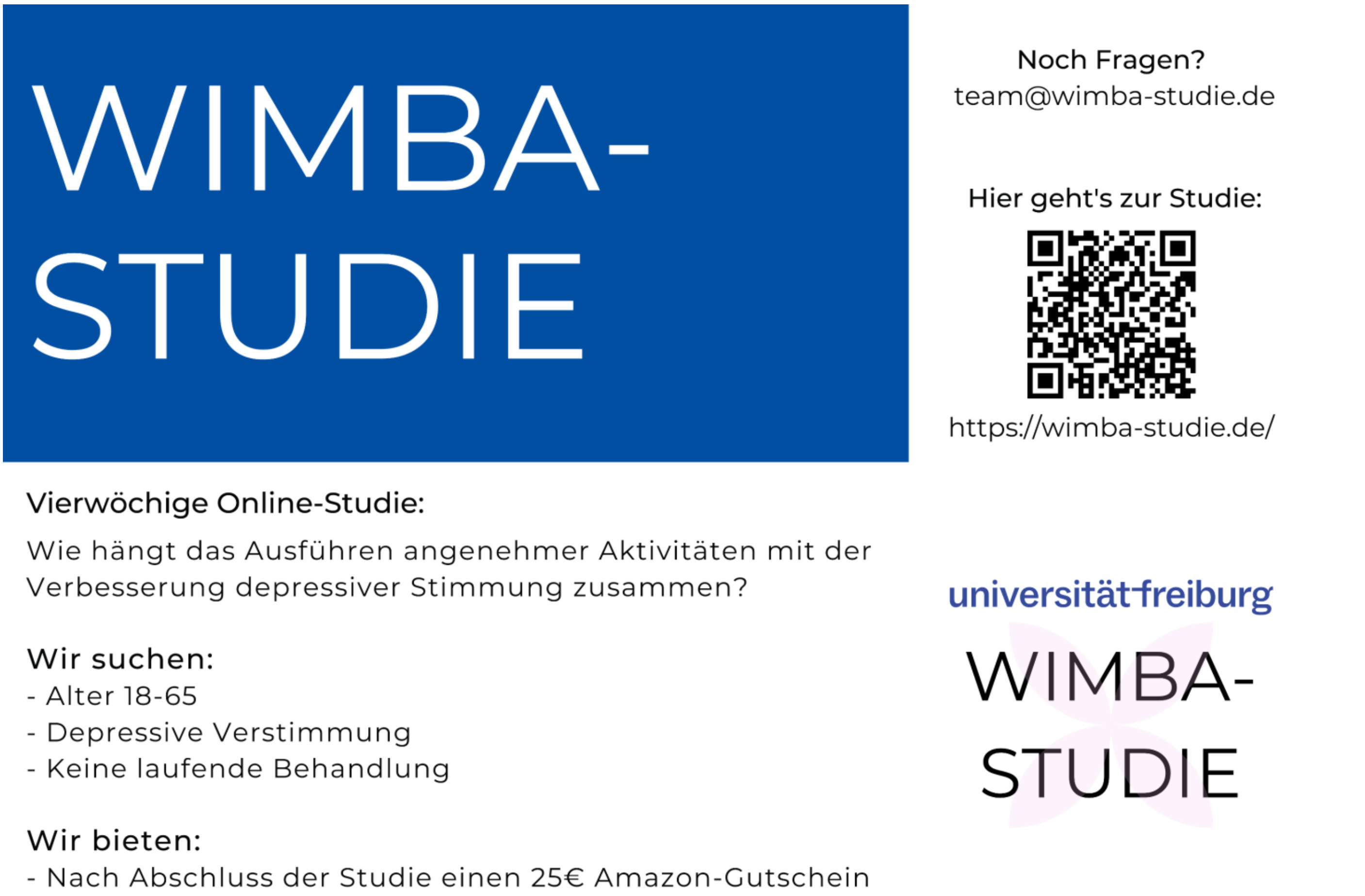
Keywords: dropout, online interventions, dropout prediction, depression, internet-based therapy

Abstract [Deutsch]

Hohe Dropoutraten stellen ein großes Problem für Online-Studien, Online-Trainings sowie Online-Interventionen dar. Die vorliegende Studie untersucht mögliche Faktoren und Gründe für den verfrühten Abbruch der Studie anhand einer Stichprobe von 95 Proband*innen einer deutschlandweiten Online-Studie. Die Studie testet eine Intervention für depressiv belastete Menschen, die mithilfe imaginationsgestützter Verhaltensaktivierung in der Planung und Ausführung angenehmer Tätigkeiten unterstützt werden sollen. Die Thesis unterscheidet sich von der bereits existierenden Literatur dahingehend, dass Faktoren wie Computer-Selbstwirksamkeit und psychiatrische Diagnosen in die Dropout-Analyse integriert wurden. Außerdem wurden Proband*innen nach ihrem Dropout nochmals kontaktiert. Damit bietet die Arbeit ein Framework zur Dropoutanalyse für zukünftige Studien. Es konnte nur einer der untersuchten, potentiell prädiktiven Dropoutfaktoren statistisch bestätigt werden. So konnte gezeigt werden, dass in der untersuchten Stichprobe die Teilnehmer*innen, die die Studie abgebrochen hatten signifikant jünger waren als diejenigen, die die Studie zu Ende geführt haben (d = 0.52). Die Thesis erläutert die Probleme hoher Abbruchraten insbesondere in online-basierten Interventionen und skizziert potentielle Strategien zur systematischen Analyse und Prävention vorzeitiger Studienabbrüche.

Keywords: Dropout, Online-Interventionen, Dropoutfaktoren, Depression, internetgestützte Therapie

Study Flyer



Computer Self-Efficacy Scale (CSE)

	Stimme nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme zu
Ich traue mir zu, Probleme am PC selbst zu lösen.	○	○	○	○	○
Ich fühle mich sicher im Umgang mit Fachbegriffen aus dem Bereich Computerhardware.	○	○	○	○	○
Ich traue mir zu, erklären zu können, wieso ein Softwareprogramm auf einem bestimmten PC funktioniert oder nicht funktioniert.	○	○	○	○	○
Ich traue mir zu, simple PC-Programme selbst zu schreiben.	○	○	○	○	○

Absenden

WVFS4XXeHm ()

Feasibility Scale

Ich habe mich während der Studie **gut geleitet** gefühlt.	0	1	2	3	4	5	6
Die Instruktionen und Arbeitsaufträge waren **verständlich** und es wurde **deutlich**, was von mir gefordert wurde.	0	1	2	3	4	5	6
Das **Online-Format** der Studie empfand ich als angenehm.	0	1	2	3	4	5	6
Ich hätte mir **mehr persönliche Interaktion** mit den Ansprechpartnern gewünscht.	0	1	2	3	4	5	6
Die **Anzahl der Sitzungen** war für mich angenehm.	0	1	2	3	4	5	6
Die **Dauer der Studie** insgesamt empfand ich als angenehm.	0	1	2	3	4	5	6
Ich würde die Teilnahme an dieser Studie einem Freund/ einer Freundin **empfehlen**.	0	1	2	3	4	5	6
Die verschiedenen Aspekte der Studie (Audio, Text, Grafiken) waren **abwechslungsreich**.	0	1	2	3	4	5	6
Die verschiedenen Aspekte der Studie (Audio, Text, Grafiken) waren **überfordernd**.	0	1	2	3	4	5	6
Ich habe die Studie **ernsthaft** durchgeführt.	0	1	2	3	4	5	6

Participant information [German original]

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Allgemeine Information für Teilnehmende der Online-Studie zum Zusammenhang zwischen Stimmung und Aktivitäten (WIMBA-Studie)

Herzlich willkommen bei unserer Online-Studie zum Zusammenhang zwischen Stimmung und Aktivitäten. Wir danken Ihnen für Ihr Interesse an dieser Studie.

Nehmen Sie sich bitte die Zeit, die folgenden Informationen zu lesen, bevor Sie sich entscheiden, ob Sie an dieser Studie teilnehmen möchten. Bitte wenden Sie sich an eine der unten genannten Kontaktpersonen, wenn Sie etwas nicht verstehen oder zusätzliche Informationen erhalten möchten.

Ausführliche Beschreibung des Forschungsvorhabens

In dieser Studie untersuchen wir, wie sich Menschen in ihrer Fähigkeit unterscheiden, sich auf alltägliche Aktivitäten einzulassen (z.B. Dinge, die wir gerne tun würden, die wir aber manchmal nicht ganz umsetzen) und Faktoren, die ebendiese Fähigkeit beeinflussen könnten, wie z.B. unser Denkstil, wie viel Freude wir an Aktivitäten haben und unsere Stimmung.

Inhalt und Zweck der Studie

Vor Beginn der Studie wird ein kurzes zweistufiges Screening durchgeführt, um zu prüfen, ob Sie die Voraussetzungen erfüllen, um an der Studie teilnehmen zu können. Der erste Teil des Screening- Verfahrens findet online statt. Hier werden Ihnen einige Fragen zur möglichen Erfahrung mit einer niedergeschlagenen, traurigen Stimmung während der letzten zwei Wochen gestellt. Wenn Sie nach diesem ersten Online-Screening die Voraussetzungen zur Teilnahme an dieser Studie erfüllen, wird ein Telefontermin für den zweiten Teil des Screenings geplant. Der zweite Teil des Screenings findet per Telefon statt. Hierfür wird vorab ein Termin mit Ihnen vereinbart. Das Telefonscreening findet mit einer Mitarbeiterin oder einem Mitarbeiter des Forschungsteams statt. Um zu prüfen, ob Sie die Voraussetzungen zur Teilnahme an dieser Studie erfüllen, werden wir Ihnen einige Fragen zu möglichen Erfahrungen mit psychischen Problemen stellen. Wenn sich nach diesem Gespräch herausstellt, dass Sie teilnehmen können und auch teilnehmen möchten, bekommen Sie einen Link zugeschickt, um mit der Online-Studie zu starten. Sollten Sie die Vorrausetzungen zur Teilnahme an dieser Studie nicht erfüllen, können Sie leider nicht teilnehmen. Sie werden dann eine entsprechende Benachrichtigung erhalten.

Die im Screening erhobenen Fragen können Hinweise auf das Vorliegen einer psychischen Störung liefern. Im Rahmen der Studie wird jedoch keine ausführliche klinische Diagnostik durchgeführt so dass wir Ihnen im Anschluss an das Screening weder eine evtl. Diagnose einer psychischen Störung mitteilen können noch konkrete Hilfsangebote vermitteln können. Sollten Sie sich, unabhängig von den Ergebnissen des Screenings, aufgrund möglicher psychischer Probleme Sorgen machen, empfehlen wir Ihnen zunächst Kontakt mit Ihrer Hausarztpraxis aufzunehmen.

Randomisierung in unterschiedliche Versuchsbedingungen

Um den Effekt des Online-Trainings zu evaluieren, werden Personen, die an dieser Studie teilnehmen, nach dem Zufallsprinzip einer von zwei Versuchsbedingungen zugeteilt: Einer aktiven Trainingsgruppe oder einer Wartelisten-Gruppe. In der aktiven Trainingsgruppe werden wir Sie bitten, Aktivitäten für die kommenden sieben Tage über einen Zeitraum von 14 Tagen einzuplanen, die Ihnen Freude bereiten könnten. Wir werden Sie im Anschluss an das Einplanen der Aktivitäten außerdem bitten, auf eine bestimmte, besonders lebhafte Art und Weise über die Aktivitäten nachzudenken.

Aktive Trainingsgruppe:

Die Studie findet über einen Zeitraum von 4 Wochen statt und gliedert sich in 4 Module. Alle 4 Module finden online statt und Sie können bequem von ihrem Computer, Tablet oder Smartphone aus teilnehmen.

Modul 1: Zunächst werden wir Sie bitten, einige Fragebögen über Ihre Persönlichkeit und Stimmung auszufüllen. Anschließend erhalten Sie einige Informationen über den Zusammenhang zwischen alltäglichen Aktivitäten und der Stimmungslage. Abschließend werden wir Sie bitten, über den Zeitraum einer Woche, also bis zum nächsten Modul, an insgesamt zwei Tagen Ihre Aktivitäten und Ihre Stimmung zu dokumentieren.

Modul 2: Im zweiten Modul werden Sie gebeten, zwei alltägliche, positive Aktivitäten auszuwählen und in einen Wochenplan einzuplanen. Sie werden außerdem eine kurze Audiosequenz hören, die sich auf die eingeplanten Aktivitäten bezieht.

Modul 3: Das dritte Modul ist identisch zu dem zweiten Modul, außer dass wir Sie diesmal bitten, 3 Aktivitäten einzuplanen.

Modul 4: Im letzten Modul werden wir Sie bitten, einige Fragebögen zu Ihrer Stimmung und Ihrem allgemeinen Aktivitätsniveau auszufüllen. Anschließend erhalten Sie nochmals einige Informationen über den Zusammenhang zwischen alltäglichen Aktivitäten und der Stimmungslage.

Zwei Wochen nach dem letzten Modul werden wir Sie per E-Mail kontaktieren und Sie bitten, nochmals einige Fragebögen zu Ihrer Stimmung und Ihrem allgemeinen Aktivitätsniveau auszufüllen.

Die Bearbeitung eines Moduls wird jeweils zwischen 10-30 Minuten in Anspruch nehmen. Insgesamt wird die Teilnahme an dieser Studie ca. 2 Stunden in Anspruch nehmen.

Wartelisten-Gruppe:

Wenn Sie der Wartelisten-Gruppe zugeordnet wurden, werden wir Sie bitten, zu insgesamt fünf Zeitpunkten eine Reihe von Fragebögen auszufüllen: Messzeitpunkt 1: zum Start der Studie; Messzeitpunkte 2-4: jeweils im Abstand von einer Woche; und Messzeitpunkt 5: zwei Wochen nach Messzeitpunkt 4. Das Ausfüllen der Fragebögen zum Messzeitpunkt 1 wird etwa 20 Minuten in Anspruch nehmen. Das Ausfüllen der Fragebögen zu den Messzeitpunkten 2 - 5 wird jeweils ca. 10 Minuten in Anspruch nehmen.

Nach dem Ausfüllen der Fragebögen zum Messzeitpunkt 5 haben Sie die Möglichkeit an der aktiven Trainingsgruppe teilzunehmen. Auf diese Weise haben Sie die Möglichkeit, das Training ebenfalls in vollem Umfang zu nutzen. Wenn Sie sich nach dem Ausfüllen der Fragebögen zum Zeitpunkt 5 dazu entscheiden, nicht an dem aktiven Training teilzunehmen, hat dies keine Auswirkungen auf die Auszahlung der Vergütung.

Vergütung

Für die Teilnahme an der Studie erhalten Sie zum Ende der Studie einen Amazon-Gutschein in Höhe von 25 €. Sollten Sie die Studie zu einem früheren Zeitpunkt beenden, haben Sie Anspruch auf eine entsprechende Teilvergütung.

Betroffener Personenkreis

Für diese Studie suchen wir Personen zwischen 18 und 65 Jahren. Es können nur Personen an dieser Studie teilnehmen, die während der letzten zwei Wochen eine mild bis mittelmäßig belastete, niedergeschlagene und traurige Stimmung erfahren haben und die diagnostischen Kriterien für eine depressive Episode/Phase erfüllen. Personen, die keine niedergeschlagene, traurige Stimmung hatten oder eine stark niedergeschlagene oder traurige Stimmung hatten, können leider nicht an der Studie teilnehmen. Des Weiteren können keine Personen teilnehmen, bei denen zum Zeitpunkt der Studienteilnahme Hinweise für das Vorliegen einer der folgenden psychischen Störungen bzw. psychischen Probleme festgestellt werden: Bipolare Störung, Psychose, Suizidalität, Substanzabhängigkeit. Dies wird im Vorfeld der Studienteilnahme mittels eines zweistufigen Screenings erfasst.

Wir bitten Sie, an dieser Studie nur teilzunehmen, wenn:

- Sie derzeit **keine Behandlung** wegen einer psychischen Erkrankung (psychotherapeutisch/medikamentös) erhalten.
- Sie fließend Deutsch sprechen und verstehen (Muttersprache oder ab C1-Niveau).

Zu erhebende Daten

In dieser Studie werden die folgenden personenbezogenen Angaben erhoben:

- Alter- E-Mail Adresse
- Nachname
- Telefonnummer
- Geschlechtsidentität
- berufliche Tätigkeit

- Bildungsabschluss
- Einstellungen/Überzeugungen (Fragebogendaten)

Analyseergebnisse der Daten

Die Auswertung der Daten erfolgt ausschließlich im Rahmen des Forschungsprojekts.

Lagerung und Weitergabe von Daten

Alle Daten werden vertraulich behandelt. Für die Erhebung wird die Online-Plattform „formr" (https://www.formr.org) genutzt, die vom Georg-Elias-Müller Institut für Psychologie der Universität Göttingen betrieben wird. Alle Daten werden verschlüsselt (SSL) übertragen, ausschließlich auf Servern in der Bundesrepublik Deutschland gespeichert und unterliegen somit der Datenschutz- Grundverordnung (DS-GVO). Über die in Punkt 4 genannten Daten hinaus, werden dabei keine personenbezogenen Daten (wie etwa IP-Adressen, MAC-Adressen, etc.) protokolliert/gespeichert. Die weitere Speicherung der Studiendaten erfolgt ausschließlich auf passwortgeschützten, institutsinternen Servern, die gegen unautorisierten Zugriff gesichert sind. Es besteht die Möglichkeit, dass vollständig anonymisierte Daten über eine Internet-Datenbank (z.B. Open Science Framework; www.OSF.io) öffentlich zugänglich gemacht werden oder mit anderen Forschenden auf Anfrage geteilt werden. Dieses Vorgehen dient der Sicherstellung guter wissenschaftlicher Arbeit. Andere Forschende können dadurch beispielsweise die Auswertung nachvollziehen oder eine alternative Auswertung testen.

Beteiligte, Datenflüsse und speichernde Stellen

Die in dieser Studie erhobenen Daten sind nur den an der Studie beteiligten Forschern der Universität Freiburg, Abteilung für Klinische Psychologie und Psychotherapie, zugänglich. **Konkrete Dauer der Speicherung**

Die Aufbewahrungsfrist für die vollständig anonymisierten Daten beträgt mindestens 10 Jahre nach Datenauswertung, bzw. mindestens 10 Jahre nach Erscheinen einer Publikation zu dieser Studie.

Pseudonymisierungsverfahren

Die Erhebung und Verarbeitung Ihrer oben beschriebenen persönlichen Daten erfolgt unter Verwendung einer Versuchspersonennummer und ohne Angabe Ihres Namens (d.h. pseudonymisiert) in der Abteilung Klinische Psychologie und Psychotherapie am Institut für Psychologie der Albert-Ludwigs-Universität Freiburg. Es existiert eine Kodierliste, die Ihren Namen mit der Nummer verbindet. Die Kodierliste ist nur den Versuchsleitern und dem Projektleiter zugänglich; das heißt, nur diese Personen können die erhobenen Daten mit Ihrem Namen in Verbindung bringen. Die Kodierliste wird sicher aufbewahrt und nach Abschluss der Datenauswertung, spätestens aber am 31. Dezember 2023, vernichtet. Ihre Daten sind dann anonymisiert. Damit ist es niemandem mehr möglich, die erhobenen Daten mit Ihrem Namen in Verbindung zu bringen.

Hinweis: Die Erhebung Ihres Nachnamens erfolgt ausschließlich zu dem Zweck, die an Sie versendeten Emaileinladungen zu personalisieren und für den telefonischen Kontakt im Rahmen des Screeningverfahrens. Wir empfehlen Ihnen die Verwendung einer Emailadresse, die keinen Rückschluss auf Ihren Klarnamen zulässt. Wie oben beschrieben, werden diese Informationen nach Abschluss der Erhebung unwiderruflich gelöscht.

Rechtsgrundlagen

Datenschutzgrundverordnung (DSGVO) sowie Ihre Einverständniserklärung zur Studienteilnahme.

Widerruf seitens des/der Betroffenen

Sie haben das Recht, jederzeit die datenschutzrechtliche Einwilligung zu widerrufen. Durch den Widerruf der Einwilligung wird die Rechtmäßigkeit der aufgrund der Einwilligung bis zum Widerruf erfolgten Verarbeitung nicht berührt (Widerruf mit Wirkung für die Zukunft). Richten Sie den Widerruf an die Verantwortlichen. Ihnen entstehen durch den Widerruf keine Nachteile. Nach Eingang des Widerrufs werden die personenbezogenen Daten gelöscht. Solange die Kodierliste existiert, können Sie die Löschung aller von Ihnen erhobenen Daten verlangen. Ist die Kodierliste aber erst einmal gelöscht, können wir Ihren Datensatz nicht mehr identifizieren. Deshalb können wir Ihrem Verlangen nach Löschung Ihrer Daten nur solange nachkommen, wie die Kodierliste existiert.

Namen, Kontaktdaten des/der Verantwortlichen

Bei Fragen oder anderen Anliegen können Sie sich an die folgenden Personen wenden:

Versuchsleitung:	**Projektleiter**:
Max Heise, M.Sc.	Dr. Fritz Renner
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Kontaktdaten des/der Datenschutzbeauftragten

Albert-Ludwigs-Universität Freiburg
Der Datenschutzbeauftragte
Fahnenbergplatz, 79085 Freiburg
datenschutzbeauftragter@uni-freiburg.de

Hinweis auf Rechte der Betroffenen

Gemäß Art. 13 Abs.2 lit. b der Datenschutzgrundverordnung haben Sie das Recht auf:

- Auskunft (Art. 15 DSGVO und §34 BDSG)
- Widerspruch (Art. 21 DSGVO und §36 BDSG)
- Datenübertragbarkeit (Art. 20 DSGVO)
- Löschung (Art. 17 DSGVO und §35 BDSG)
- Einschränkung der Verarbeitung (Art. 18 DSGVO)
- Berichtigung (Art. 16 DSGVO).

Möchten Sie eines dieser Rechte in Anspruch nehmen, wenden Sie sich bitte an die Verantwortlichen.

Weiterhin haben Sie das Recht, sich bei der für die Albert-Ludwigs-Universität zuständigen Aufsichtsbehörde über die Verarbeitung Ihrer personenbezogenen Daten durch das Forschungsprojekt zu beschweren.