Unlocking Patterns of Study Adherence and Intervention Usage in Internet-Based Interventions for Depression and Body-Focused Repetitive Behaviors

An Exploratory Analysis

Paula Wurth

Department of Clinical Psychology
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Supervisors: Per Carlbring & Steffen Moritz (University Medical Center Hamburg-Eppendorf)

Stockholms universitet

Background: Low adherence in internet-based interventions and trial settings can limit the interpretation of effectiveness coefficients in self-guided internet-based interventions. Little is known about what precedes and characterizes adherence by considering dropout prior to post-assessment and intervention usage. This study exploratively investigated the predictive power of possible predictors of study adherence and intervention usage.

Methods: A secondary analysis of two randomized controlled trials (RCTs) was conducted, separately examining an internet-based interventions for depression (*Deprexis)* and body-focused repetitive behaviors (*Free from BFRB*), involving 1,013 and 279 participants resepctively. Backward stepwise multiple linear and logistic regression identified significant predictors.

Results: Participants with higher anonymity (OR = 0.41 - 0.63), receiving guidance (OR = 0.70), and being in the intervention group (OR = 0.51) were less likely to adhere to the study, while older individuals (OR = 1.21), those having prior psychotherapy attempts (OR = 1.30), and comorbid anxiety (OR = 1.68) were more likely to adhere. Area under the curve (AUC) measures were low to moderate ($AUC_{Deprexis}$ = 0.62; $AUC_{FreeFromBFRB}$ = 0.58). Older adults and females spent more time engaging with the intervention (approx. 50 - 60 minutes longer), whereas those individuals with a comorbid posttraumatic stress disorder (PTSD) diagnosis spent less time with the intervention (approx. 112 minutes less).

Conclusions: Although predictors of internet-based intervention adherence are still widely unknown, preliminary evidence of this study suggests that factors like sociodemographic variables, anonymity, guidance, group assignment, psychotherapy experience, and comorbidities influence internet-based intervention adherence. Future research is needed to quantify their predictive power.

Keywords: internet-based interventions, adherence, depression, body-focused repetitive behaviors, exploratory analysis

Introduction

Mental disorders such as Major Depressive Disorder (MDD) affect around 280 million people globally (Institute of Health Metrics and Evaluation, 2023), yet the majority of affected individuals remain untreated (Kohn et al., 2004). The internet has changed how we communicate and connect with each other (Krotoski, 2013). In psychotherapy, computers have been used for various purposes, ranging from facilitating assessment to delivering interventions, ever since the late 90s (Marks et al., 1998). The implementation of computers, over to the development of fully computerized treatments as a subsequent step, has led to a rapidly growing body of evidence in online psychotherapy research. The steady development of digital interventions accounts for potential issues of conventional face-to-face psychotherapy, including its increased costs and limited accessibility (Andersson & Carlbring, 2022). Technology can substitute important components of therapy, for example providing text-based treatments (*bibliotherapy*), conducting a face-to-face therapy using a video call, or a full delivery of psychological treatments via the internet. Finally, since the global COVID-19 pandemic occurred, researchers and practitioners realized an increased need for online-delivered psychotherapy alternatives. Although experts marked an end of the pandemic, the demand for remote psychotherapy sustained due to its remarkable benefits. These include for instance the ability to attend sessions from the comfort of individuals' homes and flexible scheduling. Consequently, internet-based psychological treatment continued to develop and adapt to ongoing needs. While internet-based interventions have been evidenced as effective in empirical literature (e.g., Karyotaki et al., 2017), research also recognized considerable dropout rates in randomized controlled trials (RCTs) and low adherence to the taught techniques in online treatments (Kaltenthaler et al., 2008). High dropout rates and poor adherence in online treatments can undermine the effectiveness of interventions and limit the potential benefits for individuals seeking help. Little is known about what precedes low adherence. The present study examined possible predictors to explain why participants show low adherence to self-help internet-based interventions

Theoretical Background

Multiple ways prevail on how to implement digital innovations in psychotherapy. Thus, empirical research found a multitude of terms in this field, i.e. “online psychotherapy”, “internet-delivered psychotherapy”, “e-therapy”, and “teletherapy” (Smoktunowicz et al., 2020). Generally, internet-delivered treatments vary in the degree of guidance or human contact they offer. This can involve live video therapy sessions, digitalized self-help programs that operate without human guidance, or self-help interventions with some level of human interaction, such as chat messages (Andersson et al., 2019). This study will use the conceptualization of internet-based interventions according to Andersson and Carlbring (2022) as “treatments that rely on modern information technology delivered using the internet. To narrow down the scope, the focus will be on internet-delivered psychological treatment that mainly use techniques and approaches from evidence-based psychotherapies like cognitive behavior therapy” (Andersson & Carlbring, 2022, p. 194). Essentially, this paper concentrates on self-help interventions aimed at reducing symptom levels while minimizing human guidance.

Internet-based Interventions

Given the increasing demand for online mental health services, clinical researchers and practitioners are actively working to develop effective internet-based interventions. These interventions aim to address the rising prevalence of mental disorders (WHO, 2022) through online delivery. Empirical literature consistently reveals moderate effect sizes associated with internet-based interventions (e.g., Karyotaki et al., 2021). However, RCTs and meta-analyses in that field vary across several parameters. Effectiveness studies approach interventions from various perspectives: 1) comparison between internet-based interventions and various control conditions, 2) comparing guided and unguided versions, 3) contrasting guided internet-based interventions with traditional on-site psychotherapy, and 4) evaluating programs tailored to a specific diagnosis versus transdiagnostic interventions. In internet-based intervention trials, the primary outcome is usually symptom severity. Therefore, effectivenes is measured by the degree of symptom reduction in the follow-up assessment. The following paragraphs will elaborate on each parameter in detail.

Internet-based interventions versus different control conditions. Many RCTs sought to assess the effectiveness of internet-delivered psychological treatments by comparing them to a range of control conditions, such as treatment as usual and waitlist control conditions (Goldberg et al., 2023). Generally, these studies showed promising outcomes, suggesting that the use of internet-based interventions is associated with psychological symptom improvement compared to control groups across different mental and somatic conditions in RCTs (e.g., Rosso et al., 2017; Schmotz et al., 2023; Klein et al., 2016), review articles (e.g., Kumar et al., 2017; Richards & Richardson, 2012), and representative individual participant data meta-analyses (e.g., Karyotaki et al., 2017; Andrews et al., 2010). Generally, this trend underscores the potential of internet-based interventions as a valuable option in clinical practice, even in the long term (Andersson et al., 2018).

Guided versus unguided. Internet-based interventions vary in the degree of human guidance provided, rather than being strictly categorized into guided or unguided. For example, the implementation of automated feedback based on participants' input and asynchronous communication tools offer varying levels of guidance on a continuum, rather than being strictly binary. Yet, empirical research commonly compares guided and unguided interventions to quantify their potential, often as a binary distinction. Numerous studies frequently compared the effectiveness of guided internet-delivered interventions to unguided or self-help internet-based interventions programs. Guided programs typically involve support of a clinical expert who provides feedback, encouragement, and assistance throughout the treatment, whereas unguided versions rely on self-help (Andersson et al., 2019). In fact, guided programs can be further distinguished according to the consistency of support (on demand versus regular support). On-demand clinical support was linked to similar effect sizes compared to regular support (Käll et al., 2023). Across these empirical studies, a trend emerged, indicating that guided internet-based interventions yield superior outcomes (Karyotaki et al., 2021; Richards & Richardson, 2012). Mohr and colleagues developed a model to explain this trend, suggesting that the higher effectiveness and adherence seen in online interventions with human support can be attributed to what they call "Supportive Accountability" from the guiding expert (Mohr et al., 2011). Some studies, however, revealed that guided and unguided interventions were equally effective (Hagberg et al., 2023). Overall, although clinician guided internet-based interventions appear to be superior to unguided versions, people still significantly benefit from unguided interventions (Karyotaki et al., 2021; Seewer et al., 2024).

Guided internet-based interventions versus face-to-face psychological treatment. A central concern when implementing internet-based interventions as a cost-efficient alternative to the "gold-standard" on-site psychological treatment (Hedman-Lagerlöf et al., 2023) is the ability of these interventions to complement or even replace the conventional approach. It becomes increasingly important to evaluate effectiveness measures in direct comparison to traditional psychotherapy. In fact, comparing guided internet-based interventions to face-to-face psychotherapy allows researchers and clinicians to assess whether the benefits of internet-based interventions extend beyond convenience and accessibility to include comparable therapeutic outcomes. In a meta-analysis, Hedman-Lagerlöf and colleagues found similar effects in RCTs comparing therapist-supported cognitive behavior therapy and face-to-face therapy (2023). However, in comparison to the extensive body of literature in this field, relatively few studies have been found that directly compare internet-based interventions to face-to-face therapy (Andersson et al., 2014; Carlbring et al., 2018; Hedman-

Lagerlöf et al., 2023). Nevertheless, the effect sizes are homogeneous across studies and diagnoses and so far, speak for a non-inferiority of internet-based interventions compared to face-to-face treatments in terms of symptom reduction.

Tailored to diagnosis versus transdiagnostic approach. Another trend that emerged is to develop internet-based interventions to target particular psychological problems rather than treatment focusing on a specific diagnosis, like major depression (such as *Deprexis;* Meyer et al., 2009) or generalized anxiety disorder (such as *Worry program*; Titov et al., 2009). The transdiagnostic approach enables alignment with the complex clinical reality of comorbidities (Andersson & Carlbring, 2022; Andersson et al., 2011). Such interventions could target for example programs on assertiveness (Hagberg et al., 2023) or on procrastination (Rozental et al., 2015), addressing underlying mechanisms relevant across various psychological conditions. Another way to deal with comorbidities is to tailor internet-based interventions to individual needs. Unlike transdiagnostic interventions, which apply broadly to different participants, individually tailored internet-based interventions adjust treatment based on participants' unique symptom levels, preferences, or characteristics (Păsărelu et al., 2017). In a study conducted by Robert Johansson and colleagues, it was revealed that an individually tailored treatment – compared to standard treatment – demonstrated greater effectiveness for participants who had higher baseline depression scores and more comorbidities (Johansson et al., 2012). These findings underscore the potential of transdiagnostic and individually tailored interventions to effectively address complex symptomatology. Nonetheless, both approaches appear to be equally effective (Păsărelu et al., 2017; Berger et al., 2014).

An extensive body of evidence highlights considerable effectiveness of internet-based interventions. However, in further research, it becomes crucial to determine which individuals exactly benefit from internet-based interventions, as effectiveness varies among participants. Reviewing effectiveness trials, evidence varies explaining the relationship between internet-based intervention usage and psychological symptom outcomes. In a recent individual participant meta-analysis, the authors gathered information about response and remission after undergoing guided internet-based interventions. Older adults and native-born participants appeared to benefit from the treatment (Karyotaki et al., 2018). Other studies that included demographic variables to predict treatment outcome proposed female gender (Spek et al., 2008), being married or cohabiting (Høifødt et al., 2015), or working full time (Hedman et al., 2012) to be linked to better outcomes. Moreover, a Swedish prospective cohort study linked baseline treatment experience and automatic thoughts to treatment outcomes in internet-based cognitive behavior therapy for depression, while safety behaviors at baseline were predictive for panic disorder-focused internet-based cognitive behavior therapy (Niles et al., 2021). The finding that baseline psychological symptom measurements correlate with treatment effectiveness has been meta-analytically replicated (Scholten et al., 2023). Lastly, guidance and therapeutic alliance were associated with internet-based intervention effectiveness (Lindqvist et al., 2023). Overall, demographics factors, prior experience, baseline symptom severity, and treatment mode seem to be related to treatment outcomes.

Challenges in Internet-Based Interventions

While there is a widespread consensus regarding the effectiveness of internet-based interventions for various mental health conditions, non-adherence remains a notable challenge. Treatment adherence is a concern that is frequently discussed in internet-based intervention research. However, studies vary in their definitions of adherence and dropout. Some studies measure adherence based on participants leaving before post-assessment (Addington et al., 2019), while others focus on intervention usage (i.e., completion of modules), such as completing modules below a predetermined threshold (Bücker et al., 2022). While both study adherence and intervention usage are likely closely related, they address distinct issues. Both occurrences influence effect size estimates. However, the conceptualization of study adherence sheds light on attrition (i.e., the loss of participants over the course of the study). Nevertheless, it may overlook individuals who engage with the intervention, but drop out prior to post-assessment for various reasons. Due to this challenge, it is essential to also consider the usage of the intervention itself. Some individuals might disengage from the intervention trial before completing the study, yet still interact with the intervention to some extent. Generating accurate adherence data requires tracking intervention usage and adherence to the study protocol together. Consequently, it is essential to consider both study adherence and intervention usage, as they address underlying issues in internet-based interventions. Precisely, this study will examine premature discontinuation, meaning dropout prior to post-assessment (i.e., study adherence) and the total usage of the intervention itself (i.e., intervention usage).

High dropout rates in internet-based interventions, as defined in a representative meta-analysis as completing <75% of the intended modules, have been documented across multiple studies (Karyotaki et al., 2015), potentially leading to an underestimation of the true effect size of these interventions (Wright et al., 2019). However, not only do high dropout rates impact effect size estimates, but also is it crucial to explore if there are specific individuals that do not benefit from internet-based interventions, and subsequently fail to adhere to them. Non-response to internet-based interventions should also be understood as an adverse effect of psychotherapy (Rozental et al., 2019). Nonetheless, not all individuals who discontinue an internet-based intervention should be automatically labeled as non-responders. Instead, individuals who discontinue treatment can be categorized based on their motivation to do so: those who felt ready to leave treatment early versus those who terminated due to negative reasons (Lawler et al., 2021). Understanding and addressing adherence issues is crucial for optimizing the delivery and impact of internet-based interventions.

Literature offers varied insights into the correlates and predictors of adherence in internet-based interventions. One stream of research links participants' characteristics to adherence. Factors associated to adherence in internet-based interventions fall into two broad groups, as evidenced by empirical studies. First, a comprehensive meta-analysis identified male gender, lower educational level, and comorbid anxiety as associated with an increased risk of dropping out (i.e., completion of < 75% of the intended modules; Karyotaki et al., 2015). These findings on demographic variables could be replicated in further studies, with older age also emerging as a predictor to increase adherence (Fuhr et al., 2018; Beatty & Binnion, 2016). Secondly, according to RCTs, baseline symptom severity appears to negatively correlate with treatment adherence. In fact, lower subjective baseline symptom severity was evidenced to be linked to a higher adherence (Fuhr et al., 2018). Consequently, demographic variables and symptom severity at baseline can be further expected to alter the level of adherence.

While some predictors have been empirically investigated, it is likely that there are additional factors impacting adherence. First, as anonymity was found to be linked to acceptance of online interventions, this suggests that it may also impact adherence levels. However, although participants preferred computerized cognitive behavior therapy over face-to-face therapy due to its anonymous nature (Treanor et al., 2021), it is unclear how this exactly affects adherence. Anonymity and the absence of a contact person can potentially impact adherence to the program (Rost et al., 2017). A plausible reason for the favorability of anonymity in unguided internet-based interventions could be the fear of stigma in therapy (Schnyder et al., 2017), potentially leading to higher adherence. On the other hand, anonymity could also diminish adherence by lowering accountability for their actions in psychotherapy and the feeling of lower confidentiality (Wells et al., 2007; Rochlen et al. 2004). Secondly, the timing of participant engagement with internet-based interventions - whether interventions are completed in the morning versus evening or on weekdays versus weekends - may have an impact on adherence measures, yet this factor has received limited attention in the literature. Research on circadian rhythms and cognitive functions underscores that the time of the day can influence an individual's ability to process information, mood, and overall engagement

(Schmidt et al., 2007). These impairments can in turn potentially affect their persistence in an internet-based intervention. Moreover, the varying demands of individuals' schedules across the week might influence their capacity to engage meaningfully with therapeutic content, potentially leading to lower adherence at specific times. Lastly, the influence of prior psychotherapy experience and comorbidities on adherence measures in internet-based interventions represents a critical, but underexplored, area of research. Individuals with previous psychotherapy experience may have differing expectations, attitudes, and levels of engagement compared to those approaching therapy for the first time (Moradveisi et al., 2014). Prior experience could enhance adherence due to its familiarity, or conversely, it could lead to lower adherence if previous experiences were negative or if expectations were not met. Comorbidities add another level of complexity to treatment adherence in internet-based interventions. Participants with comorbid diagnoses may have greater psychological barriers to sustain engagement with internet-based interventions. Briefly, research on anonymity, completion timing, and psychotherapy experience as well as comorbidities in correspondence to psychological treatment adherence hint at potential predictive effects.

Another perspective considers intervention features in relation to treatment adherence. A common trend here is the favorability of guided over unguided versions (Karyotaki et al., 2015; Dryman et al., 2017). A theoretical foundation here is the accountability to a coach or therapist who is seen as trustworthy, which in turn increases treatment adherence (Mohr et al., 2011). This finding was further replicated by representative meta-analyses (Furukawa et al., 2021; Musiat et al., 2021). Bridging the gap between participant's characteristics and program features, a recent study by Bücker and colleagues (2022) highlights the importance of person-program-fit. The degree of autonomy and support should align with the individual's motives (Bücker et al., 2022; Jelinek et al., 2023). Hence, personalization of programs to enhance adherence should consider more factors besides symptom severity (Andrews & Williams, 2014). Although there are hints towards potential predictors of low adherence, findings remain preliminary and scattered (Treanor et al., 2021).

Current strategies to increase adherence in internet-based interventions mostly target subtle intervention features. Those applications can go beyond an increased level of guidance, a factor consistently associated with enhanced adherence (Dryman et al., 2017; Hilvert-Bruce et al., 2012). For instance, in a RCT targeting self-guided internet-delivered cognitive behavior therapy interventions for depression and anxiety, the integration of automated emails significantly elevated course completion rates (from 35% to 58%). These emails provided reminders to promote exposure to therapeutic content and the practice of learned skills (Titov et al., 2013). Similarly, the incorporation of online discussion boards and virtual badges has shown promise. According to a study by Moskowitz and colleagues (2021), the combination of virtual badges and facilitator contact is supposed to be connected to boost adherence. Thus, innovative program features such as email reminders, virtual badges, and human support can help improve adherence in participants.

Due to a lack of empirical research on adherence and the diveristy of internet-based interventions, there is no prevailing theory explaining low adherence. However, understanding the determinants of low adherence in internet-based interventions and the development of strategies to enhance engagement is essential in clinical research. Having empirically evidenced person characteristics and program features could help to foster tailored interventions that maximize therapeutic engagement and outcomes. Moreover, a proper person-program-fit could be facilitated. Adherence is positively linked to intervention effectiveness (Fuhr et al., 2018). Non-adherence and dropout in clinical trials on internet-based interventions leave researchers with missing data, posing challenges for accurate data analyses. Effectiveness values can thus be understood as an estimation of the true effect by imputing missing data. Given the potential of internet-based interventions, such as for instance in its easy accessibility, low-threshold nature, and reduced stigma, improving adherence is essential for two main reasons. First, it ensures accurate estimation of true intervention effectiveness scores. Second, understanding the reasons behind non-adherence allows for the personalized development of programs tailored to participants' needs. As researchers and clinicians continue to learn about why people do not properly engage online therapy and how to keep them involved, the landscape of online therapy is open for constant refinement and enhancement.

The Present Study

The present study aims to exploratively delve deeper into the phenomenon of adherence in internet-based interventions. Building upon the introductory paragraphs that underscore the significance of adherence issues in internet-based interventions, this study seeks to identify the characteristics and predictors of low adherence. By gathering comprehensible data, the objective is to gain insights into the profiles of individuals who discontinued participation in internet-based interventions. Ultimately, the findings of this study promise to contribute to the development of targeted strategies to enhance adherence measures and thus, the effectiveness of internet-based interventions. The overarching research question guiding this study is: *What factors predict adherence in internet-based interventions?*

Although research in that field is still preliminary, certain associations can be expected. Variations in 1) sociodemographic variables (age and gender), 2) anonymity, 3) participants' psychotherapy experience, 4) comorbidities, 5) baseline symptom severity, 6) completion time, 7) the level of guidance, and 8) group allocation are expected to predict the probability to adhere to the study and the degree of usage in an internet-based intervention.

Methods

This study uses data from two RCTs conducted by Klein et al. (2016) and Moritz et al. (2022b). Given the limited evidence on predictive variables, the analyses were considered exploratory. The choice of predictor variables was based on empirical studies on effectiveness, moderators of effectiveness, and tentative literature on adherence in internet-based interventions.

Trial design

This secondary analysis exploratively examined data collected in the context of two RCTs revealing the effectiveness of two internet-based interventions. Both trials compared an intervention group to a control group with a waitlist and care as usual conditions. Allocation to study conditions was conducted blindly and randomly, maintaining an unbiased approach, with a 1:1 ratio (for detailed information about the trial design see Klein et al., 2013 and Moritz et al., 2022b). Moritz and colleagues examined post-intervention measures six weeks after baseline assessment and Klein and colleagues after 12 weeks as well as 24 and 48 weeks after baseline. Both studies proved the interventions' effectiveness, reporting medium to large effect sizes. These trials were selected for a secondary analysis because their representative sample size and high-quality design could potentially reveal valuable insights into adherence predictors.

Procedure and Participants

Altogether, data from 1,292 participants was analyzed for this study. 1,013 people experiencing mild to moderate depression (defined as a score between 5 and 14 on the PHQ-9; Kroenke et al., 2011) participated in the *Deprexis* trial. They were recruited via inpatient and outpatient medical and psychological clinics, online forums for depression, health insurance companies and the media (female 68.6%; age M = 43.9 years, SD = 11.0 years). Baseline depression severity, averaging ten points, was equal across groups and indicated moderate symptom severity according to PHQ-9 classification (Kroenke et al., 2001; baseline depression severity: *M* = 10.29, *SD* = 2.4, range: 0 - 27; Klein et al., 2016). Additionally, 279 people experiencing body-focused repetitive behaviors (BFRBs) engaged in the *Free from BFRB* effectiveness trial. The trials were analyzed independently due to differing target diagnoses and intervention designs. They were recruited via social media (female 66%; age *M* = 32.9, *SD* = 11.53; baseline BFRB severity: *M* = 23.3, *SD* = 4.5, range: 0 - 40; Moritz et al., 2022b). History of schizophrenia, a lifetime diagnosis of bipolar disorder and acute suicidality were exclusion criteria in both trials. Participant characteristics are displayed in tables one and two.

Table 1

Participant Characteristics Deprexis

	Intervention group (*n* = 509)				Control group (*n* = 504)				Total (*n* = 1013)			
	%	*n*	*M*	*SD*	%	*n*	*M*	*SD*	%	*n*	*M*	*SD*
Sociodemographic												
Gender (female)	68.8	350			68.5	345			68.6	695		
Age			42.8	11.04			42.9	10.95			42.9	10.99
Anonymity*												
Full name	34	173			36.7	185			35.3	358		
Abbrev. Name	9.2	47			8.3	42			8.8	89		
Anonymous	28.5	145			22.6	114			25.6	259		
Work/student	6.3	32			3.6	18			4.9	50		
Other	22	112			28.8	145			25.4	257		
Psychotherapy experience (no)	43.3	221			42.9	216			56.9	576		
Comorbidities												
Anxiety	26.5	135			24.6	124			25.6	259		
PTBS	9.4	48			12.5	63			11	111		
Baseline symptom severity			10.2	2.42			10.3	2.4			10.3	2.4
Completion time												
Morning	25	127			28.8	145			26.9	272		
Midday	21.6	110			16.9	85			19.2	195		
Noon	17.9	91			21.0	106			19.4	197		

Evening	31.4	160			30.2	152			30.8	312		
Night	4.1	21			3.2	16			3.7	31		
Weekday	85.5	435			85.7	432			85.6	867		
Weekend	14.5	74			14.3	72			14.3	146		
Guidance**	62.5	318										

Note. Participant characteristics for participants in the *Deprexis* trial

*Anonymity as indicated by participants' email address categories

** Guidance received for participants with a PHQ-9 score between 10 and 14

Table 2

Participant Characteristics Free from BFRB

	Intervention group (n = 139)				Control group (n = 140)				Total (n = 279)			
	%	*n*	*M*	*SD*	*%*	*n*	*M*	*SD*	*%*	*n*	*M*	*SD*
Sociodemographic												
Gender												
Female	69.8	97			62.1	87			65.9	184		
Male	27.3	38			32.9	46			30.1	84		
Diverse	2.9	4			5.0	7			3.9	11		
Age			33.0	11.5			32.9	11.6			32.9	11.5
Anonymity*												
Full name	25.9	36			30.0	42			28	78		
Abbrev. Name	4.3	6			1.4	2			2.9	8		
Anonymous	22.3	31			24.3	34			23.3	65		
Work/student	4.3	6			7.1	10			5.7	16		
Other	43.2	60			37.1	52			40.1	112		
Psychotherapy experience (no)	51.1	71			46.4	65			48.7	136		
Comorbidities												
Depression	44.6	62			38.6	54			41.6	116		
Anxiety	34.5	48			50	70			42.3	118		
PTSD	12.9	18			8.6	12			10.8	30		
Baseline symptom severity			23.1	4.8			23.6	4.3			23.3	4.5
Completion time												
Morning	24.5	34			20	28			22.2	62		
Midday	17.3	24			11.4	16			14.3	40		
Noon	6.5	9			15	21			10.8	30		
Evening	24.5	34			29.3	41			26.9	75		
Night	27.3	38			24.3	34			25.8	72		

Weekday	75.5	105	74.3	104	74.9	209
Weekend	24.5	34	25.7	36	25.1	70

Note. Participant characteristics for participants in the *Free from BFRB* trial

*Anonymity as indicated by participants' email address categories

Intervention Description

Both interventions examined were internet-delivered and incorporated key elements of cognitive behavioral therapy. However, they targeted different diagnoses – *Deprexis* focused on addressing depressive symptoms, while the *Free from BFRB* intervention addressed body-focused repetitive behaviors (BFRBs). Additionally, interventions differed in the way the participants used it.

Deprexis is a 12-week program designed to target depressive symptoms. It consists of 12 modules covering content aligned with cognitive behavioral therapy principles, such as cognitive restructuring, behavioral activation, acceptance, mindfulness, and problem solving. Participants are encouraged to complete an introductory and a summary module to complete the content. Modules are designed to take between 10 to 60 minutes and incorporate simulated dialogues. The program maintains interactivity by prompting users to respond with selected options, tailoring subsequent content based on their responses, resulting in a conversational flow. Interactivity is further enhanced through exercises, feedback, audio recordings, summary sheets, and brief automatic daily messages. Moreover, each module contains illustrations (Meyer et al., 2009). Active guidance was provided for participants having medium depressive symptoms (PHQ-9 between 10 and 14). They were actively contacted once a week by a trained supporter who provided feedback based on the participants' use of the program over the previous weeks. Furthermore, participants could contact the supporters themselves and could respond to the messages (Klein et al, 2013; Klein et al., 2016).

The *Free from BFRB* intervention is a 12-page self-help manual (can be retrieved at no cost from: www.free-from-bfrb.org). The targeted symptoms encompass BFRBs, such as skin-picking, trichotillomania, lip-cheek biting and nail biting. According to Moritz and colleagues, these behaviors are defined as “compulsive manipulation of the skin, nails and/or hair which the patient is unable to resist, frequently resulting in severe impairment” (Moritz et al., 2022b, p. 933). The intervention is divided in a psychoeducational section followed by sections explaining the three taught techniques in more detail. The individual techniques are habit reversal training (HRT), decoupling (DC), and decoupling in sensu (DC-is). The explanation of techniques is accompanied by instructions for practice with examples for implementation. Intervention group participants were prompted to practice self-help techniques independently over six weeks.

Data Management

Trial data has been collected between August 2012 and December 2013 (Klein et al., 2016) and in 2022 (Moritz et al., 2022b). Participant data are stripped of identifying information. Data and syntax files are securely stored on an encrypted USB-stick and are available upon request.

Ethical Considerations

Ethical approval has been received for both RCTs before they were conducted. The trial by Klein and colleagues has been registered at ClinicalTrails.gov (NCT01636752) and was approved by the Ethics Committee of the German Psychological Association (reference number: SM 04_2012; Klein et al., 2016). The trial by Moritz and colleagues has also been preregistered (DRKS00024525) and was approved by the local ethics committee (LPEK-0254; Moritz et al., 2022b). In both trials, participants were informed about the aim of the study and that they could withdraw at any time without having to disclose reasons. Also, participants received an informed consent about the participation beforehand. No further ethical approval was needed to conduct a secondary analysis on the datasets. Participant confidentiality was maintained by encrypting datasets and by limiting access to the datasets.

Artificial Intelligence (AI) Use

This study made use of AI for several purposes. In the introductory paragraphs, AI was used to facilitate re-phrasing of certain parts into concise and simple text. In the results and discussion sections, this study leaned on AI to correctly interpret regression coefficients within their specific context. Thus, throughout the study, AI emerged as a central tool, contributing significantly to both clarity in presentation and depth in analysis.

Measures

Both trials assessed either depression or BFRB symptom severity as primary outcome using the PHQ-9 (Kroenke et al., 2011) to assess depressive symptoms, and the Generic BFRB Scale 8 (GBS-8; Moritz et al., 2022a) to measure BFRB severity. These scales are empirically evidenced as valid and reliable instruments to capture psychological symptom severity (Gallinat et al., 2016; Sun et al., 2020; Moritz et al., 2022a). In both trials, the investigated interventions demonstrated effectiveness, yielding medium to large effect sizes. However, the primary outcome of the present study is adherence, which is further distinguished into study adherence and intervention usage.

Outcomes

Study Adherence. Study Adherence was based on whether participants completed the post-assessment phase or not. To unify the outcomes from both studies, completion at either six (Moritz et al., 2022b) or 12 (Klein et al., 2016) week follow-up was examined. These post-intervention timepoints served as the primary endpoints in the trials. Longer-term follow-ups at 24 weeks and 48 weeks from the *Deprexis* effectiveness trial were excluded from this analysis. Study adherence was binary coded, indicating whether participants dropped out before the post-assessment or not.

Intervention Usage. Intervention usage measured how actively participants engaged with the interventions. For the *Deprexis* trial (Klein et al., 2016), this was quantified as the total minutes spent in the intervention, while excluding extreme usage above 1500 minutes. The *Free from BFRB* trial (Moritz et al., 2022b) assessed self-reported frequency of applying the taught techniques from the manual using three items on a five-point likert scale ("NOT tried" – "very much tried"). Both measures represent the degree to which users used to program, but the datasets were analyzed separately due to their distinct nature. Therefore, intervention usage data was considered on a continuous scale and was available only for participants in the intervention condition.

Potential predictors of adherence

Socio-demographic variables. Age and gender were included as sociodemographic variables. Age was transformed into standardized z-scores (raw age: $M = 42.86$, $SD = 10.99$), while the gender variable was treated on a categorical level. The 2016 *Deprexis* trial coded gender as binary (male, female), and the 2022 *Free from BFRB* study included a "diverse" gender category.

Anonymity. The level of anonymity chosen by participants when engaging in an internet-based intervention was inferred from their email addresses. Those were categorized into "private - full name" (first and last name recognizable, e.g., firstname.lastname@web.com), "private - abbreviated name" (either first or last name was abbreviated, e.g., f.lastname@web.com), "work/student mail" (institution or @info recognizable, e.g., f.lastname@company.com), "anonymous" (inclusion of fantasy terms, e.g., unicorn@web.com), and "other" (no clear allocation to the aforementioned categories). The categorization process was conducted by two independent reviewers. The resulting anonymity variable was treated as a categorical variable that includes five levels.

Psychotherapy Experience. Participants were asked to rate their prior participation in psychotherapy. They either had to choose between yes and no or had to manually quantify their number of underwent psychotherapies. In the latter case, responses were categorized as

“0”, “1 or 2”, and “3 or more”. Category allocation was validated by an independent rater. These categories were then condensed into a binary classification, distinguishing between “no psychotherapy experience” (zero value) and “psychotherapy experience" (one and more). Thus, psychotherapy experience was coded as a binary variable.

Comorbidities. The most prevalent comorbidities alongside target symptoms (Depression versus BFRBs) were screened prior to data analyses. Diagnoses were established using either the Mini-International Neuropsychiatric Interview (in Klein et al., 2016; Sheehan et al., 1998) or self-report items (in Moritz et al., 2022b). Anxiety and posttraumatic stress disorder (PTSD) were found as the most prevalent in both studies, whereas a notable proportion of participants in the *Free from BFRB* trial had a comorbid depression diagnosis. This was thus added to the data analysis. The presence of comorbidities, specifically anxiety, PTSD, and depression, was coded as a binary variable: participants were classified as either having a comorbid diagnosis or not.

Baseline symptom severity. To quantify baseline symptom severity, primary outcome levels at baseline were used. Hence, continuous data on the PHQ-9 (range 0 - 27, Cronbach's alpha = .892 according to Sun et al., 2020; Kroenke et al., 2001) and the GBS-8 (range: 0 - 40; Cronbach’s alpha = .93 according to Gallinat et al., 2016; Moritz et al., 2022a) at baseline represented the symptom severity prior to the experimental period.

Completion time. The timing of the pre-intervention assessments was categorized to gain insights into when participants engaged with the baseline evaluations. This categorization involved two dimensions: the day of the week and the time of day. Days were divided into weekday (Monday until Friday) versus weekend (Saturday and Sunday), creating a binary variable. Time of the day was broken into five daytime categories: morning (5am - 11am), midday (12am - 14pm), noon (15pm - 17pm), evening (18pm - 22pm), and night (23pm - 4am). The choice of five categories allows nuanced daytime effect analysis.

Therefore, the completion timing of the assessments was analyzed both as a binary (day of the week) and categorical with five levels (daytime).

Level of guidance. Interventions differed in their level of guidance, either being guided by an expert or being unguided, without human interaction. The *Deprexis* intervention trial offered both guided and unguided versions of the intervention, while the *Free from BFRB* program was a fully self-help based manual. Consequently, the level of guidance was coded as a binary variable with zero values indicating unguided mode and value one indicating guidance by an expert. This variable was constant in the RCT on BFRBs.

Data analysis

Data analysis was performed using IBM SPSS Statistics Software, version 29 (IBM Corporation). Cross-tabulations and descriptive statistics were employed to quantify characteristics at baseline and adherence measures between study conditions and participants. In order to predict outcome variables, multiple regression analysis was selected due to its suitability for meeting the assumptions of i.e. temporal precedence and representative samples. Analyses were conducted separately for each dataset to ensure data quality and integrity.

Regression analysis was conducted to determine the predictive power of each variable. Logistic regression was used for study adherence, and linear regression was used for intervention usage due to their different scale levels. For the prediction of study adherence, multiple logistic regression was employed to model binary outcomes. Given the exploratory nature of the study and the aim of hypothesis generation, a stepwise approach was adopted. In fact, predictors were eliminated step by step in a backward way. Following the methodology of Seewer et al. (2024), predictors were continuously excluded based on their significance levels. In the first step, all intended predictors were entered into a primary model. Subsequently, predictors with a significance level of p <. 20 from step one were retained in the model. Finally, significant variables with $p < .10$ were kept, representing the final model. Seewer and colleagues further excluded variables with $p < .05$ for the final predictive model (Seewer et al., 2024). However, as this study follows an exploratory approach, $p < .10$ was chosen as the threshold of interest and corrections for multiple comparisons were not applied (Bender & Lange, 2001). The prediction of intervention usage was conducted using multiple linear regression. A three-step approach was employed to construct a model of predictors with a significance level < .10. To draw conclusions about the the interventions, I considered unstandardized coefficients, which reveal information about the total minutes of usage (*Deprexis*) and the self-reported degree of usage of techniques to reduce BFRBs (*Free from BFRB*).

Results

In this section, results of predictive modeling analyses on adherence in internet-based interventions across two RCT datasets are presented. Initially, descriptive sample statistics and adherence values in these samples are provided. Subsequently, outcomes of multiple regression analyses for two adherence measures (study adherence and intervention usage) are reported, involving each of the seven predictors initially. Finally, after gradually excluding predictors above a given significance value, regression coefficients are described.

Descriptive statistics and adherence analysis

Baseline predictor levels were balanced between conditions and trials (see Tables 2 and 2). Only baseline variables were entered as predictors into the model. In the respective studies, a total 219 (Klein et al., 2016) and 110 (Moritz et al., 2022b) participants dropped out of the trial prior to post-assessment, corresponding to dropout percentages of 21.6% and 39.4%, respectively. Intervention usage was scaled as a continuous variable with an average engagement time of $M = 422.15$ minutes ($SD = 273.79$) in the *Deprexis* intervention. The average self-reported application of the three *Free from BFRB* techniques were 7.95 (SD = 2.16) on a possible range from 0 through 15. Adherence values are displayed in Table 3.

Table 3

Adherence Measures

	Intervention group ($n_{Deprexis\_EG}$ = 509)				Control group ($n_{Deprexis\_CG}$ = 504)				Total ($N_{Deprexis}$ = 1013)			
	%	*n*	*M*	*SD*	%	*n*	*M*	*SD*	%	*n*	*M*	*SD*
Study Adherence												
Dropout at Post [a]	22.4	114			20.8	105			21.6	219		
Intervention Usage												
Minutes			422.15	273.79								
	(n_{BFRB_EG} = 139)				*(n_{BFRB_CG} = 140)*				*(N_{BFRB} = 279)*			
	%	*n*	*M*	*SD*	%	*n*	*M*	*SD*	%	*n*	*M*	*SD*
Study Adherence												
Dropout at Post [a]	31.4	44			47.5	66			39.4	110		
Intervention Usage												
HRT [b]			3.11	1.07								
DC [b]			2.84	1.3								
DC-IS [b]			2.00	1.06								
Sum [c]			7.95	2.16								

Note. Adherence measures of participants in the *Deprexis* and *Free from BFRB* trial. HRT = habit reversal training, DC = decoupling, DC-IS = decoupling "in sensu".
[a] Dropout at post-intervention assessments, [b] Possible range: 0-5, [c] Possible range: 0-15

Predictive modeling

The exploratory analysis to predict adherence across both RCTs was structured into a three-step approach (coefficients from step 1 can be found in the supplementary material I through IV). In either of the trials and regarding both outcomes, the predictors completion time, baseline symptom severity, and comorbid depression were excluded in the final model, due to their failure to meet the significance threshold set at $p < .10$. Study adherence was treated as a binary variable, where a zero value signifies "dropout" and a value of one meaning "adherence". This coding scheme identifies "adherence" as the event of interest or the "success" event in the context of logistic regression analysis. Intervention usage was assessed on a continuous scale, while higher values indicate greater adherence levels. Details on the regression coefficients derived from step three are provided in tables 4 and 5.

Table 4

Final Stepwise Regression Model with Backward Exclusion: Deprexis Trial (Klein et al., 2016)

	Study Adherence				Intervention Usage			
	OR	*Sig.*	95% CI		*B*	*Sig.*	95% CI	
			LL	*UL*			*LL*	*UL*
Sociodemographic								
Age	**1.21**	**.01**	**1.04**	**1.42**	**48.97**	**.00**	**23.15**	**74.8**
Gender [a]	-	-	-	-	**61.93**	**.03**	**5.2**	**118.66**
Anonymity [b]								
Abbr. name	**0.62**	**.1**	**0.35**	**1.10**	-	-	-	-
Work	**0.41**	**.01**	**0.21**	**0.80**	-	-	-	-
Anonymous	**0.63**	**.02**	**0.42**	**0.94**	-	-	-	-
Other	0.72	.12	0.48	1.10	**-58.29**	**.06**	**-120.41**	**3.83**
Psychotherapy experience [c]	1.30	.11	0.95	1.76	-	-	-	-
Comorbidities								
Anxiety [d]	**1.68**	**.01**	**1.14**	**2.47**	-	-	-	-
PTSD	-	-	-	-	**-112.0**	**.02**	**-201.88**	**-22.1**
Baseline symptom severity	-	-	-	-	-	-	-	-
Completion time								
Midday [e]	-	-	-	-	-	-	-	-
Noon	-	-	-	-	-	-	-	-
Evening	-	-	-	-	-	-	-	-
Night	-	-	-	-	-	-	-	-
Weekend [f]	-	-	-	-	-	-	-	-
Guidance [g]	**0.70**	**.03**	**0.50**	**0.95**	-	-	-	-
Group [h]	-	-	-	-	-	-	-	-

Note. Regression coefficients for dropout predictors in the *Deprexis* trial

[a] reference: male, [b] reference: private – full name, [c] reference: no psychotherapy experience, [d] reference: NO current diagnosis, [e] reference: morning, [f] reference: Weekday, [g] unguided, [h] Intervention

"-" indicates: excluded in steps one or due to a lack of significance

Table 5

Final Stepwise Regression Model with Backward Exclusion: Free from BFRB Trial (Moritz et al., 2022b)

	Study Adherence				Intervention Usage			
	OR	*Sig.*	95% CI		*R*	*Sig.*	95% CI	
			LL	*UL*			*LL*	*UL*
Sociodemographic								
Age	-	-	-	-	-	-	-	-
Gender [a]								
Female	-	-	-	-	-	-	-	-
Diverse	-	-	-	-	-	-	-	-
Anonymity [b]								
Abbr. name	-	-	-	-	-	-	-	-
Work	-	-	-	-	-	-	-	-
Anonymous	-	-	-	-	-	-	-	-
Other	-	-	-	-	-	-	-	-
Psychotherapy experience [c]	-	-	-	-	-	-	-	-
Comorbidities								
Anxiety [d]	-	-	-	-	-	-	-	-
PTSD	-	-	-	-	-	-	-	-
Depression	-	-	-	-	-	-	-	-
Baseline symptom severity	-	-	-	-	-	-	-	-
Completion time								
Midday [e]	-	-	-	-	-	-	-	-
Noon	-	-	-	-	-	-	-	-
Evening	-	-	-	-	-	-	-	-
Night	-	-	-	-	-	-	-	-
Weekend [f]	-	-	-	-	-	-	-	-
Guidance [g]	-	-	-	-	-	-	-	-
Group [h]	**0.51**	**.01**	**0.31**	**0.83**	-	-	-	-

Note. Logistic regression coefficients for each predictor in the *Free from BFRB* trial

[a] reference: male, [b] reference: private – full name, [c] reference: no psychotherapy experience, [d] reference: no current diagnosis, [e] reference: morning, [f] reference: Weekday, [g] only unguided version, [h] CG

“-“ indicates: excluded in steps one or two due to a lack of significance

Study adherence

In step 3 of the exploratory analysis for the *Deprexis* RCT model to predict study adherence, the final model included age, anonymity categories, psychotherapy experience, comorbid anxiety, and guidance, after a backward elimination of the other predictors. With every unit change in standardized age (i.e., one standard deviation increase), the odds of adherence increase by a factor of 1.21, meaning they increase by 21% (*OR* = 1.21; 95%CI: [1.04, 1.42]; *p* = .01). Correlational analysis revealed non-significant and weak correlation between age and PHQ-9 baseline scores, suggesting that age's predictive power may not be attributed to chronicity or symptom severity (*r*(1011) = -.05, *p* = .11). Regarding anonymity categories, participants using email addresses with certain characteristics were less likely to adhere compared to those using their full name as a baseline. Specifically, those with an email including an abbreviated name corresponds to a 38% lower risk of adherence (*OR* = 0.62; 95%CI: [0.35, 1.10]; *p* = .10), while those using work emails had a 59% lower risk (*OR* = 0.41; 95%CI: [0.21, 0.80]; *p* = .01), anonymous email to a 37% decreased risk (*OR* = 0.63; 95%CI: [0.42, 0.94]; *p* = .02), and other to a 28% decreased risk (*OR* = 0.72; 95%CI: [0.48, 1.10]; *p* = .12) in the odds of adherence to the study, compared to those using their full name and holding the other variables constant. Individuals with a comorbid anxiety diagnosis are 1.68 times as likely to adhere to an internet-based intervention post-assessment than those without such diagnosis, indicating 68% higher odds of adherence for those who have been diagnosed with anxiety (*OR* = 1.68; 95%CI: [1.14, 2.47]; *p* = .01). Moreover, having prior psychotherapy experience corresponds to an increase in the odds of not completing post-assessment by 30%, although statistically only marginally significant (*OR* = 1.30; 95%CI: [0.95, 1.76]; *p* = .11). This variable demonstrated significance according to a *p* < .10 threshold in step 2, but it did not maintain significance in step 3. Lastly, participants using the guided version of *Deprexis* were 30% less likely to adhere compared to those using the unguided version (*OR* = 0.70; 95%CI: [0.50, 0.95]; *p* = .03). The final model could explain 3.2% of the variance in the outcome variable (Cox & Snell $R^2 = 0.032$), and the area under the curve (AUC) was found to be 0.62, indicating moderate discriminatory power of the model to distinguish between the two classes (de Hond et al., 2022). For the *Free from BFRB* intervention, group allocation emerged as a significant predictor, indicating that people in the intervention group showed a 51% decrease of the odds of adherence relative to being in the control group ($OR = 0.51$; 95%CI: [0.31, 0.83]; $p = .01$). This model explained 2.7% of the adherence variance in this RCT (Cox & Snell $R^2 = 0.027$), and the AUC was 0.58 and had thus low discriminatory power (de Hond et al., 2022).

Intervention usage

In the linear prediction of total minutes of intervention usage (*Deprexis*), age, gender, the "other" anonymity category, and a comorbid PTSD diagnosis were entered into a final model. No significant predictors were identified in the RCT by Moritz et al. (2022b). One significant predictor that emerged was age with a slope of $b = 48.97$ (95%CI: [23.15, 74.79]; $p < .001$), suggesting that for each standard deviation increase in z-scored age, there is an expected increase of 48.97 minutes in *Deprexis* usage. Gender has a linear regression coefficient of $b = 61.93$, meaning that females used the intervention for 61.93 minutes more than males (95%CI: [5.2, 118.66]; $p = .032$). The "other" anonymity category was compared against the baseline category "private - full name" and was accompanied by a significant decrease in usage by 58.29 minutes ($b = -58.29$; 95%CI: [-120.41, 3.83]; $p = .06$). The calculated confidence interval reached into the positive extent and included zero and the individual category is not meaningful when extracted from the categorical system. Finally, comorbid PTSD was linked to total intervention usage by $b = -112.0$ (95%CI: [-201.88, -22.1]; $p = .015$), saying that participants with a comorbid anxiety diagnosis used the intervention 112 minutes less than individuals without such diagnosis. The final model could explain 3.9% of the variance ($R^2 = 0.039$, $SE = 287.9$).

Discussion

This study exploratively investigated baseline variables influencing participant study adherence and intervention usage in two separate trials evaluating internet-based interventions for BFRBs and depression. Preliminary findings suggest that factors such as sociodemographic variables, anonymity, psychotherapy experience, comorbidities, guidance, and group assignment may impact adherence, albeit to a less strict significance level ($p < .10$). Notably, the study did not find significant predictive value in the completion time or baseline symptom severity on both adherence measures. However, it is important to highlight that the predictive models used in this study explained only a small portion of the variance in outcomes, indicating that the results should be seen as tentative. Also, interpretations are rather speculative. Furthermore, results from both trials are not aggregated, since two different diagnoses are targeted. BFRBs are classified as compulsive disorders, whereas depression is referred to as an affective disorder. Mechanisms through which predictors affect adherence outcomes could differ drastically. Also, despite both interventions being categorized as unguided internet-based interventions (for those with a PHQ-9 < 10 in *Deprexis*), they differ significantly in their approach. The *Deprexis* intervention is highly interactive as it follows a dialogue-like flow, whereas the intervention for BFRBs provides bibliographic material for technique instructions in a more static form. Only few predictors could be found of both adherence outcomes in the BFRB trial. It appears that the chosen exploratory predictors hardly explain variance in the notable percentage of dropout (39.4%), though the mean intervention usage reported by participants can be interpreted as moderate. The percentage of dropout in the *Free from BFRB* effectiveness trial, particularly in the waitlist control group (47.5%), is unexpectedly high, considering that most participants desire the treatment and therefore complete the post-assessment to access it. This percentage can be considered unusually high given dropout rates from previous studies (e.g., 17.4% - 30.8% in

Nissen et al., 2020 or 24.8% in Lu et al., 2023). This finding implies that there are factors influencing adherence for that particular intervention and/or condition that differ from those that are used. Accordingly, the discussion below will mainly report coefficients delivered by multiple regression analyses in the *Deprexis* trial, where a greater number of significant predictors of adherence were identified.

Study Adherence

Multiple logistic regression delivered odds ratios for each possible predictor of study adherence, which were progressively excluded based on their significance level. To systematize the significant predictors in the final model, I classified them as "protective factors" (i.e., OR ≥ 1, indicating higher odds of adherence compared to baseline) and "risk factors" (i.e., OR ≤ 1, indicating lower odds of adherence compared to baseline).

Protective Factors

When examining individuals who did adhere to completing post-assessment measures, significant effects of age could be observed in the *Deprexis* trial. In fact, as individuals get older, their odds of adherence out increase slightly. This suggests potentially higher levels of commitment in older adults or a larger time availability (Baker et al., 2005). Another explanation could be greater chronicity of depressive symptoms in older adults, leading to a stronger pursuit of any available treatment option. However, correlational analyses between age and PHQ-9 scores revealed small and insignificant results, indicating that the predictive power of age may not be attributed to chronicity or symptom severity. This result replicates previous findings on age effects (Fuhr et al., 2018; Beatty & Binnion, 2016). Secondly, the finding that previous psychotherapy experience of participants becomes significant when more variables are included in the model and loses significance when the number of variables is reduced, suggests a dynamic relationship influenced by the inclusion or exclusion of other predictors. In other words, it suggests the possibility of statistical interferences between the variables, such as multicollinearity, suppressor effects, or overfitting, which may have affected the stability of the variable's significance across different models. This implies that the predictive power of therapy experience may be contingent on other factors. While only marginally significant, there appears to be a trend suggesting that individuals with previous psychotherapy attempts may have an increased likelihood of adherence (OR = 1.30). This indicates that therapy experience might provide individuals with skills and support that make them more resilient or committed to continuing in the intervention. While also not statistically significant, this trend was observed in the BFRB trial. Thirdly, anxiety emerged as a prevalent comorbidity in both trials and was associated with a higher likelihood for adherence among participants. This finding contradicts previous research (Karyotaki et al., 2015) and suggests that individuals with anxiety diagnoses are more motivated to remain engaged in the trial. Subjects suffering from either depression with anxiety (Klein et al., 2016) or BFRB with anxiety (although this finding was not replicated by this trial; Moritz et al., 2022b) might find the intervention more relevant to their needs or experience more benefits. Anxiety severity is not measured, but it is plausible that the intervention also equips individuals with more complex symptomatology. Interestingly, although comorbid PTSD was excluded in step 2, coefficients suggest that comorbid PTSD is linked to an decreased risk to adhere (p = .12), revealing the opposite direction of effect. However, this interpretation warrants caution, as it is above the chosen significance threshold and has fewer cases ($n_{PTSD\_deprexis}$ = 48). In sum, older adults, prior psychotherapy experience and comorbid anxiety appear to increase the likelihood of adherence.

Risk Factors

Two predictors significantly decreased the odds to adhere to the study: anonymity and intervention guidance. When comparing different anonymity categories against the baseline of "private email including a full name" category (e.g., firstname.lastname@gmail.com), every other category - indicating higher degrees of anonymity (except the “other” category) - showed an reduced risk of adherence. Interestingly, individuals using their work or student email addresses had the lowest likelhood of adherence. Similarly, people with email addresses which contain fantasy names (for example “flowerpower” or “cookiemonster”) were also at a decresed risk to adhere to the trial. These findings suggest that the level of personal investment or the perceived privacy/security associated with the type of anonymity chosen might influence the participants' commitment to complete post-assessments in internet-based intervention trials. Surprisingly, another finding is that individuals receiving a guided version were less likely to adhere to the study out than those who did not. This finding contradicts the theory proposed by Mohr and colleagues about “Supportive Accountability” (Mohr et al., 2011) and also recent meta analyses (Furukawa et al., 2021; Musiat et al., 2021) regarding guided internet-based interventions. It is worth noting that more people in the *Deprexis* trial went through a guided program, which was stratified by their symptom level, possibly introducing confounding factors. Finally, in the BFRB trial, individuals in the intervention group were less likely to complete the post-assessment, although this was not replicated by the other trial. Accordingly, this result holds limited significance. In sum, the degree of anonymity and guidance could possibly be linked to an increased dropout risk.

Intervention Usage

Findings regarding the intervention usage are rather scarce in this analysis. First, predictive effects of sociodemographic variables could be evidenced, with age emerging as a significant predictor (p = .00). As individuals get older, they seem to use the internet-based intervention longer. Age categories might reveal more accurate trends about that finding, as this predictive model assumes linearity of this predictor. The interpretation of this trend aligns with the findings in study adherence, suggesting that older people may have more time available, greater commitment, or have chronicity of symptoms. Moreover, a possible mechanism could also be slower information processing in older adults (Torrens-Burton et al., 2017). Additionally, female participants spent more time with the intervention, although with a wide confidence interval. This pattern was also observed in the BFRB trial though related to the self-reported usage of techniques (although $p > .10$). This result is in line with prior research (Karyotaki et al., 2015). These gender differences hint at differences in help-seeking behaviors, or preferences in engaging with mental health interventions. Secondly, the anonymity indicator "other" was related to a decreased use of intervention by approximately an hour less (compared to "private email including a full name"). Given the high number of cases within that category, this effect is possibly due to high heterogeneity within that category and hence, the influence of confounding variables. Lastly and interestingly, comorbid PTSD diagnoses are linked to a significant decrease in total usage of the intervention (about 112 minutes less). This finding could be due to unique challenges with PTSD in engaging with mental health interventions (Kazlauskas, 2017) or a possible interference of symptoms with their ability to fully participate in the intervention. Briefly, the mentioned factors might support the identification of low adherence and to explore the reasons to do so.

Strengths

This is the first study to explore adherence characteristics in internet-based interventions following a two-sided perspective on adherence while including novel factors. This approach sheds light on the distinct challenges associated with different forms of adherence, underscoring the importance of maintaining the distinction between study adherence and intervention usage. A notable strength of this study is the inclusion of a large and representative sample, ensuring that predictive regression analyses were based on a robust dataset with an adequate number of cases per predictor. Additionally, analyzing baseline measures to predict later trial dropout and intervention usage adheres to the core assumption of temporal precedence in regression analysis. Through a thorough analysis of a wide range of predictors, this study has identified potential trends and factors influencing adherence in internet-based interventions. By uncovering these insights, the findings not only contribute to the existing literature but also provide valuable guidance for future research. Moving forward, replication of these findings by other researchers will be crucial for validating their robustness and generalizability. Furthermore, longitudinal studies exploring the dynamic interplay between predictors and adherence outcomes could offer deeper insights into the underlying mechanisms.

Limitations

Some limitations should be acknowledged. First, only a limited number of predictors were included, potentially leaving room for confounding variables. A crucial covariate could be the heterogeneity of depression between affected participants. PHQ-9 scores might fail to capture the individual expression of depressive symptoms. Subgroup analysis and the inclusion of further depression diagnostics would help to explain more variance. Also, concurrent therapy and selective serotonin reuptake inhibitor (SSRI) intake was not controlled for in this analysis, which might affect reported symptom scores. Additionally, regarding the predictive power of anonymity categories, three key shortcomings are worth addressing. The "other" category's substantial size raises concerns of misclassification bias and information loss. Additionally, assumptions underlying the choice of the "private – full name" category as baseline might introduce bias. The assumption would be that this is either the most common category, or that participants in that category have the lowest risk of dropping out. Given current empirical research, this is also likely (e.g., Rost et al., 2017), but could be a potential source of bias. Generally, the discriminatory power of the categorization system is debatable. Second, assumptions of linearity in the outcome predictor intervention usage in minutes warrants reflection on the interpretation. Sudden improvements might precede early dropout and should not always be confused with a poor effectiveness (Haller et al., 2023). Not just sudden gains, but also cognitive capacities may confound this relationship, i.e., few minutes spent in the intervention could be due to fast information processing speed. Additionally, intervention usage measures of the trials should not be confused. Data in the *Free from BFRB* trial was only available for those who completed post-intervention measures, but not for those who might have done the intervention and did not participate in the survey. The possibility of usage overestimation is present in this trial. Given the varying in intervention approaches and sample characteristics, it might have been prudent to focus the analysis of both adherence outcome variables on one group of data (e.g., from the *Deprexis* trial) followed by attempting to validate or confirm the findings in the other group (e.g., the *Free from BFRB* trial). Generally, the comparativeness of the two studies is disputable, also given their differences in sample size (1,013 in Klein et al., 2016 versus 279 in Moritz et al., 2022b). Third, concerns of overfitting and noise capture in the models necessitate caution. Future explorative research in that field could consider using cross-validation approaches. Fourth, this study used the *p*-value to narrow down meaningful predictors. However, the informative value is disputed (Amrhein et al., 2018). Excluded predictors should not be dismissed as irrelevant. Lastly, despite meeting statistical assumptions, causal relationships cannot be inferred from the given approach. Generally, findings are explorative and corrections for multiple comparisons were not applied.

Implications for future research

Adherence in internet-based interventions, i.e. study adherence and intervention usage, still seems to be confounded by unknown factors, which replicates empirical research on adherence in the past (Treanor et al., 2021). Addressing this issue requires extensive empirical and controlled research. Maintaining the distinction between study adherence and intervention usage is crucial due to their different meanings and consequences. Given the heterogeneity and low variance explanation, future research should consider moderation and intercorrelation analyses on mentioned predictors. This would possibly reveal relationships that could not be quantified using a multiple regression tool. Moreover, to account for the possibility of non-adherence due to sudden gains (Hedman et al., 2014), which could be erroneously interpreted as an ineffective intervention, regular measurements of adherence, effectiveness, and symptom levels should be examined during an internet-based intervention. Another implication of this is the need to empirically investigate the interaction between the outcome variables study adherence and intervention usage in the context of sudden gains. Using a within-subject or similar statistical design could provide high-quality inisghts into the interrelation of different forms of adherence in internet-based interventions. The high prevalence of comorbidities in the two trials, reflective of real-life psychiatric care circumstances (Andersson & Carlbring, 2022), and its effect on adherence, underscores the importance of individually tailored and transdiagnostic interventions.What can also be included into an individuals' psychopathological profile, alongside comorbidities, is previous psychotherapy experience. Further exploration is needed to understand the implications of past therapy attempts on an individual's willingness to engage in new interventions. Furthermore, findings suggest that anonymity levels seem to have an impact on how committed participants are to the trial. More research is needed to examine the relationship between anonymity and adherence. Generally, these findings can potentially be translated into applications reducing the risk of low adherence, such as a recommendation to use internet-based interventions rather for those who already underwent psychotherapy in the past or targeting recommendations towards older adults. On a more broad scale, the findings highlight the importance of tailoring interventions to individual needs, rather than assuming that internet-based interventions are universally effective. However, more research is required to replicate these findings.

Conclusion

This exploratory study delved into two internet-delivered interventions targeting depression and body-focused repetitive behaviors. Analyses used RCT data to predict adherence as a two-armed construct - including study adherence and intervention usage - through multiple linear and logistic regression models. While the developed models had rather low explanatory power in terms of variance explained, findings underscore the influence of factors including sociodemographic variables, psychotherapy experience, comorbidities, guidance, and anonymity on participant adherence. Despite the preliminary nature of the results, the low to moderate area under the curve values hint at potentially meaningful effects worthy of further exploration in future research. Low adherence in internet-based interventions can skew effect size measures and diminish patient outcomes. Understanding the characteristic patterns of individuals with low adherence in interventions can help overcome these challenges. This study contributes to the growing body of literature on internet-based interventions, highlighting potential possibilities to optimize participant engagement and intervention delivery.

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Supplementary Material

Table I: Stepwise Regression Analysis Deprexis

Step 1:

	Study Adherence				Intervention Usage			
	OR	*Sig.*	95% CI		*B*	*Sig.*	95% CI	
			LL	*UL*			*LL*	*UL*
Sociodemographic								
Age	**1.24**	**.01**	**1.06**	**1.45**	**51.02**	**.00**	**24.73**	**77.31**
Gender [a]	1.16	.40	.83	1.62	**46.75**	**.11**	**-11.4**	**104.91**
Anonymity [b]								
Abbr. name	**.60**	**.08**	**.34**	**1.06**	-0.77	.99	-95.86	94.32
Work	**.42**	**.01**	**.21**	**.82**	-34.0	.55	-146.65	78.65
Anonymous	**.62**	**.02**	**.41**	**.92**	34.84	.30	-30.91	100.59
Other	**.71**	**.12**	**.47**	**1.10**	**-52.65**	**.14**	**-123.55**	**18.24**
Psychotherapy experience [c]	**1.30**	**.11**	**.95**	**1.78**	3.05	.90	-50.22	56.31
Comorbidities								
Anxiety [d]	**1.76**	**.01**	**1.19**	**2.61**	7.13	.82	-53.47	67.72
PTSD	**.65**	**.01**	**.40**	**1.01**	**-118.96**	**.01**	**-210.79**	**-27.13**
Baseline symptom severity	1.02	.70	.91	1.15	11.32	.26	-8.4	31.04
Completion time								
Midday [e]	1.27	.32	.79	2.04	-6.91	.85	-81.12	67.3
Noon	.92	.70	.58	1.44	**54.27**	**.18**	**-24.53**	**133.08**
Evening	.95	.80	.63	1.42	32.04	.36	-36.51	100.6
Night	.96	.92	.42	2.20	**120.33**	**.17**	**-51.16**	**291.82**
Weekend [f]	1.04	.84	.67	1.63	-5.47	.88	-79.87	68.3
Guidance [g]	**.62**	**.11**	**.34**	**1.12**	42.19	.40	-56.06	68.92
Group [h]	.92	.59	.67	1.25	-	-	-	-

Note. Regression coefficients for dropout predictors in the *Deprexis* trial

[a] reference: male, [b] reference: private – full name, [c] reference: no psychotherapy experience, [d] reference: NO current diagnosis, [e] reference: morning, [f] reference: Weekday, [g] unguided, [h] Intervention

Table II: Stepwise Regression Analysis Deprexis

Step 2:

	Study Adherence				Intervention Usage			
	OR	*Sig.*	95% CI		*B*	*Sig.*	95% CI	
			LL	*UL*			*LL*	*UL*
Sociodemographic								
Age	**1.22**	**.01**	**1.05**	**1.43**	**48.23**	**.00**	**22.4**	**74.07**
Gender [a]	-	-	-	-	**59.29**	**.04**	**2.55**	**116.03**
Anonymity [b]								
Abbr. name	**.61**	**.01**	**.35**	**1.10**	-	-	-	-
Work	**.41**	**.01**	**.21**	**.81**	-	-	-	-
Anonymous	**.63**	**.02**	**.42**	**.93**	-	-	-	-
Other	.72	.11	.47	1.08	**-58.23**	**.07**	**-120.5**	**4.05**
Psychotherapy experience [c]	**1.32**	**.08**	**1.00**	**1.80**	-	-	-	-
Comorbidities								
Anxiety [d]	**1.75**	**.01**	**1.18**	**2.59**	-	-	-	-
PTSD	.68	.12	.42	1.10	**-113.97**	**.01**	**-203.83**	**-24.18**
Baseline symptom severity	-	-	-	-	-	-	-	-
Completion time								
Midday [e]	-	-	-	-	-	-	-	-
Noon	-	-	-	-	36.09	.29	-31.28	103.46
Evening	-	-	-	-	-	-	-	-
Night	-	-	-	-	128.48	.13	-37.61	294.57
Weekend [f]	-	-	-	-	-	-	-	-
Guidance [g]	**.69**	**.03**	**.50**	**.96**	-	-	-	-
Group [h]	-	-	-	-	-	-	-	-

Note. Regression coefficients for dropout predictors in the *Deprexis* trial

[a] reference: male, [b] reference: private – full name, [c] reference: no psychotherapy experience, [d] reference: NO current diagnosis, [e] reference: morning, [f] reference: Weekday, [g] unguided, [h] Intervention

Table III: Regression Free from BFRB

Step 1:

	Study Adherence				Intervention Usage			
	OR	*Sig.*	95% CI		*R*	*Sig.*	95% CI	
			LL	*UL*			*LL*	*UL*
Sociodemographic								
Age	1.00	.99	.77	1.31	0.14	.67	-0.52	0.8
Gender [a]								
Female	.81	.50	.43	1.51	**1.43**	**.09**	**-0.21**	**3.08**
Diverse	NA*	1.00	.00	-	1.56	.33	-1.65	4.77
Anonymity [b]								
Abbr. name	1.47	.64	.30	7.07	-1.56	0.58	-7.2	4.07
Work	1.60	.45	.47	5.43	0.01	.99	-2.88	2.91
Anonymous	.89	.76	.41	1.92	0.35	.75	-1.83	2.53
Other	1.45	.27	.74	2.83	1.07	.21	-0.61	2.75
Psychotherapy experience [c]	**1.51**	**.16**	**.84**	**2.70**	-0.13	.87	-1.7	1.44
Comorbidities								
Anxiety [d]	.69	.26	.36	1.32	.94	.29	-.84	2.72
PTSD	1.41	.49	.53	3.72	0.38	.76	-2.12	2.88
Depression	1.52	.21	.80	2.90	-0.38	.65	-2.06	1.3
Baseline symptom severity	1.00	.94	.94	1.10	0.02	.77	-0.13	0.18
Completion time								
Midday [e]	1.02	.97	.42	2.50	0.89	.44	-1.43	3.21
Noon	1.94	.24	.64	5.94	0.19	.88	-2.4	2.78
Evening	1.03	.93	.48	2.23	0.9	.37	-1.12	2.9
Night	.61	.22	.28	1.34	**1.27**	**.2**	**-0.7**	**3.24**
Weekend [f]	1.05	.87	.57	1.95	-0.28	.73	-1.96	1.39
Guidance [g]	-	-	-	-	-	-	-	-
Group [h]	**.48**	**.01**	**.28**	**.83**	-	-	-	-

Note. Logistic regression coefficients for each predictor in the *Free from BFRB* trial

[a] reference: male, [b] reference: private – full name, [c] reference: no psychotherapy experience, [d] reference: no current diagnosis, [e] reference: morning, [f] reference: Weekday, [g] only unguided version, [h] Intervention Usage values applicable for CG; *OR of 904901374

Table IV: Regression Free from BFRB

Step 2:

	Study Adherence				Intervention Usage			
	OR	*Sig.*	95% CI		*R*	*Sig.*	95% CI	
			LL	*UL*			*LL*	*UL*
Sociodemographic								
Age	-	-	-	-	-	-	-	-
Gender [a]								
Female	-	-	-	-	.92	.11	-.22	2.05
Diverse	-	-	-	-	-	-	-	-
Anonymity [b]								
Abbr. name	-	-	-	-	-	-	-	-
Work	-	-	-	-	-	-	-	-
Anonymous	-	-	-	-	-	-	-	-
Other	-	-	-	-	-	-	-	-
Psychotherapy experience [c]	1.49	.12	.90	2.46	-	-	-	-
Comorbidities								
Anxiety [d]	-	-	-	-	-	-	-	-
PTSD	-	-	-	-	-	-	-	-
Depression	-	-	-	-	-	-	-	-
Baseline symptom severity	-	-	-	-	-	-	-	-
Completion time								
Midday [e]	-	-	-	-	-	-	-	-
Noon	-	-	-	-	-	-	-	-
Evening	-	-	-	-	-	-	-	-
Night	-	-	-	-	.88	.18	-.41	2.17
Weekend [f]	-	-	-	-	-	-	-	-
Guidance [g]	-	-	-	-	-	-	-	-
Group [h]	**.50**	**.01**	**.30**	**.83**	-	-	-	-

Note. Logistic regression coefficients for each predictor in the *Free from BFRB* trial

[a] reference: male, [b] reference: private – full name, [c] reference: no psychotherapy experience, [d] reference: no current diagnosis, [e] reference: morning, [f] reference: Weekday, [g] only unguided version, [h] CG