Exploring the Link between Symptom Severity and the Moment of Dropout in Online Interventions: an Exploratory Analysis

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Abstract

Digital Mental Health Interventions are an effective tool for treating many mental health problems and have numerous advantages over traditional face to face therapy. However, they suffer from high dropout rates. While dropout has been investigated, a gap in the literature is present in the relationship between the severity of anxiety, depression, sleep quality and the moment of dropout. Thus, this study aimed to explore the relationship between these variables by analyzing the data from three independent Digital Mental Health Interventions. The final sample comprised 110 participants. To analyze the relationship between the severity of anxiety, depression, sleep quality and the moment of dropout, survival analysis was used. Kaplan-Meier estimates were computed, and log-rank tests were conducted, comparing groups of differing severities of the independent variables. The log-rank tests did not show significant results. The Kaplan-Meier estimates showed that a large proportion of the participants dropped out before finishing the first module of their respective intervention. This study adds to the literature by highlighting the need for tailoring or support especially in the first modules of a Digital Mental Health Intervention. It also highlights that tailoring should not be conducted based on the severity of anxiety, depression or quality of sleep in interventions not aimed at treating these variables specifically.

Keywords: Digital Mental Health Intervention, dropout, moment of dropout, survival analysis, log-rank test

Introduction

Mental health disorders are a common occurrence in our society. Almost one third of the human population will experience a mental health disorder in their lifetime (Steel et al., 2014). However, mental health needs are often unmet in vulnerable groups such as particularly young and old people, those who live in poverty and ethnic minorities (Rens et al., 2020). Reasons for this unmet need can include stigma, but also language differences or health care facility factors such as the incapacity to provide long-term care for patients who need it. Thus, while there is a large demand for mental health care, it is often unmet. However, Digital Mental Health Interventions (DMHIs) are a promising tool to increase access to mental health care (Andersson et al., 2019).

This study utilizes the definition of Lehtimaki et al. (2021) to describe DMHIs as "Information, support, and therapy for mental health conditions delivered through an electronic medium with the aim of treating, alleviating, or managing symptoms" (p. 3). Thus, DMHIs can differ by how much support is offered, whether they are used in conjunction with face-to-face therapy, or on which platforms they are used. Different degrees of support can include interventions with human guidance (e.g. Högdahl et al., 2016; Dominguez-Rodriguez et al., 2024), those without human guidance (e.g. Dominguez Rodriguez et al., 2023), and those that are supported by a chat-bot (e.g. Fitzpatrick et al., 2017). DMHIs also include online tools used in conjunction with face-to-face therapy, such as blended treatment (e.g. Kooistra et al., 2019). Thus, the term DMHI in this thesis includes many different types of interventions.

The effectiveness of DMHIs in reducing symptoms of various mental health disorders has been demonstrated in multiple studies. A systematic literature review and meta-analysis examining the effectiveness of different DMHIs, confirmed their usefulness in reducing symptoms of depression when compared to a waiting-list control group (Königbauer et al., 2017). Further, there were no differences between the interventions examined in terms of effectiveness, despite differing amounts of human support, duration of treatment, and the therapeutic approach used. DMHIs are also able to treat psychological disorders such as phobias (Kumar et al., 2017) or reduce symptoms of depression, post-traumatic stress disorder and anxiety, as well as risk of suicide and hopelessness (Dominguez-Rodriguez et al., 2023). Lastly, DMHIs can also have positive effects on health behaviors and knowledge among participants, such as maintaining weight loss, increasing nutritional knowledge, or promoting physical activity (Wantland, 2004). Thus, DMHIs are a valuable tool for promoting positive health behaviors and reducing the severity of various psychological problems over a longer period.

Additionally, for therapists overseeing online treatment, DMHIs offer the advantages of overcoming physical distance, being discrete, and being flexible with time, but also being able to help underserved populations (Schuster et al., 2018). Further advantages include easier access to care from more rural areas, avoiding stigma as a patient, as well as the treatment being more time efficient for the therapist overseeing it (Hedman et al., 2014). Thus, next to their effectiveness, DMHIs also offer advantages over more traditional forms of psychological interventions due to their digital nature. However, despite their effectiveness and advantages, DMHIs struggle to retain user engagement over time.

Dropout

The dropout rates in DMHIs present a significant disadvantage. For example, Bär et al. (2021) reported a dropout rate of 31% in their intervention. Melville et al. (2012) found in their literature review investigating dropout in DMHIs a weighted average of 31%, with dropouts ranging from 2% to 83% and a median dropout rate of 19%. As many psychological disorders have significant personal and societal consequences, these high dropout rates present a serious problem. For example, depression has been shown to lead to a variety of health complaints (Penninx et al., 2013), social phobia leads to large economic burden (Acarturk et al., 2008) and mental health problems present a risk factor for suicide (Bertolote & Fleischmann, 2002). Not receiving the full intervention might lead to less effectiveness in treatment and thus to further consequences for those suffering from mental health problems.

Previous research has identified multiple predictors for dropping out of DMHIs prematurely. For example, low scores in the traits assertiveness and dutifulness, and increased scores in self-affirmation (Högdahl et al., 2016), being male, having a lower education, or presenting a comorbidity of anxiety in treatment for depression were found to predict dropout (Karyotaki et al., 2015). Furthermore, dropout is also reported to occur due to personal reasons not related to the intervention, not agreeing with treatment protocol or being happy with the achieved progress (Postel et al., 2010), thinking the intervention content is not personal enough or experiencing general difficulties with the technology used to access the intervention (Beatty & Binnion, 2016). Lastly, in blended treatment, therapist characteristics were found to predict dropout (Högdahl et al., 2016). In summary, many factors can lead to dropout in online interventions, including personal characteristics, intervention characteristics and life circumstances unrelated to treatment. However, understanding not only why participants drop out of DMHIs but also when they do so would provide researchers the necessary knowledge to further tailor interventions to prevent dropout.

Moment of Dropout

Previous researchers have investigated the moment of dropout within DMHIs. For example, Ciharova et al. (2023) investigated the link between the type of reasons for dropout (person-related or intervention-related) and the stage of the intervention in which participants dropped out. However, no significant association was found. Other studies found that dropout, especially at the beginning of therapy, is predicted by treatment credibility (Alfonsson et al., 2016). Later treatment dropout was linked to not finding the treatment rewarding (Alfonsson et al., 2016) or feeling satisfied with the progress made (Postel et al. 2010). However, such variables can be identifiable in participants only during the intervention or after participants have already discontinued their participation. It would be more beneficial to researchers developing DMHIs to be able to predict when a participant is likely to drop out of the intervention before they start the intervention. This would allow them to offer further support specifically targeting those who are likely to need help, preventing a waste of resources. Thus, variables that would be especially high of interest would be those which can easily be measured before the beginning of an intervention. In this case, the severity of mental health problems would be a fitting variable, as they are commonly measured at the start of an intervention in trials already (e.g. Levin et al., 2025; Szigethy et al., 2023; Van Straten et al., 2008).

The levels of depression, anxiety and the quality of sleep have previously been investigated regarding dropout in DMHIs. In a study examining dropout in Internet Cognitive Behavioral Therapy in children, approximately 20% of children with an anxiety disorder dropped out, while almost 39% of children with subthreshold anxiety dropped out. This difference in the moment of dropout was significant, as proven by a log-rank test (Kaajalaakso et al., 2024). The authors hypothesized that participants fulfilling the criteria of an anxiety disorder might suffer from its symptoms more acutely than those with subthreshold anxiety and thus are more motivated to participate in the full program. In a similar manner, participants who do not suffer from anxiety as severely as other participants might decide to drop out faster than those who have more severe symptoms of anxiety. Regarding sleep quality, a study on dropout in a DMHI for insomnia revealed that if participants left their bed between 4:30 AM and 6:55 AM and left their bed in less than 66 minutes, the chance of dropout decreased (Bremer et al., 2020). Thus, if characteristics of sleep quality such as the time of getting up have an influence on dropout from an intervention, it might also have an influence on the moment of dropout. Other researchers have highlighted that higher severity of depression and anxiety are predictors of dropping out before finishing the third session of the intervention (Duhne et al., 2022). In summary, the relationship between anxiety, depression, sleep quality and dropout has been explored, and the variables are connected to dropout. However, the effect of these variables on the moment in which participants drop out of the intervention was not previously explored. Thus, a gap in the literature is present regarding the relationship between dropout predictors and the moment of dropout within the intervention.

If a link was established between depression, anxiety and sleep quality and the moment of dropout, it would be useful in two ways. First, as variables are used as predictors that are measured in most interventions already, there is no added burden for the participants to fill out more questionnaires or on the researchers to develop and implement new questionnaires to measure other variables. Second, it would allow for more possibilities of preventing dropout by offering tailoring or support for the moment in the intervention where dropout is most likely to occur for a group of participants.

Current Study

To investigate the link between the severity of anxiety, depression, sleep quality and the moment of dropout, this study utilizes data from participants in three different DMHIs. Since predictors of dropout from DMHIs have been investigated, a gap in the literature is present regarding the moment of dropout. Thus, this study will explore the association between the levels of anxiety, depression and sleep quality of participants and the moment of dropout. Survival analysis will be utilized in this study to address the uneven distribution of moments of dropout in the sample (Clark et al., 2003), as well as to more accurately investigate probabilities and risks associated with each stage of DMHIs analyzed. This study's approach of analyzing data from three interventions presents a unique way of investigating intervention dropout, as other studies on the topic of dropout in DMHIs commonly analyze data from only one intervention (e.g. Högdahl et al., 2016; Kaajalaakso et al., 2024). Thus, this approach can lead to decreased variance and increased external validity through the heterogeneity of the combined sample (Bangdiwala et al., 2016).

The results of this study will inform researchers and developers of DMHIs on the topic of offering tailored support to participants of DMHIs based on their severity of anxiety, depression and the quality of sleep. Furthermore, the results could enable the tailoring of the intervention to the needs of participants with specific characteristics, as suggested by Karyotaki et al. (2015). Significant results linking the variables of interest could highlight which participants specifically to support and at which point in the intervention it would be most effective. Insignificant results would inform future research by highlighting which variables are not significantly linked with the moment of dropout, redirecting research efforts to more promising variables. Thus, the research questions of this study are:

1. "What is the relationship between participants' level of anxiety and the moment of dropout?"
2."What is the relationship between participants' level of depression and the moment of dropout?"
3. "What is the relationship between the participants' sleep quality and moment of dropout?"

Methods

Design

This study used an exploratory design to investigate the link between participants' severity of anxiety, depression, quality of sleep and the moment of dropout in the intervention. The analyzed sample consisted of participants who dropped out of one of three distinct DMHIs. The independent variables of anxiety severity, depression severity and sleep quality were measured before each of the three online interventions. The moment of dropout of each participant was determined by assessing which was the last module a participant completed. Thus, this study uses data previously gathered through surveys from three different DMHIs.

Participants

The sample of this study comprises participants from three independent studies, totaling 116 individuals. From this sample, six participants were excluded from the analysis. Four participants were excluded due to having finished the intervention content, but not the study, while two participants were excluded because they were younger than 18 years old. The Mental Health COVID study sample was collected through intentional, nonprobabilistic, subject-type sampling. The Grief COVID and Healthcare Worker COVID studies used convenience sampling to gather participants. An overview of the sample characteristics is presented in Table 1.

Table 1

Sample characteristics

Characteristic	Mental Health COVID (N = 36)	Grief COVID (N = 70)	Healthcare Worker COVID (N = 4)	Combined Sample (N = 110)

Sex, n (%)				
Female	31 (86.11%)	60 (85.71%)	4 (100.00%)	95 (86.36%)
Male	5 (13.89%)	10 (14.29%)	0 (0.00%)	15 (13.64%)
Age (years)				
Mean (SD)	33.22 (11.74)	37.97 (9.94)	31.00 (7.53)	36.16 (10.69)
Median (range)	30.00 (18-60)	37.50 (18-63)	30.50 (23-40)	36.00 (18-63)
Nationality, n (%)				
Mexican	36 (100.00%)	70 (100.00%)	3 (75.00%)	109 (99.09%)
Ecuadorian	0 (0.00%)	0 (0.00%)	1 (25.00%)	1 (0.91%)
Employed, n (%)				
Yes	19 (52.78%)	46 (65.71%)	4 (100.00%)	69 (62.73%)
No	17 (47.22%)	24 (34.29%)	0 (0.00%)	41 (37.27%)
Education level, n (%)				
Middle school	0 (0.00%)	3 (4.29%)	0 (0.00%)	3 (2.73%)
High school	7 (19.44%)	9 (12.86%)	0 (0.00%)	16 (14.55%)
Bachelor's degree	24 (66.67%)	46 (65.71%)	3 (75.00%)	73 (66.36%)
Master's degree	4 (11.11%)	11 (15.71%)	1 (25.00%)	16 (14.55%)

Doctorate	0 (0.00%)	1 (1.43%)	0 (0.00%)	1 (0.91%)
Other	1 (2.78%)	0 (0.00%)	0 (0.00%)	1 (0.91%)

Note. N = number of participants per intervention; n = number of participants per subgroup.

Materials

Mental Health COVID

The Mental Health COVID intervention was a part of a randomized controlled trial testing the difference in efficacy between a self-administered web-based intervention with and without support through a chat function in the Mexican population (Dominguez-Rodriguez et al., 2020; Dominguez-Rodriguez et al., 2024). The intervention was designed to help participants focus on and improve their virtues and strengths. Participants were recruited through digital advertisements and social media platforms. Eligibility criteria for the study included the availability of technology which could access the intervention and basic skills in using the technology. Exclusion criteria included having been diagnosed with a psychotic disorder or receiving treatment for it in the form of psychological or pharmacological aid. Furthermore, participants could not stay logged out of the website for more than 20 days without being excluded from the study. The participants were randomly assigned to one of the conditions using the permuted blocks method with a 1:1 ration. In the experimental condition, participants were able to use the self-administered intervention with the option to receive help through a chat in the experimental condition. In the control condition, they were able to use the same intervention, but without further assistance. Anxiety, depression and sleep quality was measured before the start of the intervention.

The Mental Health COVID intervention was a self-administered program providing content based on positive psychology, as well as CBT and BA. The intervention consisted of 15 modules in total, each containing a video with a length 10 to 20 minutes and including homework, which could be downloaded as a PDF-file. After finishing a module, there was a waiting period of at least 1 day before being able to access the next module. Content from the modules included psychoeducation about anxiety and gratitude, increasing self-control and satisfaction in daily life and physical and mental exercise. The study received ethical approval by the Free School of Psychology University of Behavioral Science ethics committee in Chihuahua, Mexico. For a more detailed account of this study and the intervention, please see Dominguez-Rodriguez et al. (2020) and Dominguez-Rodriguez et al. (2024).

Grief COVID

Grief COVID was a free, web-based intervention created to prevent the development of complicated grief disorder and to increase quality of life in participants during the COVID-19 pandemic (Dominguez-Rodriguez et al., 2021; Dominguez-Rodriguez et al., 2023). It also aimed to reduce symptoms of depression and anxiety, as well as increase sleep quality. The intervention was tested in a randomized controlled trial with a predominantly Mexican population, with participants primarily being recruited through social media platforms. Inclusion criteria for the study were efficacy in using digital devices, fluency in Spanish and the presence of one of the following symptoms: symptoms of state anxiety, symptoms of depression or grief symptoms of acute stress disorder. Participants were not included in the study if they had received a diagnosis of a psychotic disorder, a diagnosis of posttraumatic stress disorder, high risk of suicide or if the death of a loved one had occurred more than 6 months prior. Participants were randomly assigned to one of two groups using a permuted block algorithm. The intervention group received the intervention without further manipulation, while the control group was able to access the intervention after a waiting period of 36 days. Questionnaires measuring anxiety, depression and sleep quality were administered before the start of the intervention. The study received approval by the Research Ethics Committee of the Autonomous University of Ciudad Juárez, Mexico (approval ID: CEI-2020-2-226).

The Grief COVID intervention consisted of 12 modules, each of which was available in either text or video form. At the end of each module, the participants' knowledge on the delivered content was tested with a quiz containing 5 questions. If the participants answered 3 out of 5 questions correctly, they were permitted to work on the next module after a 3-day waiting period. The intervention was designed according to user experience design principles, with the aim of enhancing its perceived utility and ensuring a user-friendly interface. The intervention could also be adapted to any screen size, ensuring good usability on computers, tablets and smartphones. The content of the modules was designed using elements of Cognitive Behavioral Therapy (CBT), mindfulness, positive psychology and behavioral activation (BA; Dominguez-Rodriguez et al., 2022). It included content on themes such as the grief process, exploration of coping strategies and resources, helping participants reactivate previous daily routines and re-experiencing positive emotions. For a more detailed account of the study and the intervention, please see Dominguez-Rodriguez et al. (2021) and Dominguez-Rodriguez et al. (2023).

Healthcare Worker COVID

The Healthcare Worker COVID intervention was part of a randomized controlled trial which aimed to compare two versions of a DMHI developed to help healthcare workers in Mexico decrease symptoms of anxiety and depression (Dominguez-Rodriguez et al., 2022b).

Participants were voluntarily participating workers in the healthcare system and were recruited through social networks. To be allowed to participate in the study, they needed to be healthcare workers with sufficient means to access the internet. They were excluded from the study if they had received a mental health disorder diagnosis, were receiving treatment for it, or reported either current suicide ideation or a recent suicide attempt. Participants were randomly assigned to one of two groups while sociodemographic variables were controlled for. The experimental group received a self-administered intervention, while the control group received the same intervention content as the other group through video calls with a therapist. The times in which content was delivered was the same for both groups. Measurements of anxiety, depression and sleep quality were taken before the start of the intervention.

The Healthcare Worker COVID intervention consisted of 12 modules, of which 9 modules were theoretical modules and 3 modules were complementary modules. The topics of the modules mainly related to CBT and BA, but also included content on insomnia, positive psychology and the Health Belief Model. Each module's content and the recommended activities were presented in an animated video. Content of the intervention included psychoeducation about emotions, anxiety, compassion, planned reuptake of pleasant activities, sleep improvement and guidance on how to improve physical and emotional health. The study received ethical approval by the Autonomous University of Juarez City Ethics Committee on the 21st of March 2021. For further information on the study or the intervention, please see Dominguez-Rodriguez et al. (2022b).

Measures

To explore the link between anxiety, depression, sleep quality and the moment of dropout, this study analyzed data from four different questionnaires. The three original studies used the Generalized Anxiety Disorder 7-item Scale (GAD-7; Spitzer et al., 2006), the Center for Epidemiologic Studies Depression Scale - Revised (CES-D-R; González-Forteza et al., 2008), the Beck Depression Inventory second version (BDI-II; Dozois et al., 1998) and the Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989) to measure anxiety, depression and sleep quality. The reasons for the inclusion of these measures for data analysis are their relevance and practicality. First, these questionnaires measure variables that have been shown to be connected to dropout in the literature and thus further analysis of these variables was relevant. Second, anxiety and sleep quality were measured through the same questionnaire by all three studies, while depression was measured by two different questionnaires. This limited the amount of data that had to be transformed to enable a comparison between all participants. Thus, these measures were included in this study, whereas measures which were either practical or relevant, but did not meet the other criteria, were excluded from analysis.

Generalized Anxiety Disorder 7-Item Scale

All three interventions examined used the Generalized Anxiety Disorder 7-item Scale (GAD-7; Spitzer et al., 2006) to identify the strength of symptoms of generalized anxiety disorder. The questionnaire consists of 7 items that present problems for which the participant is asked to indicate how often they are experiencing them. The problems are scored on a Likert-scale from 0-3, with 0 indicating “not at all” and 3 indicating “nearly every day”. The items describe problems such as “Feeling nervous, anxious or on edge” or “Trouble relaxing”. The questionnaire has very good internal consistency (Cronbach’s $\alpha = 0.92$) as well as good test-retest reliability (intraclass correlation = 0.83) and good validity (Spitzer et al., 2006). All interventions used the Spanish version of the questionnaire developed by Garcia-Campayo et al. (2010).

The questionnaire was scored using the coding scheme from Spitzer et al. (2006). To enable log rank tests, the participants were sorted into groups based on the original cut-offs also recommended by Spitzer et al. (2006). Participants with a total score between 0 and 4 were sorted into the "subthreshold anxiety" group, participants with scores between 5 and 9 were sorted into the group "mild anxiety", participants with scores between 10 and 14 were sorted into the group "moderate anxiety", and participants with a score of 15 and higher were sorted into the group "severe anxiety".

The Pittsburgh Sleep Quality Index

The Pittsburgh Sleep Quality Index (Buysse et al., 1989) was used in all three interventions to assess sleep disturbances and sleep quality. It consists of 19 items which either require the participant to indicate exact hours, durations or to the frequency of specific events on a scale from 0-3. Answers on a Likert-scale ranged from "*not during the past month*" to "*three or more times a week*". Questions include „*During the past month, how long (in minutes) has it usually taken you to fall asleep each night?*", or "*During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?*". The questionnaire was described by Buysse et al. (1989) as having good internal consistency (Cronbach's α = .83) and admissible validity. All three studies used the Spanish version of the questionnaire developed by Jiménez-Genchi et al. (2008).

The questionnaire was scored using the original coding scheme of Buysse et al. (1989). To enable comparison between different levels of sleepers, the participants were sorted into two groups: good sleepers and poor sleepers. Based on the cutoffs established by Buysse et al. (1989), participants were labeled "good sleepers" if their global PSQI score was below 5 and "poor sleepers" if their score was 5 or higher.

Questionnaires Measuring Depression

Mental Health COVID used the Beck Depression Inventory second version (BDI-II; Dozois et al., 1998). The questionnaire contains 21 items assessing the strength of depressive symptoms. The items are scored on a 4-item Likert-scale from 0-3. The questionnaire has good reliability (Cronbach's α = .91) and validity. The items represent topics, such as "14. Worthlessness", where 0 to 3 indicate the strength of agreement. For example, options for item 14. would include "0. I do not feel I am worthless.", "1. I Don't Consider Myself As worthwhile And Useful as I used to.", "2. I feel more worthless as compared to others." and "3. I Feel Utterly Worthless".

Grief COVID and Healthcare Worker COVID used a modified Spanish version of the CES-D-R by González-Forteza et al. (2008). The questionnaire was validated for Mexican adolescents with good internal consistency (Cronbach's α = 0.93).

The BDI-II was scored using the coding scheme described in Dozois et al. (1998), while the CES-D was scored using the coding schemes mentioned by Eaton et al. (2004). To enable a comparison of the severity of depression between participants of the different interventions, the CESD scores were transformed to enable the application of cut-offs recommended for the BDI-II by Dozois et al. (1998). To achieve this, the Patient-Reported Outcomes Measurement Information System (PROMIS; Cella et al., 2010) was utilized. Choi et al. (2014) linked the PROMIS Depression to the BDI-II and the CES-D, providing tables to convert each of the mentioned scale's scores into the PROMIS scores. As Grief COVID and Healthcare worker COVID used the CES-D-R. As outlined by Eaton et al. (2004), the CES-D-R scores can be converted to be comparable to CES-D scores by removing the added questions beyond the original 20 and transforming the Likert-scale from a 5-point scale back into a 4-point scale by converting all ratings of 4 into ratings of 3. After converting CES-D-R scores into CES-D scores, they were converted into PROMIS scores. Next, the BDI-II cutoff scores were converted into PROMIS scores, allowing the cutoffs to be applied to the CES-D-R scores.

Procedure

First, the three interventions Mental Health COVID, Grief COVID and Healthcare Worker COVID were studied by reading the articles explaining the intervention's content and procedure. Then, the available datasets of the three interventions were examined. Simultaneously, a review of the literature on dropout in online interventions was conducted to determine which variables were of interest and suitable for analysis. Then, through further research regarding suitable ways to analyze the time of dropout in different groups, the method of analysis was determined.

To conduct a log-rank test to determine whether different groups of participants have distinct survival curves, the questionnaires from each study were examined to identify which to include. Then, the method of standardization for each questionnaire was determined through a review of the literature pertaining to standardization of different questionnaires.

Afterwards, the datasets of each study were prepared separately. First, the sociodemographic data, the questionnaire scores from the GAD-7, PSQI, BDI-II and the CESD-R as well as the number of modules completed by each participant were imported separately into R studio. The data was linked by ID, to ensure that each participant was connected to their respective scores.

Lastly, the final scores for the questionnaires were computed and participants were assigned to groups of different severities for anxiety, depression and sleep quality as described above. Lastly, the three separate datasets were merged, and data analysis was conducted.

Data Analysis

First, descriptive statistics were obtained describing the sample's demographic variables and the distribution of participants across the standardized groups. Then, survival analysis was conducted, which is used to analyze the time for a specified event to occur within a predefined time frame (Clark et al., 2003). The observation period for this study spans from the start of the intervention until the end of the intervention, defined as completing the last module. The event of interest is participants dropping out of the intervention. As participants were not monitored daily for active participation in the intervention, the time to the event will be measured with the number of modules completed. As this sample only included participants that had dropped out of the intervention, all participants had experienced the event and no data was censored. Survival analysis will produce the survival probability $S(t)$, which is the probability of an individual not experiencing the specified event until the time t. It can further show the cumulative hazard rate $H(t)$ or the instant hazard rate $h(t)$. The cumulative hazard rate $H(t)$ expresses the total or cumulative risk a participant has experienced until the time t. The instant hazard rate $h(t)$ denotes the probability of a participant experiencing the event at the time t. For more in-depth information on survival analysis, see Clark et al. (2003).

Thus, Kaplan-Meier estimates showing survival probability $S(t)$ were calculated to obtain an overview of the sample's survival characteristics. To aid in understanding of the samples' moment of dropout, the survival curve was plotted. The x-axis shows the number of modules completed and the y-axis shows the survival probability.

Then, log-rank tests were conducted comparing participants with differing severities of anxiety, depression and sleep quality to test the research questions of this study. Thus, the dependent variable was the number of modules completed until dropout, with the severity of anxiety, depression and quality of sleep as the independent variables. The groups compared with each other for a log rank test conducted to answer the research question *"What is the relationship between participants' level of anxiety and the moment of dropout"*, were *subthreshold anxiety*, *mild anxiety*, *moderate anxiety* and *severe anxiety*. To examine the research question *"What is the relationship between participants' level of depression and the moment of dropout",* the groups were *non-depressed*, *dysphoric* and *depressed*. For the log rank test conducted to answer the research question *"What is the relationship between the participants' sleep quality and moment of dropout"*, the groups were *good sleepers* and *bad sleepers*.

Results

Descriptive statistics were obtained, depicting the distribution of participants across severity levels of anxiety, depression and quality of sleep and are presented in Table 2.

Table 2

Descriptive statistics

Variable	Subgroup	n (%)
Anxiety	Subthreshold	16 (14.55%)
	Mild	52 (47.27%)
	Moderate	25 (22.73%)
	Severe	17 (15.45%)
Depression	Non-depressed	31 (28.18%)
	Dysphoric	31 (28.18%)
	Depressed	48 (43.64%)
Sleep Quality	Good sleeper	5 (4.55%)
	Bad sleeper	105 (95.45%)

Note. n = participants per subgroup; percentages are calculated within each variable.

Kaplan-Meier survival estimates were obtained for the whole sample, with the event of interest being the participants' dropout, the number of modules completed as the time to event variable, and the last module completed as the time of the event. The times at which events occurred, the number of participants at risk, the number of events that occurred, the Kaplan-Meier survival estimate, the standard error, and the lower and upper limits of a 95% confidence interval for the survival estimate are shown in Table 3. The Kaplan-Meier survival curve can be found in Figure 1.

Table 3

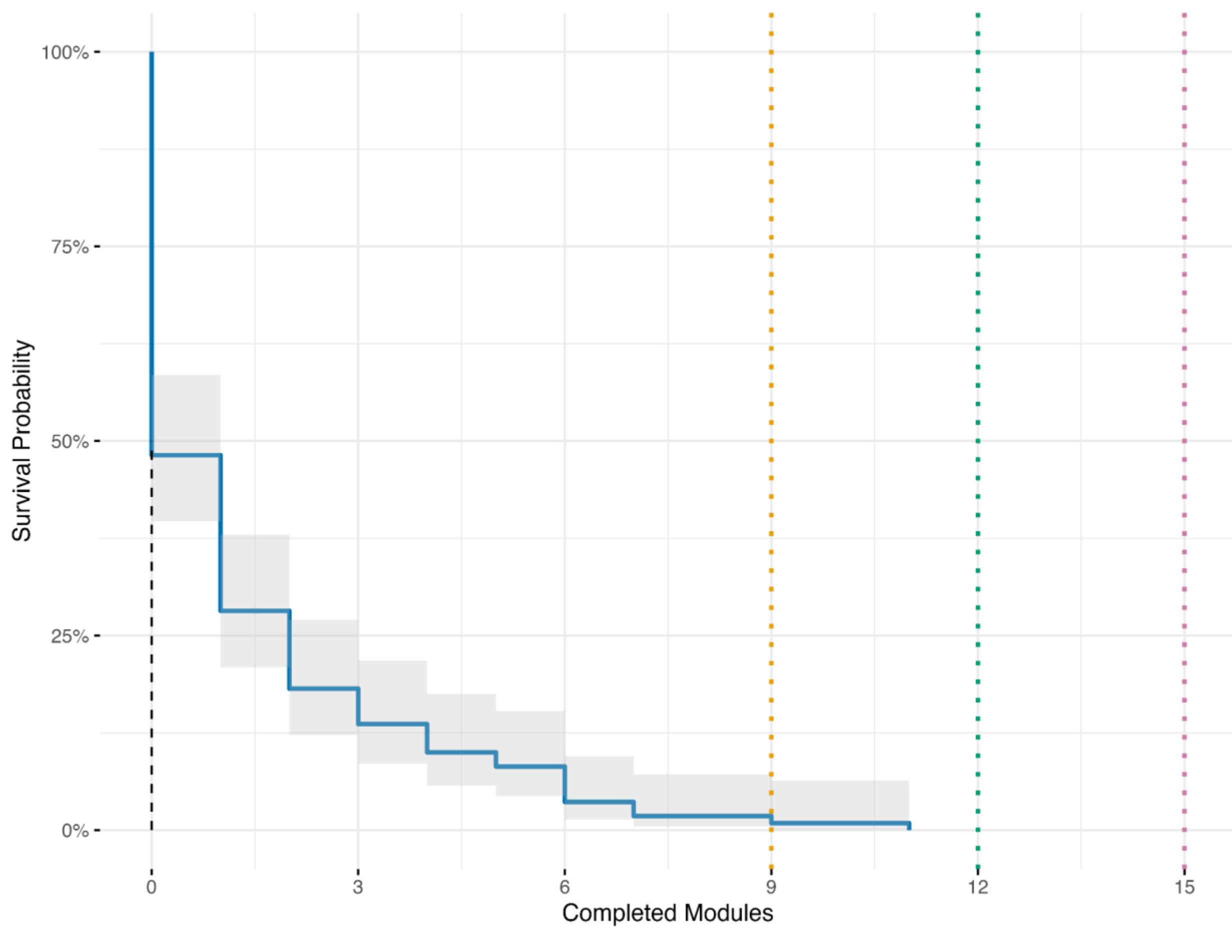
The results of the Kaplan-Meier survival analysis

Time	Number at risk	Number of events	Survival estimate	Standard error	Lower limit	Upper limit
0	110	57	0.48	0.05	0.40	0.58
1	53	22	0.28	0.04	0.21	0.38
2	31	11	0.18	0.04	0.12	0.27
3	20	5	0.14	0.03	0.09	0.22
4	15	4	0.10	0.03	0.06	0.18
5	11	2	0.08	0.03	0.04	0.15
6	9	5	0.04	0.02	0.01	0.10
7	4	2	0.02	0.01	0.00	0.07
9	2	1	0.01	0.01	0.00	0.06
11	1	1	0.00	-	-	-

Note. Time = the last module that has been completed; Number at risk = participants still actively participating in the intervention; Number of events = number of participants who dropped out after this module; Survival estimate = probability of participating in the intervention until this point.

Figure 1

The Kaplan-Meier survival curve



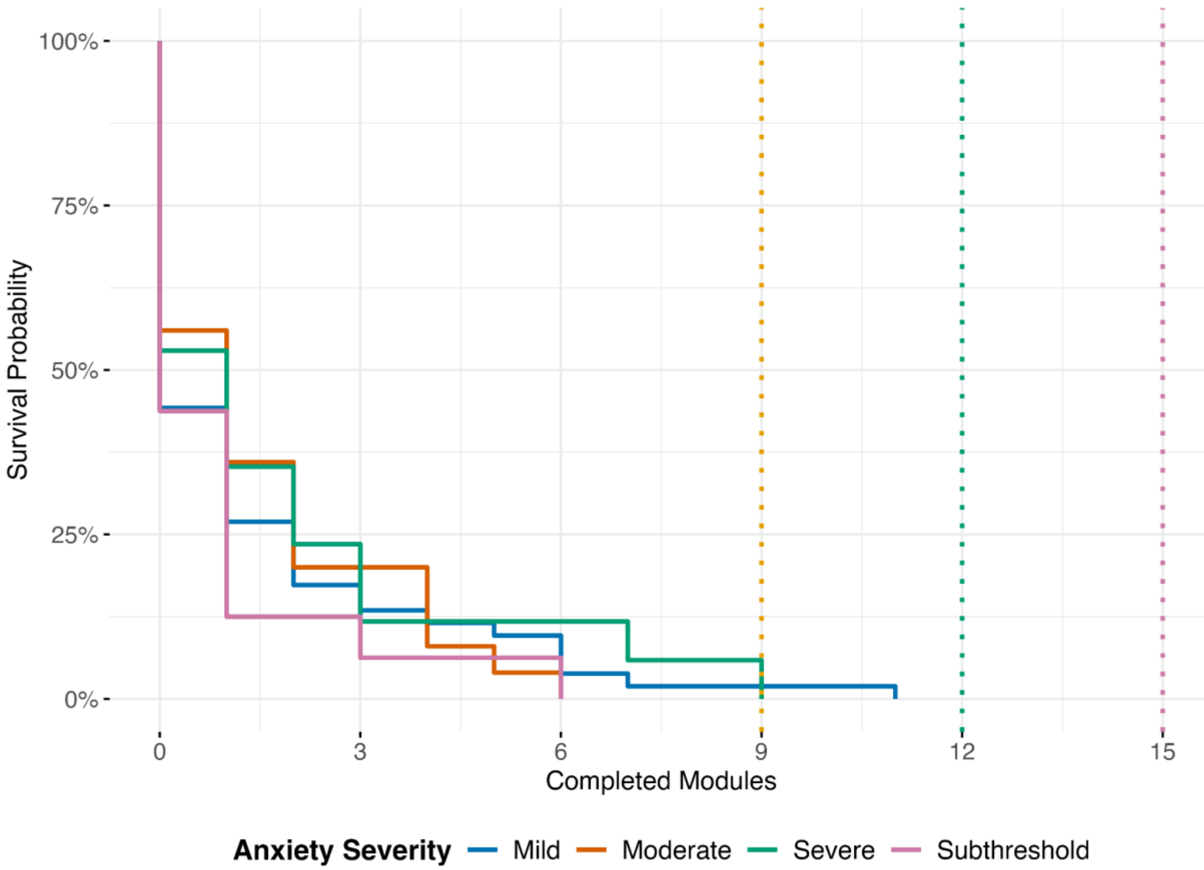
Note. The x-axis shows the number of modules a participant completed before dropping out; the y-axis shows the probability of still participating in the intervention after having completed module x; the black dotted line represents the point at which 50% of the participants have dropped out of the intervention; the grey area around the survival curve represent the 95% confidence interval of the survival estimates; the orange dotted line represents the end of the theoretical modules from the Healthcare Worker COVID intervention; the green dotted line represents the end of the complementary modules from the Healthcare worker COVID intervention and the end of the Grief COVID intervention; the pink dotted line represents the end of the Mental Health COVID intervention.

Anxiety

A log rank test was conducted, with the time being the number of modules completed and the different groups being "subthreshold", "mild", "moderate" and "severe" anxiety participants. The number of participants were 16 for "subthreshold", 52 for "mild", 25 for "moderate" and 17 for "severe". The log rank test did not reveal a significant difference between the survival curve of the groups, X^2 (3) = 1.40, p = .71. Thus, the null hypothesis that all groups have the same time to dropout cannot be rejected. The survival curves of the four groups are shown in Figure 2.

Figure 2

The survival curves of participants grouped by the severity of their anxiety symptoms



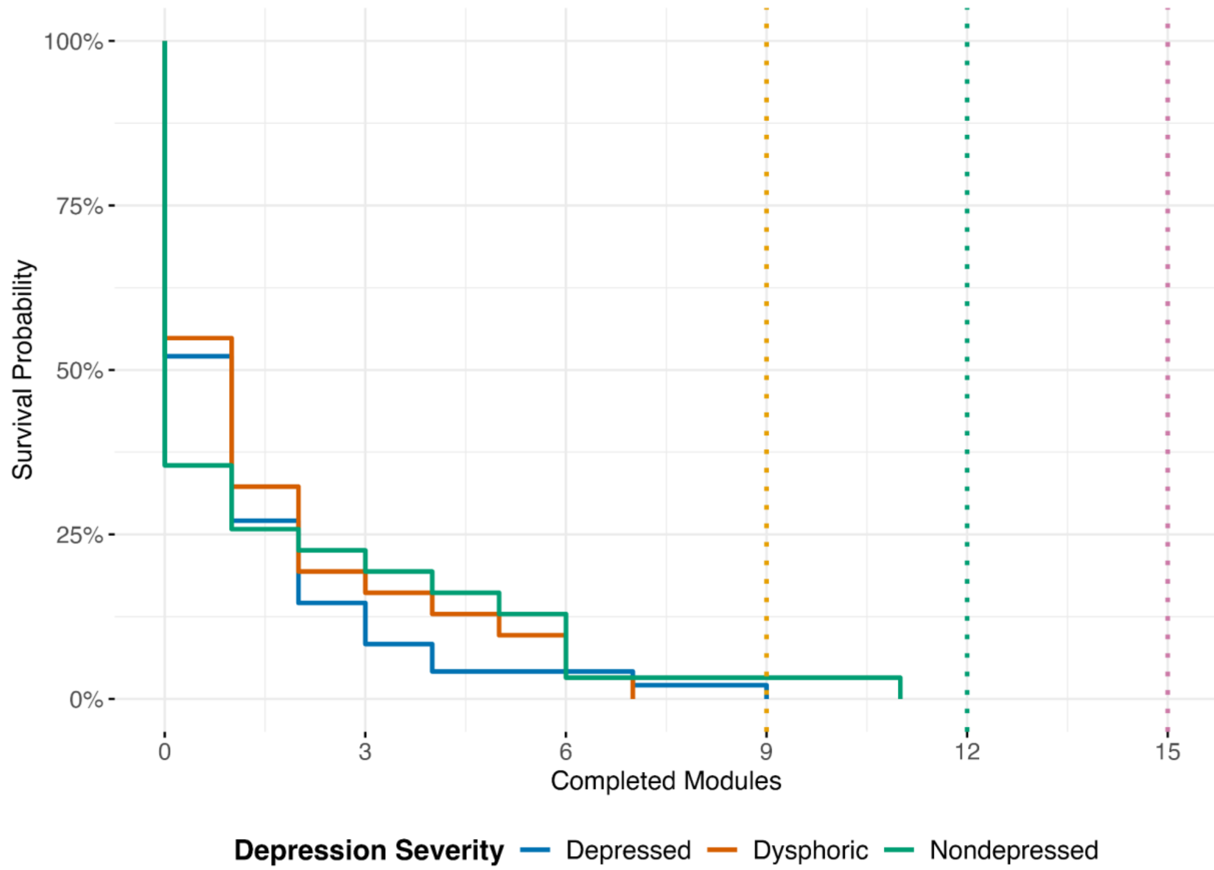
Note. The x-axis shows the number of modules a participant completed before dropping out; the y-axis shows the probability of still participating in the intervention after having completed module x; the orange dotted line represents the end of the theoretical modules from the Healthcare Worker COVID intervention; the green dotted line represents the end of the complementary modules from the Healthcare worker COVID intervention and the end of the Grief COVID intervention; the pink dotted line represents the end of the Mental Health COVID intervention.

Depression

Next, a log rank test was conducted to measure the difference in survival curves based on severity of depression. Again, the amount of modules completed acts as the time passed. The different groups were “non-depressed”, “dysphoric” and “depressed”. The number of participants were 31 for “non-depressed”, 31 for “dysphoric” and 48 for “depressed”. The log rank test did not reveal a significant difference between the survival curve of the groups, X^2 (2) = 0.38, p = .83. Thus, the null hypothesis that all groups have the same time to dropout cannot be rejected. The survival curves of the three groups are shown in Figure 3.

Figure 3

The survival curves of participants grouped by the severity of their depression symptoms



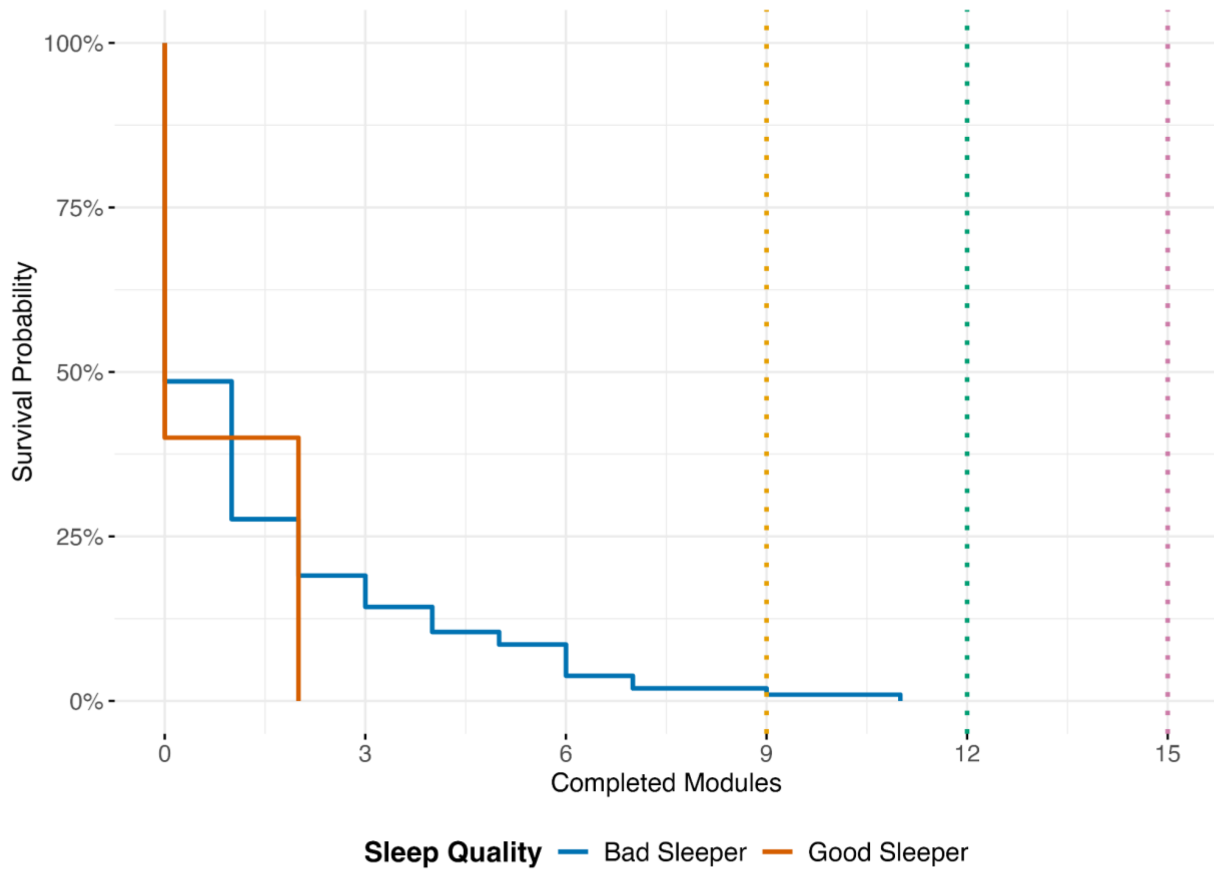
Note. The x-axis shows the number of modules a participant completed before dropping out; the y-axis shows the probability of still participating in the intervention after having completed module x; the orange dotted line represents the end of the theoretical modules from the Healthcare Worker COVID intervention; the green dotted line represents the end of the complementary modules from the Healthcare worker COVID intervention and the end of the Grief COVID intervention; the pink dotted line represents the end of the Mental Health COVID intervention.

Sleep Quality

Lastly, a log rank test was conducted, with the time being the number of modules completed and the different groups being “good sleepers” and “bad sleepers”. The number of participants were 105 for the “bad sleeper” group and 5 for the “good sleeper” group. The log rank test did not reveal a significant difference between the survival curve of the groups, $X^2(1) = 0.36$, $p = .55$. Thus, the null hypothesis that the two groups have the same time to dropout cannot be rejected. The survival curves of the two groups are shown in Figure 4.

Figure 4

The survival curves of participants grouped by whether they are a good or a bad sleeper according to the PSQI



Note. The x-axis shows the number of modules a participant completed before dropping out; the y-axis shows the probability of still participating in the intervention after having completed module x; the orange dotted line represents the end of the theoretical modules from the Healthcare Worker COVID intervention; the green dotted line represents the end of the complementary modules from the Healthcare worker COVID intervention and the end of the Grief COVID intervention; the pink dotted line represents the end of the Mental Health COVID intervention.

Demographic Variables

Lastly, to exhaustively explore differences in moments of dropout, log-rank tests were conducted for the demographic variables of gender, whether participants were actively working at the time of the intervention, their education, age and the intervention they were participating in. The results of the log-rank tests, including the degrees of freedom, chi-square and the p-value per log- rank test can be found in table 4.

Table 4

Results of the log-rank tests for demographic variables and intervention differences

Variable	Groups	*df*	χ^2	*p*
Gender	Female (N=95), Male (N=15)	1	0.21	0.65
Actively Working	Yes (N=69), No (N=41)	1	0.13	0.72
Education	Middle School (N=3), High School (N=16), Bachelor's Degree (N=73), Master's degree (N=16), Doctorate (N=1), Other (N=1)	5	7.24	0.20
Age	18-24 (N=17),	2	3.34	0.19

	25-40 (N=56), 41+ (N=37)			
Intervention	Mental Health COVID (N=36), Grief COVID (N=70), Healthcare Worker COVID (N=4)	2	4.47	0.11

Note. df = degrees of freedom; N = number of participants included in the analysis; χ^2 = chi-square.

Discussion

The objective of this study was to explore the relation between participants' level of anxiety, depression and sleep quality and the moment of dropout in a sample composed of participants who have dropped out of one of three DMHIs. The research questions of this study were:

1. "What is the relationship between participants' level of anxiety and the moment of dropout?"
2."What is the relationship between participants' level of depression and the moment of dropout?"
3. "What is the relationship between the participants' sleep quality and moment of dropout?"

Discussion of General Findings

The Kaplan-Meier estimates of this study show that a large proportion of the dropouts happen even before the intervention started, with the survival estimate indicating that the probability of actively participating in the intervention, even before having finished the first module, is 50%. Afterwards, the survival curve gradually flattens, showing that most dropouts occur in the first three to four modules. This pattern is also present in the study by Kaajalaakso et al. (2024), but only in the part of the sample that did not receive a diagnosis for anxiety disorder. Duhne et al. (2022) also reported dropout before even starting the intervention at a rate of 29.08%, with 54.09% dropping out of the intervention before finishing at least three modules. These results seem to be in line with this study's results, showing a large proportion of the dropouts happening at the beginning of the intervention.

However, in another study examining dropout in a program promoting nutrition through SMS texts, the Kaplan-Meier survival curves of different intervention showed a much more gradual slope, with the first intervention to achieve a survival probability of 0.5 reaching it after more than 50 days (Grutzmacher et al., 2018). This difference in results could be explained by the present study only including participants who dropped out of the intervention instead of including participants who finished the intervention. This could lead to a smaller percentage of the participants dropping out being reported in other studies.

Anxiety and the Moment of Dropout

Regarding research question one, the analysis has not yielded significant results. There was no significant difference between the survival curves of participants with subthreshold, mild, moderate and severe anxiety. The results of this study are unexpected considering previous findings. Kaajalaakso et al., (2024) conducted a log-rank test in their study on dropout comparing participants with a diagnosis of an anxiety disorder and those who did not receive a diagnosis of an anxiety disorder. Contrary to this study's results, their log-rank test showed a significant difference between the two groups at the moment of dropout. This difference might be explained by the methodological differences between the two studies. Kaajalaakso et al.,

(2024) conducted their study on Internet Cognitive Behavioral Therapy (ICBT) for anxiety. Thus, the study found a significant difference between severities of anxiety in an intervention specifically designed to treat anxiety. Their explanation for the finding was that participants fulfilling the diagnostic criteria for an anxiety disorder would suffer from its symptoms more acutely, incentivizing them to fully complete the intervention. This explanation would also account for the insignificant results of this study. As only the Healthcare Worker COVID intervention specifically aimed to treat anxiety, while the two other interventions did not, many participants might have been included in the analysis that did not participate to treat anxiety. Thus, it would not have been a motivator for people to continue their engagement in the intervention, even if it was more present than other symptoms.

Furthermore, in the study by Kaajalaakso et al., (2024) only two groups of participants were compared. With 234 total participants and only two groups, the group sizes were much larger than in this study. Thus, statistical differences would have been easier to find than in this study, which had much smaller groups. Secondly, when conducting log rank tests, finding significant differences between two groups would be much easier than finding differences between four groups.

Depression and the Moment of Dropout

In regard to research question two, the analysis has not produced significant results, either. The log-rank test did not detect a significant difference in survival curves between participants who were non-depressed, dysphoric or depressed. Regarding the relation between depression and the moment of dropout, the outcomes of this study are also unexpected. Duhne et al. (2022) found more severe depression to be predictive of early dropout. This was defined as dropping out before completing the third module of an intervention. Thus, it could have been expected to find that higher severity of depression would have distorted the survival curve and produced a significant difference in a log-rank test in this study. A key methodological difference to this study is that participants were partaking in one of two treatment modalities, only one of which was a DMHI. Still, depression severity was found to be predictive of early dropout in both treatment modalities. Furthermore, both treatments were aimed at treating depression, whereas only the Healthcare Worker COVID intervention from this study was specifically aimed at decreasing symptoms of depression. Perhaps, this study would have found significant differences in the moment of dropout based on the severity of depression if the main objective of all interventions had been to treat depression. A possible explanation for this finding might be similar to that offered on the topic of anxiety (Kaajalaakso et al., 2024). Alignment between the disorder addressed by the intervention and acute symptoms of this disorder experienced by the participants might increase the participants motivation to stay in the intervention longer. For example, a participant acutely suffering from depression might be more motivated to complete an intervention aimed at treating depression than those who do not suffer from it as severely. In a similar manner, participants suffering from symptoms of depression might experience less motivation to participate fully in an intervention when the focus of the intervention was on multiple areas of mental health, with depression not as the main focus.

Sleep Quality and the Moment of Dropout

Pertaining to research question three, the analysis was not able to detect significant differences in the survival curves of participants who were identified as either good or bad sleepers. Thus, no significant findings can be reported for this research question. In a similar manner to the previous research questions, these results are also unexpected. Bremer et al. (2020) investigated dropout in a DMHI for insomnia. They found that the time when people left their bed and how long it took them predicted dropout. These variables are connected to sleep quality, as the time of getting out of bed is also measured in the PSQI, which this study used to measure quality of sleep. The difference in findings between the two studies might be due to multiple reasons. First, Bremer et al. (2020) used a dataset of all participants which partook in the intervention, as opposed to only dropouts. Secondly, the larger sample containing 151 participants might have increased the ability to detect small but significant correlations. Lastly, their study found significant predictors of dropout in a variable related to the treatment goal of the intervention. This study assessed multiple variables that were not directly or exclusively related to the goal of the intervention. These methodological differences might have led to differences in findings.

A difference between this study and the discussed studies is that this study only included participants who did not complete the intervention. Previous studies on dropout used participants who completed the studies in conjunction with those who dropped out. This puts emphasis on the difference between participants who dropped out and those who did not, whereas this study tried to identify differences between participants who dropped out based on their severity of anxiety, depression and quality of sleep. This methodological difference could explain the non-statistically significant findings of this study.

Limitations and Strengths

A limitation of this study pertaining to the comparison between groups through the log rank test is the uneven distribution between the groups representing good and bad sleep quality. With a group of only five participants experiencing good sleep quality, the group size might have introduced too much variability, as the data might not be representative of the population of participants experiencing good sleep quality. Thus, the result from the log-rank test regarding differences between good and bad sleep quality is not as robust as it could have been with larger group sizes and does not allow for generalizability to a larger population.

Further, the demographic characteristics of this sample could be considered a limitation of this study. The combined sample from the three studies shows a large proportion of female participants and a high level of education with around four out of five participants having achieved at least a bachelor's degree. Being male and low levels of education have been highlighted as predictors of dropout in general (Karyotaki et al., 2015). However, due to the underrepresentation of males and participants with lower levels of education, possible effects of these variables on the moment of dropout might have been more difficult to detect.

Lastly, the uneven distribution of participants from the different interventions could be considered a limitation of this study. The Healthcare Worker COVID intervention only contributed the data of four participants to this study, as opposed to the 39 participants from Mental Health COVID and the 70 participants from Grief COVID. Thus, the unique characteristics that the sample from the Healthcare Worker COVID might have experienced due to their profession during the COVID-19 outbreak could have been underrepresented. With a more balanced distribution of participants between the three interventions, results might have been different. They would have been more representative of the characteristics of healthcare workers, as well as more generalizable due to a better representation of different groups.

The strengths of this study lie in its unique sample. First, the participants of the three different interventions varied in their needs and reasons for wanting to partake in a DMHI, as well as in their life circumstances. Participants from Mental Health COVID included a more general sample of participants wanting to work on their mental health by improving virtues and strengths. Participants from Grief COVID included those who had recently lost a loved one and wanted to prevent further mental health complications as well as work on increasing their life quality. Participants from the Healthcare Worker COVID consisted of only healthcare workers during the COVID-19 pandemic who wanted to decrease their symptoms of anxiety and depression. This combination of participants with unique needs and life circumstances is the first aspect of the sample's strengths.

Secondly, the inclusion of three different interventions experienced by participants presents a strength. The interventions had varying lengths ranging from 9 to 15 modules and different treatment goals, either preventative or building on strengths and resources. They also had different modalities of how intervention material was delivered and differing control group conditions. Participants experienced content with or without chat support, were able to choose either text or video format for the presentation of the content or could even experience it through online meetings with a therapist in one control condition. This study's sample comprising participants with different life circumstances, with different needs and experiencing different interventions presents a significant strength of this study.

While there might be limitations regarding the specific distributions of participants within subgroups, any results found in this study would have been more robust and generalizable than studies using only participants from one intervention, as it would benefit from decreased variance and increased external validity (Bangdiwala et al., 2016).

Implications

The results of the Kaplan-Meier survival curve and the corresponding estimates show that amongst the participants who dropped out of the intervention, 50% did so before having finished the first module of the intervention. As the consequences of dropping out of an intervention and thus not receiving treatment for possible psychological problems could be severe (Bertolote &

Fleischmann, 2002), researchers and developers of DMHIs should focus on offering further support or tailoring to participants in the beginning of DMHIs. For example, a coach could be provided to all participants for the first three modules of a DMHI. This human supervision could enhance adherence to the intervention as suggested in the Supportive Accountability Model by Mohr et al., (2011). Additional support in the phase of the intervention where dropout is most likely to occur might aid participants in adhering to the intervention for longer, receiving more help for mental health symptoms.

As dropout decreases after the first three to four modules, support should then be decreased or stopped. A longer period of offering support could be inefficient, possibly making this addition unachievable due to increased costs and necessity of finding suitable personnel. Furthermore, it could present as counterproductive, as offering supervision for longer than needed could decrease intervention adherence (Mohr et al., 2011). Thus, if support is offered, it should only be offered during the first three to four modules of the intervention.

Moreover, the results of the log rank tests demonstrate that the severity of anxiety, depression and sleep quality, as well as demographic variables, do not lead to differences in the moment of dropout. Thus, participants are not likely to benefit from differing treatment such as increased support or other tailoring based on the severity of symptoms that are not the main focus of the intervention. Therefore, researchers should not differentiate between participants in the amount of support they offer based on severity of anxiety, depression, or sleep quality in DMHIs which are not specifically aimed at treating them.

In summary, researchers and developers of DMHIs should offer additional support to all participants for the first three to four modules of the intervention which should be discontinued after this time span. Lastly, the support should not be specifically offered to only one group of participants based on demographic characteristics or the severity of anxiety, depression or sleep quality in interventions that are not designed to treat these specific disorders.

Future Recommendations

Future research should further investigate predictors of dropout, specifically in those individuals who drop out especially early in the intervention. Of interest would be further studies investigating the link between symptom severity and dropout in interventions that focus specifically on treating the variable of interest. For example, the link between the moment of dropout and the severity of depression should be investigated in an intervention designed to treat depression. Insights from these studies would expand on this study's results and could lead to better understanding of the possibilities of tailoring based on symptom severity of mental health disorders. If no significant results were found, researchers and developers of DMHIs should not conduct tailoring based on severity of symptoms. However, if significant results were found, tailoring for the highlighted variable in the corresponding context should be conducted, as it might increase retention rate of the intervention.

Furthermore, researchers should attempt to explore other variables in relation to the moment of dropout in online interventions, which have previously been associated with dropout in general, such as personality traits or comorbidities of mental health diagnosis (Högdahl et al., 2016; Karyotaki et al., 2015). These variables would stay relatively stable over the course of the intervention and can easily be measured at the start of the intervention. Significant results of such analysis would enable further tailoring of interventions to the needs of participants and thus might increase the retention in interventions and could lead to better mental health outcomes for the population.

Furthermore, studies using more than one independent variable in survival analysis would be of interest. This study divided the sample into groups and compared the groups with each other in an attempt to find differences in the moment of dropout. An interesting variation of this study would be to instead investigate predictors of increased risk for dropout throughout the intervention. For example, the Cox Proportional Hazards Model (Bradburn et al., 2003) could be used to investigate predictors of increased hazard rates, as well as possible collinearities within the independent variables.

Lastly, in accordance with the implication from this study that support is needed in the beginning of the intervention, researchers should investigate the effect of providing further support for the first three to four modules of an intervention. Specifically, it should be investigated if this support decreases dropout from the intervention or if dropout is just delayed, leading to an increased number of dropouts after the support ends. The results of this kind of study would give further insights into the practicality of temporary support.

Conclusion

The aim of this study was to explore the differences in the moment of dropout in participants from three different DMHIs, using log rank tests based on symptom severity of depression and anxiety, as well as sleep quality. The log rank tests did not produce significant results, indicating these variables do not predict differences in moment of dropout in a heterogeneous sample of participants who dropped out of an online intervention. Thus, tailoring should not occur for participants based solely on the severity of the symptoms of anxiety, depression and sleep quality. Further research should be conducted regarding the link between the severity of symptoms specifically aimed to be treated by a DMHI and the moment of dropout.

References

Acarturk, C., Smit, F., De Graaf, R., Van Straten, A., Have, M. T., & Cuijpers, P. (2008). Economic costs of social phobia: A population-based study. *Journal of Affective Disorders*, *115*(3), 421–429. https://doi.org/10.1016/j.jad.2008.10.008

Alfonsson, S., Olsson, E., & Hursti, T. (2016). Motivation and Treatment Credibility predicts dropout, treatment adherence, and clinical outcomes in an Internet-Based Cognitive Behavioral Relaxation program: a randomized controlled trial. *Journal of Medical Internet Research*, *18*(3), e52. https://doi.org/10.2196/jmir.5352

Andersson, G., Titov, N., Dear, B. F., Rozental, A., & Carlbring, P. (2019). Internet-delivered psychological treatments: from innovation to implementation. *World Psychiatry*, *18*(1), 20–28. https://doi.org/10.1002/wps.20610

Bär, J., Ziehn, P., Ewert-Altenhain, D., Seidl, L., Schaeuffele, C., & Boettcher, J. (2021). Behandlungsschwierigkeiten bei geleiteter Online-Therapie. *Psychotherapeut*, *66*(5), 439–446. https://doi.org/10.1007/s00278-021-00522-5

Bangdiwala, S. I., Bhargava, A., O'Connor, D. P., Robinson, T. N., Michie, S., Murray, D. M., Stevens, J., Belle, S. H., Templin, T. N., & Pratt, C. A. (2016). Statistical methodologies to pool across multiple intervention studies. *Translational Behavioral Medicine*, *6*(2), 228–235. https://doi.org/10.1007/s13142-016-0386-8

Beatty, L., & Binnion, C. (2016). A systematic review of predictors of, and reasons for, adherence to online psychological interventions. *International Journal of Behavioral Medicine*, *23*(6), 776–794. https://doi.org/10.1007/s12529-016-9556-9

Bertolote, J. M., & Fleischmann, A. (2002). *Suicide and psychiatric diagnosis: a worldwide perspective*. https://pmc.ncbi.nlm.nih.gov/articles/PMC1489848/

Bradburn, M. J., Clark, T. G., Love, S. B., & Altman, D. G. (2003). Survival Analysis Part II: Multivariate data analysis – an introduction to concepts and methods. *British Journal of Cancer*, *89*(3), 431–436. https://doi.org/10.1038/sj.bjc.6601119

Bremer, V., Chow, P. I., Funk, B., Thorndike, F. P., & Ritterband, L. M. (2020). Developing a process for the analysis of user journeys and the prediction of dropout in digital health interventions: Machine Learning approach. *Journal of Medical Internet Research*, *22*(10), e17738. https://doi.org/10.2196/17738

Buysse, D. J., Reynolds, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research*, *28*(2), 193–213. https://doi.org/10.1016/0165-1781(89)90047-4

Cella, D., Riley, W., Stone, A., Rothrock, N., Reeve, B., Yount, S., Amtmann, D., Bode, R., Buysse, D., Choi, S., Cook, K., DeVellis, R., DeWalt, D., Fries, J. F., Gershon, R., Hahn, E. A., Lai, J., Pilkonis, P., Revicki, D., . . . Hays, R. (2010). The Patient-Reported Outcomes Measurement Information System (PROMIS) developed and tested its first wave of adult self-reported health outcome item banks: 2005–2008. *Journal of Clinical Epidemiology*, *63*(11), 1179–1194. https://doi.org/10.1016/j.jclinepi.2010.04.011

Choi, S. W., Schalet, B., Cook, K. F., & Cella, D. (2014). Establishing a common metric for depressive symptoms: Linking the BDI-II, CES-D, and PHQ-9 to PROMIS Depression. *Psychological Assessment*, *26*(2), 513–527. https://doi.org/10.1037/a0035768

Ciharova, M., Cuijpers, P., Amanvermez, Y., Riper, H., Klein, A. M., Bolinski, F., De Wit, L. M., Van Der Heijde, C. M., Bruffaerts, R., Struijs, S., Wiers, R. W., & Karyotaki, E. (2023). Use of tailoring features and reasons for dropout in a guided internet-based transdiagnostic individually-tailored cognitive behavioral therapy for symptoms of depression and/or anxiety in college students. *Internet Interventions*, *34*, 100646. https://doi.org/10.1016/j.invent.2023.100646

Clark, T. G., Bradburn, M. J., Love, S. B., & Altman, D. G. (2003). Survival Analysis Part I: Basic concepts and first analyses. *British Journal of Cancer*, *89*(2), 232–238. https://doi.org/10.1038/sj.bjc.6601118

Dominguez-Rodriguez, A., De La Rosa-Gómez, A., Jiménez, M. J. H., Arenas-Landgrave, P., Martínez-Luna, S. C., Silva, J. A., Hernández, J. E. G., Arzola-Sánchez, C., & Guzmán, V. A. (2020). A Self-Administered Multicomponent Web-Based Mental Health Intervention for the Mexican population during the COVID-19 pandemic: Protocol for a randomized controlled trial. *JMIR Research Protocols*, *9*(11), e23117. https://doi.org/10.2196/23117

Dominguez-Rodriguez, A., Martínez-Luna, S. C., Jiménez, M. J. H., De La Rosa-Gómez, A., Arenas-Landgrave, P., Santoveña, E. E. E., Arzola-Sánchez, C., Silva, J. A., Nicolas, A. M. S., Guadián, A. M. C., Ramírez-Martínez, F. R., & Vargas, R. O. C. (2021). A Self-Applied Multi-Component psychological online intervention based on UX, for the prevention of complicated grief disorder in the Mexican population during the COVID-19 outbreak: Protocol of a randomized clinical trial. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.644782

Dominguez-Rodriguez, A., Martínez-Arriaga, R. J., Herdoiza-Arroyo, P. E., Bautista-Valerio, E., De La Rosa-Gómez, A., Vargas, R. O. C., Lacomba-Trejo, L., Mateu-Mollá, J., De Jesús Lupercio Ramírez, M., González, J. a. F., & Martínez, F. R. R. (2022). E-Health Psychological Intervention for COVID-19 Healthcare Workers: Protocol for its

Implementation and Evaluation. *International Journal of Environmental Research and Public Health*, *19*(19), 12749. https://doi.org/10.3390/ijerph191912749

Dominguez-Rodriguez, A., Sanz-Gomez, S., Ramírez, L. P. G., Herdoiza-Arroyo, P. E., Garcia, L. E. T., De La Rosa-Gómez, A., González-Cantero, J. O., Macias-Aguinaga, V., & Miaja, M. (2023). The Efficacy and usability of an Unguided Web-Based Grief Intervention for adults who lost a loved one during the COVID-19 pandemic: Randomized Controlled trial. *Journal of Medical Internet Research*, *25*, e43839. https://doi.org/10.2196/43839

Dominguez-Rodriguez, A., Sanz-Gomez, S., Ramírez, L. P. G., Herdoiza-Arroyo, P. E., Garcia, L. E. T., De La Rosa-Gómez, A., González-Cantero, J. O., Macias-Aguinaga, V., Landgrave, P. A., & Chávez-Valdez, S. M. (2024). Evaluation and Future Challenges in a Self-guided Online Intervention with and without Chat Support for Depression and Anxiety Symptoms during the COVID-19 Pandemic: A Randomized Control Trial (Preprint). *JMIR Formative Research*, *8*, e53767. https://doi.org/10.2196/53767

Dozois, D. J. A., Dobson, K. S., & Ahnberg, J. L. (1998). A psychometric evaluation of the Beck Depression Inventory–II. *Psychological Assessment*, *10*(2), 83–89. https://doi.org/10.1037/1040-3590.10.2.83

Duhne, P. G. S., Delgadillo, J., & Lutz, W. (2022). Predicting early dropout in online versus face-to-face guided self-help: A machine learning approach. *Behaviour Research and Therapy*, *159*, 104200. https://doi.org/10.1016/j.brat.2022.104200

Eaton, W. W. E., Smith, C. S., Ybarra, M. Y., Muntaner, C. M., & Tien, A. T. (2004). Center for Epidemiologic Studies Depression Scale: Review and Revision (CESD and CESD-R) [PDF]. In *The Use of Psychological Testing For Treatment Planning and Outcome*

Assessment (Third edition, Vol. 3, pp. 363–375). https://www.researchgate.net/publication/284664681_Center_for_Epidemiologic_Studies_Depression_Scale_Review_and_revision_CESD_and_CESD-R

Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (WoeBot): a randomized controlled trial. *JMIR Mental Health*, *4*(2), e19. https://doi.org/10.2196/mental.7785

Garcia-Campayo, J., Zamorano, E., Ruiz, M. A., Pardo, A., Perez-Paramo, M., Lopez-Gomez, V., Freire, O., & Rejas, J. (2010). Cultural adaptation into Spanish of the generalized anxiety disorder-7 (GAD-7) scale as a screening tool. *Health and Quality of Life Outcomes*, *8*(1), 8. https://doi.org/10.1186/1477-7525-8-8

González-Forteza, C., Jiménez-Tapia, J. A., Ramos-Lira, L., & Wagner, F. A. (2008). Aplicación de la Escala de Depresión del Center of Epidemiological Studies en adolescentes de la Ciudad de México. *Salud Pública De México*, *50*(4), 292–299. https://doi.org/10.1590/s0036-36342008000400007

Grutzmacher, S. K., Munger, A. L., Speirs, K. E., Vafai, Y., Hilberg, E., Duru, E. B., Worthington, L., & Lachenmayr, L. (2018). Predicting Attrition in a Text-Based Nutrition Education Program: Survival Analysis of Text2BHealthy. *JMIR Mhealth and Uhealth*, *7*(1), e9967. https://doi.org/10.2196/mhealth.9967

Hedman, E., Ljótsson, B., & Lindefors, N. (2014). Cognitive behavior therapy via the Internet: a systematic review of applications, clinical efficacy and cost–effectiveness. *Expert Review of Pharmacoeconomics & Outcomes Research*, *12*(6), 745–764. https://doi.org/10.1586/erp.12.67

Högdahl, L., Levallius, J., Björck, C., Norring, C., & Birgegård, A. (2016). Personality predicts drop-out from therapist-guided internet-based cognitive behavioural therapy for eating disorders. Results from a randomized controlled trial. *Internet Interventions*, *5*, 44–50. https://doi.org/10.1016/j.invent.2016.07.002

Jiménez-Genchi, A., Monteverde-Maldonado, E., Nenclares-Portocarrero, A., Esquivel-Adame, G., & De La Vega-Pacheco, A. (2008). [Reliability and factorial analysis of the Spanish version of the Pittsburg Sleep Quality Index among psychiatric patients]. *PubMed*, *144*(6), 491–496. https://pubmed.ncbi.nlm.nih.gov/19112721

Kaajalaakso, K., Luntamo, T., Korpilahti-Leino, T., Ristkari, T., Hinkka-Yli-Salomäki, S., & Sourander, A. (2024). Predictors of dropout, time spent on the program and client satisfaction in an internet-based, telephone-assisted CBT anxiety program among elementary school children in a population-based sample. *European Child & Adolescent Psychiatry*, *34*(1), 249–258. https://doi.org/10.1007/s00787-024-02486-8

Karyotaki, E., Kleiboer, A., Smit, F., Turner, D. T., Pastor, A. M., Andersson, G., Berger, T., Botella, C., Breton, J. M., Carlbring, P., Christensen, H., De Graaf, E., Griffiths, K., Donker, T., Farrer, L., Huibers, M. J. H., Lenndin, J., Mackinnon, A., Meyer, B., . . . Cuijpers, P. (2015). Predictors of treatment dropout in self-guided web-based interventions for depression: an 'individual patient data' meta-analysis. *Psychological Medicine*, *45*(13), 2717–2726. https://doi.org/10.1017/s0033291715000665

Königbauer, J., Josefine, L., Philipp, D., David, E., & Harald, B. (2017b). Internet- and mobile-based depression interventions for people with diagnosed depression: A systematic review and meta-analysis. *Journal of Affective Disorders*, *223*, 28–40. https://doi.org/10.1016/j.jad.2017.07.021

Kooistra, L. C., Wiersma, J. E., Ruwaard, J., Neijenhuijs, K., Lokkerbol, J., Van Oppen, P., Smit, F., & Riper, H. (2019). Cost and effectiveness of blended versus standard cognitive behavioral therapy for outpatients with depression in routine specialized mental health care: pilot randomized controlled trial. *Journal of Medical Internet Research*, *21*(10), e14261. https://doi.org/10.2196/14261

Kumar, V., Sattar, Y., Bseiso, A., Khan, S., & Rutkofsky, I. H. (2017). The effectiveness of Internet-Based Cognitive Behavioral therapy in treatment of psychiatric disorders. *Cureus*. https://doi.org/10.7759/cureus.1626

Lehtimaki, S., Martic, J., Wahl, B., Foster, K. T., & Schwalbe, N. (2021). Evidence on Digital Mental Health Interventions for Adolescents and Young People: Systematic Overview. *JMIR Mental Health*, *8*(4), e25847. https://doi.org/10.2196/25847

Levin, M. E., Mukasa, M. N., Bowers, E. M., Klimczak, K. S., & Aller, T. B. (2025). A pilot randomized controlled trial of a Single-Session digital Acceptance and Commitment therapy intervention. *Behavioral Sciences*, *15*(1), 75. https://doi.org/10.3390/bs15010075

Melville, K. M., Casey, L. M., & Kavanagh, D. J. (2009). Dropout from Internet-based treatment for psychological disorders. *British Journal of Clinical Psychology*, *49*(4), 455–471. https://doi.org/10.1348/014466509x472138

Mohr, D. C., Cuijpers, P., & Lehman, K. (2011). Supportive Accountability: A model for providing human support to enhance adherence to eHealth interventions. *Journal of Medical Internet Research*, *13*(1), e30. https://doi.org/10.2196/jmir.1602

Penninx, B. W., Milaneschi, Y., Lamers, F., & Vogelzangs, N. (2013). Understanding the somatic consequences of depression: biological mechanisms and the role of depression symptom profile. *BMC Medicine*, *11*(1). https://doi.org/10.1186/1741-7015-11-129

Postel, M. G., De Haan, H. A., Ter Huurne, E. D., Becker, E. S., & De Jong, C. A. (2010). Effectiveness of a web-based intervention for problem drinkers and reasons for dropout: randomized controlled trial. *Journal of Medical Internet Research*, *12*(4), e68. https://doi.org/10.2196/jmir.1642

Rens, E., Dom, G., Remmen, R., Michielsen, J., & Van Den Broeck, K. (2020). Unmet mental health needs in the general population: perspectives of Belgian health and social care professionals. *International Journal for Equity in Health*, *19*(1). https://doi.org/10.1186/s12939-020-01287-0

Schuster, R., Pokorny, R., Berger, T., Topooco, N., & Laireiter, A. (2018). The advantages and Disadvantages of online and blended therapy: Survey study amongst licensed psychotherapists in Austria. *Journal of Medical Internet Research*, *20*(12), e11007. https://doi.org/10.2196/11007

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder. *Archives of Internal Medicine*, *166*(10), 1092. https://doi.org/10.1001/archinte.166.10.1092

Steel, Z., Marnane, C., Iranpour, C., Chey, T., Jackson, J. W., Patel, V., & Silove, D. (2014). The global prevalence of common mental disorders: a systematic review and meta-analysis 1980–2013. *International Journal of Epidemiology*, *43*(2), 476–493. https://doi.org/10.1093/ije/dyu038

Szigethy, E., Wolfson, D., Sinclair-McBride, K., Williams, K., Jhe, G., Lee, E. H., Bialostozky, M., Wallace, M., Bhatnagar, S., Demaso, Yealy, D. M., & Hollenbach, K. (2023). Efficacy of a digital mental health intervention embedded in routine care compared with treatment as usual in adolescents and young adults with moderate depressive symptoms:

protocol for randomised controlled trial. *BMJ Open*, *13*(3), e067141. https://doi.org/10.1136/bmjopen-2022-067141

Van Straten, A., Cuijpers, P., & Smits, N. (2008). Effectiveness of a Web-Based Self-Help intervention for symptoms of depression, anxiety, and stress: randomized controlled trial. *Journal of Medical Internet Research*, *10*(1), e7. https://doi.org/10.2196/jmir.954

Wantland, D. J., Portillo, C. J., Holzemer, W. L., Slaughter, R., & McGhee, E. M. (2004). The Effectiveness of Web-Based vs. Non-Web-Based Interventions: A Meta-Analysis of Behavioral Change Outcomes. *Journal of Medical Internet Research*, *6*(4), e40. https://doi.org/10.2196/jmir.6.4.e40