Investigation of Expectations and Barriers to Motivation in Dropout from Web-Based Interventions: A Multi-Method Qualitative Study

Sina Lea Beyer

s2091836

Faculty of Behavioural, Management and Social Sciences (BMS)

University of Twente

Positive Clinical Psychology and Technology (PCPT)

1st supervisor: Alejandro Domínguez Rodríguez, PhD
2nd supervisor: prof. dr. Gerben Westerhof
External supervisor: dr. Johannes Steinrücke

August 6th, 2024

Abstract

Background: Web-based interventions (WBIs) are an effective alternative for face-to-face treatment, particularly during the COVID-19 pandemic. However, WBIs experience high dropout rates, and factors influencing dropout need to be further explored to improve their effectiveness. Two such factors, expectations for the intervention, as well as barriers to motivation are relevant to dropout. Text mining offers a way to comprehensively analyze complex qualitative data to provide new insights.

Objective: This paper aimed to investigate what expectations were held by participants who dropped out of a WBI, sentiments underlying them and barriers to motivation they experienced to continue with the intervention.

Methods: Open-ended questions adapted from a previous study researching attitudes towards WBIs were filled out by 80 participants who dropped out of one of three WBIs, Mental Health COVID, Grief COVID or Healthcare Workers COVID. The resulting data was analyzed with text mining via Orange, including topic analysis and semantic analysis, as well as with thematic analyses via Atlas.ti.

Results: Expectations ranging from ‘Emotional Support’, ‘Understanding oneself’, ‘Professional Support’, ‘Expectations’ and ‘Support during the Pandemic’ with several sub themes were found. Moreover, there are neutral sentiments underlying the expectations and the overall experience of the intervention. Barriers to motivation could be sorted into intervention-related barriers such as ‘Additional Support’, and person-related barriers such as ‘Lack of Time’.

Conclusions: Overarching expectations between multiple WBI have been found, however their role in dropout is uncertain and needs to be further explored. Multiple nuanced barriers to motivation in WBIs, such as time and support, have been identified and further research into their mechanisms is required. This study provides guidance for the design of future WBIs on areas of relevance for dropouts and highlights the differences in individual needs.

Keywords: *web-based interventions, dropout, expectations, motivation, text mining, topic modeling, sentiment analysis*

Acknowledgements

First and foremost, I would like to thank my first supervisor, Alejandro Domínguez Rodríguez, for his continuous motivation for the topic, as well as his invaluable feedback and guidance during my master thesis, especially in moments where I felt stuck during the writing. I would also like to express my gratitude to my second supervisor, prof. dr. Gerben Westerhof, whose feedback and thoughtful suggestions allowed me to improve my thesis. I would also like to thank dr. Johannes Steinrücke for taking the time to provide feedback, especially for the method section.

Special thanks go to Melina Renzelberg, with whom I spent hours exchanging feedback and suggestions for our theses, as well as my friend Jules who took the time to read through my thesis and provide me with feedback.

Lastly, I would also like to thank my boyfriend Ruben for providing invaluable support during the writing of my thesis, both in the form of emotional support as well as offering valuable suggestions.

Table of Contents

Introduction

In March 2020, the World Health Organization (WHO) declared the new coronavirus outbreak with SARS-CoV-2 (COVID-19) a global pandemic (Ye et al., 2022). The impact of the pandemic on the mental health of the general public was widespread due to an increase in stressors introduced in people's lives, ranging from loss of control and personal freedom, to changes in everyday life and the future, as well as fear for the personal health and the health of friends and family (Bueno-Notivol et al., 2021). In turn, some studies found an increase in mental health problems such as anxiety, depression, addiction, and post-traumatic stress disorder (Dominguez-Rodriguez et al., 2021; Winter et al., 2023).

One of the more affected groups who experienced emotional distress during the pandemic were healthcare workers, due to factors such as increased workload, exposure to the virus, and concern of transmitting it to loved ones (Cullen et al., 2020; Pfefferbaum, & North, 2020). Burnout, insomnia, secondary traumatic stress and emotional exhaustion were some of the consequences they experienced during the pandemic (Martínez-Arriaga et al., 2023). Another vulnerable group during the COVID-19 pandemic were people who lost someone, both due to COVID-19 related complications, but also due to unrelated reasons (Eisma, & Tamminga, 2020). The pandemic caused disruptions in the normal grieving processes of a bereaved person, by circumstances such as limited ability or inability to perform death rituals, diminished social support and secondary stressors (Eisma, & Tamminga, 2020). This caused people who lost someone during the pandemic to experience higher feelings of acute grief compared to before the pandemic, one of the strongest predictors for disturbed grief (Eisma, & Tamminga, 2020). Disturbed grief, such as complicated grief disorder, can present in the form of intense emotional distress that impairs the daily functioning, as well as the well-being and health of a person (Dominguez-Rodriguez et al., 2021).

However, the guidelines and restrictions that were put in place to reduce the spreading of the virus, for instance social distancing and recommendations to stay at home, made face-to-face treatment for emotional distress impossible (Pfefferbaum, & North, 2020; Wind et al., 2020). Moreover, the number of professionals needed to provide treatment exceeded the number of professionals available. In Mexico, for example, a rate of 3.71 psychiatrists was available per 100.000 inhabitants, while the recommended rate is 5 psychiatrists per 100.000 participants (Carmona-Huerta et al., 2021). Instead, healthcare providers turned to online psychological interventions, such as web-based interventions, as an alternative (Wind et al., 2020; Ye et al., 2022; Yao et al., 2020).

Web-Based Interventions: Self-Help and Human-Supported

Web-based interventions (WBIs) have been widely shown to have efficacy in treating mental health problems (Erbe et al., 2017). They aim to lessen mental health problems by bringing cognitive, affective, and behavioral changes in the users (Beatty, & Binnion, 2016). These WBIs are based on empirically supported face-to-face treatments, for instance cognitive behavioral therapy (CBT), and require active engagement from the user. Moreover, they provide various advantages, such as easy accessibility, cost-efficiency, anonymity, non-reliance on available therapists, and the ability to use the treatment according to the patient's own schedule (Beatty, & Binnion, 2016; Karyotaki et al., 2015; Saddichha et al., 2014).

The WBIs can be sorted into two categories: human-supported and self-administered WBIs (Beatty, & Binnion, 2016; Montero-Marín et al., 2015). Self-administered WBIs are designed to be used independently by the user without any synchronous or asynchronous contact with professionals. On the other hand, human-supported WBIs include the support of professionals in various forms, ranging from video or phone calls to synchronous or asynchronous texting. Regarding the effectiveness of human-support compared to self-help WBIs, the findings in the literature differ. In the study of Montero-Marín et al. (2015), it is stated that human-supported WBIs for depression are more effective in treating depressive symptoms and further have an average adherence rate of 72% compared to 26% in self-administered WBIs. Van Gemert-Pijnen et al. (2018), similarly, concluded that WBIs with human-support compared to automated support showed similar results in adherence and effectiveness but concluded that support in WBIs is generally beneficial. More recently, Koelen et al. (2022) stated that adherence in internet treatment is generally low, even if the intervention includes human guidance. This is reflected in one of the main limitations observed in WBIs, a high dropout rate.

Dropout in Web-Based Interventions

The term dropout is generally referred to as "*pre-mature termination, non-usage, low attrition, or retention"* (Smink et al., 2021, p. 2). However, there is no clear definition of dropout. It can refer to someone who did not fully complete an intervention, or *"a person quitting the treatment before completing an adequate number of tasks in the intervention"* (Puolakanaho et al., 2023, p.2). Others argue that a dropout can only be identified by a professional, as a client might already have received the most benefit they can from the intervention before completing it (Smink et al., 2021).

Lack of clear definition notwithstanding, dropout can have a negative impact on both patients and therapists, as it limits the effectiveness of interventions and has a negative impact on treatment outcomes (Bowker, 2021). The study of Karyotaki et al. (2015) mentioned an average adherence rate of 26% for unguided WBIs for depression, while a systematic review and meta-analysis revealed a dropout rate of 10.3% to 58.8% in WBIs for bereavement care (Wagner et al., 2020). Moreover, a systematic comparison found that usage of WBIs in trial-based research was

4.06 times higher than real-world usage of the same program (Baumel et al., 2019). Because of this high dropout rate and the negative impact of it, the influencing factors and predictors for dropout need to be further explored (Dominguez-Rodriguez et al., 2020).

Treatment Expectations and Barriers to Motivation in Web-Based Interventions

A factor that has been more frequently found to be linked to dropout are expectations held by the patient regarding the treatment (Swift, & Callahan, 2011). Expectations are a long-established factor influencing therapy outcomes (Constantino et al., 2011). According to Tinsley et al. (1993), counseling psychologists theorized that the expectations of a patient have "an important influence on their decision to enter into and remain in therapy and that their expectations moderate the effectiveness of therapy." (p.46). In general, too high, or too low expectations of a patient regarding treatment is seen as having a negative impact (Bowker, 2021; Delgadillo et al., 2016; Tinsley et al., 1993).

There are a variety of expectations associated with treatment, such as treatment duration expectations. A study found that patients are more likely to expect shorter treatment than needed, which can result in more dropouts (Swift, & Callahan, 2011). Further, there are outcome expectations, which are a patient's belief about the consequences of taking part in a treatment and can range from high expectations that the treatment will be successful and improve the patients' symptoms, to low expectations that the treatment will make no difference or improvement (Bowker, 2021).

The importance of various types of expectations for face-to-face treatment have been investigated thoroughly in the literature, but there is less known about expectations regarding WBIs (Pontén et al., 2024). A recent study by Pontén et al. (2024), for example, found that expectations between face-to-face and online treatment were similar. Whether expectations have an impact on dropout from WBIs, however, has shown mixed results. One study found that a combination of certain variables, among those low expectancy, lead to an increased risk of dropout (Bowker, 2021; Delgadillo et al., 2016). Furthermore, Schindler et al. (2013) found that less positive outcome expectancy was able to predict the possibility of dropout in a CBT intervention for depression (Bowker, 2021). In contrast, in the study of Bowker (2021), it was found that pre-treatment outcome expectancy did not predict dropout from the treatment, reflecting similar results found by Berke et al. (2019).

A possible explanation for the relevance of expectations on the treatment outcome is the Expectation-Confirmation Theory, which has been around for many decades in the field of customer satisfaction (e.g. Patterson, 1993). It has been described by Jiang and Klein (2009), who state that expectations held by the user before an event, such as the use of a product or a service, and the evaluation of the event afterwards can determine the satisfaction felt regarding the event. If an event, or in this case a web-based intervention (WBI), confirms to or outperforms the participants expectations after the usage, they will be satisfied with it. If a WBI does not fulfill their expectations, they are more likely to be dissatisfied, which might result in dropout. As such, disconfirmation, or dropout, arises from the discrepancy between the expectations and actual performance. Another possible explanation for the relevance of expectations in dropout is the Goal Theory, as mentioned in the paper by Bowker (2021). Goal theory suggests that an individual with positive outcome expectations feels more motivated and as such is more likely to apply themselves to a goal (Austin & Vancouver, 1996).

Additionally, the Goal Theory highlights the importance of motivation in preventing dropout from WBIs. Motivation of the participant to participate in an intervention is an important factor influencing the effectiveness of, and attrition to WBIs (Alfonsson et al., 2016; Donkin, &

Glozier, 2012). However, multiple barriers can hinder the motivation of a participant to continue with an intervention and cause them to drop out. A qualitative study of participants from an eHealth intervention treating depressive symptoms found time constraints and competing priorities as some of the more frequently mentioned barriers (Donkin, & Glozier, 2012). Considering the importance of motivation to continue with a WBI, it is beneficial to further qualitatively investigate barriers to motivation in WBI, to decrease dropout from interventions.

Moreover, what most studies about expectations have in common is the way of measuring expectancy in patients. Investigating expectancy as a variable has been most commonly done with quantitative measures, by letting the patient rate their expectancies on a scale such as the Credibility and expectancy questionnaire by Devilly and Borkovec (2000) (Pontén et al., 2024; e.g. Bowker, 2021; e.g. Cohen et al., 2015; e.g. Delgadillo et al., 2016). Similarly, analyzing dropout in WBIs in general has most commonly been done with quantitative methods (Fernández-Álvarez et al., 2017). And while quantitative methodologies can find general trends in data, using qualitative methodologies enables the capturing of participants experiences (Fernández et al., 2023; Grönberg et al., 2021). However, analyzing the responses of the participants manually can be a laborious task. Text mining offers an alternative by analyzing the data in a more systematic and less time-consuming way, while increasing the accuracy and allowing the identification of patterns that might be missed with traditional methods (Talib et al., 2016).

Text Mining

Text mining can be described as "a process of extracting useful information from document collections through the identification and exploration of interesting patterns" (Yu et al., 2011, p.731). Text mining is a relatively new tool from an interdisciplinary field that combines natural language processing (NLP), machine learning, and computational linguistics techniques. Since it is an automated process, there is no expected predetermined outcome from the analysis, which enables a more unbiased exploration of the data without any preconceptions of an analyst. In psychological research, it has mostly been used to analyze large corpora from forums and social media platforms such as Reddit (e.g. Park et al., 2018) and X-Twitter (e.g. Öztürk, & Ayvaz, 2018), but also for analyzing feedback texts between patient and therapist with the help of techniques such as sentiment analysis, which allows determining the emotional tone of a text (e.g. Smink et al., 2019). There have been few qualitative psychology studies conducted with text mining that involve data from open-ended survey questions. Nonetheless, using text mining to analyze this type of data has been done before in other fields, such as education (Buenaño-Fernández et al., 2020) and very commonly, to analyze customer reviews to adapt and improve a product according to customer needs (Pal et al., 2023; Park et al., 2023).

However, text mining does not come without its challenges. One such challenge is applying text mining methods to short-text data that can be commonly found in online social networks, due to factors such as data sparsity, limited co-occurrence of words within a document, non-meaningful words and grammatical or spelling mistakes (Albalawi et al., 2020). As such, this study combines the text mining approach with a qualitative thematic analysis to add depth to the results. This approach has been used in other studies such as the one by Luo et al. (2023), where they supplemented their text mining techniques with a qualitative analysis (thematic analysis) to fully understand their data as well as to avoid ambiguity caused by a lack of contextual information.

Present Research

Due to the high rates of dropout despite the beneficial nature of WBIs, further investigation of factors influencing dropout from WBIs is increasingly relevant to understand what participants expect from WBIs and why they drop out to improve the usage of WBIs. Additionally, gaining a more nuanced understanding of the reasons for dropping out of WBIs during a pandemic will be beneficial for designing interventions in general, as well as for possible future pandemics (van Doorn, 2021). Thus, this study aims to investigate expectations of dropouts from three different online interventions, Mental Health COVID, Grief COVID, and Healthcare Workers COVID, during the COVID-19 pandemic and furthermore to investigate barriers in a participants' motivation to complete a WBI.

However, studies on dropout and expectations regarding treatment oftentimes use quantitative measures, which are not capable of displaying the sometimes complex and unique reasons for dropout that users experience (Khazaie et al., 2016). Moreover, research on dropout usually focuses on one type of disorder or sample group (Fernández-Álvarez et al., 2017), or on diffuse treatments and subtypes of disorders which makes the comparison of the results between studies more difficult (Smink et al., 2021). This study aims to fill this gap in knowledge by addressing the following research questions with data from three different WBIs implemented during the COVID-19 pandemic:

1) What are the expectations expressed by participants who dropped out from web-based interventions?
2) What are the sentiments underlying the expectations expressed by participants who dropped out from web-based interventions?
    a. Based on the Expectation-Confirmation Theory described by Jiang and Klein (2009), it is hypothesized that greater negative sentiments underlying the

evaluation of web-based interventions compared to sentiments underlying expectations result in dropout.

3) What barriers to motivation did participants who dropped out of web-based interventions experience?

Method

Design

In this mixed-methods study, to answer the research questions, an exploratory design was employed. Responses to a post-intervention evaluation questionnaire sent to participants who dropped out from one out of three WBIs were analyzed, using a mixed methods approach with text-mining and thematic analysis. In this study, dropout refers to participants who did not finish the full intervention, irrespective of how far they got and the reason for dropping out.

Materials

Mental Health COVID

Mental Health COVID (*Salud Mental COVID*, www.saludmentalcovid.com) is a 15 module long, self-administered web-based intervention offered during and after the COVID-19 pandemic to reduce symptoms of anxiety and depression, and to increase sleep quality and positive emotions. It was designed with the principles of positive psychology and is supported by elements of cognitive behavioral therapy as well as behavioral activation therapy and delivered through a telepsychology system. The participants were sorted into two groups. One group received the treatment in conjunction with support from a trained psychologist via chat who provided motivation, support and guidance. The other group received the intervention without support. An overview of the study design can be found in the appendix (Appendix A). The protocol for this intervention was described in the study by Dominguez-Rodriguez et al. (2020) and data obtained from this intervention was used to investigate the impact of fear caused by the COVID-19 pandemic in the study by Chávez-Valdez et al. (2021). Further, this intervention is evaluated in the study by Dominguez-Rodriguez et al. (pre-print). The intervention has been approved by the Ethics Committee of the Free School of Psychology University of Behavioral Sciences in Chihuahua, Mexico (reference number Folio 2008) and is in Clinical Trials (NCT04468893).

Grief COVID

Grief COVID (*Duelo COVID*, www.duelocovid.com) is a 12 module long, WBI focused on dealing with complicated grief (Dominguez-Rodriguez et al., 2021). Specifically, minimizing the chance of developing a complicated grief disorder, maximizing life quality, and a secondary focus on minimizing depression, anxiety, and improving sleep quality. For that, 12 modules were designed based on mindfulness, acceptance and commitment therapy, positive psychology, and cognitive behavioral therapy, with a time-lock of three days between each module. The participants were randomly divided into two groups, one group who started the intervention immediately, and the other group who was on a waitlist for 36 days before receiving the designed treatment. To increase adherence, the intervention was designed with the principles of User Experience (UX) and adjusted to a sample of participants. See the appendix for an overview of the study design (Appendix B). Multiple studies were published about this intervention. One study describes the protocol of this intervention (Dominguez-Rodriguez et al., 2021), one used data from the intervention to investigate prevalence of grief among the general Mexican population (Dominguez-Rodriguez et al., 2022) and one study evaluated it (Dominguez-Rodriguez et al., 2023). This intervention has been approved by the Research Ethics Committee of the Autonomous

University of Ciudad Juárez, Mexico, (approval ID: CEI-2020-2-226) and is registered in Clinical Trials (NCT04638842).

Healthcare Workers COVID

Healthcare Workers COVID (*Personal Salud COVID*, www.personalcovid.com) is focused on decreasing depression, anxiety, compassion fatigue and burnout in health care workers, as well as amplifying self-care, abilities to deliver bad news, sleep quality, and quality of life (Dominguez-Rodriguez et al., 2022). The intervention consists of nine nuclear and three complementary modules based on approaches such as acceptance and commitment therapy, mindfulness, and cognitive behavioral therapy. Participants were randomly assigned to one of two groups, one group received teletherapy, for the other group treatment was self-applied. The creators of this intervention expected the web-based intervention design to cause more dropout, which they thus hoped to circumvent by using the principles of user experience. An overview of the study design can be found in the appendix (Appendix C). Furthermore, a description of the intervention can be found in the papers by Martínez-Arriaga et al. (2023) and Dominguez-Rodriguez et al. (2022). This intervention was approved by the Ethics Committee in the Research of Autonomous University of Juarez City (approval ID: CEI-2021-1-266) and registered in Clinical Trials (NCT04890665).

ATLAS.ti

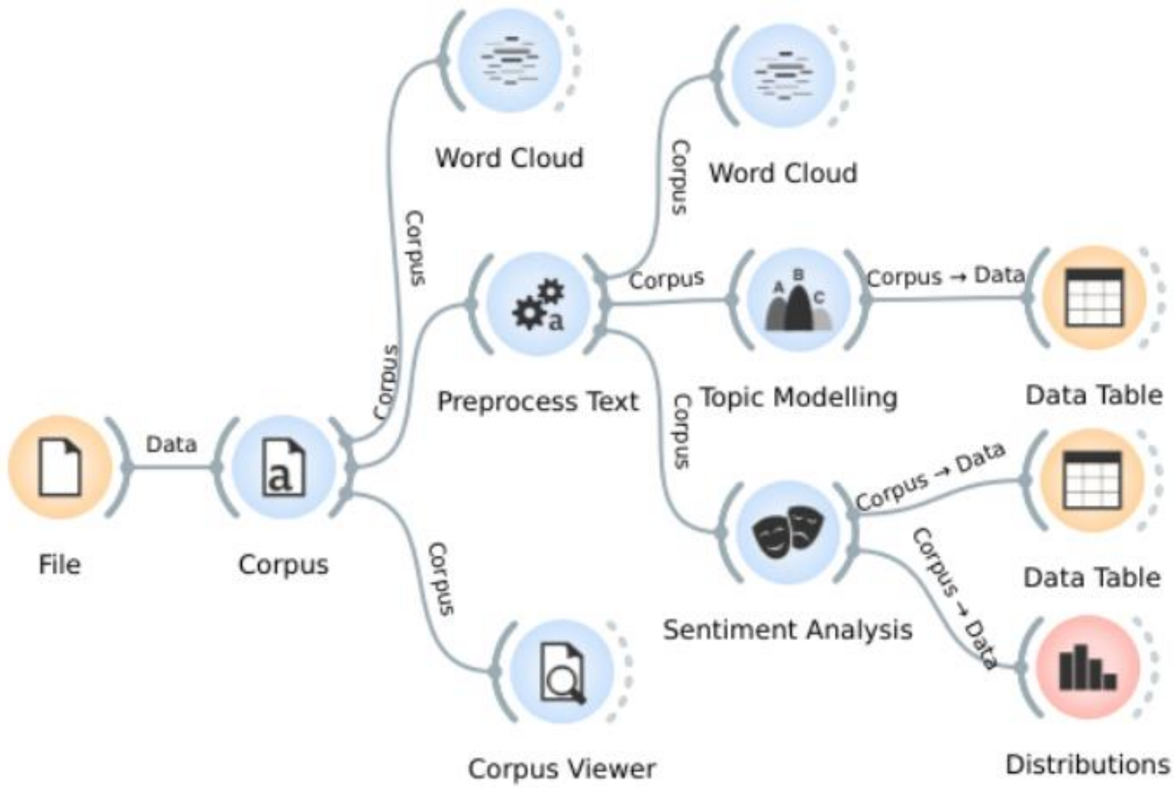
ATLAS.ti is a Computer Assisted Qualitative Data Analysis Software (CAQDAS), Which was designed to help assist with qualitative data analysis (Soratto et al., 2020). This software was developed and first published by Muhr (1993). The software offers multiple tools to analyze qualitative data. For this study, the tool to create quotations, which is the marking of relevant segments within a document, and the labeling of those, called codes, was used.

Orange

The program used to analyze the data in this study is the Orange Data Mining Platform version 3.35.0. Orange is a user-friendly data mining tool that allows the building of comprehensive data analysis schemas by combining widgets that represent different data analysis tasks into a visual workflow, or *pipeline* (Orange, n.d.). It can be used through a visual programming interface, called Orange Canvas, which lists its functionalities into categories, and allows the user to place the functionalities as widgets on the canvas (Jović et al., 2014). To program, the widgets can be connected from one widget's output to another widget's input. The amount of widgets Orange offers can be considered limited compared to other programs, nonetheless, the standard text mining techniques are considered to be covered well (Jović et al., 2014). The pipeline used in this study, meaning the specific connection of widgets utilized for programming, is depicted in Figure 1. It involves keyword extraction, a word cloud, topic modeling, and sentiment analysis, which will be further explained in the following section.

Figure 1

Orange Pipeline



Participants

The responses were collected from a raw sample of 93 participants, of which nine did not respond to the questions, and four respondents did complete their intervention, leading to a sample of 80. Overall, there were 67 female participants and 13 male participants with a mean age of 37. An overview of the participants and their socio-demographic information for each intervention can be found in Table 1.

Table 1

Sociodemographic Information

Characteristics		MHC (n=25)	GC (n=51)	HWC (n=4)	All (n=80)
Sex					
	Female	21	42	4	67
	Male	4	9	0	13

Age				
Min	20	18	23	18
Max	60	63	40	63
Mean	34.12	38.92	31	37.02
Education Level				
Primary Education	3	4	0	7
Secondary Education	0	2	0	2
University - Undergraduate	19	36	3	48
University - Master's Degree	2	8	1	11
University - Doctorate	0	1	0	1
Other	1	0	0	1
Last module completed				
0	12	20	0	32
1	3	15	0	18
2	1	7	3	11
3	2	3	0	5
4	1	3	0	4
5	1	0	1	2
6	2	2	0	4
7	1	1	0	2
9	1	0	0	1
10	0	0	0	0
11	1	0	0	1
Human-Support				
Chat	38	0	0	38
Teletherapy	0	0	0	0

Note. Education level according to Mexican classification (“Preparatoria”, “Secundaria”, “Universidad - Licenciatura”, “Universidad - Maestría”, “Universidad - Doctorado”, and “Otros”). MHC has a total of 12 modules to complete, GC has a total of 15 modules to complete and HWC has a total of 12 modules to complete (nine nuclear and three complementary modules).

The participants were asked to fill out a survey adapted from the article by Schröder et al. (2015). The original 16-item tool was developed to measure attitudes towards psychological online interventions, of which five items were included in this study: (1) *“What were your* *expectations of the intervention before enrolling?"*, (2) *"What do you think would have motivated you to continue doing the intervention modules?"*, (3) *"What were the reasons that you consider influenced for not continuing with the intervention modules?"*, (4) *"What has been your experience using the intervention modules?*" and (5) *"What do you think could be improved in the intervention modules?"* To answer Research Question 1, the answers to item 1 will be used. To answer Research Question 2 and Hypothesis 2a, the answers to item 1 and item 4 will be used. Finally, to answer Research Question 3, the answers to item 2 will be used.

Analysis

To analyze the data, the first step was to remove the participants that did not give any answers or who completed the intervention (n=13), resulting in a sample of 80 participants. Then, the final data set was translated from Mexican Spanish to English using the translation tool DeepL. The translated responses were then checked by a native Mexican Spanish speaker, AD-R, to check the accuracy of the translations, correcting for spelling mistakes and vagueness where possible. The resulting translations were transferred into a data file containing the respondents in the rows and their answers to the feedback in the columns.

After transferring it to Orange, the data was ready for pre-processing. Pre-processing refers to the cleaning of data to prepare it for use in natural language processing tools such as text mining (Anandarajan et al., 2019). The pre-processing was done via the settings in the pre-processing widget in Orange and involved several steps. Data transformation, which is the transformation of the data into a format that is usable by the tool, includes steps such as lowercase and accent removal. Tokenization is the process of breaking the data up into meaningful parts, such as sentences or words called tokens. In this study, the data will be split into words, called word tokenization. As an example, the sentence: "I had no expectations." will be tokenized into “I”, “had”, “no”, “expectations”. This step also involves the removal of word punctuation. Further, filtering was selected to produce a more meaningful analysis by removing stop words such as “the”, “a”, and “so”, and numbers. The option to remove regular expression filters and document frequency was also selected to remove tokens outside a certain frequency in the corpus (a specific filler word list can be found in Appendix C). Finally, Normalization, a step to improve the accuracy of later analyses, was employed by selecting the UDPipe lemmatizer in Orange. This step reduces words to their base form for a more equal comparison of words. That means that “dealing” gets lemmatized to its base form “deal”, thus removing the “-ing” suffix. These pre-processing steps transform the unstructured data into a structured format, allowing the possibility to apply the subsequent analyses.

Word Cloud

The first analysis employed is a word cloud. A word cloud is an exploratory tool that shows the most frequently used words within a corpus, allowing a general overview of the data. Based on the word cloud, other potentially meaningless words might be removed that were missed by the pre-processing steps. In this data, several words were added to the specific filler word list (Appendix C).

Topic Modeling

Topic modeling is an unsupervised machine-learning method that allows the identification of hidden themes or topics in a corpus of text. The first step of topic modeling is to define the number of topics inside the data. Since the research questions of this paper are exploratory, and there is no given set of topics, the number of topics will first need to be estimated. This can be done by optimizing log perplexity, which indicates how well the topic model predicts the data, with lower scores indicating a better predictive power. Furthermore, coherence scores indicate the coherence of the topics and how well the words in it relate to each other. A higher score is indicative of better coherence of the topics. Log perplexity scores and coherence scores are shown within the Orange topic modeling widget. For this study, coherence, and log perplexity scores for up to ten topics will be checked, since more topics tend to have greater overlap of keywords, particularly in smaller sample sizes, which in turn increases the difficulty to name the separate topics.

To perform the topic modeling, the topic modeling widget within the program Orange was selected, which displays the log perplexity scores and coherence scores. The topic modeling analysis was performed with Latent Dirichlet Allocation (LDA), a generative probabilistic modeling algorithm and one of the most common topic modeling algorithms. LDA collects words within a document and attributes them to a limited amount of (pre-determined) topics (Chen et al., 2015). LDA is a method that was first introduced in 2003 by Blei, et al, and is particularly suited for exploratory and descriptive research (Buenaño-Fernandez et al., 2020). Buenaño-Fernandez et al. (2020), for example, make use of topic modeling, and more specifically LDA, while successfully uncovering underlying topics within their unstructured data. Similarly, Gottipati et al. (2018a) use the LDA model to analyze textual student feedback, thus prompting the use of the method for this study. Since topic modeling does not provide an overall term for those topics, the list of keywords per topic, as well as answers that scored high in a specific topic got examined and manually given a word or sentence summarizing all the words in that topic.

Sentiment Analysis

Sentiment analysis, also called opinion mining, is a natural language processing technique that identifies and categorizes opinions and affective states into positive, negative, or neutral polarities (Gottipati et al., 2018b). The lexicon-based and rule-based Valence Aware Dictionary for Sentiment Reasoning (VADER) method was used in this thesis, which provides sentiment scores based on the words used and sorts them into positive or negative categories. The VADER method was chosen since this method was designed to analyze social media texts, which often consists of short text messages and is comparable to the data used in this study (Elbagir & Yang, 2019). Further, the VADER method has been confirmed as a powerful sentiment analysis tool for online reviews (Pal et al., 2023; Omar et al., 2020). It creates a score for each word to determine its positivity or negativity on a scale of -1 to 1, which will allow the investigation of underlying sentiments regarding the expectations of people who dropped out, as well as whether there is discrepancy between the sentiments regarding the expectations and the evaluation of the WBIs.

Thematic Analysis

To analyze the data further, a reflexive thematic analysis based on Braun and Clark's method (2006, further elaborated in 2023) was conducted. First, the translated, non-pre-processed data was transferred to the program ATLAS.ti and read through multiple times, while initial ideas were marked down as quotations. Following this, a series of codes based on the data and marked quotations (inductive approach) as well as previous results gained by the topic modeling analyses (theoretical approach) were developed. These codes were then sorted into main themes and further into sub themes. This was an iterative process to ensure the accuracy of the developed themes and their relevance to the data, involving multiple re-codings and sortings, resulting in the final version that can be found in the Results section (Table 3 and 5).

Results

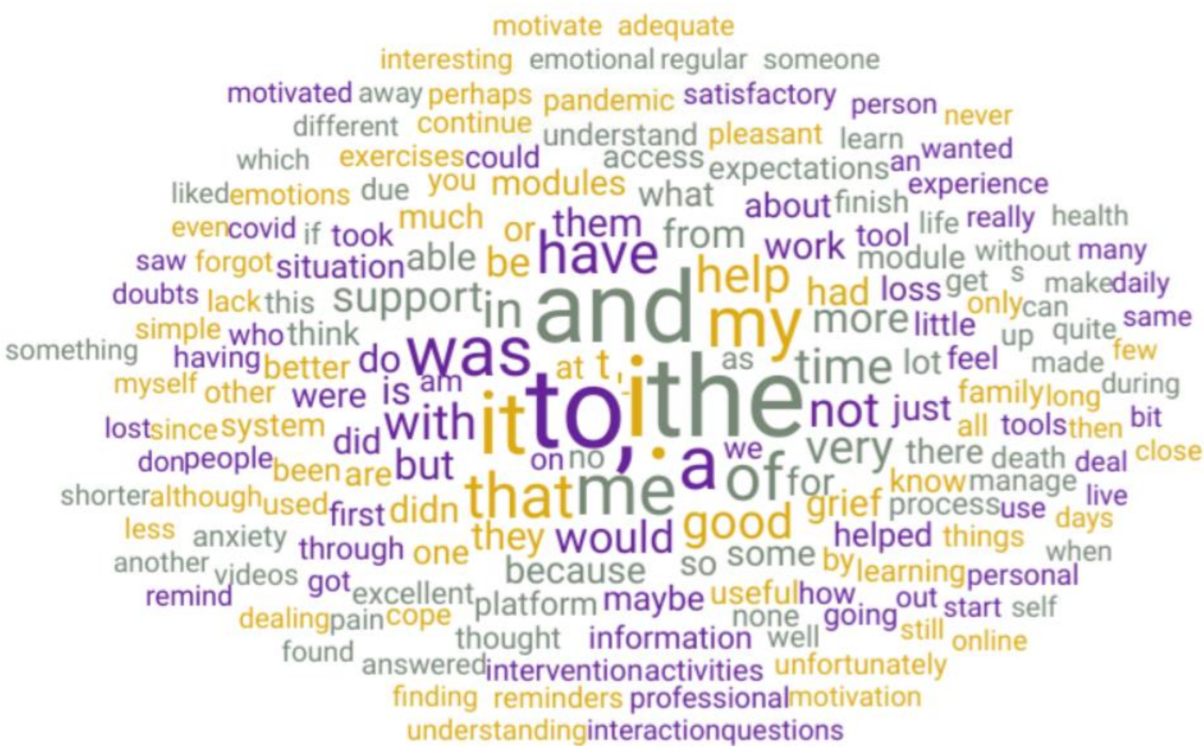
Descriptive Statistics

Word Cloud

The final word cloud including the data from items 1, 2 and 4 can be found in Figure 2. The five most mentioned words after pre-processing include help, time, support, grief, and work. Word clouds for the individual items after pre-processing can be found in the Appendix (Appendices D, E and F).

Figure 2

Word cloud Before Pre-Processing



Word cloud After Pre-Processing

Note. The first figure shows the word cloud before the pre-processing of the data and includes words such as 'and', 'to', etc. that do not provide any information. The second figure shows the word cloud after the iterative pre-processing steps described above.

Research Questions

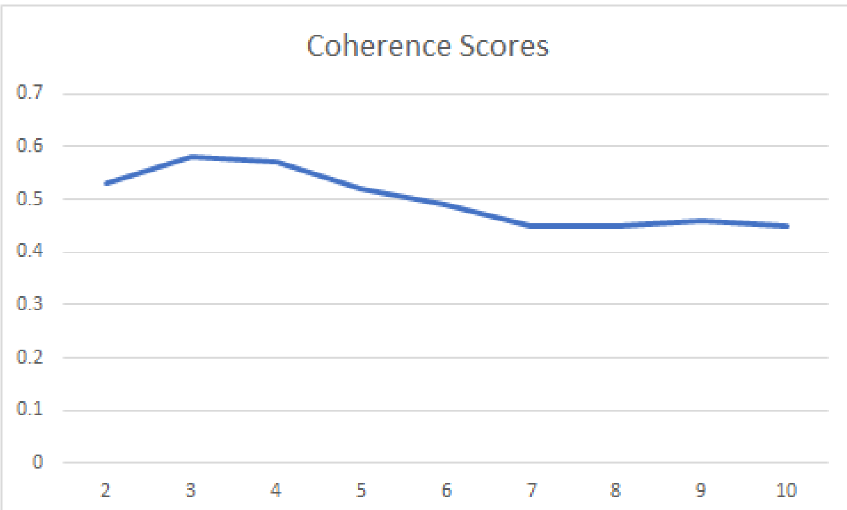
Research Question 1 - What are the expectations expressed by participants who dropped out from web-based interventions?

Topic Modeling

A topic modeling analysis on item 1, *"What were your expectations of the intervention before enrolling?",* was conducted. The coherence scores for up to ten topics can be seen in Figure 2. The highest coherence score was found for three topics with 0.58 (score of 63.58 for log perplexity). The lowest coherence score of 0.45 is for ten, eight and seven topics. Topics nine, six, five, and two range between 0.46 (nine topics) and 0.57 (four topics). Thus, three topics would result in the most meaningful and interpretable topics based on the coherence score. However, this does not take the log perplexity scores into account yet.

Figure 2

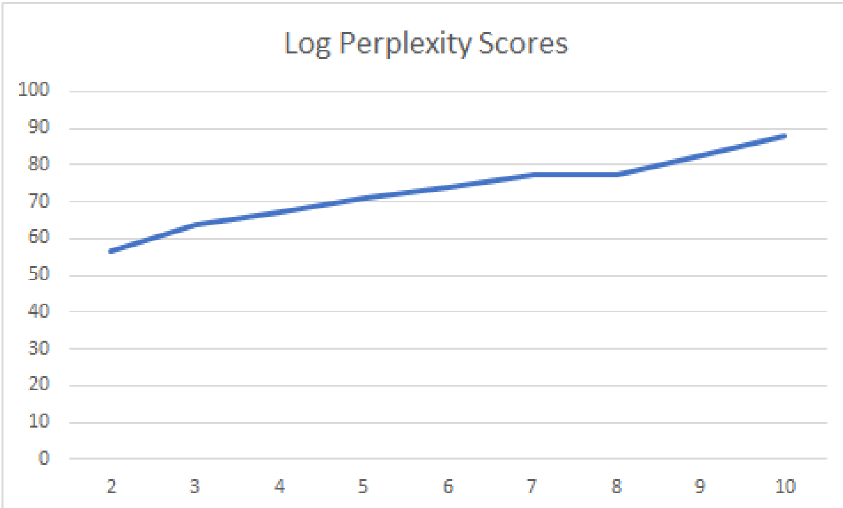
Coherence Scores per topic for the LDA analysis



The log perplexity scores for up to ten topics can be seen in Figure 3. The lowest log perplexity score could be found for two topics with 56.43 (score of 0.53 for coherence). From this score, the numbers keep increasing with the number of topics, and the highest score for log perplexity was found for ten topics with a score of 87.8 (0.45).

Figure 3

Log Perplexity Scores per topic for the LDA analysis



Taking the log perplexity scores into account, a lower number of topics is further supported. While the lowest log perplexity score is found for two topics, three topics have the second lowest log perplexity score, indicating that three topics will provide the most coherence with accurate prediction. As such, the topic modeling analysis revealed three underlying topics within the feedback about expectations regarding WBIs. The topics were given the topic names *"Receiving Support and Tools to Deal with the Pandemic", "Receiving Help for Loss and Anxiety"* and *"Grief Support".* A detailed overview for each topic and the ten related words can be found in Table 2.

Table 2

Topic Modeling Analysis of Item 1 - Expectations

Topic	Topic Name	Topic Keywords
1	Receiving Support and Tools to Deal with the Pandemic	help, time, support, pandemic, able, get, better, tools, situation, grief
2	Receiving Help for Grief and Anxiety	help, grief, pain, little, feel, anxiety, expectations, module, intervention, life

3	Grief Support	grief, support, process, help, death, manage, able, good, system, finding

Note. This table shows the three topics found in the topic modeling analysis with their manually chosen topic names, and their respective topic keywords.

Some examples for answers belonging to topic one include *"To have tools to support me in solving emotional problems."* (Participant 2) and *"To be able to cope with the isolation situation better and to help my family to do so."* (Participant 81). It also includes answers such as *"I was looking forward to processing and having tools that will help me get through the death of my family member."* (Participant 85), which highlights the overlap between three topics, particularly the keyword grief.

In topic two, answers revolving around the topic grief and anxiety, such as *"That it was going to help me a lot in dealing with my grief and implementing techniques in my life to help me."* (Participant 5) and *"To manage my grief, after the death of my father. Getting out of the anxious and depressive state I am in."* (Participant 65). Moreover, multiple answers including the word expectations, such as "*My expectations were high, I wanted to get out of my grief fast* […]" (Participant 31) and "*My expectations were to have support during the pandemic, […]"* (Participant 90), which shows overlap with topic 1.

Finally, in topic three, participants' answers mainly focused on grief support, for example *"I wanted to heal the grief of my grandmother's death, so I could process everything better, because there are things I still don't understand."* (Participant 8) and *"I was looking forward to processing and having tools that will help me get through the death of my family member."* (Participant 16).

Thematic Analysis

Due to the great overlap between the topics of the topic modeling analysis, which made it difficult to classify the three identified topics, a thematic analysis was conducted to get a more detailed and clarified overview of expectations expressed by the participant, as well as to identify overlapping topics between the WBIs. Five main themes with multiple underlying sub themes have been identified. An overview including example phrases can be found in Table 3.

Table 3

Thematic Analysis of Item (1) - Expectations.

Main Themes	**Sub Themes**	**Example Phrase**
Emotional Support	Dealing with Grief	“finding help during the grieving process”
	Managing Emotions	“learning how to manage emotions”
	Coping with Anxiety	“To help me feel less anxious”
	Improvement	“Improvement in my mental health and self-care.”
	Cope with the Pandemic	“To be able to cope with the isolation situation better”
Understanding oneself	Understanding Emotional Pain	“Understanding what was wrong with me“
	Identifying patterns	“resolve doubts, identify patterns“
Professional Help	-	“get expert help”
Expectations	Positive Expectations	“The truth is that I had good expectations from the course”
	No expectations	“I had no expectations”
Intervention System	-	“A user-friendly system“

Note. This table shows the main themes including sub-themes found in the topic modeling analysis. Quotes from the data have been added to provide examples.

The thematic analysis allowed the identification of multiple expectations within one answer, giving nuance to the findings. An example phrase is *"To help me feel less anxious, accept my loss and feel a little better."* (Participant 34), where the participant expresses expectations for grief support, support for anxiety, as well as improvement of their emotional state.

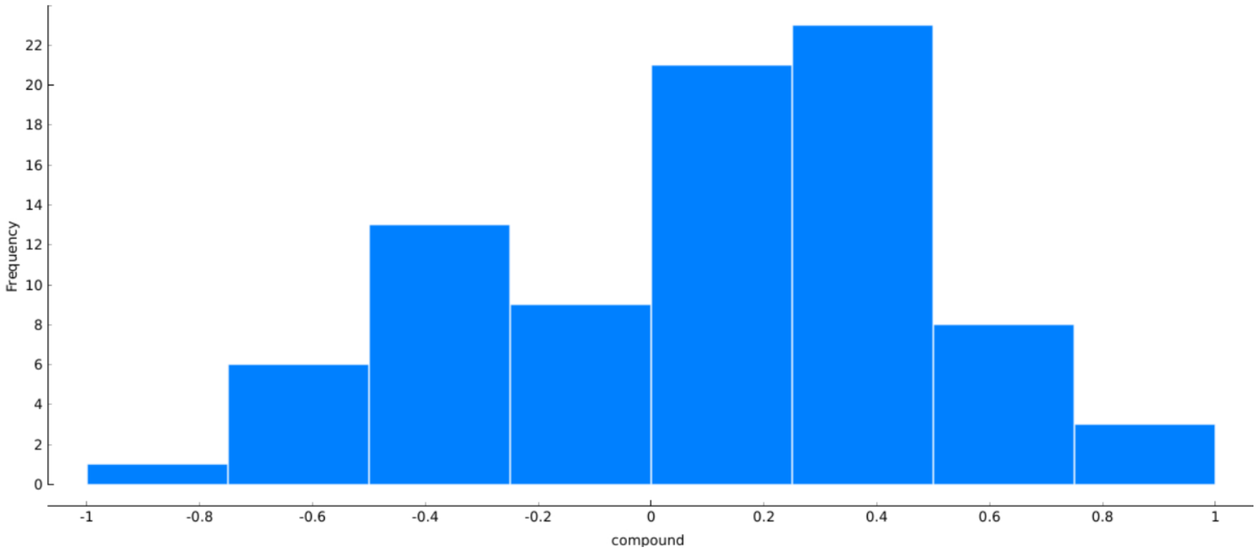
Research Question 2 - What are the sentiments underlying the expectations expressed by participants who dropped out from web-based interventions?

Sentiment Analysis

The sentiment analysis on item 1, *"What were your expectations of the intervention before enrolling?"*, revealed neutral sentiments to be present with a mean value of 0.66. Positive sentiments were present with a mean of 0.18, while negative sentiments were present with a mean of 0.15. The compound score, a combination of the positive, negative, and neutral sentiments, shows a mean of 0.07. This suggests that the overall tone of the data is a cohesive neutral sentiment with a slight trend towards positive sentiments. Its distribution can be found in Figure 4.

Figure 4

Frequency of the compound score within item 1.



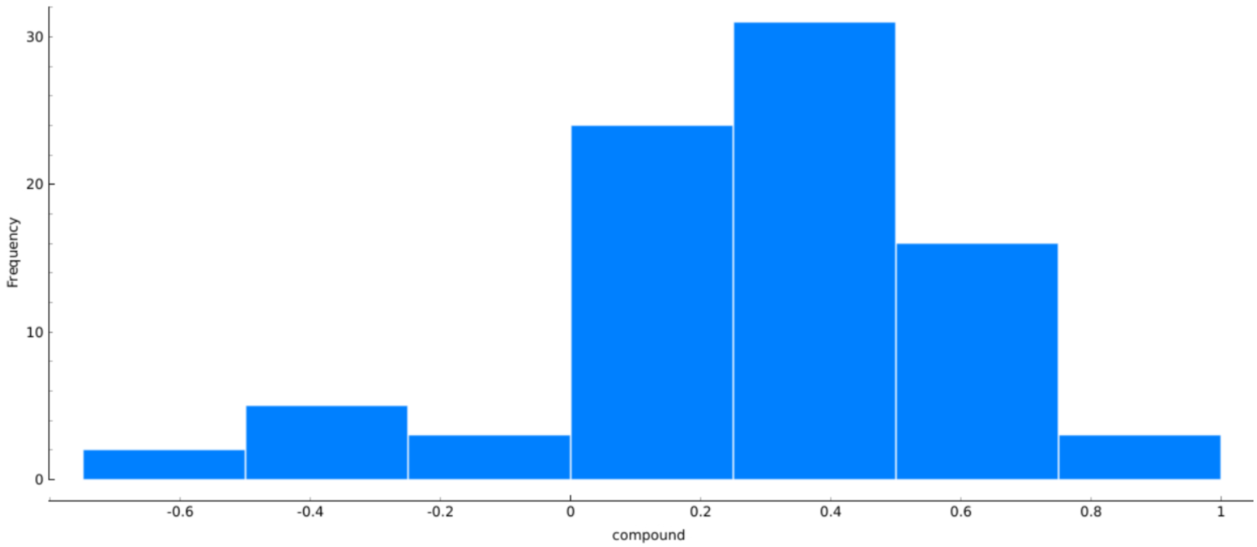
Hypothesis 2a - Based on the Expectation-Confirmation Theory described by Jiang and Klein (2009), it is hypothesized that greater negative sentiments underlying the evaluation of web-based interventions compared to sentiments underlying expectations result in dropout.

Sentiment Analysis

Sentiment analysis for item 4, *"What has been your experience using the intervention modules?*", shows an overall tone of neutral with a mean value of 0.56, showing that participants expressed mostly neutral sentiments regarding their experience with the WBI. The positive sentiments had a mean of 0.37, and negative sentiments showed a mean of 0.03. The compound score had a mean of 0.26 and its distribution can be found in Figure 5. This suggests that the overall sentiment about the experience regarding the WBIs was rather neutral, but with a greater trend towards positive sentiments compared to the sentiments about the expectations. As such, the hypothesis that greater negative sentiments underlying the evaluation of the web-based interventions compared to sentiments underlying expectations result in dropout is rejected.

Figure 5

Frequency of the compound score within item 4.



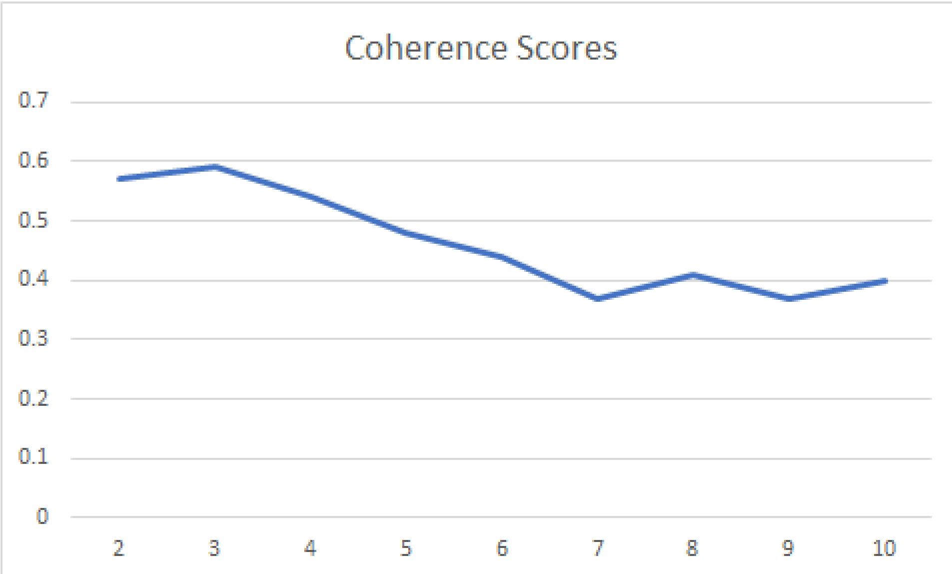
Research Question 3 – What barriers to motivation did participants who dropped out of web-based interventions experience?

Topic Modeling

A topic modeling analysis on item 2, *"What do you think would have motivated you to continue doing the intervention modules?"*, was conducted. The coherence scores for up to ten topics can be seen in Figure 6. The highest coherence score was found for three topics with 0.59 (score of 72.17 for log perplexity). The lowest coherence score of 0.37 is at nine and seven topics. The other topics range between 0.40 (ten topics) and 0.57 (two topics).

Figure 6

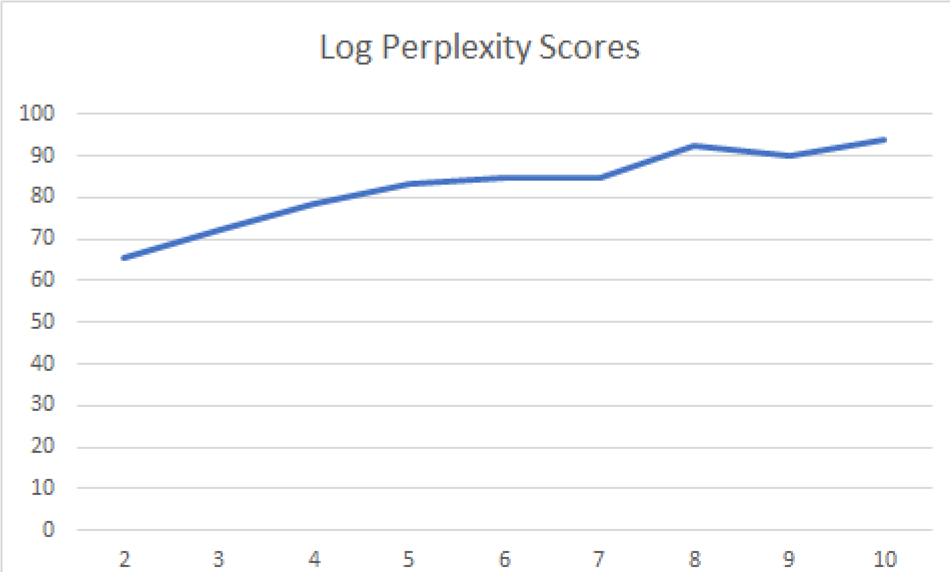
Coherence Scores per topic for the LDA analysis



The log perplexity scores for up to ten topics can be seen in Figure 7. The lowest log perplexity score was found for two topics with 65.34 (coherence score of 0.57). The highest log perplexity score is for ten topics with a score of 93.91 (score of 0.4 for coherence). The other topics range between a score of 92.58 (eight topics) to 72.17 (three topics).

Figure 7

Log Perplexity Scores per topic for the LDA analysis



Since the results of the two scores again show little variance between the ideal number of topics, three topics, with a log perplexity score of 72.17 and a coherence score of 0.59, was decided on. Thus, there are three underlying topics revealed by the topic modeling analysis that would be motivation for participants to continue with the intervention: "*Lack of Time, Lack of Support"*, "*Reminders from the Platform*", and "*Accessibility Problems*". Table 3 gives a detailed overview for each topic and its' ten related words.

Table 4

Topic Modeling Analysis of Item 2 – Barriers to Motivation

Topic	Topic Name	Topic Keywords
1	Lack of Time, Lack of Support	time, support, lack, module, without, someone, help, application, less, motivation
2	Reminders from the Platform	platform, work, person, activities, time, another, continue, remind, lost, something

3	Accessibility Problems	time, access, system, work, forgot, lack, able, since, daily, unfortunately

Note. This table shows the three topics found in the topic modeling analysis for barriers to motivation, with manually chosen topic names and their respective topic keywords.

For the first topic, a lack of time and support were often named as barriers to motivation, such as the answer by participant 41: *"In the face of loss, one is not self-taught and what one needs is help without having to read or watch videos. Just talk to someone who will listen to you or motivate you."* or the answer by participant 6: *"Time, returning to my work routine distracted me from attending to the platform."*.

The second topic contained answers about reminders: "*Set a personal alarm to remind me of the days and times or rather to remind me that I had this tool*." (Participant 43), but also other topics such as a lack of social interaction "*the lack of social interaction is a big disadvantage for the use of technological tools, I think the system lacks nothing."* (Participant 70) and time-locked modules as a barrier (Participant 7).

Lastly, for topic three, participants mentioned troubles accessing the intervention, such as participant 81: "*The modules never loaded properly. I thought it was my internet connection. But I tried at work and at home and couldn't get access to the content*." However, some answers in this topic are similar to topic one, for example the barrier mentioned being a lack of time *"for work reasons I have not been able to access the system, since I am part of the health personnel and we have not stopped working since the pandemic started." (Participant 23).*

Thematic Analysis

Again, to complement the topic modeling analysis, a qualitative analysis was done to further analyze the topics regarding barriers to motivations in continuing with the WBIs, to get a more detailed and nuanced overview. Two codes with multiple underlying sub-codes have been identified. An overview can be found in Table 4.

Table 5

Thematic Analysis of Item (2) - Barriers to Motivation

Main Themes	Sub Themes	Example Phrase
Intervention-related reasons	Additional Support	“Support from a professional“, “Maybe do it together with someone else, have an online support group.“
	Reminders	“Set a personal alarm to remind me of the days and times or rather to remind me that I had this tool.“
	Time-locked modules	“Leave them open to do them at my own pace“
	Intervention Design	“they were repetitive exercises.”
	System	“The modules never loaded properly”, “To be a mobile phone compatible tool“
Person-related reasons	Lack of Time	“Basically it was my lack of time due to my work schedule.”,
	Personal reasons	“I forgot :(”, “to worry more about myself“

Note. This table shows the main themes including sub-themes found in the topic modeling analysis. Quotes from the data have been added to provide examples.

The themes about barriers to motivation expressed by the participants can be sorted into two main themes: The first main theme was identified as “Intervention-related reasons” and includes barriers to motivation that were related to the intervention in some form, such as a wish for additional features or a critique of already existing features. The second main theme identified was “Person-related reasons” and includes barriers to motivation based on the person, such as a busy work schedule or forgetting about the intervention.

Discussion

The overall aim of this study was to investigate two common influencing factors on dropout from WBIs. The data was collected from three different WBIs, Mental Health COVID, Grief COVID and Healthcare Workers COVID and a combination of text mining and thematic analysis was used to analyze the data. The analyses revealed that participants expected emotional support, to understand oneself better, professional help, non-specific expectations as well as expectations for the intervention system. Moreover, sentiment analyses revealed that participants experienced rather neutral sentiments regarding the expectations and the general experience with the WBIs despite dropping out. Finally, two categories of barriers to motivation to continue with the WBIs were found.

Discussion of Research Question 1

To answer research question 1, a topic modeling analysis was conducted. What can be observed from the identified topics, *“Receiving Support and Tools to Deal with the Pandemic”, “Receiving Help for Loss and Anxiety”* and *“Grief Support”*, is that participants from the three interventions all expected to receive some kind of help or support in dealing with their emotional problems in general and specific to the goal of the separate interventions. This could imply that topic modeling is able to distinguish between participants from different interventions and that they build their expectations based on the goal of the intervention. However, when inspecting the answers for the specific topics, a mix of all three WBIs was present in each topic, which could mean that the topics are overarching between the interventions. Perhaps the names given to the topic were not well chosen and a different approach for naming the topics is needed. Previous research, for example, has made use of language learning models to label topics generated by topic modeling (Filmer, 2023). However, the three topics and their associated keywords also showed great overlap, which could be attributed to factors such as multiple expectations mentioned in one answer. It is also a common problem observed with the use of LDA in the case of short text (Yan et al., 2013).

Thus, to help refine the topics and to gain a more nuanced answer for the research question, a thematic analysis was conducted. It revealed overarching themes between the three WBIs, such as emotional support and expectations for professional support. Further, there were expectations regarding the intervention platform, understanding themselves better, and participants who expressed having no expectations for the intervention. These findings are reflected in the study of Montero-Marín et al. (2015), who interviewed both professionals and patients about their expectations for WBIs for depression in general. They found that patients expressed expectations for having personalized interactions and supervision, while also being able to practice reflectiveness. Considering that those expectations were present before the usage of WBIs, and still were present after dropout indicates that they are factors that play an important role in the perception of WBIs and as such are important to keep in consideration.

Finally, since this study is one of the first investigations of the expectations of participants who dropped out of one of three WBIs, there are few previous findings to compare to. Rodrigues et al. (2024), for example, conducted the first randomized controlled trial investigating the use intention and user expectations of human-supported and self-administered WBIs. Their findings suggest that doubts about the intervention's helpfulness and ease of use should be paid attention to and people who have those negative expectations could benefit from additional human support. For this reason, the authors recommend to screen user expectations to optimize WBI uptake. This is in line with the advice given by Glombiewski and Rief (2016) who recommend addressing mixed or negative expectations of participants regarding an intervention to optimize WBIs.

Discussion of Research Question 2 and Hypothesis 2a

To answer the second research question, a sentiment analysis was conducted. This analysis revealed mostly neutral sentiments underlying the expectations, with a small trend towards positive sentiments. Previous research about sentiment analysis on expectations in WBIs has, to this author's knowledge, not been done before. However, looking at related literature, it has been found that mixed or negative attitudes and expectations prior to the use of a WBI can be an important obstacle and cause for dropout (Glombiewski & Rief, 2016; Teles et al., 2021). Yet the sentiments regarding expectations found in this thesis are mostly neutral even though the participants dropped out of their WBI. This could imply that the expectations were not part of the reason why the participants dropped out of the WBIs. However, since there is not much research into sentiments of participants who dropped out yet, it is a point worth investigating for future research.

Furthermore, the Expectation-Confirmation Theory described by Jiang and Klein (2009) was introduced as a possible explanation of how prior expectations and how participants evaluate an event after it happened can influence the satisfaction a user feels about it (Jiang, & Klein, 2009). This would posit that if a participant experiences discrepancy between their expectations and their evaluation of the WBI overall, their satisfaction with it would be low, thus resulting in dropout. However, the hypothesis had to be rejected. Both sentiment analyses showed mostly neutral sentiments expressed by the participants, meaning that they did not rate their experience with the intervention as negative or positive. More, the sentiments regarding their experience with the interventions are skewed towards positive. A possible explanation was proposed by Smink et al. (2021), who stated that users who dropped out already experienced a positive effect from the WBI and as such did not feel the need to continue with the intervention, which is why only a professional should be able to identify a dropout. Moreover, it could also imply that the participants were not unsatisfied with the WBIs and that their reasons for dropout are not caused by the WBI itself, but rather due to factors external to the interventions. However, for research question 3, results regarding barriers experienced in the motivation to continue with a WBI found multiple intervention-related barriers.

Research Question 3

To answer the third research question, a topic modeling analysis and a thematic analysis were conducted. The findings are in line with multiple studies such as Donkin and Glozier (2012), who found time-constraints and competing priorities as barriers to the motivation to continue with the intervention. Observable from the identified themes is that they can be sorted into two distinct categories, barriers in motivations rooted in the interventions themselves, such as their design and features, and personal barriers. This distinction has been identified before in multiple studies, such as the study of Eccles et al. (2021) who investigated barriers to the use of WBI designed to prevent depression. They found three personal barriers, including time, stress level, as well as perception of depression prevention, and three intervention-related barriers including content, functionality, and dangers. Similarly, Čihařová et al. (2023), identified those two categories as reasons for dropout. In their study, person-related includes factors such as a 'busy schedule' and 'major life changes' as reasons for dropout, while intervention-related includes factors such as 'Lack of personal contact' and 'Lack of access'.

Differing to the studies by Eccles et al. (2021) and Čihařová et al. (2023), the theme time in this study was present in both personal- and intervention-related barriers. This is reflected in the top five most frequent words, among which 'time' was the second most frequently used word. Further investigation of sentences containing the word 'time' showed that participants often used the word to refer to a lack of time to complete modules due to personal-related barriers such as work ("Time, returning to my work routine distracted me from attending to the platform."). However, they also mentioned the time-locked modules, which is a feature of the Grief COVID and the Healthcare Workers COVID intervention to give the participants time to complete the exercises and to mimic in-person treatment. While one of the frequently named advantages of online interventions is their all-time availability, the participants feedback shows that a lack of time was still a reason for dropout (Smink et al., 2021). These findings are in line with Johansson et al. (2015), who state that time constraints in WBIs have been found to be a reason for dropout in previous studies. They concluded that while the majority of participants are able to work better with time constraints, there are those who focus more on fixed elements such as module deadlines and thus perceive the intervention as inflexible and in turn drop out.

Finally, a frequently mentioned barrier to motivation was a lack of additional support from professionals or from online support groups, despite a majority of the participants receiving support in some kind of form. An explanation for the lack of support as a barrier despite there being support present for nearly half the participants was suggested by Debrot et al. (2022), who investigated tailoring in WBIs and stated that not all individuals need the same type of guidance.

Regarding the inclusion of human-support overall, previous research comparing self-administered and human-supported WBIs has shown that they have similar levels of effectiveness, but the level of dropout is higher in self-administered WBIs (Hegerl, & Oehler, 2020). The present study highlights that support was a frequently mentioned expectation of participants who dropped out of an intervention, underlining the advantage of having support of some kind in WBIs, to improve attrition rates. It is also in line with the systematic review and meta-analysis on web-based bereavement care with seven randomized controlled trials (N = 1,257) by Wagner et al. (2020), who recommended both support in WBIs and a duration of more than six sessions, including personal feedback and guidance to avoid dropout caused by frustration. However, this often proves to be a limitation of WBIs, as they are designed to be used by large groups, which in turn limits the possibility to provide professional support for every user. Especially in countries where a lack of personnel is one of the prominent causes for the treatment gap (the percentage of people who suffer from mental illnesses and those that do not receive treatment) (Jiménez-Molina et al., 2019). A possible solution is the inclusion of automated support, which has been found to be similarly effective as human support (Mira et al., 2017). Furthermore, peer-support can be an essential recovery tool for people who struggle with mental health problems and the inclusion of such features in WBI appears to be a feasible option (Fortuna et al., 2020).

Strengths and Limitations

Limitations

It should be noted that there are several limitations. The data used in this study is limited to a sample of 80 respondents, which is a small sample to be used for text mining, a tool developed to process large amounts of data. Moreover, the data consists mostly of short text with only a few words, further inhibiting the effectiveness of text mining due to the data sparsity. To improve the effectiveness of topic modeling, this study employed LDA as a method, as it has shown to be able to obtain good results even with short text (Albalawi et al., 2020). However, even with the LDA method, the ten keywords identified per topic were difficult to be named, due to a lack of context and overlap between the keywords per topic. Thus, the findings of the topic analyses had to be supplemented by thematic analyses, which was done independently of the topic modeling analyses.

Furthermore, this study investigated the dropout patterns between three different studies to look for overarching themes, yet the feedback for the three WBIs was unequally distributed. Most of the feedback was for the Grief COVID intervention with 51 responses, while feedback for the intervention for healthcare workers, Healthcare Workers COVID, only consists of four responses. The reason for the limited responses from the Healthcare Workers COVID intervention is not discernible from the data, however, healthcare workers had a heavy workload during the pandemic, which in turn would limit the time they have available to respond to surveys (Spoorthy et al., 2020). This unequal distribution is observable in the topics that have been identified in the topic analyses, as topics related to grief (Grief COVID) and anxiety (Mental Health COVID) emerged, while no specific topics for the Healthcare Workers COVID intervention could be identified.

When looking at the demographic information, the majority of the participants were female and with a higher education level (university degree or university undergraduate) and are thus not representative for the general population. Further, these findings do not align with previous studies, where it was found that the majority of dropouts are male and of lower education (Karyotaki et al., 2015; Moshe et al., 2022; Rotondi et al., 2024). One explanation for these results could be that those of the female gender and of higher education are more likely to participate in WBIs and as such their percentage is simply higher in the sample that was collected. Or it could follow the same pattern that male participants were more likely to also drop out of the questionnaire. Regardless, this unequal distribution of demographic information is still a limitation in gaining a varied and representative picture of people who are willing to participate in WBIs but end up dropping out.

Finally, out of all participants in this study, nearly half (n=32) did not complete the first module in their WBIs. This makes the findings of this study less applicable to the actual WBI content, as a lot of participants did not experience the WBIs for long. However, their experiences are still important to research, as it sheds light on initial barriers experienced by the participants. Future research could focus specifically on whether there are differences between participants who completed modules and who did not. More, future research could specifically look into what barriers to motivation participants who dropped out before completing any modules experienced, whether they were rooted in the intervention or was perhaps person-related and focus on implementing ways to prevent that.

Strengths

Regarding strengths, this study is one of the first that investigates dropout with data from three WBIs that differ in target group and design. The WBIs included are Grief COVID, which was designed to help support people dealing with grief via self-administered modules. Further, Mental Health COVID, which was created to reduce symptoms of anxiety and depression as well as increase sleep quality and positive emotions, was either completely self-administered or human-supported via chat. And Healthcare Workers COVID, which was designed to support the mental well-being of healthcare workers and was either self-administered or human-supported via teletherapy. This variety in the target group and the intervention design results in greater variety of the data and allows the identification of overarching themes across the differing interventions.

Furthermore, this study investigates the expectations of participants regarding a WBI from qualitative data in the form of open-ended questions, while it has commonly been investigated with Likert-scales (e.g. Bowker, 2021). Qualitative data allows for a more in-depth investigation of the expectations participants had. While there are studies such as Walsh et al. (2018), who have conducted interviews to explore the acceptability of potential positive psychology interventions to help with depression and anxiety or the previously mentioned study by Montero-Marín et al. (2015), this study was able to explore the expectations of participants for interventions that have already been implemented.

Moreover, this study is one of the first to use sentiment analysis to investigate dropout from WBIs. Previous studies have made use of sentiment analysis to investigate and predict dropout of students from massive open online courses (MOOCs), such as the study of Lundqvist et al. (2020) who used the VADER sentiment algorithm to assess student experiences in a MOOC and recommended the use of sentiment analysis to design MOOCs. Similarly, using sentiment analysis to investigate dropout in WBIs gave further insight into how sentiments might play a role in dropout.

Finally, the data from this study was collected from the general Mexican population, which experiences a high treatment gap (Carmona-Huerta et al., 2021). In general, research into the application of WBI in Latin American countries is limited and their effectiveness is unclear (Fu et al, 2020; Jiménez-Molina et al., 2019). This study contributes knowledge about sociodemographic information of Mexican participants who dropped out of WBIs, their expectations and barriers to motivation that they experienced, which has not been investigated before.

Implications and Future Recommendations

Interestingly, the theme time was quite prevalent in this study, showing up as the most frequently mentioned word and being identifiable in both person- and intervention-related barriers. However, time did not get mentioned as part of the expectations, suggesting that participants did not consider time when thinking of the intervention, but later experienced it as a barrier to their motivation. As mentioned in the introduction, it has been found that participants in face-to-face treatment tend to expect shorter treatment than needed, which can lead to dropout (Swift, & Callahan, 2011). In their study, they also found that addressing those treatment duration expectations before the beginning of an intervention caused participants to stay significantly longer and more likely to complete the treatment. Whether these effects can be observable in WBIs as well, despite their non-presence in the expectations identified in this study, could be a point of future research.

Additionally, multiple findings of this study, including the time-locked modules, the request for additional human-support and the possibility to have reminders point towards a common critique of WBIs and Electronic Health (eHealth) in general, the "one-size fits all" approach (Kip et al., 2018). Making it possible for participants to adjust certain features of the intervention, such as the time-locked modules, could reduce the dropout rates. Nonetheless, further research into the inclusion of time-locked modules and human-support in WBIs and what participants expect and require from the intervention in that regard is still needed.

Another point of interest is that this study had a small sample size, which creates some limitations for text mining, resulting in overlapping and unclear topics and had to be supplemented with thematic analyses. In that line, investigating this topic with a bigger sample could be beneficial in validating the findings of this study or in gaining new findings. Especially the sentiment analysis revealed that participants experienced the WBIs as neutral to positive, possibly suggesting the reasons for dropout are not intervention-related. Yet a lot of barriers to motivation are related to intervention factors. Whether this is because sentiments underlying expectations and the experience of the WBI do not play a role in dropout, or since the expectations are collected after the intervention and therefore might differ from expectations at the start of the WBIs, or other implications, could be a point of future research, as this, to this author's knowledge, has not been researched before.

Finally, this study found expectations that participants expressed for WBIs and factors that could have motivated them to continue with the intervention, overarching between multiple interventions. However, as mentioned, the data sample was relatively small with a total of 80 respondents, and as such it is not possible to say how important those topics are or how frequently they appear among larger sample sizes. Using the themes identified in the TAs as a base, a quantitative measure (such as an instrument) could be created and given to a greater sample of participants. This would allow further investigation regarding the influence of certain expectations on dropout, as well as which barriers to motivation to continue with a WBI have the greatest impact.

Conclusion

To the best of this author's knowledge, this paper is one of the first to apply text mining to qualitative data of feedback from participants who dropped out from multiple WBIs within the psychological field. Results showed that the expectations of participants who dropped out are comparable to expectations prior to a WBI, suggesting that these expectations do not change over time. Furthermore, sentiment analyses revealed neutral sentiments underlying both the expectations and the overall experience with the interventions, which would suggest that the reasons for dropout are less likely to be caused by the participant disliking certain intervention content. Barriers to motivation, however, showed both personal reasons as well as commonly researched topics such as time-constraints and human-support. Possible suggestions to reduce barriers to motivation are the inclusion of tailoring options for the participants that allow them to change certain features of the WBIs themselves. These findings can help inform the design of future WBIs to reduce dropout.

References

Albalawi, R., Yeap, T. H., & Benyoucef, M. (2020). Using topic modeling methods for short-text data: A comparative analysis. *Frontiers in artificial intelligence*, *3*, 42. https://doi.org/10.3389/frai.2020.00042

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), e5352. https://doi.org/10.2196/jmir.5352

Baumel, A., Edan, S., & Kane, J. M. (2019). Is there a trial bias impacting user engagement with unguided e-mental health interventions? A systematic comparison of published reports and real-world usage of the same programs. *Translational behavioral medicine*, *9*(6), 1020-1033. https://doi.org/10.1093/tbm/ibz147

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*, 776-794. https://doi.org/10.1007/s12529-016-9556-9

Berke, D. S., Kline, N. K., Wachen, J. S., McLean, C. P., Yarvis, J. S., Mintz, J., Young 96 McCaughen, S., Peterson, A. L., Foa, E., Resick, P. A., & Litz, B. T. (2019). Predictors of attendance and dropout in three randomized controlled trials of PTSD treatment for active duty service members. Behaviour Research and Therapy, 118, 7 17. https://doi.org/10.1016/j.brat.2019.03.003

Buenaño-Fernández, D., González, M., Gil, D., & Luján-Mora, S. (2020). Text Mining of Open-Ended Questions in Self-Assessment of University Teachers: An LDA Topic Modeling Approach. *IEEE Access*, *8*, 35318–35330. https://doi.org/10.1109/access.2020.2974983

Bueno-Notivol, J., Gracia-García, P., Olaya, B., Lasheras, I., López-Antón, R., & Santabárbara, J. (2021). Prevalence of depression during the COVID-19 outbreak: A meta-analysis of community-based studies. *International journal of clinical and health psychology*, *21*(1), 100196. https://doi.org/10.1016/j.ijchp.2020.07.007

Carmona-Huerta, J., Durand-Arias, S., Rodriguez, A., Guarner-Catalá, C., Cardona-Muller, D., Madrigal-de-León, E., & Alvarado, R. (2021). Community mental health care in Mexico: a regional perspective from a mid-income country. *International Journal of Mental Health Systems*, *15*, 1-10. https://doi.org/10.1186/s13033-020-00429-9

Chávez-Valdez, S. M., Rodríguez, A. D., Esparza-Del Villar, O. A., Jiménez, M. J. H., de la Rosa-Gómez, A., Arenas-Landgrave, P., ... & Salinas-Saldívar, J. T. (2021). Coping strategies associated to widespread fear and post-traumatic stress criteria in a Mexican sample during COVID-19 pandemic: A cross-sectional study. *Salud mental*, *44*(4), 159-166. https://www.sidalc.net/search/Record/oai:scielo:S0185-33252021000400159

Čihařová, M., Cuijpers, P., Amanvermez, Y., Riper, H., Klein, A. M., Bolinski, F., De Wit, L., Van Der Heijde, C., Bruffærts, R., Struijs, S. Y., 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.brat.2021.104028

Cullen, W., Gulati, G., & Kelly, B. D. (2020). Mental health in the COVID-19 pandemic. *QJM: An International Journal of Medicine*, *113*(5), 311-312. https://doi.org/10.1093/qjmed/hcaa110

Cohen, M., Beard, C., & Björgvinsson, T. (2015). Examining patient characteristics as predictors of patient beliefs about treatment credibility and expectancies for treatment outcome. *Journal of Psychotherapy Integration*, *25*(2), 90. https://doi.org/10.1037/a0038878

Debrot, A., Berthoud, L., Caspar, F., Berger, T., & Pomini, V. (2022). Tailoring guidance in internet-based interventions with motive-oriented therapeutic relationship. *Frontiers in digital health*, *4*, 842487. https://doi.org/10.3389%2Ffdgth.2022.842487

de la Rosa Gómez, A., Dominguez-Rodriguez, A., Rodríguez Huitrón, A. M., Flores-Plata, L. A., Santillán Torres-Torija, C., Martínez Arriaga, R. J., ... & Bautista Valerio, E. (2023). Resilience and post-traumatic stress disorder among healthcare workers during the COVID-19 outbreak. Electron J Gen Med. 2023; 20 (5): em505. https://doi.org/10.29333/ejgm/13265

Delgadillo, J., Moreea, O., & Lutz, W. (2016). Different people respond differently to therapy: A demonstration using patient profiling and risk stratification. *Behaviour Research and Therapy*, *79*, 15-22. https://doi.org/10.1016/j.brat.2016.02.003

Dominguez-Rodriguez, A., De La Rosa-Gómez, A., Jiménez, M. J. H., Arenas-Landgrave, P., Martínez-Luna, S. C., Silva, J. A., ... & 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., Hernández Jiménez, M. J., De La Rosa-Gómez, A., Arenas-Landgrave, P., Esquivel Santoveña, E. E., ... & 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*, 644782. https://doi.org/10.3389/fpsyg.2021.644782

Dominguez-Rodriguez, A., Herdoiza-Arroyo, P. E., Martínez Arriaga, R. J., Bautista Valerio, E., Mateu Mollá, J., de la Rosa-Gómez, A., ... & Martínez-Luna, S. C. (2022). Prevalence of anxiety symptoms and associated clinical and sociodemographic factors in mexican adults seeking psychological support for grief during the COVID-19 pandemic: a cross-sectional study. *Frontiers in Psychiatry*, *13*, 211. https://doi.org/10.3389/fpsyt.2022.749236

Dominguez-Rodriguez, A., Sanz-Gomez, S., González Ramírez, L. P., Herdoiza-Arroyo, P. E., Trevino Garcia, L. E., de la Rosa-Gómez, A., ... & 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

Donkin, L., & Glozier, N. (2012). Motivators and motivations to persist with online psychological interventions: a qualitative study of treatment completers. *Journal of medical Internet research*, *14*(3), e91. https://doi.org/10.2196/jmir.2100

Eccles, H., Nannarone, M., Lashewicz, B., Attridge, M., Marchand, A., Aiken, A., ... & Wang, J. (2021). Barriers to the use of web-based mental health programs for preventing depression: qualitative study. *JMIR formative research*, *5*(7), e16949. https://doi.org/10.2196%2F16949

Elbagir, S., & Yang, J. (2019, March). Twitter sentiment analysis using natural language toolkit and VADER sentiment. In *Proceedings of the international multiconference of engineers and computer scientists* (Vol. 122, No. 16). sn.

Eisma, M. C., & Tamminga, A. (2020). Grief before and during the COVID-19 pandemic: Multiple group comparisons. *Journal of pain and symptom management*, *60*(6), e1-e4. https://doi.org/10.1016/j.jpainsymman.2020.10.004

Erbe, D., Eichert, H. C., Riper, H., & Ebert, D. D. (2017). Blending face-to-face and internet-based interventions for the treatment of mental disorders in adults: systematic review. *Journal of medical Internet research*, *19*(9), e306. https://doi.org/10.2196/jmir.6588

Fernández-Álvarez, J., Díaz-García, A., González-Robles, A., Baños, R., García-Palacios, A., & Botella, C. (2017). Dropping out of a transdiagnostic online intervention: a qualitative analysis of client's experiences. *Internet Interventions*, *10*, 29-38. https://doi.org/10.1016/j.invent.2017.09.001

Fernández, O., Pérez, J. C., Fernández, S., Krause, M., Cáceres, C., & Espinosa-Duque, D. (2023). Understanding the use/non-use of an internet-based intervention complementing standard depression treatment: A qualitative study of user's experiences. *Digital Health*, *9*, 20552076231203920. https://doi.org/10.1177/2055207623120392

Filmer, H. (2023). *Online Treatment of adolescent sleep problems: A text mining analysis of written feedback from CBT-I therapists* (Master's thesis, University of Twente).

Fortuna, K. L., Naslund, J. A., LaCroix, J. M., Bianco, C. L., Brooks, J. M., Zisman-Ilani, Y., ... & Deegan, P. (2020). Digital peer support mental health interventions for people with a lived experience of a serious mental illness: systematic review. *JMIR mental health*, *7*(4), e16460. https://doi.org/10.2196/16460

Fu, Z., Burger, H., Arjadi, R., & Bockting, C. L. (2020). Effectiveness of digital psychological interventions for mental health problems in low-income and middle-income countries: a systematic review and meta-analysis. *The Lancet Psychiatry*, *7*(10), 851-864. https://doi.org/10.1016/S2215-0366(20)30256-X

Geraghty, A. W., Wood, A. M., & Hyland, M. E. (2010). Attrition from self-directed interventions: Investigating the relationship between psychological predictors, intervention content and dropout from a body dissatisfaction intervention. *Social science & medicine, 71(1), 30-37.* https://doi.org/10.1016/j.socscimed.2010.03.007

Glombiewski, W. R. J. A., & Rief, W. (2016). Expectation-focused psychological interventions (EFPI). *Verhaltenstherapie*, *26*, 00-00.

Gottipati, S., Shankararaman, V., & Lin, J. (2018a). Latent Dirichlet Allocation for textual student feedback analysis. *Proceedings of the 26th International Conference on Computers in Education ICCE 2018: Manila, Philippines, November 28-30*. 220-227. https://ink.library.smu.edu.sg/sis_research/4215

Gottipati, S., Shankararaman, V., & Lin, J. R. (2018b). Text analytics approach to extract course improvement suggestions from students' feedback. *Research and Practice in Technology Enhanced Learning*, *13*, 1-19. https://doi.org/10.1186/s41039-018-0073-0

Grönberg, N., Knutas, A., Hynninen, T., & Hujala, M. (2021). Palaute: An online text mining tool for analyzing written student course feedback. *IEEE Access*, *9*, 134518-134529. https://doi.org/10.1109/ACCESS.2021.3116425

Hegerl, U., & Oehler, C. (2020). Promises and risks of web-based interventions in the treatment of depression. *Dialogues in Clinical Neuroscience*, *22*(2), 161-168. https://doi.org/10.31887/DCNS.2020.22.2/uhegerl

Jiang, J. J., & Klein, G. (2009). Expectation-confirmation theory: Capitalizing on descriptive power. In *Handbook of research on contemporary theoretical models in information systems* (pp. 384-401). IGI Global. DOI: 10.4018/978-1-60566-659-4.ch022 https://doi.org/10.1016/j.invent.2015.02.006

Jiménez-Molina, Á., Franco, P., Martínez, V., Martínez, P., Rojas, G., & Araya, R. (2019). Internet-based interventions for the prevention and treatment of mental disorders in Latin America: a scoping review. *Frontiers in psychiatry*, *10*, 477672. https://doi.org/10.3389/fpsyt.2019.00664

Johansson, O., Michel, T., Andersson, G., & Paxling, B. (2015). Experiences of non-adherence to Internet-delivered cognitive behavior therapy: A qualitative study. *Internet Interventions*, *2*(2), 137-142. https://doi.org/10.1016/j.invent.2015.02.006

Karyotaki, E., Kleiboer, A., Smit, F., Turner, D. T., Pastor, A. M., Andersson, G., ... & 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

Kip, H., Beerlage-de Jong, N., van Gemert-Pijnen, L., Sanderman, R., & Kelders, S. M. (Eds.). (2018). *eHealth research, theory and development: A multi-disciplinary approach*. Routledge.

Koelen, J., Vonk, A., Klein, A. M., De Koning, L., Vonk, P., De Vet, S., & Wiers, R. W. (2022). Man vs. machine: A meta-analysis on the added value of human support in text-based internet treatments ("e-therapy") for mental disorders. *Clinical Psychology Review*, *96*, 102179. https://doi.org/10.1016/j.cpr.2022.102179

Lundqvist, K., Liyanagunawardena, T., & Starkey, L. (2020). Evaluation of student feedback within a MOOC using sentiment analysis and target groups. *The International Review of Research in Open and Distributed Learning*, *21*(3), 140-156. https://doi.org/10.19173/irrodl.v21i3.4783

Luo, Y., Feng, X., Wang, D., Zheng, M., & Reinhardt, J. D. (2023). Understanding early experiences of Chinese frontline nurses during the COVID-19 pandemic: A text mining and thematic analysis of social media information. *Nursing & Health Sciences*, *25*(3), 389-401. https://doi.org/10.1111/nhs.13037

Martínez-Arriaga, R. J., Dominguez-Rodriguez, A., Herdoiza-Arroyo, P. E., Robles-Garcia, R., de la Rosa-Gómez, A., Figueroa González, J. A., & Muñoz Anacona, Y. A. (2023). Suicide risk and associated factors in healthcare workers seeking psychological support during COVID-19: a cross-sectional study. *Psychology, Health & Medicine*, 1-15. https://doi.org/10.1080/13548506.2023.2216469

Melville, K. M., Casey, L. M., & Kavanagh, D. J. (2010). Dropout from Internet-based treatment for psychological disorders. *British Journal of Clinical Psychology, 49*(4), 455-471. https://doi.org/10.1348/014466509X472138

Mira, A., Bretón-López, J., García-Palacios, A., Quero, S., Baños, R. M., & Botella, C. (2017). An Internet-based program for depressive symptoms using human and automated support: a randomized controlled trial. *Neuropsychiatric disease and treatment*, 987-1006. https://doi.org/10.2147/NDT.S130994

Montero-Marín, J., Prado-Abril, J., Botella, C., Mayoral-Cleries, F., Baños, R., Herrera-Mercadal, P., ... & García-Campayo, J. (2015). Expectations among patients and health professionals regarding Web-based interventions for depression in primary care: a qualitative study. *Journal of Medical Internet Research*, *17*(3), e3985. doi:10.2196/jmir.3985

Moshe, I., Terhorst, Y., Paganini, S., Schlicker, S., Pulkki-Råback, L., Baumeister, H., ... & Ebert, D. D. (2022). Predictors of dropout in a digital intervention for the prevention and treatment of depression in patients with chronic back pain: secondary analysis of two randomized controlled trials. *Journal of Medical Internet Research*, *24*(8), e38261. doi:10.2196/38261

Omar, M. A., Makhtar, M., Ibrahim, M. F., & Aziz, A. A. (2020). Sentiment analysis of user feedback in e-learning environment. *International Journal of Engineering Trends and Technology (IJETT)*, 153-157. doi:10.14445/22315381/CATI2P224

Orange (n.d.). *Orange Data Mining - Visual Programming*. Orange Data Mining. https://orangedatamining.com/home/visual-programming/ Retrieved 14.12.2023

Oyebode, O., Ndulue, C., Adib, A., Mulchandani, D., Suruliraj, B., Orji, F. A., ... & Orji, R. (2021). Health, psychosocial, and social issues emanating from the COVID-19 pandemic based on social media comments: text mining and thematic analysis approach. *JMIR medical informatics*, *9*(4), e22734. doi:10.2196/22734

Öztürk, N., & Ayvaz, S. (2018). Sentiment analysis on Twitter: A text mining approach to the Syrian refugee crisis. *Telematics and Informatics*, *35*(1), 136-147. https://doi.org/10.1016/j.tele.2017.10.006

Pal, S., Biswas, B., Gupta, R., Kumar, A., & Gupta, S. (2023). Exploring the factors that affect user experience in mobile-health applications: A text-mining and machine-learning approach. *Journal of business research*, *156*, 113484. https://doi.org/10.1016/j.jbusres.2022.113484

Park, A., Conway, M., & Chen, A. T. (2018). Examining thematic similarity, difference, and membership in three online mental health communities from reddit: a text mining and visualization approach. *Computers in human behavior*, *78*, 98-112. https://doi.org/10.1016/j.chb.2017.09.001

Park, J., Yang, D., & Kim, H. Y. (2023). Text mining-based four-step framework for smart speaker product improvement and sales planning. *Journal of Retailing and Consumer Services*, *71*, 103186. https://doi.org/10.1016/j.jretconser.2022.103186

Patterson, P. G. (1993). Expectations and product performance as determinants of satisfaction for a high-involvement purchase. *Psychology & Marketing*, *10*(5), 449-465. https://doi.org/10.1002/mar.4220100507

Penninx, B. W., Benros, M. E., Klein, R. S., & Vinkers, C. H. (2022). How COVID-19 shaped mental health: From infection to pandemic effects. *Nature medicine*, *28*(10), 2027-2037. https://doi.org/10.1038/s41591-022-02028-2

Pfefferbaum, B., & North, C. S. (2020). Mental health and the Covid-19 pandemic. *New England journal of medicine*, *383*(6), 510-512. 10.1056/NEJMp2008017

Pontén, M., Jonsjö, M., Vadenmark, V., Moberg, E., Grannas, D., Andersson, G., ... & Jensen, K. (2024). Association between expectations and clinical outcomes in online v. face-to-face therapy–an individual participant data meta-analysis. *Psychological Medicine*, *54*(6), 1207-1214. https://doi.org/10.1017/S0033291723003033

Puolakanaho, A., Kaipainen, K., Keinonen, K., Lappalainen, P., Lappalainen, R., & Kiuru, N. (2024). Factors anticipating adolescents' adherence and dropout in an online ACT intervention during the COVID-19 pandemic. *Child & Family Behavior Therapy*, *46*(2), 126-146. https://doi.org/10.1080/07317107.2023.2270544

Rodrigues, T. R. C., Reijnders, T., Breeman, L. D., Janssen, V. R., Kraaijenhagen, R. A., Atsma, D. E., & Evers, A. W. (2024). Use Intention and User Expectations of Human-Supported and Self-Help eHealth Interventions: Internet-Based Randomized Controlled Trial. *JMIR Formative Research*, *8*(1), e38803. https://doi.org/10.2196/38803

Rotondi, A. J., Belnap, B. H., Rothenberger, S., Feldman, R., Hanusa, B., & Rollman, B. L. (2024). Predictors of Use and Drop Out From a Web-Based Cognitive Behavioral Therapy Program and Health Community for Depression and Anxiety in Primary Care Patients: Secondary Analysis of a Randomized Controlled Trial. *JMIR Mental Health*, *11*, e52197. doi:10.2196/52197

Saddichha, S., Al-Desouki, M., Lamia, A., Linden, I. A., & Krausz, M. (2014). Online interventions for depression and anxiety–a systematic review. *Health Psychology and Behavioral Medicine: An Open Access Journal*, *2*(1), 841-881. https://doi.org/10.1080/21642850.2014.945934

Schindler, A., Hiller, W., & Witthöft, M. (2013). What predicts outcome, response, and drop out in CBT of depressive adults? A naturalistic study. Behavioural and Cognitive Psychotherapy, 41(3), 365. http://doi.org/ 10.1017/S1352465812001063

Schröder, J., Sautier, L., Kriston, L., Berger, T., Meyer, B., Späth, C., ... & Moritz, S. (2015). Development of a questionnaire measuring Attitudes towards Psychological Online Interventions–the APOI. *Journal of affective disorders*, *187*, 136-141. https://doi.org/10.1016/j.jad.2015.08.044

Smink, W., Sools, A. M., van der Zwaan, J. M., Wiegersma, S., Veldkamp, B. P., & Westerhof,

G. J. (2019). Towards text mining therapeutic change: A systematic review of text-based methods for Therapeutic Change Process Research. *PloS one*, *14*(12), e0225703. https://doi.org/10.1371/journal.pone.0225703

Smink, W. A., Sools, A. M., Postel, M. G., Tjong Kim Sang, E., Elfrink, A., Libbertz-Mohr, L. B., ... & Westerhof, G. J. (2021). Analysis of the Emails From the Dutch Web-Based Intervention “Alcohol de Baas”: Assessment of Early Indications of Drop-Out in an Online Alcohol Abuse Intervention. *Frontiers in Psychiatry*, *12*, 575931. https://doi.org/10.3389/fpsyt.2021.575931

Soratto, J., Pires, D. E. P. D., & Friese, S. (2020). Thematic content analysis using ATLAS. ti software: Potentialities for researchs in health. *Revista brasileira de enfermagem*, *73*, e20190250. https://doi.org/10.1590/0034-7167-2019-0250

Spoorthy, M. S., Pratapa, S. K., & Mahant, S. (2020). Mental health problems faced by healthcare workers due to the COVID-19 pandemic–A review. *Asian journal of psychiatry*, *51*, 102119. https://doi.org/10.1016/j.ajp.2020.102119

Swift, J. K., & Callahan, J. L. (2011). Decreasing treatment dropout by addressing expectations for treatment length. *Psychotherapy Research*, *21*(2), 193-200. https://doi.org/10.1080/10503307.2010.541294

Talib, R., Hanif, M. K., Ayesha, S., & Fatima, F. (2016). Text mining: techniques, applications and issues. *International journal of advanced computer science and applications*, *7*(11), 414-418.

Teles, S., Ferreira, A., & Paul, C. (2021). Assessing attitudes towards online psychoeducational interventions: Psychometric properties of a Brief Attitudes Scale. *Health & Social Care in the Community*, *29*(5), e1-e10. https://doi.org/10.1111/hsc.13227

van Doorn, H. R. (2021). The epidemiology of emerging infectious diseases and pandemics. *Medicine*, *49*(10), 659-662. https://doi.org/10.1016/j.mpmed.2021.07.011

van Gemert-Pijnen, L., Kelders, S. M., Kip, H., & Sanderman, R. (2018). *eHealth research,* *theory and development: a multi-disciplinary approach*. Routledge.

van Lotringen, C., Jeken, L., Westerhof, G. J., Klooster, P. M. T., Kelders, S. M., & Noordzij, M. L. (2021). Responsible Relations: A Systematic scoping review of the therapeutic alliance in Text-Based Digital Psychotherapy. *Frontiers in Digital Health*, *3*. https://doi.org/10.3389/fdgth.2021.689750

Wagner, B., Rosenberg, N., Hofmann, L., & Maass, U. (2020). Web-based bereavement care: a systematic review and meta-analysis. *Frontiers in psychiatry*, *11*, 537629. https://doi.org/10.3389/fpsyt.2020.00525

Walsh, S., Kaselionyte, J., Taylor, S. J., & Priebe, S. (2018). What might affect acceptability of online positive psychology interventions for depression: a qualitative study on patient expectations'. *BMC psychiatry*, *18*, 1-12. https://doi.org/10.1186/s12888-018-1812-x

Wiegersma, S., Hidajat, M., Schrieken, B., Veldkamp, B., & Olff, M. (2022). Improving web-based treatment intake for multiple mental and substance use disorders by text mining and machine learning: Algorithm development and validation. *JMIR mental health*, *9*(4), e21111. doi:10.2196/21111

Wind, T. R., Rijkeboer, M., Andersson, G., & Riper, H. (2020). The COVID-19 pandemic: The 'black swan'for mental health care and a turning point for e-health. *Internet interventions*, *20*. 10.1016/j.invent.2020.100317

Winter, S., Jesser, A., Probst, T., Schaffler, Y., Kisler, I. M., Haid, B., ... & Humer, E. (2023). How the COVID-19 pandemic affects the provision of psychotherapy: results from three online surveys on Austrian psychotherapists. *International journal of environmental research and public health*, *20*(3), 1961. https://doi.org/10.3390/ijerph20031961

Yan, X., Guo, J., Lan, Y., & Cheng, X. (2013, May). A biterm topic model for short texts. In

Proceedings of the 22nd international conference on World Wide Web (pp. 1445-1456). https://doi.org/10.1145/2488388.2488514

Yao, H., Chen, J. H., & Xu, Y. F. (2020). Rethinking online mental health services in China during the COVID-19 epidemic. *Asian journal of psychiatry*, *50*, 102015. 10.1016/j.ajp.2020.102015

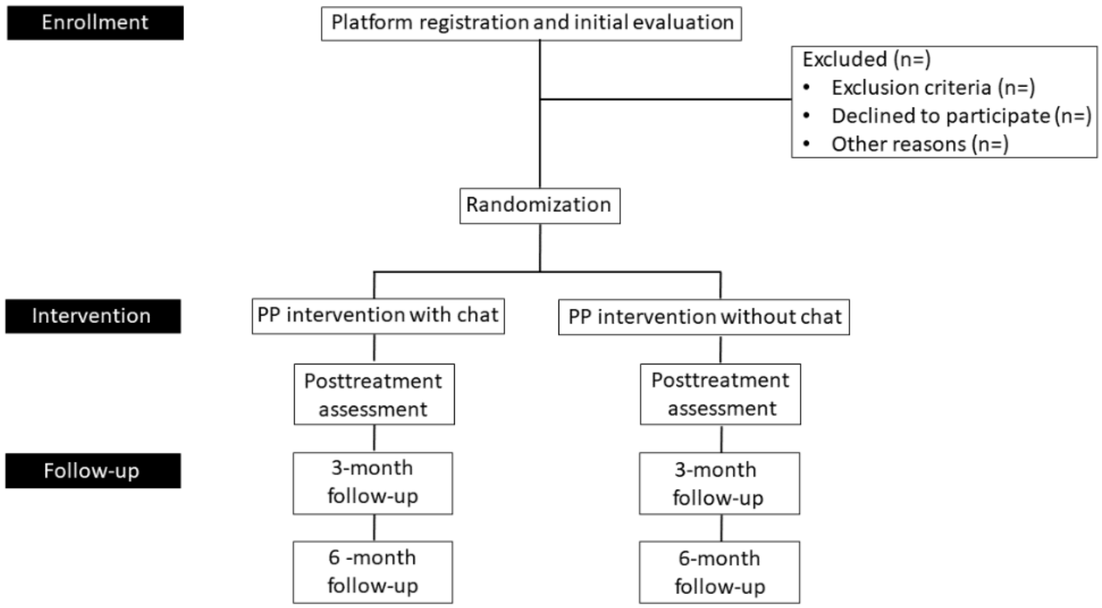
Ye, Z., Li, W., & Zhu, R. (2022). Online psychosocial interventions for improving mental health in people during the COVID-19 pandemic: A systematic review and meta-analysis. *Journal of Affective Disorders*, *316*, 120-131. https://doi.org/10.1016/j.jad.2022.08.023

Yu, C. H., Jannasch-Pennell, A., & DiGangi, S. (2011). Compatibility between text mining and qualitative research in the perspectives of grounded theory, content analysis, and reliability. *Qualitative Report*, *16*(3), 730-744. http://www.nova.edu/ssss/QR/QR16-3/yu.pdf

Appendices

Appendix A

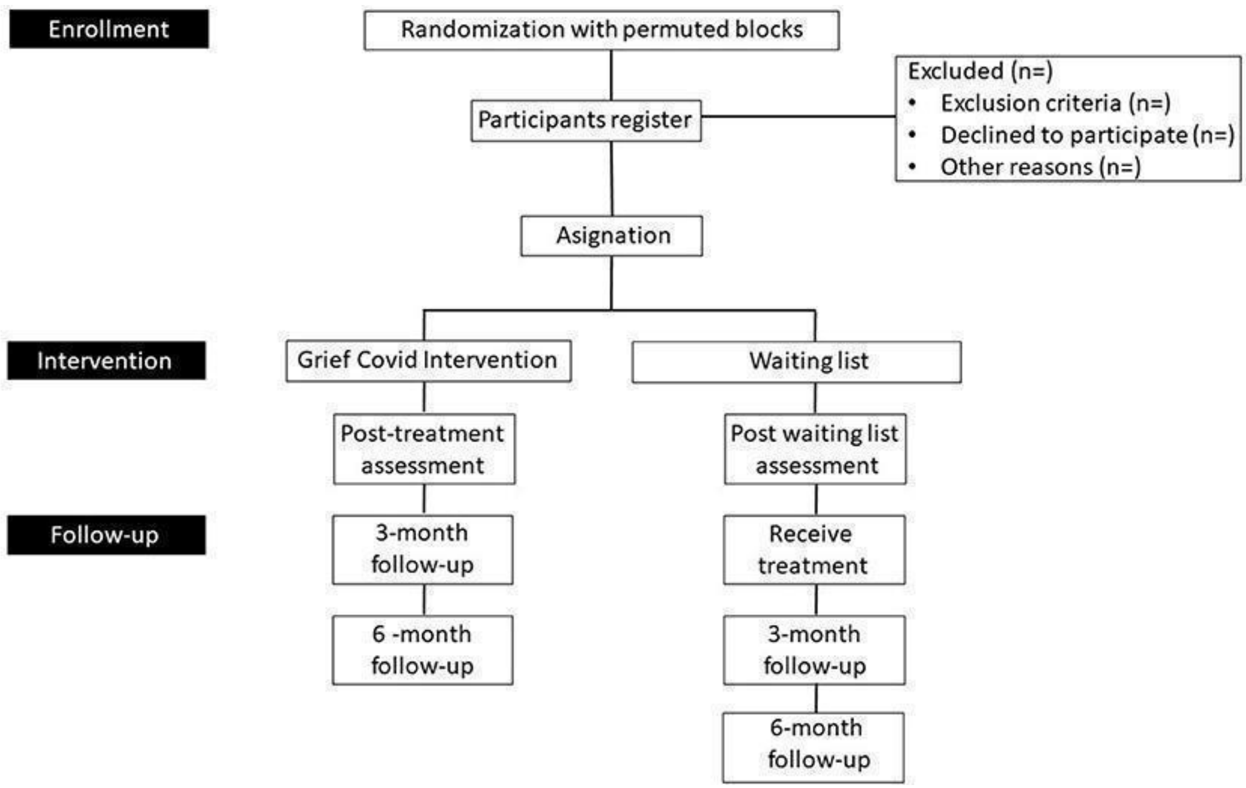
An overview of the study design for the WBI Mental Health COVID.



Note. By Dominguez-Rodriguez et al. (2020).

Appendix B

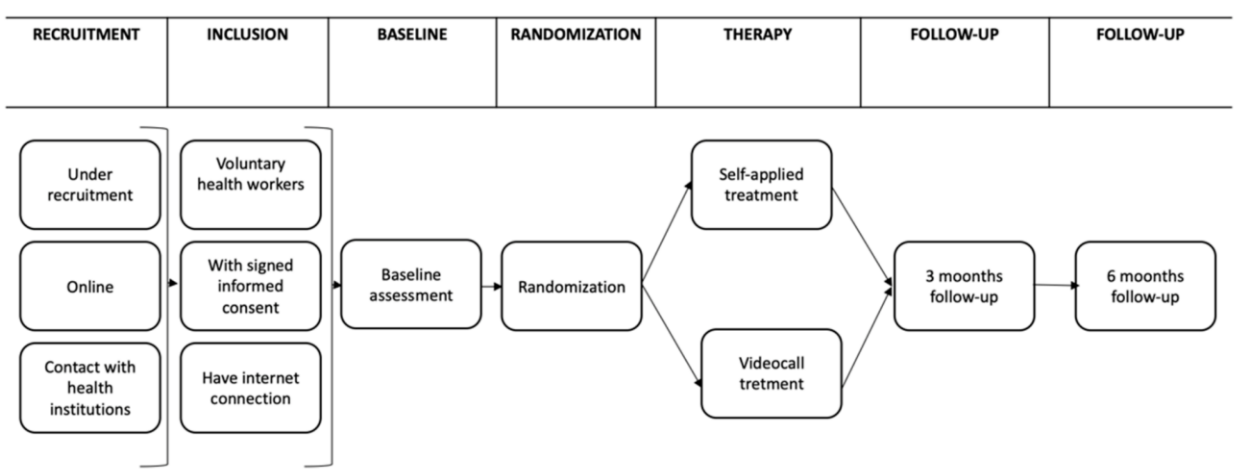
An overview of the study design for the WBI Grief COVID.



Note. By Dominguez-Rodriguez et al. (2021).

Appendix C

An overview of the study design for the WBI Healthcare Workers COVID.



Note. By Dominguez-Rodriguez et al. (2022).

Appendix D

Specific filtering word list:

would, could, should, due, perhaps, yes, maybe, one, much, x

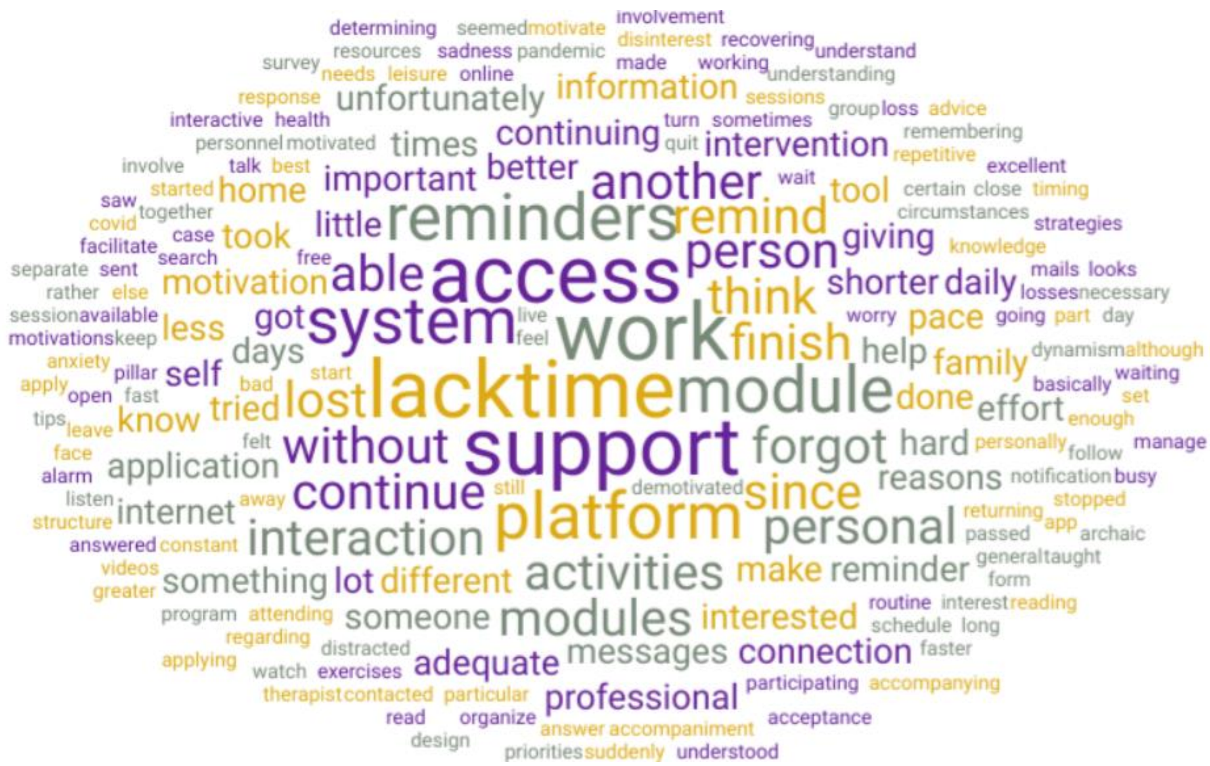
Appendix E

Individual word cloud of item (1) (expectations)

Note. The five most frequently mentioned terms are help (23), support (13), grief (13), expectations (7) and able (7).

Appendix F

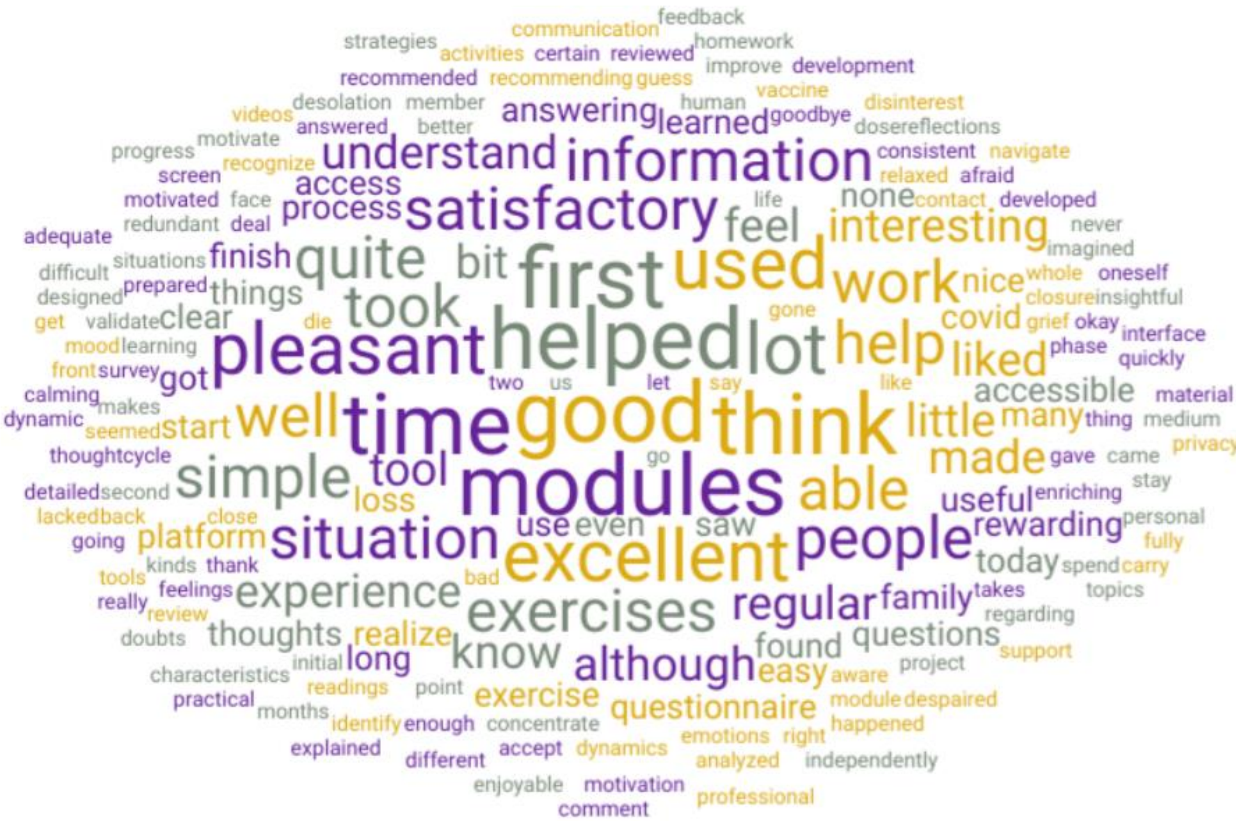
Individual word cloud of item (2) (motivations)



Note. The five most frequent words are time (17), support (7), work (6), lack (5) and access (5).

Appendix G

Individual word cloud of item (4) (experience)



Note. Good (22), modules (7), helped (7), think (6) and time (6) are the five most mentioned words.