Web-Based Interventions: Using Text Mining to Investigate Intervention- and Person-Related Reasons for Dropout

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Abstract

The COVID-19 pandemic led to an increase in mental health concerns such as depression and anxiety, which caused a discrepancy between needed and available resources. Hence, the development and use of Web-Based Interventions (WBIs) increased to make mental health care more accessible. However, research shows that WBIs are challenged by high dropout rates. To improve WBI efficiency, this research investigates explanations about dropout. It utilises a pre-defined framework, which divides explanations into person- and intervention-related reasons and compares those to understand the major motivation for dropout. Further, this study uses text mining, a quantitative approach to analyse qualitative data, to achieve detailed results. The sample comprises 80 participants who dropped out from three WBIs during the COVID-19 pandemic, differing in aspects such as target participants, type of therapist support, and number of modules. Those participants were asked to answer five open questions about their experience with the intervention, created based on research investigating attitudes toward WBIs. The data gathered was analysed with the text mining approach, specifically, with Topic Modelling and Sentiment Analysis. The results show that both person- and intervention-related reasons are related largely to neutral sentiments and are both mentioned equally often. This suggests neither is more important and highlights the importance of addressing both when designing and improving WBIs, rather than focusing on either, and underlines the complexity of dropout from WBIs. In conclusion, this research shows individuals explain their dropout from WBIs in person- and intervention-related themes, and while each person emphasizes each differently, the sample suggests that overall, both factors matter.

Keywords: Web-Based Interventions, Dropout, COVID, Text Mining, Sentiment Analysis, Topic Modelling, Person-related Reasons, Intervention-Related Reasons

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Introduction

COVID-19 Pandemic

On March 11th, 2020, the World Health Organization (WHO) proclaimed the Corona Virus Disease (COVID-19) a pandemic after being recognized as a public health concern (WHO, 2024). In the European region, more than 2 million people died due to this virus (WHO, 2024), and the pandemic had a great impact.

Multiple studies showed a trend of a significant increase in the prevalence of mental health problems in the general population (Daly et al., 2020; Di Fazio et al., 2022; Ludwig-Walz et al., 2022). Specifically, Cénat et al. (2022) reported in their meta-analysis of longitudinal studies related to the COVID-19 pandemic that the overall scores of loneliness, posttraumatic stress disorder (PTSD), anxiety, psychological distress, suicidal ideation, depression, and insomnia showed an increase during the first wave of the pandemic. During this time, safety measures such as social isolation were first introduced and the majority of the coronavirus-related deaths in Europe and North America occurred, which according to Cénat et al. (2022) might have added to said increase in mental health problems such as depression, anxiety, and psychological distress. To conclude, the pandemic causes a significant increase in mental health problems in the population.

Among the people who were most affected by the pandemic were healthcare workers, who according to Diolaiuti et al. (2021) self-isolated to avoid infecting people they care about. Additionally, individuals who worked in healthcare during the pandemic have been at an elevated risk for psychological pressure and developing mental illness (Vizheh et al., 2020). The causes for this not only included self-isolation but also working in high-risk departments, which meant a threat to their lives leading to high levels of fear and stress (Vizheh et al., 2020). Hence, healthcare workers were more susceptible to mental health problems due to the nature of their profession.

A similar increase in pandemic-related mental health concerns affected those who lost loved ones, as Diolaiuti et al. (2021) showed in their research. According to the authors, restrictions intended to stop the virus from spreading included prohibitions of mourning rituals, which are integral to the correct coping with grief. Further, Diolaiuti et al. (2021) stated that even in countries where mourning rituals were not prohibited, the anxiety caused by possibly losing a loved one could be a substantial cause of developing trauma (Diolaiuti et al., 2021). This nonadaptive coping or the development of trauma may lead to complicated grief, which describes the experience of symptoms such as severe emotion, strong intrusive thoughts, and excessive loss of interest in personal activities continuing for over a year following the loss (Horowitz et al., 2003). Hence, among the people who were affected more by the pandemic were individuals who experienced loss during this time and healthcare workers, both of whom were at higher risk for mental illness during the pandemic.

While the number of mental health problems grew, the incentive to stop the pandemic from spreading caused restrictions for mental health services (Moreno et al., 2020; Peng et al., 2020; Zangani et al., 2022). Similar findings were reported by the WHO (2022), which reported an increase in mental health concerns, and disruptions limiting mental health services in the amount of treatment they could provide. In addition, Moreno et al. (2020) pointed out how the pandemic might also have increased the disparity in health care with a disproportionate effect on socially disadvantaged groups such as ethnic minorities. Moreover, the pandemic could have enhanced the scale and cost-effectiveness of interventions (Stefana et al., 2020). Overall, mental health care providers had to adapt to provide the needed treatment for the challenges and demand, and also prepare for possible similar emergencies occurring in the future (Moreno et al., 2020; Peng et al., 2020; Zangani et al., 2022). Further, the WHO (2022) stated that mental health services decided to address these limitations to their services by introducing digital technologies. Thus, the use of digital mental health services was needed more than ever before.

Web-Based Interventions

One of the digital mental health services are web-based interventions (WBIs; web-based intervention: WBI). These types of interventions are administered digitally and can be guided, either with teletherapy which means contact with a therapist via video, audio, or chat, or self-administered, meaning without the guidance or support of another person (Krämer et al., 2022). Thus, they offer the advantage of being accessible regardless of location, such as during the COVID-19 pandemic where the possibility of face-to-face treatment was limited (Dominguez-Rodriguez et al., 2020). Examples of WBIs are for instance Mental Health COVID (Dominguez-Rodriguez et al., 2020), Grief COVID (Dominguez-Rodriguez et al., 2021), and Health Care Workers Covid (Dominguez-Rodriguez, et al., 2022).

Another example of a self-administered WBI that was applied during COVID-19 is the intervention by Mullarkey et al. (2022). The intervention showed a positive effect on having control over anxiety and comparable emotions and hence suggests the efficacy of self-administered WBI. Additionally, Sevilla-Llewellyn-Jones et al. (2018) conducted a meta-analysis of WBIs, in which they examined 12 studies. They found that WBIs are effective in some areas, specifically, mindfulness-based WBIs reduce anxiety and depression, as well as enhance mindfulness skills and quality of life. As patients were unable to attend face-to-face treatment, WBIs offered a suitable and effective alternative to support them with their mental health concerns, which highlights the importance of this kind of treatment, and in turn, also highlights that WBIs should continuously be improved to maintain and enhance this effectiveness. Specifically, when considering participants leaving the treatment prematurely.

Previous research has been conducted on participants leaving WBIs prematurely. For instance, Bäuerle et al. (2021) created the WBI "Coping with Corona: Extended Psychosomatic care in Essen" (CoPE), to help people overcome psychological distress related to COVID-19. The authors mention that out of 440 participants, only 114 finished all modules, leading to a dropout rate of 74.09%. The previously mentioned WBI by Mullarkey et al. (2022) reported that at the two-week follow up 43 out of 522 participants had dropped out. Van Straten et al. (2008) also created a WBI aimed at reducing mental health problems such as depression, anxiety, and stress, in which, out of the 107 participants in the intervention group, only 59 individuals finished the intervention, 10 participants dropped out before the intervention began, and 38 during the intervention. To conclude, a significant number of participants tend to leave WBIs before completing the treatment.

The mentioned interventions experienced participants leaving the treatment prematurely, meaning participants decided to drop out. This phenomenon is not unusual for self-applied WBIs (Dominguez-Rodriguez et al., 2023). Previous research into dropout from WBIs has aimed to understand the causes of this.

Web-Based Intervention Dropout Causes

There are several studies that assessed reasons for dropout from WBIs. Lawler et al. (2021) for example, investigated dropout from WBIs by conducting interviews via telephone and analysing the qualitative data with a descriptive-interpretative approach. They concluded that there are different motivations for dropout, and two groups can be identified, who differ concerning their change in motivation. One group has negative reasons to leave the intervention, such as obstacles from relationships or commitments, or dissatisfaction with the received support. The other group leaves the intervention due to being satisfied with the premature treatment results and feeling that no further treatment is needed to make them feel better. So, the reasons for dropout can vary and are not necessarily negative.

Other previous research into causes for dropout was done by Scheutzow et al. (2022), who listed dropout reasons they found through their systematic review of WBIs that focused on helping members of the workforce. These included privacy concerns, lower education, younger age, technical difficulties, lack of time or motivation, no need for additional help, and dissatisfaction with the treatment. Further, participant dropout is also related to participant engagement with the intervention. This means that if participants do not show a sufficient degree of engagement with the treatment, they are more likely to drop out of the intervention (Windle et al., 2020). Moreover, Postel et al. (2010), who designed an online intervention for problem drinkers, found that possible motivations include personal reasons. These included having a sick family member and being unsatisfied with the treatment program. Fernández-Álvarez et al. (2017) conducted qualitative research on clients who dropped out of a transdiagnostic online intervention. Among the reasons listed by the participants, the main points were that the participants disliked the treatment's content lacked tailoring to their problems, and the lack of support from a therapist.

This reason for dropout, the lack of support from a therapist, was also investigated by Renfrew et al. (2020), who divided participants of a WBI into three randomized conditions of human support. First, a standard condition in which participants received automated emails, second, a condition in which additionally to the email, participants received a personalized SMS-message, or third, a condition in which additionally to the email participants received support via weekly videoconferencing. Participants were informed about the three possible conditions and were asked for their preference. The results showed that out of 605 initial participants, 147 participants dropped out before the prequestionnaire, about 22% of the first condition, about 19% out of the second condition (additional SMS), and about 31.5% out of the third condition (additional Videoconferences), leading to 458 registered participants. Of those, 138 did not complete the postquestionnaire, however, there appeared no between-group differences in adherence during the intervention and in non-completion of the postquestionnaire. Thus, Renfrew et al. (2020) conclude, that dissatisfaction with the allocated support condition influenced dropout, while the support condition had no impact on adherence to the WBI. Further, participants who were allocated to the preferred condition did not show greater adherence or better outcomes. This might allude to human support type itself being not as significant for dropout or treatment result quality, but rather the participants' preference for support type being important for adherence. That is due to the dropout that occurred after allocation and before the prequestionnaire which could be explained by participants not having received their preferred type of support.

Overall, many factors appear to contribute to participant dropout from WBIs. A pattern that could be observed is the possible divide between factors motivating participant dropout to be either related to the intervention, such as privacy concerns or type of support, or to personal reasons, such as a lack of time.

Person- and Intervention-Related Reasons for Dropout

The idea that dropout reasons could be divided into reasons relating to the intervention and to personal factors is not novel. Čihařová et al. (2023) investigated WBI dropout reasons and similarly found multiple reasons for dropout, which they categorized into personal- and intervention-related reasons. For instance, person-related reasons included a busy schedule and major life changes, and intervention-related reasons included lack of personal contact and lack of pressure to follow the intervention. In total, there are 14 sub-topics, 7 for each category. A table created by Čihařová et al. (2023) that gives an overview of these categories can be found in the Methods section (Table 2). Among the reasons mentioned most often were a busy schedule, needing a different kind of help, or the lack of personal contact (Čihařová et al., 2023). Moreover, the authors state that intervention dropout still needs further research, and they mention the limitation of not having asked the participants specifically about ways to improve the treatment or its advantages. Further, the authors did not mention which causes were mentioned more frequently, and whether person- or intervention-related reasons were used more commonly by participants to explain dropout. Hence, to understand the intricacies of the causes of dropout, additional analysis is recommended, and similar to the research conducted by Lawler et al. (2021) and Fernández-Álvarez et al. (2017), qualitative research could be beneficial. However, Pietsch and Lessmann (2018) argue that analysing responses to open questions is associated with a high workload, as well as susceptibility to errors, and consequently recommend text mining to circumvent these disadvantages.

Text Mining

To assess intervention dropout, a qualitative analysis would allow for in-depth exploration of phenomena, and social experiences (Mulisa, 2021). Specifically, using qualitative data to investigate dropout causes lowers the chances of bias, as possibly leading categories that are often present within quantitative research are absent. Hence, the reasons participants use to explain their dropout can be assessed more authentically. Further, qualitative research is often utilized when exploring individuals' opinions, behaviours, and experiences that cannot be adequately assessed with quantitative research (Mulisa, 2021). Consequently, text mining is a method suitable to assess explanations for dropout from WBIs.

Further, text mining adds to the data analysis with unique devices. To process qualitative data more efficiently the approach of text mining allows one to find patterns that might not be visible at first, and in general helps to gain information from unstructured written data, such as electronic data from online transactions (Kaushik & Naithani, 2016). This is done with techniques such as text analysis, natural language processing, information retrieval, and visualization (Kaushik & Naithani, 2016).

While research focusing on dropout from WBIs using text mining is, to the best knowledge of this author, scarce, similar research has used this method. For instance, the study by Buenaño-Fernandez et al. (2020), who analysed the answers of University teachers to open-ended questions from a self-assessment questionnaire, by making use of topic modelling. Topic modelling aims to find latent information and relationships among text files. They also advocated that strategies such as text mining are needed, due to the increase of text data created in surveys, and social media, making a tool to process these amounts of data necessary. Additionally, they mention the usefulness of open questions to understand the attitudes and thoughts of the participants, but that it is often avoided to utilize these due to the amount of effort and time needed to analyse the responses. Thus, their study encourages methodologies such as text mining, to find and work with the important information offered via responses to open questions.

Nonetheless, the text mining approach has an important limitation that needs to be considered, namely that of ambiguity. For instance, Talib et al. (2016) state that techniques such as text mining that use term-based approaches struggle with assessing synonyms and polysemy sufficiently. Polysemy describes a phrase or word that has multiple meanings (Gries, 2019), which can cause ambiguity, as a text mining program might have problems with differentiating these meanings, and thus would not yield accurate or trustworthy results. Further, if the data is written in an informal language or contains spelling and grammar mistakes, the program might miss phrases or words or interpret them incorrectly. To add, Talib et al. (2016) state that limitations such as ambiguity can decrease the efficiency and effectiveness of decision-making, as well as it can have an impact on the accuracy and relevance of the results that text mining yields. These ambiguities within text mining should be considered.

Present Research

The COVID-19 pandemic led to an increase in mental health problems and a decrease in accessibility of resources to combat those. Hence, the administration and use of WBIs, digital interventions that can be accessed via phone applications or the Internet either with guidance from a professional or with a self-administered design, has increased. However, WBIs tend to show a high dropout rate, and previous research lists several reasons, such as lack of time or dislike of the intervention design. Those reasons have been assigned to two overarching categories by Čihařová et al. (2023), namely the intervention- and person-related reasons.

Further research into this divide, for example, whether one category is more commonly used to describe reasons for dropout, has not been conducted as of yet. To understand dropout from WBIs it is important to investigate these reasons to improve WBIs so that participants can benefit from the treatment. Understanding if one category of reasons is more commonly mentioned can help WBIs designers to focus on combatting that factor to improve WBIs more efficiently. Consequently, this research aims to answer the question: "Do participants explain their dropout more with person- or intervention-related reasons?"

Methods

Design

The research question will be answered by analysing qualitative data collected from three interventions conducted during the COVID-19 pandemic. For that, the participants who dropped out from either of the three WBIs were contacted via e-mail and asked to fill in a post-intervention evaluation questionnaire. Within this survey, open questions were asked, of which the replies are the focus of this study. For this qualitative data, text mining is utilized to analyse the replies for patterns and themes in a quantitative way, meaning this study has a mixed-methods design.

Materials

Participants were asked to fill out a survey adapted from the article by Schröder et al. (2015), who aimed to create measurement tools for assessing attitudes towards WBIs. Hence, Schröder et al. (2015) collected a sample of 1004 participants and asked them to reply to the 35 items they created, and which they further assessed with an exploratory factor analysis. This led to a final set of 16 items, which was cross validated.

In this paper, five open questions of those designed by Schröder et al. (2015) were chosen. This was done on the basis of which questions fit the aim of understanding how participants explain their dropout from the WBI, and which items were considered most interesting. The questions included are: “What were your expectations of the intervention before enrolling?”, “What do you think would have motivated you to continue doing the intervention modules?”, “What were the reasons that you consider influenced for not continuing with the intervention modules?”, “What has been your experience using the intervention modules?” and “What do you think could be improved in the intervention modules?”.

Interventions

Mental Health COVID

Mental Health COVID (Salud Mental COVID, www.saludmentalcovid.com) is a self-administered web-based intervention offered during and after the COVID-19 pandemic to reduce symptoms of anxiety and depression and increase sleep quality and positive emotions. It was designed with the principles of positive psychology and is supported by elements of cognitive behavioural therapy as well as behavioural activation therapy. It is also delivered through a telepsychology system. The users 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 a self-administered intervention, meaning without support. An overview of the study design can be found in Appendix A. This intervention was described and evaluated in a study by Dominguez-Rodriguez et al. (2024). It has also been approved by the Ethics Committee of the Free School of Psychology University of

Behavioural Sciences in Chihuahua, Mexico (reference number Folio 2008) and is in Clinical Trials (NCT04468893).

Healthcare Workers COVID

Healthcare Workers COVID (*Personal Salud COVID*, www.personalcovid.com) is focused on decreasing depression, anxiety, compassion fatigue, and burnout in healthcare 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 behavioural therapy. Participants were randomly assigned to one of two groups, one group received treatment from a therapist and the other group received the WBI. The creators of this intervention expected the WBI design to cause more dropouts, which they thus hoped to circumvent by using the principles of user experience. An overview of the study design can be found in Appendix B. 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 the Autonomous University of Juarez City (approval ID: CEI-2021-1-266) and registered in Clinical Trials (NCT04890665).

Grief COVID

Grief COVID (Duelo COVID, www.duelocovid.com) is a self-applied web-based intervention 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 behavioural therapy, with a time-lock of three days between each module. The participants were randomly divided into two groups, one group that started the intervention immediately, and the other group that 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 Appendix C for an overview of the study design. The intervention is described and evaluated in the study by Domínguez-Rodríguez 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).

Classification Categories

As aforementioned, Čihařová et al. (2023) found a list of possible causes for dropout, divided into the two main categories of person- and intervention-related reasons. Both categories were divided into seven sub-topics each, which are listed in Table 2. Because this summary includes varying causes for dropout, it allows for an extensive overview of possible motivations for dropout. Hence, this overview will be utilized as a guide for recognizing and categorizing the explanations given by the participants regarding their dropout from the treatment. A version of this table with Quotes from the data at hand can be found in Appendix D.

Table 2

Reasons for Dropout as defined by Čihařová et al. (2023)

Topic	Reason
Person-Related	Too busy schedule
	Major life changes
	Mild symptoms
	Improvement in symptoms
	Need for different help
	Impact of depressive symptoms
	Perfectionism
Intervention-Related	Lack of personal contact
	Lack of pressure to follow the intervention
	Preference of speaking over writing
	Too basic/superficial
	Perceived lack of effectiveness
	Previous experience with a similar intervention
	Lack of access to the internet

Note. This table shows the fourteen reasons for dropout, divided into the two main topics: person- and intervention-related reasons as defined by Čihařová et al. (2023).

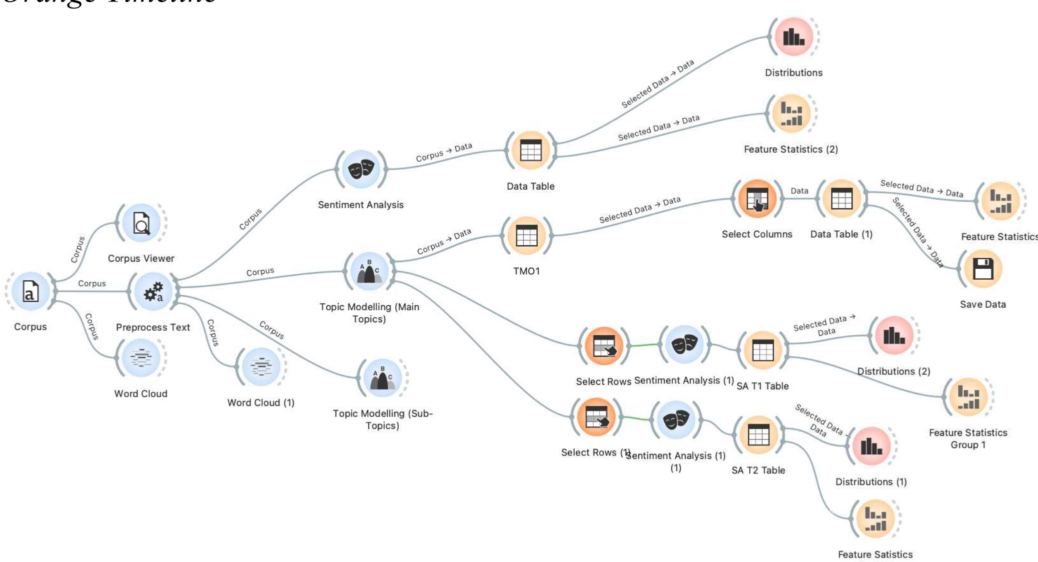
Programs

Orange

The program used to analyse 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.). Orange is based on Python and was created at the Bioinformatics Laboratory of Ljubljana University. 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 a 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, and topic modelling, which will be further explained in the following section.

Figure 1

Orange Timeline



Note. This figure depicts the used Orange pipeline, starting with pre-processing, a sentiment analysis for the data overall, topic modelling for the two main topics, and topic modelling for the 14 sub-topics. For each of the two main topics, person- and intervention-related reasons for dropout, an additional sentiment analysis was conducted.

RStudio

In this study, R (Version 1.3.1073) was used to create graphs and visualize the data. This was done by uploading the pre-processed data into the program and using functions from packages such as ggplot. R is an open-source programming language and tool. The programming language can be extended with packages for all kinds of computational tasks (Jović et al., 2014).

Participants

The three interventions included in this study are Salud Mental COVID (Mental Health COVID) with 28 participants, Duelo COVID (Grief COVID) with 51 participants, and Personal Salud COVID (Healthcare Workers COVID) with 4 participants. The responses were collected from a raw sample of 93 participants, of which nine participants did not respond to the questions, and four participants did not drop out of the intervention and were falsely assigned to the survey, leading to a sample of 80. The sociodemographic data was collected from the participants and can be found in Table 1. The sample consisted of 13 men and 67 women, who had a mean age of about 37 (SD = 11.03) and an education level of mainly a bachelor’s degree. Most participants left the intervention before completing a module.

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
SD	12.10	10.40	7.53	11.03
Education Level				
High School	3	4	0	7
Secondary	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 Intervention Module Completed				
0				
1	12	20	0	32
2	3	15	0	18
3	1	7	3	11
4	2	3	0	5
5	1	3	0	4
6	1	0	1	2
7	2	2	0	4
9	1	1	0	2
10	1	0	0	1
11	0	0	0	0
	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). SD = Standard Deviation.

Data Analysis

Analysis Plan

Data Pre-Processing.

The data is translated from Mexican Spanish to English with DeepL and the involved researcher AD-R, who is fluent in Mexican Spanish, cross-checked the translation to ensure its accuracy. Further, participants who did not answer the questions were excluded. Then, to gain a general overview of the data the replies are looked at. The Excel data file, in which there is one row per participant and a column for each question, is uploaded to the Orange workflow. Also, the required rows are selected, a corpus is created, and the corpus is viewed within the corpus viewer, as well as a word cloud to check the results. In the next step, the text not needed for further analysis is removed, such as punctuation, accents, and the filler words 'and, think, would, could, yes, no, also, well, course, really, exactly, actually, say, know, everything, always, would, should'. This is done iteratively by looking at the word cloud and then adjusting the list of filler words. Then *Tokenization* is done to break up the text into words, and phrases. Further, the text is *Normalized* by lemmatizing with the UDPipe Lemmatizer, due to its simplicity and effectiveness, to account for word stems and find similarities within word meanings. Only the participants' replies are selected for further analysis, and the data is checked again with the corpus viewer, as well as with a word cloud, which should show more relevant themes after pre-processing. To get a nuanced overview and understanding of the data, a mix of approaches is conducted. The overall data pre-processing is done iteratively, by going back to adjust the settings and re-evaluating the results.

Sentiment Analysis.

First, a sentiment analysis is done, which helps find out whether the explanations given by the participants in general consisted of negative, positive, or neutral words. As the questions relate to the interventions, a negative sentiment might help to understand whether dropout was reasoned for with dissatisfaction with the intervention, hinting at intervention-related reasons for dropout. For this, a lexicon-based approach is used, specifically the Valence Aware Dictionary for Sentiment Reasoning (VADER) sentiment, as it is rule-based and supports intensity estimation, and it offers sentiment ratings often ranging between -1 and 1 (Borg & Boldt, 2020). The results are examined with a data table, distribution, and the feature statistics widgets. This process is repeated after topic modelling for the identified two main topics of person- and intervention-related reasons for dropout, to observe if there is a difference in sentiment between participants who explain their drop out mainly with person- or intervention-related reasons.

Topic Modelling.

The two main topics are identified with Latent Dirichlet Allocation (LDA), which is used to run a topic model, and then the results are checked in a data table. Topic modelling algorithms such as LDA examine the data for words that co-occur frequently to categorize them into clusters or topics. The program can divide the data into the number of topics proposed by its user, for instance, the user specifies a number of four topics and the algorithm will sort the data into four clusters. For each number of topics, a coherence score is calculated, which indicates the internal coherence of the words clustered into topics. To interpret the coherence score, a graph will be created containing the coherence scores for a number of topics to gain a general understanding of the average topic coherence in the data at hand and functioning as a baseline for comparison.

Additionally, log perplexity will be inspected, because it offers insight into how well the topic model fits the data at hand, with a lower score indicating a higher fit. Then the results are related to the previously chosen categories where possible. That way participants can be grouped into intervention- and person-related reasons for dropout, and the groups can be compared. This is done once for the two main topics, person- and intervention-related, and secondly for the 14 sub-topics. Due to topic modelling only offering a number of most frequently used words within a topic, and not providing an overall term for the topics, this step involves human interpretation. The list of topic keywords is examined to locate words overlapping with the pre-set themes. In addition, to minimize the possibility of bias, high-scoring text samples for each topic are picked from the data to assess in which context the topic keywords were used to increase the validity of the interpretation.

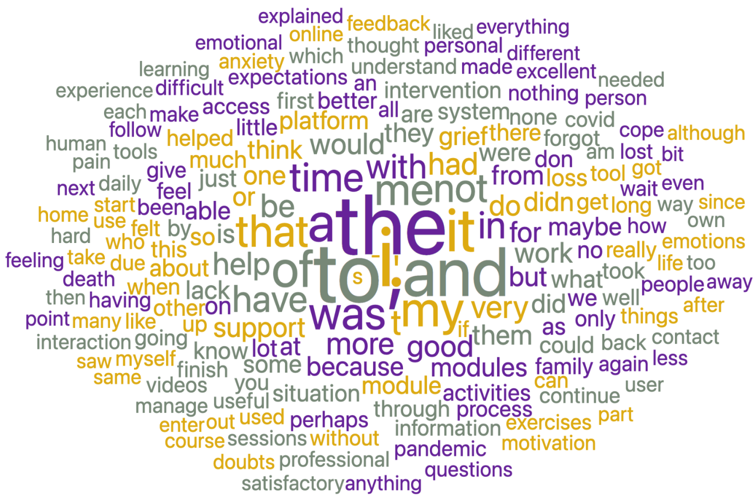
Results

Descriptive Statistics

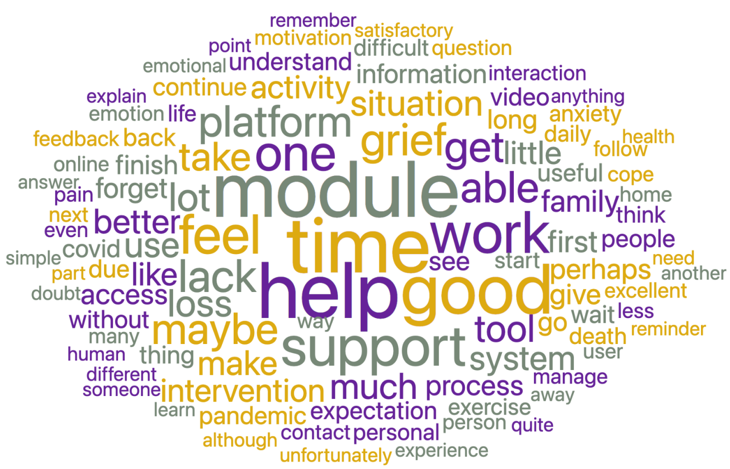
The data was examined with a word cloud before and after pre-processing. The word clouds are shown in Figure 2. After pre-processing the distribution of the most frequent terms within the data was listed: time = 58, help = 44, module = 36, good = 31, work = 25, support = 24.

Figure 2

Word Cloud Before pre-processing



Word Cloud After pre-processing



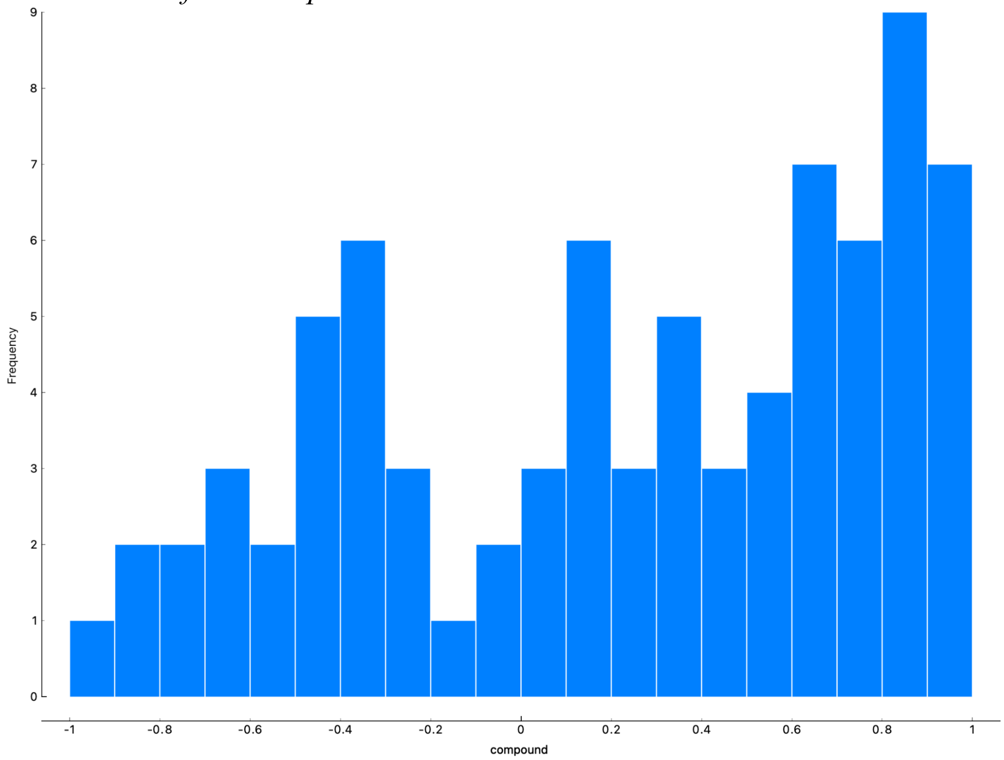
Note. The first word cloud shows the most frequent words in the data before pre-processing, the second word cloud shows the most frequent words in the data after pre-processing. The pre-processing process included the removal of unneeded text, such as punctuation, accents, and the filler words ‘and, think, would, could, yes, no, also, well, course, really, exactly, actually, say, know, everything, always, would, should’. This was done iteratively by looking at the word cloud and then adjusting the list of filler words.

Sentiment Analysis

The sentiment analysis showed that the main sentiment within the replies is neutral, with a mean value of about 0.74, a negative sentiment was present with a mean value of about 0.11, while positive sentiment showed a mean value of about 0.15. The compound score can range from -1 to 1 and displays the combination of neutral, positive, and negative scores, and its distribution within the data at hand can be seen in Figure 3. The compound score is about 0.22, meaning the overall data is skewed slightly towards a positive sentiment. Considering the high number of replies with a neutral sentiment, it can be said that the sample overall shows high neutrality, rather than many positive and negative sentiments that balance each other out, meaning the responses are rather cohesive in their sentiment. Further, a mainly positive sentiment could have suggested that the participants used more positive words when explaining their dropout, and hence might have felt more positive about the intervention. In that instance, explanations for dropout would have been related to personal reasons, and a mainly negative sentiment could have suggested that participants disliked the intervention and hence were more likely to drop out due to intervention-related reasons. As the data shows a mainly neutral sentiment, it does not indicate whether participants have a positive or negative attitude towards the intervention, and thus more analysis is needed to understand the reasons underlying dropout from the intervention.

Figure 3

Distribution of the Compound Score



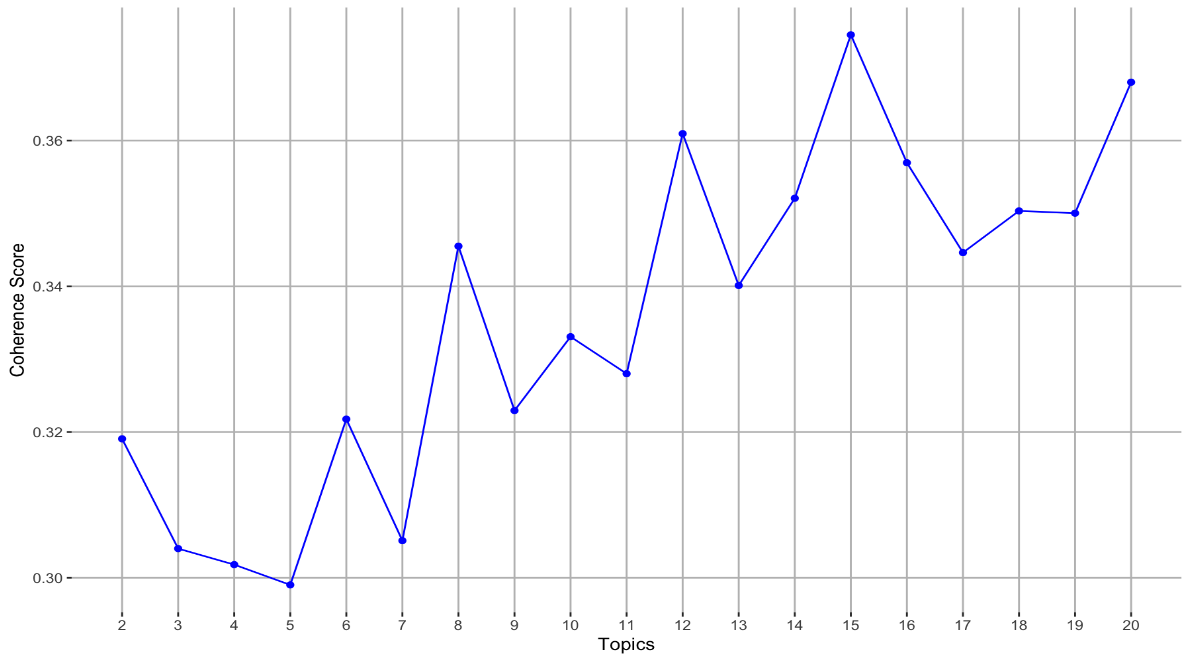
Note. This figure shows the distribution of the compound score from the sentiment analysis. The x-axis shows the sentiment score, ranging from negative (-1) to positive (1). The y-axis shows the frequency with which each sentiment score was present in the data.

Topic Modelling

First, the topic modelling analysis for the two pre-defined topics was done, with a coherence score of about 0.32. Similar to the works of Behrendt-Richter (2018) and Duong (2023), a baseline of coherence scores was created, to compare the coherence scores to a different number of topic models. Figure 4 shows the different coherence scores for up to 20 topics. It can be seen that the coherence score for two topics can be considered low coherence when compared to, for instance, 15 topics. However, the coherence scores all range from about 0.30 at least to about 0.38 at most, meaning that the variation between coherence scores overall is not high. Further, a model with two topics has a log perplexity score of about 25.04, while a model with 15 topics has a log perplexity of about 41.61. Thus, while the coherence for 15 topics is higher, the model is less likely to fit the data. Considering the comparably small difference in coherence scores between two and 15 topics, and the significant increase in log perplexity from two to 15 topics, a two-topic model can be considered a good fit for the data.

Figure 4

Coherence Scores for Different Number of Topics



Note. This graph shows the coherence scores for up to 20 topics. The x-axis shows the number of topics, and the y-axis shows the coherence scores.

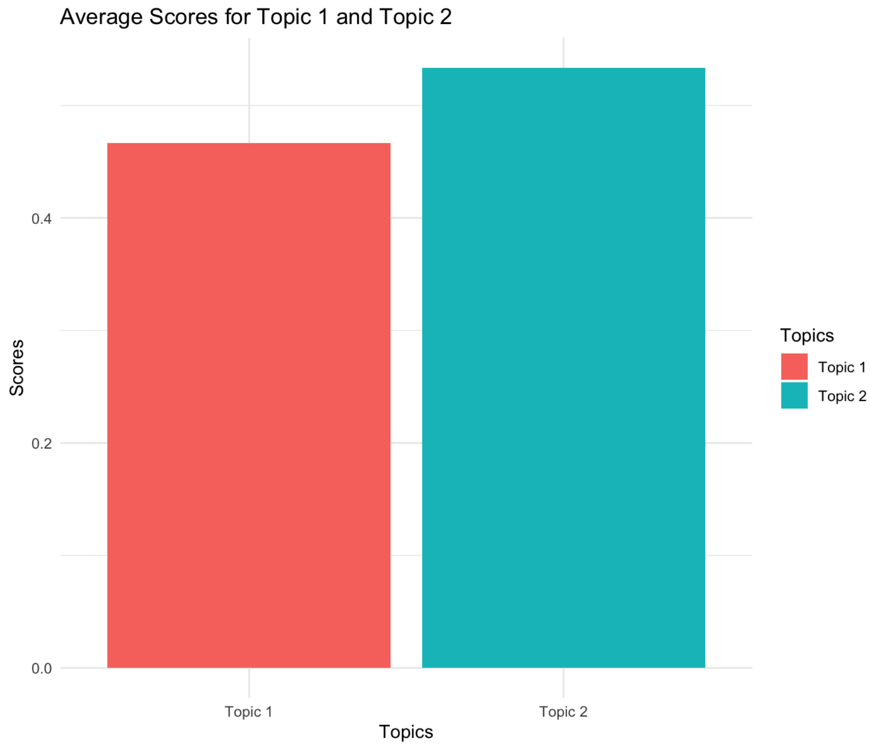
Topic 1 consists of the topic keywords ‘time, work, module, good, tool, use, lack, platform, activity, intervention’, and is present within the responses with a mean value of about 0.47, relating to 47% of the data. Topic 2 consists of the topic keywords ‘help, time, support, module, good, feel, get, one, take, grief’, and is present within the replies with a mean value of about 0.53, relating to 53% of the data. Topic 1 has keywords that are more technical in nature and thus is assigned the intervention-related reasons, while Topic 2 has keywords that are more affective in nature and thus is assigned to person-related reasons. Each participant has a score for how present topic 1 and topic 2 are in their replies, the scores add up to 1.

The participant with the highest score on topic 1, with about 0.975, answered the second question about what could have motivated them to continue the intervention with: “Include a video on the platform, even a small one, sharing something about the value of life. That would have given me the confidence to continue.” This reply focuses on how to improve the intervention. In comparison, the participant who scored the highest on topic 2, with about 0.973, answered the same question with: “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.” The reply focuses on the emotional needs of the client, such as direct support from a therapist. Further, both replies are in direct contrast to each other, as the first reply suggests adding a video, while the second reply states that a video would not be sufficient. Hence, there appears to be a difference between the explanations that score higher on topic 1 or topic 2.

Moreover, as the topics are nearly equally present within the replies, it suggests both reasons have a similar impact on dropout, with person-related reasons occurring within this sample just slightly more often. The distribution of Average Scores of the Main Topics can be seen in Figure 5.

Figure 5

Distribution of Average Scores of the Main Topics

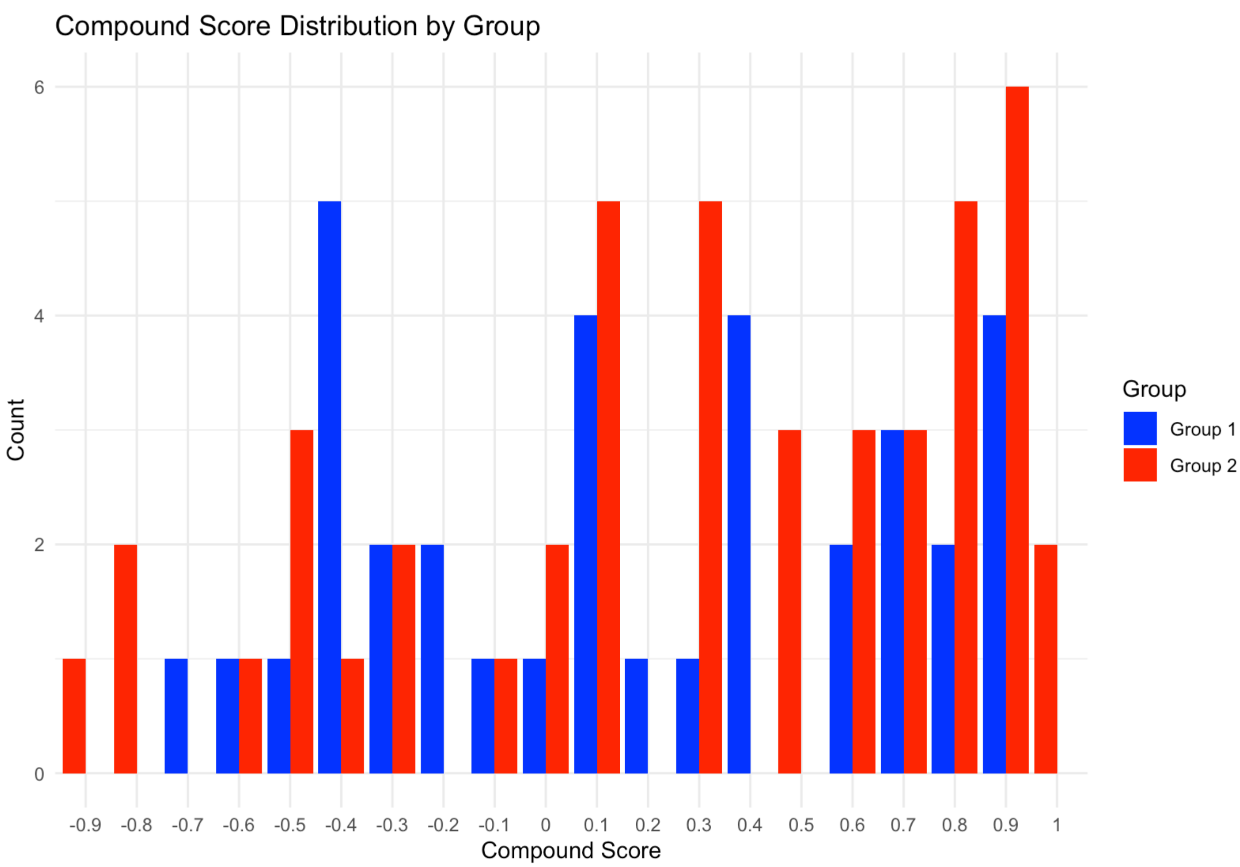


Note. This figure shows the distribution of the main topics. Topic 1 can be related to intervention-related reasons and Topic 2 can be related to person-related reasons for dropout.

For further analysis, the select rows widget was used to divide the data into group 1, consisting of participants with intervention-related reasons (topic 1) score over 0.5, and group 2 consisting of participants with a person-related reasons (topic 2) score over 0.5. Out of the 80 participants, 35 were assigned to group 1, and the other 45 were assigned to group 2. While this divide appears similar to the distribution of main scores in Figure 5, the assignment into groups focuses on the more prevalent topic for each participant instead of the distribution within all the replies.

Then, for both groups a sentiment analysis was conducted to gain a general understanding of whether there are differences in the sentiment between the groups. The observed differences are small, similarly to the full data, the sentiment within the replies of both groups is mostly neutral with a mean of about 0.76 and 0.71 for groups 1 and 2 respectively. A positive sentiment could be found within the replies with a mean of about 0.13 and 0.17 for groups 1 and 2 respectively, and a negative sentiment with a mean of about 0.11 and 0.12 for groups 1 and 2 respectively. The greatest difference between both groups can be seen in the compound scores, as group 1 shows a mean of about 0.12, and group 2 has a mean of about 0.30. The distributions of the compound scores can be seen in Figure 6.

Figure 6



Note. The figure shows the distribution of the compound scores of the sentiment analyses for groups 1 and 2. The blue bars show the distribution for group 1, participants more influenced by intervention-related reasons, and the red bars show the distribution for group 2, participants more influenced by person-related reasons. The x-axis shows the sentiment score, ranging from negative (-1) to positive (1). The y-axis shows the frequency with which each sentiment score was present amongst the data.

Second, the topic modelling analysis was performed to investigate whether the 14 sub-topics defined by Čihařová et al. (2023) can be identified in our dataset. The analysis results in a coherence score of about 0.35, and a log perplexity of about 40.19. This means that while the coherence of the 14 topics is decent, the log perplexity indicates that the model of 14 topics does not fit the data very well. The topic keywords responding to each topic can be found in Table 3. When looking at the topic keywords it can be noticed that some keywords often overlap, for instance, *time, help,* and *support*. This makes it difficult to find a connection between the pre-set sub-topics and the sub-topics defined by the topic analysis. While some topic keywords can be connected to the defined categories, such as topic 3 with keywords such as t*ime, lack, work, family, life,* and *motivation,* could fit the sub-topic of 'Too busy schedule', overall, the high log perplexity and the overlap of topic keywords makes a clear distinction not possible.

Table 3

Overview of the Sub-Topics

Topic	Topic Keywords
1	module, time, intervention, able, process, activity, work, little, tool, without
2	time, help, feel, one, take, module, good, like, long, maybe
3	time, lack, use, even, tool, work, family, life, motivation, intervention
4	forget, help, good thing, family, time, feel, lot, start, tool
5	good, time, perhaps, take, quite, much difficult, tool, give, video
6	get, support, feel, covid, good, personal, situation, finish, cope, different
7	time, help, support, loss, module, take, able, lack, covid, useful
8	access, system, grief, maybe, good, get, lack, better, module, point
9	work, time, death, platform, loss, good, lack, useful, able, support

10	module, help, maybe, grief, little, good, lot, able, finish, much
11	help, support, get, contact, video, pandemic, feel, much, continue, question
12	time, work, module, user, lack, help, satisfactory, little, access, platform
13	feedback, daily, time, activity, see, exercise, learn, good, grief, support
14	long, able, pain, time, first, platform, give, better, situation, another

Note. This table shows the fourteen topics found in the topic modelling analysis, with their respective topic keywords.

Overall, the analysis shows that the data can be divided into person- and intervention-related reasons for dropout as defined by Čihařová et al. (2023). However, the sub-topics defined by the same authors could not be clearly assigned to the data at hand, further, the analysis suggests that a model with 14 topics is not well suited to the sample at hand. Additionally, the analysis indicates a mainly neutral sentiment within the replies, highlighting that the participants did not show a strong positive or negative attitude toward the intervention.

Discussion

This study aimed to answer the research question: “Do participants explain their dropout more with person- or intervention-related reasons?”. To find an answer, text mining was applied to a sample of participants who dropped out of either one of the three WBIs: Mental Health COVID, Healthcare Worker COVID, and Grief COVID. These WBIs were conducted during the COVID-19 pandemic to offer the general population, healthcare workers, and individuals who lost someone during the pandemic respectively, treatment to cope with mental health concerns during the COVID-19 pandemic. The results showed a neutral sentiment in the replies, as well as a topic model with two topics that appeared to fit the data well and appeared to match the labels of intervention- and person-related reasons. However, the 14-topic model did not fit the data as well, and interpretation of topic labels was not possible.

Sentiment Analysis Results

The sentiment analysis showed a mainly neutral sentiment within the replies. Further, after assigning participants to groups based on whether they scored higher on intervention- or person-related reasons for dropout, a second sentiment analysis for intervention-related reasons had a similarly neutral sentiment. Considering that the questions the participants answered were focused on the intervention, a negative sentiment would have implied that participants disliked the intervention, and a positive sentiment that the participants liked the intervention, so dropout would have been more likely explained with personal reasons.

In a related study, Wells et al. (2023) investigated participants dropping out from a post-traumatic stress disorder treatment and found that disliking aspects related to core components or the intervention structure, such as the repetitive nature of the exposure, was a factor that caused individuals to stop treatment prematurely. Hence, individuals disliking the WBIs and showing a high negative sentiment could imply that disliking the intervention had caused dropout, and therefore the participants would have explained it with intervention-related reasons. However, as the sentiment was mainly neutral, the sentiment analysis did not suggest which reasons were mentioned more frequently and further analysis was needed to answer the research question. Nonetheless, it should be taken into account, that the varying questions the participants answered, possibly influenced these results, as, for instance, a question about expectations may not lead to negative or neutral sentiments.

Topic Modelling Analysis

Intervention-Related Reasons

The topic modelling analysis revealed that intervention-related reasons were mentioned within 47% of the data, which is almost half of the data, and indicates they were not the main explanation for dropout. In the research by Čihařová et al. (2023), in which the authors split the reasons for dropout that they found into person- and intervention-related reasons, a similar result of person-related reasons being mentioned slightly more was found. Additionally, the topic keywords belonging to intervention-related reasons are ‘time, work, module, good, tool, use, lack, platform, activity, intervention’. According to those, the participants who had intervention-related reasons for dropout seemed to focus, for instance, on the modules, platform, and activity. This aligns with the provided example of an answer to a question from the participant who scored high on the intervention-related topic, which focuses on improving the intervention by adding videos.

In contrast, Wagner et al. (2020) found in their meta-analysis of WBIs for grief that there exists a considerable range of dropout numbers within the interventions they examined. They state that the highest dropout rates could be associated with interventions that lacked direct support or guidance, and only offered informative feedback. This suggests that intervention-related reasons for dropout are more common, specifically lack of support or guidance. That is further supported by the meta-analysis conducted by Wright et al. (2019), who found that guided WBIs are also more effective compared to self-guided WBIs. Lincke et al. (2022) argue that participants, specifically those who have been in psychiatric treatment before, value the therapeutic relationship and perhaps worry that an online setting is not able to create a similar relationship. Further, they recommend creating an intervention with design features portraying a bidirectional therapeutic relationship, as the therapeutic alliance is rated lower on self-administered interventions. While this source used a psychiatric sample, which differs to the sample at hand, it still might hint at the importance of intervention-related reasons causing dropout as an important and persisting underlying factor.

Additionally, Van Daele et al. (2020), who made recommendations for the practice of WBIs, seem to focus on intervention-related reasons and address dropout. The authors indicate that certain client groups, such as chronically ill people or men, are prone to dropping out and need tailoring and personalization of the intervention. Further, they recommend maintaining guidance via email or phone calls for self-administered interventions. Similarly, Becker (2019) also poses recommendations for WBIs and states that personalization and improvement tracking indicate the highest potential for client outcomes. Overall, the evidence suggests that intervention-related reasons were not used to explain dropout exceedingly more than person-related reasons, and the participants did not seem to have a positive or negative attitude toward the intervention.

Person-Related Reasons

According to the topic modelling analysis, person-related reasons were present within 53% of the data, which is slightly more than half of the data, and also slightly more compared to the presence of intervention-related reasons. Comparable results were found in the study by Čihařová et al. (2023). Nonetheless, the difference between both topics is small, and hence, while person-related reasons are important for dropout, the distribution does not suggest that person-related reasons are the most frequently used explanation for dropping out of WBIs.

Moreover, the topic keywords consisted of ‘help, time, support, module, good, feel, get, one, take, grief’. This aligns with the provided example of an answer to a question from the participant who scored high on the person-related topic, which focuses on needing to talk to someone rather than, for example, a video. Therefore, participants who used person-related reasons to explain dropping out of the WBIs focused on, for instance, help, support, and grief. The type of support varied per WBI, with some participants receiving support from a counselor and others not, it implies that participants wanted a different kind of support from the intervention, which would suggest a reason related to the intervention design. Further, the example of an answer from a high-scoring participant adds to this, as the participant equally indicated a wish for more contact. This leads to the question if the topic model of two topics (person- and intervention-related reasons) is the best way to describe the data, as the theme of support is assigned to the category of intervention-related reasons by Čihařová et al. (2023) who first proposed the distinction. However, the topic analysis at hand created a model of two topics in which support was related to person-related reasons. One cause for this finding could be a lack of context, as the keywords are mainly shown without the context in which they were used. The context can determine the meaning of the words; hence support might refer to support from a therapist during the treatment (intervention-related), or to support from friends and family (person-related). Considering the example of the participant scoring high on person-related reasons, the individual mentions wanting to talk to someone rather than watching videos. In this example, it is not clear if they refer to a therapist or a friend/family member. Overall, while the two-topic model appears to fit the data well according to the coherence and log perplexity scores, the interpretation of what constitutes the topics remains ambiguous, which relates to the limitation of ambiguity in the text mining domain mentioned by Talib et al. (2016), and the finding should be further investigated in a future study.

The results seem to be in contrast with other findings, for instance, those by Børtveit et al. (2022). They conducted a scoping review about guided WBIs for depression and noted that the main cause for dropout seemed to be a lack of time to fulfill the treatment. Other reasons that were mentioned often were participants' personal needs not being met, and participants struggling with personal problems or sickness. Hence, according to the results by Børtveit et al. (2022), it appears that when an intervention is guided or with support from a therapist, dropout seems to then be motivated by person-related reasons rather than intervention-related reasons, while participants dropping out from self-guided interventions often mention that they disliked the lack of support of or contact to a therapist. To conclude, due to a neutral sentiment in the data, and the lack of evidence that person-related reasons significantly outweigh the intervention-related reasons, participants do not use person-related reasons significantly more to explain their decision to drop out.

Main Findings

The research question of whether dropout from WBIs is explained more with intervention- or person-related reasons cannot be concretely answered, as both intervention- and person-related reasons were shown to be important to dropout, but neither proved to be more common and significant than the other. Furthermore, considering other research, some studies show that intervention-related reasons are more common (Wagner et al., 2020), while others suggest person-related reasons to be a common motivator for dropout (Børtveit et al., 2022). Therefore, limiting our understanding of dropout to one type of reason is not possible, nor recommended, and the results imply that both topics are equally important for understanding dropout and should both be taken into account when creating and improving WBIs. Instead, the findings suggest that individuals can show a preference for either intervention- or person-related reasons to explain dropout, leading to a mostly balanced distribution within a population.

Moreover, when dividing the data into the two topics the topic modelling analysis showed a comparatively sufficient coherence score with a relatively low log perplexity score, while a topic model with 14 topics has a higher coherence score, but also a higher log perplexity. This shows that dividing the data into two topics is a rather accurate description of the data, while dividing the data into 14 topics might generate more coherent topics but they do not fit the data accurately. In addition, assigning the sub-topics as defined by Čihařová et al. (2023) was not possible due to the topic keywords being too similar and non-descriptive, which might have been related to the five questions of the survey having different themes. In conclusion, while the two topics intervention- and person-related reasons help understand dropout, the 14 pre-defined sub-topics for dropout from WBIs do not appear to be accurate descriptors for dropout, thus suggesting that the causes for dropout are more complex.

Furthermore, the word cloud after data pre-processing shows that among the most used words are the terms ‘time, help, module, good, work, support’. These keywords hint at the main causes for dropout from the WBIs. Two discernible common themes seem to be present, for one, *time* and *work*, which can be related to participants lacking the time for completing the intervention by, for example, being too occupied with work. Notable is also that *time* is the most common term and is also present in the topic keywords for both main topics, and in the majority of the 14 sub-topics. The research by Børtveit et al. (2022) supports this, as they mention that the most commonly mentioned reason for dropout from guided WBIs for depression is a lack of time to finish the intervention. The other theme that can be noticed within the most common words of the data can be seen in the keywords *help*, *module*, and *support*, which can be related to participants arguing for needing a different kind of help due to either disliking the modules, or the type of support they received or did not receive from a counsellor.

Support

The theme of support as a reason for dropout aligns with the findings of Wagner et al. (2020), who identified a lack of support or guidance as the most commonly mentioned reason for dropout. This reason for dropout was also investigated by Renfrew et al. (2020), who divided participants of a WBI into three randomized conditions of human support. First, a standard condition in which participants received automated emails, second, a condition in which additionally to the email, participants received a personalized SMS-message, or third, a condition in which additionally to the email participants received support via weekly videoconferencing. Participants were informed about the three possible conditions and were asked for their preference. The results showed that out of 605 initial participants, 147 participants dropped out before the prequestionnaire, about 22% of the first condition, about 19% out of the second condition (additional SMS), and about 31.5% out of the third condition (additional Videoconferences), leading to 458 registered participants, of which 138 did not complete the postquestionnaire, however there appeared no between-group differences in adherence during the intervention and in non-completion of postquestionnaire. Thus, Renfrew et al. (2020) conclude, that dissatisfaction with the allocated support condition influenced dropout, while the support condition had no impact on adherence to the WBI. Further, participants who were allocated to the preferred condition did not show greater adherence or better outcomes. This might allude to human support type itself being not as significant for dropout or treatment result quality, but rather the participants preference for support type being important for adherence. That is due to the dropout that occurred after allocation and before the prequestionnaire which could be explained by participants not having received their preferred type of support.

Those findings of not receiving the preferred type of support causing dropout, rather than the type of support itself, could explain the differences between the high-score examples of the participant replies from the data at hand. The intervention-related reasons participant stated that a specific video could have motivated them to continue the intervention, while the person-related reasons participant explained not needing a video, but rather someone to talk to directly to continue the intervention. Further, due to the participants belonging to different WBIs, with varying aims, the expectations and needs of participants might have differed.

Sociodemographic Data

Taking the sociodemographic data into account, the data shows that the majority of dropouts are women, with 67 women and 13 men, which aligns with the results of Wu et al. (2022), who investigated dropout from a blended-care CBT intervention before beginning the treatment and during treatment and found that for both conditions, women were more likely to drop out. A reason for this might be that the majority of participants are often female. Kauer et al. (2014) state that women are overrepresented within face-to-face treatment and online mental healthcare, which is a phenomenon that can be observed in more recent studies as well (see: Schleider et al., 2020; Galante et al. 2021). According to Chatmon (2020), men are less likely to seek mental health care due to stigma. Influenced by culture and traditional masculine norms of, for instance, restricting behaviors such as crying, makes men less willing to receive mental health care. Hence, the imbalance between women and men in mental health treatment could be caused by reasons such as stigma.

Wu et al. (2022) had a sample of 3566 participants based in the US, who had a mean age ranging from about 31.9 to 33.2, which is only slightly lower compared to the mean age of about 37 found within the data at hand. To add, Kauer et al. (2014) also found that individuals who did not have a college degree tended to drop out before the treatment began. Considering the data at hand consisting mostly of undergraduates, the results seem to differ in this regard, while they align in the aspect that the majority of participants dropped out before the treatment began. A reason for this might be that the intervention perhaps did not meet the expectations and needs of the participant. As discussed previously, findings by Renfrew et al. (2020) suggest that the type of support is not necessarily the cause for dropout, but rather not receiving the support the participant wants. For instance, if a participant joined a WBI with the expectation to talk to a counsellor and then notices that there are self-administered modules or they expected self-administered modules and were contacted by a counsellor, they may not start the intervention.

Also notable is that the data mainly consists of participants from the Grief COVID intervention, which was self-applied. This is due to Grief COVID having 114 participants overall, while, for instance, Healthcare Workers COVID only had 49 participants. Furthermore, as reported by Newson et al. (2021), psychological research often utilizes samples from western, educated, industrialized, rich, and democratic populations, as well as a majority of research published in leading psychological services utilizing samples gathered in English-speaking or European nations (92%). The authors report that Latin American samples were present within 1% of published studies. Hence, this research consisting of participants from Mexico includes an underrepresented demographic in research.

Strengths & Limitations

Regarding the limitations of this study, it can be said that the number of participants from each WBI was different, and for example, only four participants from the Healthcare Workers COVID intervention were included, this limits the interpretability of the results, as the findings may be biased to Grief COVID, whose participants make up the majority of the sample. Future research could add dropouts from the WBIs and compare the results to understand which themes are common and remain the same. Moreover, text mining was applied to analyse the data, which can have the limitation of ambiguity. For instance, there was no context for the topic keywords, which may have caused the wrong interpretation by the researcher. While text examples were considered to minimize this, the possibility of misinterpretation remains, as not all text files were viewed. An example for this ambiguity or possible misinterpretation is the keyword *support,* which was assigned to the topic of person-related reasons by the text mining program, while Čihařová et al. (2023) assigned it to intervention-related reasons. It is unclear whether support was related to the intervention design in the form of contact with a therapist, or perhaps to personal circumstances such as support from family or friends. This ambiguity is a limitation related to text mining (Talib et al., 2016), which should be investigated further to understand whether *support* is related to personal circumstances or if the categories might not be a sufficient match to the topic models created by the text mining program.

Regarding the strengths of this study, it should be mentioned that data from three different interventions was used, which resulted in a more diverse sample. For instance, the participants experienced different treatment lengths due to varying numbers of modules, and some participants received guidance while others did not. Grief COVID is a self-applied treatment, Mental Health COVID is self-applied but includes the option to chat with a therapist, and Healthcare Workers COVID divided the participants randomly into self-applied and therapist-guided groups. This variety increases the reliability of the results, as both topics are present within the sample for participants from all three WBIs. To add, the comparable time frame of the COVID-19 pandemic further increases reliability. In addition, the data was collected in Mexico, which is an underrepresented sample in previous research (Newson et al., 2021). That allows for comparing the results with samples from other countries to assess which reasons impact dropout regardless of factors such as ethnicity or culture. Another strength is that the framework of two main reasons for dropout, person- and intervention-related reasons by Čihařová et al. (2023) was used, because the theory was based on previous research and findings, and to the best knowledge of the author, this framework has not been researched further as of yet. Additionally, the approach of text mining added to this research, as qualitative data, which is richer in information compared to quantitative data, was analysed in a quantitative and therefore faster and less subjective way. Consequently, more data and information were processed while bias was minimized, due to text mining utilizing algorithms and being independent of the interpretation of researchers.

Future Research

This research suggests that intervention- and person-related reasons could be equally important to understanding dropout from WBIs and how to prevent it. Further, the study suggests that each participant can put more importance on either intervention- or person-related reasons. This needs to be further investigated in future research, for example by considering what characteristics make a person more likely to highlight one reason over the other for dropout, and consequently how to recognize this distinction when participants join a WBI so consecutive tailoring can be done. That also implies that future research could assess how to adjust WBIs on person- and intervention-related factors to reduce dropout. For instance, one commonly mentioned reason in the present research and other studies was that participants lacked the time to complete the intervention, while studies also found that more treatment sessions led to better treatment outcomes. Investigating how to combine an effective treatment that is not too time-consuming, or how to pace the intervention to make it more manageable for participants with a busy schedule could be interesting future research topics. To add, there is a lack of research into dropout from WBIs that has been done with the help of text mining. As text mining utilizes quantitative methods to analyse qualitative data, which tends to be richer in information and context as participants can give details and explanations for their experiences and decisions, using text mining can add to the understanding of the complex topic of dropout by minimizing the effort required to analyse the qualitative responses. Additionally, as shown the lack of context for the keywords found via the topic modelling analysis caused ambiguity during interpretation of the results. This ambiguity is a common limitation of text mining (Talib et al., 2016), and the findings should thus be investigated in a future study that aims to decrease said ambiguity.

Moreover, a study by Litvin et al. (2020) stated that WBIs and smartphone-delivered treatment have low engagement and high dropout because using the applications and similar is not a part of daily routine for most. Hence, they aimed to decrease dropout by using Gamification, which describes designing the treatment as a game. The authors found higher engagement and lower dropout in comparison to control conditions (CBT application and waitlist). Future research could use this approach of adjusting the intervention to address personal reasons for dropout and investigate how person-related reasons for dropout can be circumvented by intervention design. Further, future research should investigate tailoring WBIs and personalizing them to the participant, as individual opinions and needs can differ, such as differences in treatment pacing.

Conclusion

Intervention-related reasons and person-related reasons are both common and important motivators for dropout from WBIs. This research suggests that individuals emphasize one reason more than the other in their explanation of why they dropped out, which can lead to a balance of how present both reasons are in the general population. Further, especially often mentioned causes, seem to be a lack of time to finish the intervention and a lack of guidance or support during the intervention, however, other underlying causes could not be clearly distinguished. Hence, focusing either on improving the intervention or on tailoring the intervention to participants' personal needs is not sufficient to understand dropout and how to reduce the possibility of it. Future research should focus on both, person- and intervention-related reasons, as both are equally important to researching dropout, and on how to distinguish between people who prioritize intervention- or person-related reasons to understand how to motivate them to continue the WBI. Further research is needed to assess other factors for dropout, and how to adjust WBIs to participants' needs.

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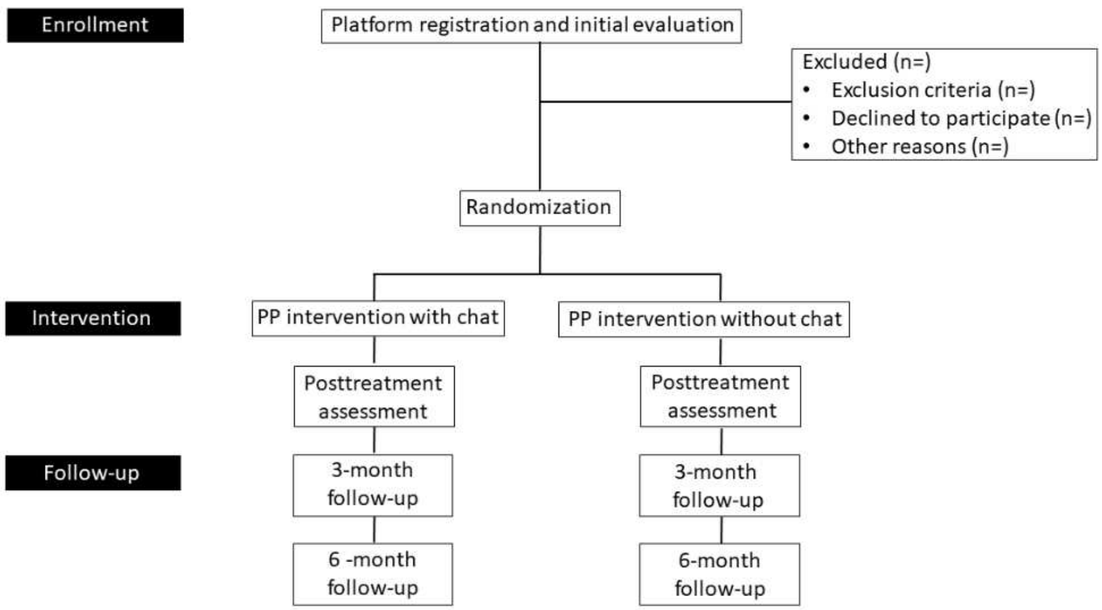
Appendices

Appendix A

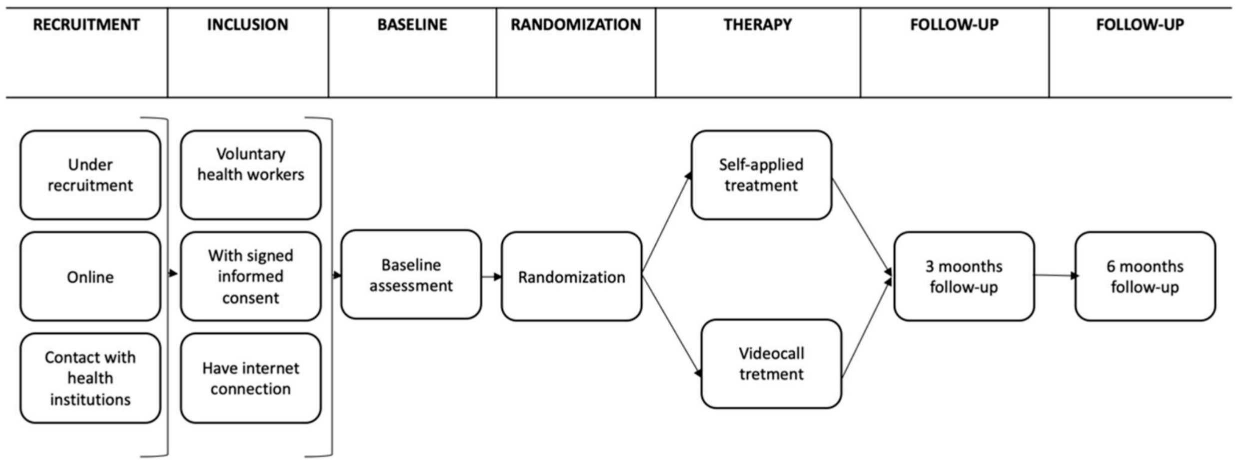
An overview of the study design for the web-based intervention Mental Health COVID.



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

Appendix B

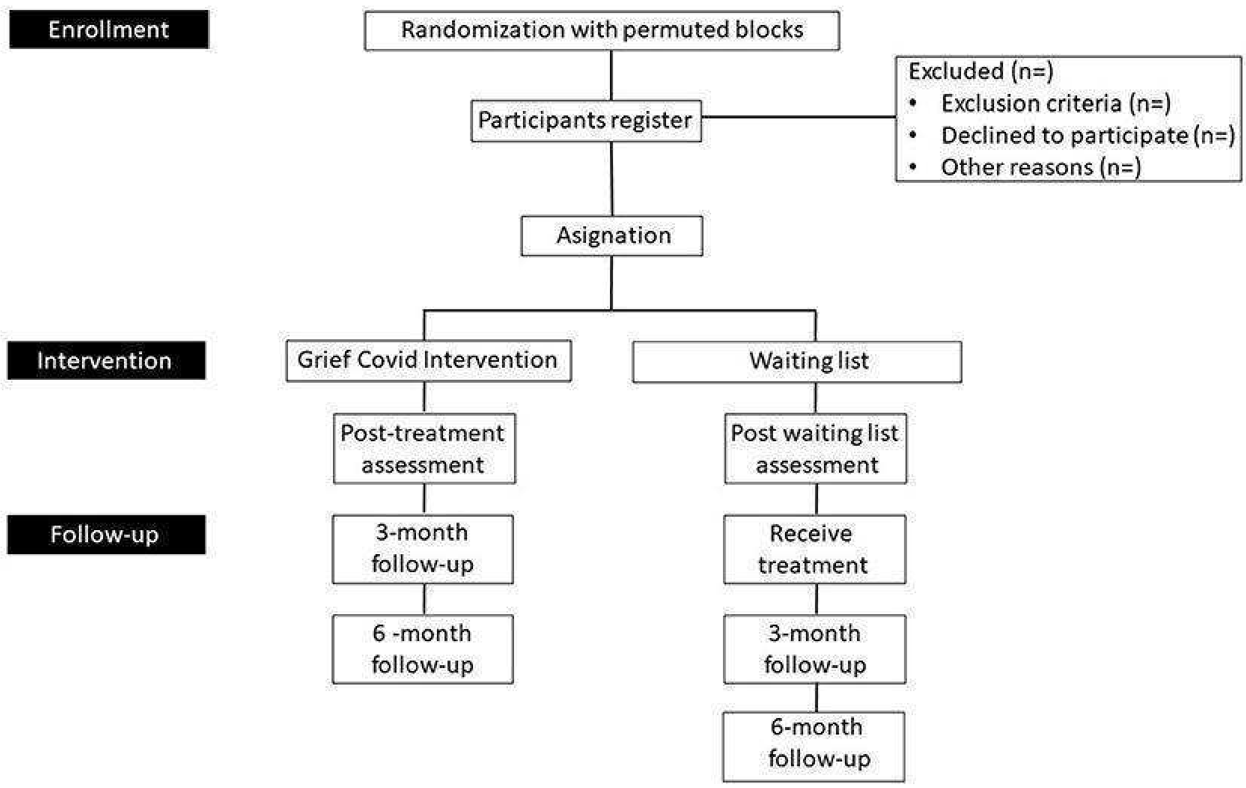
An overview of the study design.



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

Appendix C

An overview of the study design for the web-based intervention Grief COVID.



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

Appendix D

Reasons for Dropout as defined by Čihařová et al. (2023) with Quotes from the Data at Hand

Topic	**Reason**	**Quote**
Person-Related	Too busy schedule	The work and commuting schedules, adapting again to the routines on the one hand distracted me from the platform and on the other hand, I came back very tired.
	Major life changes	my personal and economic problems overtook me
	Mild symptoms	[...] I did not feel terrible, so I took care of my daily life and the consequences of putting together the pieces that were scattered [...]
	Improvement in symptoms	I was feeling better
	Need for different help	[...] I didn't continue any further, because I felt that I needed urgent help right away and I asked for it by phone.
	Impact of (depressive) symptoms	Fatigue, a lot of online work, one's own emotions about the pandemic and the loss of a loved one which as you know affects everything at home.
	Perfectionism	-
Intervention-Related	Lack of personal contact	More personal interaction
	Lack of pressure to follow the intervention	That I did not set reminders to enter the platform.
	Preference of speaking over writing	In the face of loss, [...] what one needs is help without having to read or watch videos. Just talk to someone who will listen to you or motivate you.
	Too basic/superficial	more activities or examples to follow

Perceived lack of effectiveness	Did not help me
Previous experience with a similar intervention	-
Lack of access (to the internet)	My economic situation did not allow it, I was without Internet and telephone service, with very little money, just to eat.

Note. This table shows the fourteen reasons for dropout, divided into the two main topics person- and intervention-related reasons as defined by Čihařová et al. (2023). Added to it are Quotes from the data used in this research. For the categories *Perfectionism* and *Previous experience with a similar intervention* no fitting quotes could be found.