Understanding Dropout in Web-Based Interventions: Identifying Latent User Subgroups and Influencing Factors

Jasper R. Wrana (s2698277)

Department of Psychology, Health, and Technology

Faculty of Behavioural, Management and Social Sciences

First Supervisor: Dr. Alejandro Dominguez Rodriguez

Second Supervisor: Dr. Johannes Steinrücke

Date: 28.05.2025

Word Count: 8579

Abstract

Background: Web-Based Interventions (WBIs) offer promising solutions to the global mental health treatment gap. Despite advantages such as their accessibility and scalability, WBIs often suffer from high dropout rates. While both person- and intervention-related factors have been linked to early dropout, research has yet to fully explore the relationship between these elements. Therefore, this study investigates whether specific subgroups of users can be identified based on dropout patterns. Further, it explores what influence User Experience (UX) design choices, participants attitudes towards WBIs, and usability scores have on dropout patterns. **Methods:** Data were collected from 87 participants who dropped out of one of three WBIs developed during the COVID-19 pandemic. A Latent Profile Analysis (LPA) was conducted to identify groups of users based on age, education level, symptom severity, usability scores, and number of modules completed. Additional statistical tests were used to assess the impact of usability and UX design on adherence. **Results:** The LPA revealed four distinct user profiles, each differing in symptom severity (on scales measuring sleep disturbances, depression & anxiety), point of dropout, and demographic characteristics. One subgroup with moderate symptoms and high education levels, showed significantly higher module completion than the rest. However, hypothesis testing showed no significant relationship between system usability, user attitudes, or UX design features and adherence rates. **Conclusion:** The findings imply that dropout is not solely driven by usability or design choices but by a complex interplay of personal and contextual factors. Implementing a UX-focused design did not significantly improve adherence, and both highly symptomatic and low-symptom users dropped out for different reasons. These results highlight the need for more personalised, context-specific approaches when designing WBIs.

Table of Contents

Introduction 5

Present Study 9

Methods 11

Design 11

Materials 11

Interventions 11

Questionnaires 13

Participants 16

Data analysis 18

Results 20

Latent Profile Analysis 20

Model Selection 20

Latent Profile Characteristics 23

Hypothesis Testing 24

Hypothesis 1 24

Hypothesis 2 25

Hypothesis 3 25

Hypothesis 4 26

Discussion 26

Limitations 33

Strengths 34

Suggestions for Further Research 35

Conclusion 36

References 38

Appendices 48

Introduction

Worldwide, people are suffering from psychological distress. Overall, throughout their lives, around one third of the population meet the diagnostic criteria for psychopathology (Sevilla-Llewellyn-Jones et al., 2018), making it the main cause for disability and pre-mature death (Arias et al., 2022). For instance, it is estimated that around the globe, 350 million individuals suffer from depression, making it the second largest driving factor for burden of disease (Serrano-Ripoll et al., 2021). While these numbers are already pressing, there is evidence that the number of people living with depression is further rising globally, particularly in low-income countries (Serrano-Ripoll et al., 2021). However, even in high-income nations, the majority of individuals with depression do not receive treatment (Serrano-Ripoll et al., 2021). Currently, around the world, the need for effective psychological treatments exceeds the capacity of traditional face-to-face methods to meet it (Cowpertwait & Clarke, 2013; Pelucio et al., 2024). Consequently, there is a treatment gap and a corresponding need for more alternative treatment options that can easily be disseminated.

To address this treatment gap, there has been an increase in the development of web-based interventions (WBI). WBI's are delivered digitally and can be either guided, with therapist interaction through video, audio, or chat, or self-administered, completed independently without external support (Krämer et al., 2022). The theoretical framework of the majority of WBI's treating depressive symptoms is built on evidence-based techniques used in cognitive behavioural therapy (CBT) as described by Gili et al., (2020), such as cognitive restructuring, behavioural experiments, and homework (Cowpertwait & Clarke, 2013; Krämer et al., 2022). Furthermore, many WBIs are supported by multimedia tools available digitally, such as images, animations, and videos, to convey the content typically discussed in standard CBT sessions (Cowpertwait & Clarke, 2013). A benefit of these multimedia formats is their link to the increased engagement of users (Davies et al., 2014). Therefore, WBIs can be a valuable alternative in addressing the treatment gap.

Evidence suggests that WBIs effectively treat individuals in different contexts and with a range of symptoms. For instance, a meta-analysis by Davies et al. (2014) has found a reduction of symptoms of depression and anxiety using WBIs in student populations. Other studies have found WBIs to be effective in alleviating symptoms and increasing mental well-being in a workplace context (Carolan et al., 2017), in individuals with chronic health conditions (White et al., 2022), and in individuals suffering from complicated grief disorder due to the loss of a loved one during the COVID-19 pandemic (Dominguez-Rodriguez et al., 2023). Consequently, WBIs are particularly valuable due to their broad applicability.

Inherent to their digital nature, WBIs provide a chance to overcome barriers related to traditional therapy and come with a list of advantages for people in need of treatment. Firstly, online interventions allow for anonymous access to therapy, thereby limiting the fear of stigmatisation surrounding psychopathologies (Cowpertwait & Clarke, 2013; Koelen et al., 2022). Furthermore, they increase accessibility for individuals with low access to clinics (Cowpertwait & Clarke, 2013). Moreover, a meta-analysis by Koelen et al (2022) suggests that online therapy, while involving high initial costs during the design process, also poses a cost-effective alternative for face-to-face mental health interventions. Consequently, overall WBIs offer a promising and accessible solution to bridge the mental health treatment gap, making evidence-based support more widely available.

While WBIs have many advantages, a major disadvantage relates to their dropout rates. Overall, many studies seem to report strong variability in dropout rates (Boucher & Raiker, 2024). For instance, a meta-analysis by Jabir et al. (2024) showed an average of 21.84% dropout for mental health interventions delivered by chatbots. However, this rate itself varied, depending on the length of the intervention: dropout rates in shorter interventions lasting for 8 weeks or less were lower compared to long term studies lasting more than 8 weeks (18.05% & 26.59% dropout respectively) (Jabir et al., 2023). Furthermore, reviews by Baños et al. (2022) and Melville et al. (2010), found dropout rates ranging from 20% to 50% and from 2% to 83% respectively in WBIs in general, further underlining this strong variability around dropout rates.

This high variability in adherence could be explained by different factors influencing users' engagement. The factors causing individuals to drop out are manifold and can generally be divided into two categories, namely person-and intervention related factors (Ciharova et al., 2023). Firstly, the expectations users have towards an intervention, such as the intervention length or the number of modules have an influence on engagement rates (Swift, & Callahan, 2011). Another intervention related factor stems from the design and usability of the program, as poor usability was found to be the biggest driver of drop-out (Alqahtani & Orji, 2020). To counteract this, some interventions include users in the design choices of the intervention and further implement a usability scale to increase adherence rates (Dominguez-Rodriguez et al., 2024; González-Cantero et al., 2024). Thus, these findings highlight the importance of incorporating user expectations and needs when creating digital interventions.

In addition to intervention-related factors, individual characteristics play a crucial role in predicting dropout from WBIs. Particularly, a meta-analysis by Karyotaki et al. (2015) found being young, male, having lower education, and lastly experiencing co-morbid anxiety symptoms to be significant predictors of higher rates of dropout. Furthermore, earlier dropout has been associated with higher symptom severity for both anxiety (Binnie & Boden, 2016; Christensen et al., 2009) and depression (Lippke et al., 2021). Therefore, individual factors such as demographic variables need to be considered in the development of WBIs.

Another important factor related to intervention effectiveness and dropout rates lie in the design. In particular, incorporating user feedback during the design process can help address users' needs (Lemon et al., 2020). Supporting this, Ciharova et al. (2023) found that WBIs that were pilot tested by users before implementation and featured clearly structured content were associated with lower dropout rates. Although no significant differences were found in self-rated usability or perceived treatment credibility, a study by Hentati et al. (2022) describes that interventions designed based on user experience (UX) principles led to higher engagement compared to WBIs without such implementations. However, research in this area remains limited and needs further investigation (Lemon et al., 2020).

A key determinant of WBI effectiveness is related to the degree of guidance and external support provided by the intervention. Generally, WBIs are divided into self-guided and guided interventions (Pelucio et al., 2024). While some studies suggest that guided interventions yield slightly better outcomes (e.g. Vangrunderbeek et al., 2022), others indicate no significant difference between guided and unguided formats in reducing symptoms (e.g. Krämer et al., 2022; Pelucio et al., 2024), with long-term benefits observed in both cases. Additionally, research suggests that therapist-supported WBIs may produce similar outcomes to face-to-face CBT in treating anxiety (Pelucio et al., 2024). These findings highlight the potential of self-guided digital interventions as a promising direction for further exploration in mental health treatment.

Lastly, while many studies report drop-out and engagement rates at a sample level and point out to the previously mentioned unique isolated factors related to dropout, recently there has been growing interest into potential different clusters of users, which could explain the strong variability in drop-out rates (Boucher & Raiker, 2024). Consequently, more research is needed into possible combinations of factors or subgroups of samples that could then predict different types of users.

Present Study

Given the global rise in psychological distress and the growing need for mental health solutions, WBIs are promising tools for addressing the treatment gap. While WBIs have shown efficacy across various populations and settings, high dropout rates remain a significant challenge, with engagement strongly influenced by both intervention- and person-related factors. Additionally, the variability in dropout rates across studies suggests that unique user subgroups may experience and interact with WBIs differently, highlighting the need for a more nuanced understanding of user engagement.

The present study aims to address this gap by investigating the interplay between user characteristics related to early dropout (age, level of education, severity of symptoms) and intervention design features (perceived usability). Building on prior findings, this study explores whether specific clusters of users that differ in their engagement patterns can be identified. Examining these subgroups aims to provide deeper insights into the variability in engagement rates and offer recommendations for tailoring WBIs to meet the needs of diverse users better. Furthermore, this study aims to contribute to understanding how design improvements and user-centered approaches can enhance adherence and outcomes in digital mental health interventions.

Lastly, most existing studies analyse dropout rates within a single intervention, limiting the generalisability of findings across different WBI designs. To the best of this author's knowledge, there is a lack of studies examining multiple interventions simultaneously. A comparative approach could provide valuable insights into factors influencing engagement and dropout, thereby informing the development of more effective and user-centred intervention strategies.

Therefore, this study expands current knowledge about factors related to dropout from WBIs, using data from participants who discontinued their engagement with one of three web-based psychological interventions conducted during the COVID-19 pandemic. The three interventions, Salud Mental COVID (Mental Health COVID), Duelo COVID (Grief COVID), and Personal Salud COVID (Healthcare Workers COVID), were designed to address diverse mental health issues, including anxiety, depression, grief, burnout, and compassion fatigue.

Consequently, the following exploratory research question will be investigated:

Question 1: What latent subgroups of users who drop out of interventions can be identified?

Q2: Does incorporating a User Experience (UX)-focused approach in the design of a web-based intervention (WBI) improve adherence rates among participants?

Related to Q2, the following hypotheses will be investigated:

Hypothesis 1:

There is a significant relationship between the System Usability Scale (SUS) score and the number of modules completed. Specifically, higher SUS scores are expected to be associated with a greater number of modules completed.

Hypothesis 2:

A significant relationship exists between participants' attitudes (as measured by the APOI scale) and the number of modules completed. Participants with more positive attitudes toward the system are expected to complete more modules.

Hypothesis 3:

The type of intervention, specifically whether it included UX design, significantly affects the number of modules completed. Interventions that included UX design ("personal COVID" and "duelo COVID") are expected to result in a higher number of modules completed compared to the intervention without UX ("mental-health COVID").

Hypothesis 4:

The relationship between the inclusion of UX design and the number of modules completed is moderated by the SUS score. Specifically, the effect of UX design on the number of modules completed is expected to be stronger for participants with higher SUS scores.

Methods

Design

This three-arm cross-sectional study aimed to explore factors contributing to dropout from three distinct WBI`s conducted during the COVID-19 pandemic. The study employed a quantitative, exploratory approach, with data from both the post-intervention evaluation and the interventions themselves. These data were analysed using statistical techniques. This approach aimed to identify latent profiles out of the following common factors: usability scores, education levels, age, mental health scores, and the number of modules completed. By examining these data across three interventions, the study offers a broader perspective on engagement and disengagement patterns in digital mental health interventions.

Materials

Interventions

Mental Health COVID. Mental Health COVID (www.saludmentalcovid.com) is a self-administered, 15-module web-based intervention designed to reduce anxiety and depression symptoms while improving sleep quality and positive emotions. Developed during and after the COVID-19 pandemic, the program is grounded in principles of positive psychology and incorporates elements of cognitive behavioural therapy (CBT) and behavioural activation therapy. The intervention is delivered via a telepsychology platform and divides participants into two groups: one group receives self-administered treatment independently, while the other receives additional support from trained psychologists via chat, offering motivation, guidance, and assistance.

Dominguez-Rodriguez et al. (2020, 2024) have described the study protocol and findings related to this intervention in two studies. The intervention was approved by the Ethics Committee of the Free School of Psychology University of Behavioural Sciences in Chihuahua, Mexico (reference number Folio 2008) and registered in Clinical Trials (NCT04468893). Additional details, including an overview of the study design, are provided in Appendix A.

Grief COVID. Grief COVID (https://www.duelocovid.com) is a self-applied, 12-module web-based intervention designed to address complicated grief in Mexican individuals who lost a loved one. Its primary goal is to reduce the likelihood of developing complicated grief disorder while enhancing quality of life. Secondary objectives include minimizing depression and anxiety symptoms and improving sleep quality. The intervention is based on mindfulness, acceptance and commitment therapy, positive psychology, and cognitive behavioural therapy, with a three-day delay between modules to ensure gradual progression. Due to the randomised controlled trial, participants were randomly assigned to one of two groups: an immediate-start group or a waitlist group that began the intervention after 36 days. To improve adherence and usability, the intervention was designed using UX principles and tailored to participant needs.

Grief COVID has been extensively studied, with published research describing its protocol (Dominguez-Rodriguez et al., 2021) and evaluating its effectiveness (Dominguez-Rodriguez et al., 2023). The intervention was 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). Further details on the study design are available in Appendix B.

Healthcare Workers COVID. Healthcare Workers COVID (www.personalcovid.com) is a web-based intervention designed to reduce depression, anxiety, compassion fatigue, and burnout among healthcare workers in the Mexican population. It also aims to enhance self-care, the ability to deliver bad news, sleep quality, and overall quality of life (Dominguez-Rodriguez et al., 2022). The intervention comprises nine core modules and three complementary modules, drawing on approaches of acceptance and commitment therapy, mindfulness, and cognitive behavioural therapy. The content of the intervention could be accessed via computers, tablets, or smartphones. In line with the randomised controlled trial, participants were randomly assigned to one of two groups: one group participated in the self-administered web-based intervention, while the other received additional online guidance by a therapist. Anticipating higher dropout rates than traditional therapy, the intervention was designed with UX principles to improve adherence and engagement. These principles were for instance intuitive navigation and personalised reminders.

The intervention was approved by the Ethics Committee of the Autonomous University of Juarez City (approval ID: CEI-2021-1-266) and is registered in Clinical Trials (NCT04890665). Further details on the study design are available in the work of Dominguez-Rodriguez et al. (2022) and Appendix C.

Questionnaires

The three interventions Mental Health Covid, Grief Covid, and Healthcare Workers Covid used a variety of different questionnaires to measure the symptoms of participants among various dimensions. However, only the questionnaires relevant to this study will be named and described in detail in the following section. For further information regarding the additional questionnaires used, see Dominguez-Rodriguez et al. (2022; 2023; 2024).

Generalised Anxiety Scale (GAD-7). The GAD-7 scale is a brief assessment tool designed to measure the severity of generalized anxiety symptoms. Participants rate their symptoms over the past week using a 4-point Likert scale, with response options ranging from 0 ("not at all") to 3 ("nearly every day"). The total score ranges from 0 to 21, with higher scores indicating greater anxiety severity. Scores between 0 and 4 suggest no significant anxiety, while scores between 15 and 21 indicate severe anxiety (Spitzer et al., 2006). For these interventions, the Spanish version by García-Campayo et al. (2010), was used, which was found to have overall excellent psychometric properties.

Pittsburgh Sleep Quality Index (PSQI). The PSQI by Buysse et al. (1989) is a self-administered, 19-item questionnaire designed to evaluate sleep quality and disturbances over the past month. Participants rate the frequency or severity of sleep disturbances on a scale from 0 ("not during the past month") to 3 ("three or more times per week"). The questionnaire measures seven component scores: sleep duration, sleep disturbances, sleep latency, daytime dysfunction, sleep efficiency, overall sleep quality, and use of sleep medication. The total PSQI score, ranging from 0 to 21, is calculated by summing the component scores, with higher scores indicating poorer sleep quality (Buysse et al., 1989). A meta-analysis investigating the psychometric properties of the PSQI found the questionnaire to have strong reliability and validity in multiple samples (Mollayeva et al., 2015).

System Usability Scale (SUS). The SUS is a tool designed to evaluate the usability of a system. It consists of 10 items, each rated on a 5-point Likert scale, ranging from 1 ("completely disagree") to 5 ("completely agree"). To calculate the overall score, the item values are summed and multiplied by 2.5, resulting in a total score ranging from 0 to 100, where higher scores indicate better usability (Brooke, 1996). The SUS has been found to have acceptable psychometric properties for various types of virtual products and has been translated to many languages (Khan et al., 2025).

Becks Depression Inventory 2 (BDI-II). The Mental Health Covid Intervention made use of the BDI-II to measure participants level of depression. The BDI-II is a widely recognized questionnaire containing 21 self-report items to assess the severity of depression in both adolescents and adults (Beck et al., 1996). Each item on the BDI-II offers response options ranging from 0 to 3. Based on the total score, the severity of depression is classified as follows: scores between 0 and 13 indicate "Minimal" depression, scores from 14 to 19 indicate "Mild" depression, scores ranging from 20 to 28 indicate "Moderate" depression, and scores from 29 to 63 indicate "Severe" depression (Halfaker et al., 2011). Psychometric assessments of the Spanish version of the BDI-II for the Mexican population have been carried out by Jurado et al. (1998) and González et al. (2015), demonstrating strong reliability, with Cronbach's alpha coefficients ranging from 0.87 to 0.92.

Center for Epidemiologic Studies Depression Scale Revised (CESD-R). Both Grief Covid & Healthcare Workers Covid used the CESD-R to measure depression levels of participants. The CESD-R is a self-report scale that assesses symptoms of depression in the past 2 weeks. The CESD-R score is calculated by summing the responses to all 20 questions, with each item scored as follows: "Not at all or less than one day" = 0, "1-2 days" = 1, "3-4 days" = 2, "5-7 days" = 3, and "Nearly every day for 2 weeks" = 3. The total score can therefore range from 0 to 60, with higher scores indicating more severe symptoms (CESD-R, n.d.). With a Cronbach's alpha of 0.93, the CESD-R has been found to be a reliable scale for the Mexican population (González-Forteza et al., 2008).

Attitudes towards Psychological Online Interventions Scale (APOI). The APOI scale is a self-report questionnaire aimed at measuring the attitudes of participants towards an intervention. The version used in the present study is an adapted version of a questionnaire developed by Botella et al. (2009). It was specifically modified and tailored to align with the requirements of the three interventions. However, due to its ad-hoc nature, no established psychometric properties or validity measures are available for the APOI.

Participants

This study included responses from participants who dropped out of the following three interventions: Mental Health COVID with 32 participants, Grief COVID with 56 participants, and Healthcare Workers COVID with 5 participants. From an initial pool of 93 participants, 2 participants of the Mental Health COVID intervention were below the age of 18, and another 4 were mistakenly part of the sample, as they completed all 15 intervention modules. These 6 participants were therefore excluded from further analyses.

The final sample consisted of 87 participants, 74 women and 13 men, with a mean age of 37 years (SD = 10.71). Most participants had attained a bachelor's degree as their highest education level and left the intervention before completing the first module. Detailed socio-demographic information for each intervention can be found in Table 1.

Table 1

Sociodemographic Information

Characteristics		**MHC (n=26)**	**GC (n=56)**	**HWC (n=5)**	**All (n=87)**
Sex					
	Female	22	47	5	74
	Male	4	9	0	13
Age					
	Min	20	18	23	18
	Max	60	63	40	63
	Mean	34.6	38.8	31.6	37.10

Education Level					
	Primary education	3	5	0	8
	Secondary Education	0	3	0	3
	University – Undergraduate	20	38	4	62
	University – Master's degree	2	9	1	12
	University – Doctorate	0	1	0	1
	Other	1	0	0	1
Last module completed					
	0	12	25	0	37
	1	4	15	0	19
	2	1	7	4	12
	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
	8	0	0	0	0
	9	1	0	0	1
	10	0	0	0	0
	11	1	0	0	1

Note. Education level according to Mexican classification ("Secundaria" (Junior High School), "Preparatoria" (High School), "Universidad - Licenciatura" (Undergraduate Studies), "Universidad - Maestría" (Postgraduate Studies), "Universidad - Doctorado" (PhD Degree), and "Otros" (Others)). 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).

Data analysis

To answer the first research question aimed at exploring underlying patterns among different users, a Latent Profile Analysis (LPA) was conducted. LPA is a statistical method used to identify unobserved subgroups within a population based on patterns in a set of variables (Spurk et al., 2020). This approach assumes that individuals can be probabilistically classified into distinct categories, each characterized by unique combinations of personal and/or environmental attributes (Spurk et al., 2020). The analysis was exploratory in nature, aiming to uncover potential latent profiles without prior hypotheses about the number of profiles or their characteristics.

The following variables were included in the LPA:

1. Usability Score: Participants' overall evaluation of the intervention's usability (SUS).
2. Age: Measured in years, capturing the demographic diversity of the sample.
3. Education Level: Coded as an ordinal variable reflecting the highest level of education attained by participants.
4. Symptom Level of Pathology: The questionnaires included to determine the symptom level of pathology were the PSQI, the GAD-7, the CESD-R, and the BDI-II.
5. Number of Modules Completed: Representing participants' point of dropout of the intervention.

Prior to conducting the LPA, one participant who showed NAs was removed from the dataset, as LPAs cannot deal with missing data. Consequently, the LPA was conducted with 86 participants. Next, all variables were standardized to ensure comparability and to account for differences in measurement scales. Since each intervention used either the CESD-R or the BDI-II to measure depression, it was necessary to combine these scores into a single variable to enable comparisons across all participants. To achieve this, the total scores of both scales were computed and then translated into the PROMIS scale by Choi et al. (2014), which is a scale combining multiple depression questionnaires into one. This process ensured that all participants had a comparable depression score, regardless of which scale was used. Finally, all standardised symptom scores (PSQI, GAD-7, PROMIS-depression score) were combined to a single variable, namely the overall level of symptoms. The results of the LPA are presented in the Results section, accompanied by visualizations of the identified profiles to facilitate interpretation.

In order to investigate the second research question including the 4 hypotheses, the following analyses were conducted:

To test hypothesis 1, a Spearman's rank-order correlation was conducted to examine the relationship between System usability Scores and the number of modules completed. For hypothesis 2 another Spearman's rank-order correlation tested the relationship between APOS scores and the number of modules completed. Next, for hypothesis 3, Welch's t-test was used to compare the number of modules completed across the different intervention types (UX vs. non-UX). Lastly, for hypothesis 4, a moderation analysis using negative binominal regression tested whether SUS scores moderate the effect of UX design on the number of modules completed.

All analyses were performed using R (Version Number 2024.12.1+563).

Results

Latent Profile Analysis

Model Selection

An LPA was conducted to identify distinct profile groups within the data. First, models with one to six classes were estimated and compared using multiple fit statistics to determine the optimal number of classes (see Table 2). Here, the Bayesian Information Criterion (BIC; Schwarz, 1978), Akaike Information Criterion (AIC; Akaike, 1987), and Bootstrap Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000) were examined as primary indicators of model fit.

Based on several criteria, the four-class solution emerged as the optimal model. Firstly, it showed the combination of the lowest BIC value (2042.18) and the AIC value (1973.46). Furthermore, while the entropy value (Celeux & Soromenho, 1996) for the four-class model (0.760) was lower than that of the two-class solution (0.979), it remained within the acceptable range between 0.60 and 0.80, indicating appropriate classification quality (Spurk et al., 2020). Next, the BLRT test was significant for the four-class model (p = .01), suggesting that this model fit significantly better than the three-class solution. Lastly, the four-class model maintained reasonable class proportions, with the smallest class comprising 4.65% of the sample and the biggest one 66.3%.

Next to statistical criteria, visualisations were used to help interpret and compare the different latent profile models. Figure 1 shows a multi-panel box plot displaying the distributions of the five included variables (Age, SUS Sum, Symptom Level, Last Completed Module, and Study Grade) across six potential latent profile solutions. Each panel represents a different class model, from a one-class solution (top left) to a six-class solution (bottom right). A closer visualisation of the distribution of the five key variables belonging to the four-class solution can be found in Figure 2.

Based on this comprehensive evaluation of fit indices and considering both statistical criteria and theoretical interpretability of the plots, the four-class solution was selected as the optimal model for further analysis and interpretation.

Table 2

Fit Statistics for Latent Profile Analysis Models with One to Six Classes

Classes	**LogLik**	**AIC**	**BIC**	**Entropy**	**BLRT_p**	**n_min**	**n_max**
1	-998.19	2016.37	2040.92	1.000	-	100%	100%
2	-982.93	1997.86	2037.13	0.979	.010	4.65%	95.3%
3	-979.63	2003.26	2057.26	0.773	.792	4.65%	83.7%
4	-958.73	1973.46	2042.18	0.760	.010	4.65%	66.3%
5	-955.79	1979.59	2063.04	0.765	.782	4.65%	52.3%
6	-949.71	1979.43	2077.61	0.803	.317	4.65%	44.2%

Note. LogLik = log-likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; BLRT = Bootstrap Likelihood Ratio Test.

Figure 1

Comparison of Variable Distributions Across Six Latent Profile Classes

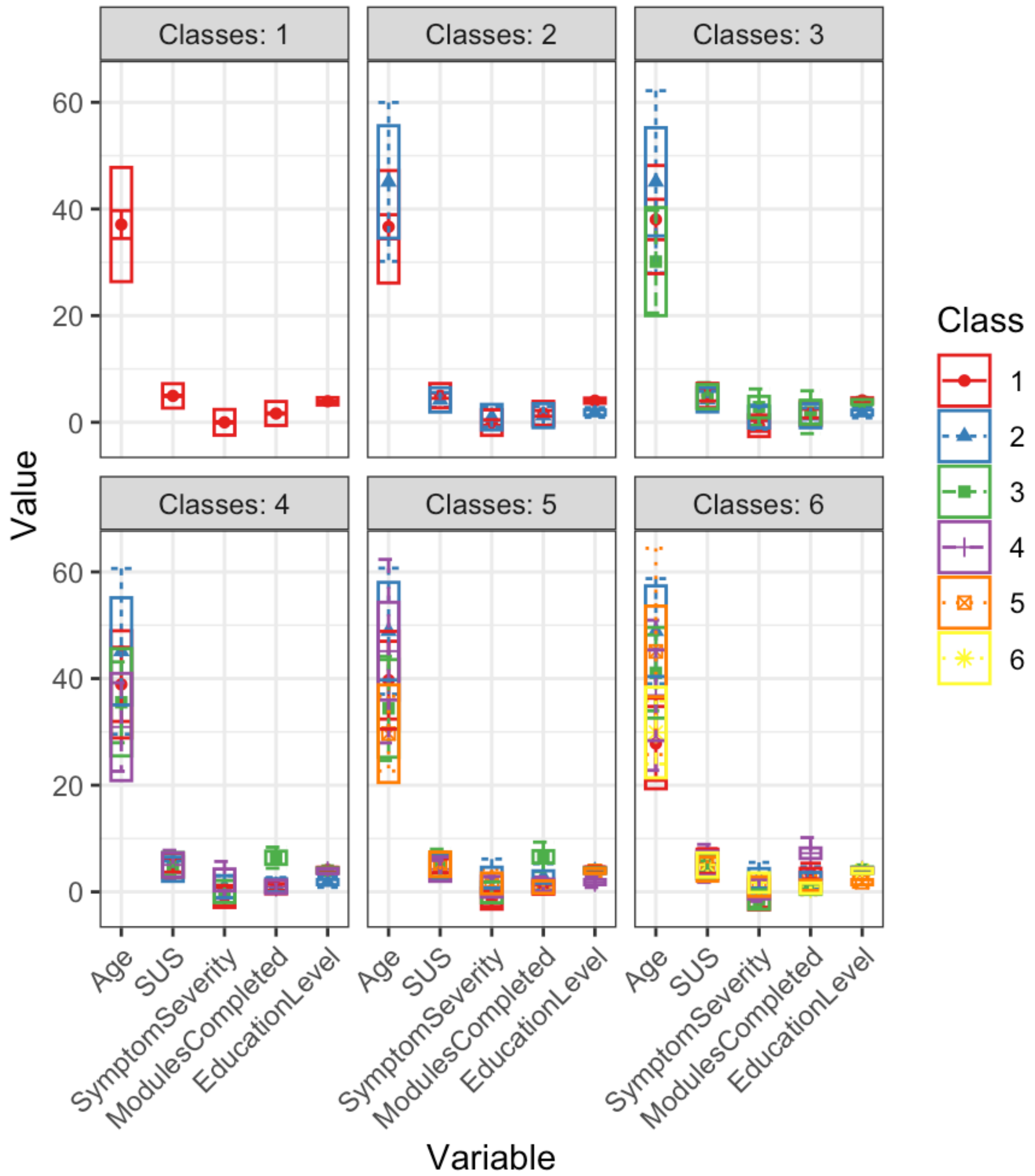
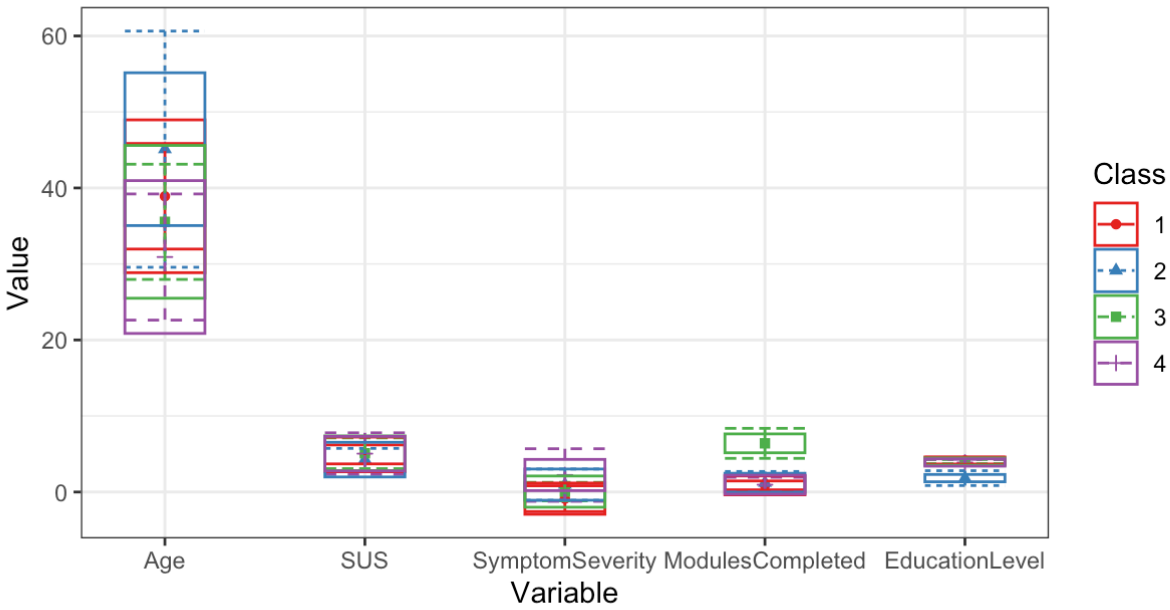


Figure 2

Distribution of Key Variables Across the Four Latent Profile Classes



Latent Profile Characteristics

After identifying the four-class solution as the best-fitting mode, the characteristics of each profile were examined. Table 3 presents the means and standard deviations of the five indicators for each profile.

Table 3

Means and Standard Deviations of Key Variables by Latent Profile

Variable	**Profile 1 (*n* = 57)**	**Profile 2 (*n* = 4)**	**Profile 3 (*n* = 11)**	**Profile 4 (*n* = 14)**
Age	38.91 (10.05)	45.10 (10.05)	35.54 (10.05)	30.91 (10.05)
SUS	4.95 (2.28)	4.26 (2.28)	5.10 (2.28)	5.05 (2.28)
Symptom Level	-0.88 (2.05)	0.97 (2.05)	0.05 (2.05)	2.23 (2.05)
Modules Completed	0.87 (1.24)	1.22 (1.24)	6.40 (1.24)	0.96 (1.24)
Study Grade	4.12 (0.48)	1.83 (0.48)	4.00 (0.48)	3.88 (0.48)

Note. Values represent means with standard deviations in parentheses.

Each of the four profiles revealed distinct patterns across the measured variables. First, profile 1 (Mean age = 38.91) constitutes the biggest group, containing 57 participants. It is characterised by the lowest symptom levels (*M* = -0.88) and highest educational degree (*M* = 4.12), while also having the lowest amount of completed modules (*M* = 0.87). Next, profile 2 makes up the oldest and smallest group (n = 4, mean age = 45.10) with moderate symptom levels (*M* = 0.97) and notably lower study grades (*M* = 1.83) than all other profiles. The number of modules completed (*M* = 1.22) was in the lower medium range in comparison to the other profiles. Profile 3 (n = 11, mean age = 35.54) shows significantly higher module completion (*M* = 6.40, $p < .001$) compared to all other profiles, while maintaining neutral symptom levels (*M* = 0.05) and good academic performance (*M* = 4.00). This profile represents highly engaged participants with substantial progress through the intervention. Lastly, profile 4 (n = 14) was the youngest group (Mean age = 30.91) with the highest symptom levels (*M* = 2.23) but relatively good adherence (*M* = 3.88).

The standard deviations for age (10.05), SUS (2.28), symptom level (2.05), last completed module (1.24), and study grade (0.48) were equal across all profiles in this model, as indicated by the identical variance estimates across the classes.

Several variables showed statistically significant differences across profiles. Age varied significantly among profiles ($p < .001$), with Profile 2 having the oldest members and Profile 4 the youngest. The amount of completed modules was significantly higher in Profile 3 ($p < .001$), while study grades were significantly lower in Profile 2 ($p < .001$). Symptom levels were highest in Profile 4 and lowest in Profile 1 ($p < .05$).

Hypothesis Testing

Hypothesis 1

To examine the relationship between SUS scores and the number of modules completed, a Spearman's rank-order correlation was conducted. It was hypothesised that higher SUS scores would be associated with a greater number of completed modules. However, the analysis revealed only a weak positive correlation, which was not statistically significant, $r(85) = .09$, $p = .39$. This suggests that usability, as measured by SUS, was not strongly associated with module completion. These findings indicate that SUS scores may not be a significant predictor of adherence in this context. Therefore, hypothesis 1 had to be rejected.

Hypothesis 2

A Spearman's rank-order correlation was conducted to examine the relationship between participants' attitudes towards the intervention (as measured by the APOI scale) and the number of modules completed. It was hypothesised that more positive attitudes toward the system would be associated with completing more modules. However, the analysis revealed a weak negative correlation, which was not statistically significant, $r(91) = -.01$, $p = .94$. These results suggest that attitudes toward the system, as measured by the APOI scale, were not meaningfully associated with module completion in this study. Consequently, hypothesis 2 was rejected.

Hypothesis 3

A Levene's test of homogeneity of variances indicated a significant difference in group variances, $F(1, 85) = 6.76$, $p = .011$. Therefore, to test hypothesis 3, a Welch's t-test was conducted to compare the number of modules completed between interventions that did not incorporate UX design (group 0) and those that did incorporate UX design (group 1). Although, contrary to the hypothesis, participants in the non-UX intervention ($M = 2.3$, $SD = 3.2$) completed slightly more modules on average than those in the UX-based interventions ($M = 1.3$, $SD = 1.7$), this difference was not statistically significant ($t(31) = 1.46$, $p = .153$, $d = 0.43$). The 95% confidence interval for the mean difference ranged from -

0.38 to 2.31. Therefore, the results did not provide sufficient evidence to support hypothesis 3.

Hypothesis 4

Lastly, a negative binomial regression was conducted to investigate whether perceived usability moderated the relationship between UX design and the number of completed modules. The negative binomial model was appropriate for the overdispersed data, with a dispersion parameter of 0.80 (SE = 0.22). Furthermore, the model's AIC was 308.68, and the residual deviance was 89.16 on 83 degrees of freedom. However, none of the predictors were statistically significant. UX design (β = -0.16, SE = 0.74, z = -0.22, p = .826), perceived usability (β = 0.10, SE = 0.11, z = 0.89, p = .374), and their interaction (β = -0.07, SE = 0.13, z = -0.54, p = .590) all failed to significantly predict module completion. These findings suggest no moderating effect of perceived usability on the relationship between UX-design condition and user engagement. Therefore, hypothesis 4 had to be rejected.

Discussion

This study aimed at expanding current knowledge around the widespread issue of early dropout in WBIs by analysing data from participants who discontinued their engagement with one of three different WBIs conducted during the COVID-19 pandemic. Instead of examining isolated predictors of dropout as done in previous studies, this study adopted a broader approach by investigating whether distinct latent subgroups of users could be identified based on personal characteristics, symptom severity, and dropout patterns. This approach aimed to offer deeper insights into the underlying mechanisms of dropout. Additionally, the study explored the potential impact of usability and design differences by comparing interventions with and without UX-focused designs. Therefore, two key research questions guided the analysis: (1) What latent subgroups of users who drop out of interventions can be identified? and (2) Does incorporating a UX-focused approach in the design of a WBI improve adherence rates among participants?

Regarding the first research question, the LPA revealed four distinct user profiles among participants engaging with WBIs for mental health support. These profiles highlight significant variations in symptom severity, engagement patterns, system usability perceptions, and demographic characteristics. In the following, the four profiles will be described and interpreted in more detail.

Firstly, profile 1 represents the majority of participants (66.3%) with an average age of 38.91 years. These individuals reported moderate system usability scores (SUS Sum = 4.95) and the highest academic degree (4.12). Further, most importantly, they displayed the lowest symptom levels (-0.88) among all profiles. Their engagement with the mental health intervention was very low, completing less than one module on average (0.87). Interestingly, despite having the highest level of education among all four profiles, members of this group dropped out very early in the intervention. This contrasts with previous findings suggesting that individuals with higher educational degrees show lower dropout rates compared with individuals who obtained lower educational levels for both web-based (Karyotaki et al., 2015; Reinwand et al., 2015), as well as face-to-face interventions (Fenger et al., 2010; Hanevik et al., 2023).

Another way in which this profile differs from previous findings is in its low symptom severity. While Christensen et al. (2009) identified low symptom severity as a predictor of higher retention, this does not appear to apply to Profile 1. A possible explanation is that this group reported by far the lowest symptom levels among all profiles, with a z-score of –0.88, which potentially falls below the threshold at which individuals still perceive a need for therapeutic support. This interpretation is supported by a study from Price et al. (2012), which found that low perceived relevance of the intervention content was the strongest predictor of dropout in WBIs following a disaster. In line with this, perhaps participants in Profile 1 did not view the intervention as relevant to their current mental health needs, leading to early dropout.

Next, profile 2 makes up the smallest group, comprising only 4.7% of participants with the highest average age (45.10 years). They reported the lowest system usability scores (SUS Sum = 4.26) and relatively high symptom levels (0.97). While their engagement with the mental health intervention was slightly higher when compared to the others, members of this profile still approximately only completed one module on average (1.22). Most notably, this group showed the lowest academic achievement (1.83). Here, both the high symptomatology (Binnie & Boden, 2016; Lippke et al., 2021) and the low academic achievement (Karyotaki et al., 2015; Reinwand et al., 2015) could explain the completion of only one intervention module, as these two factors have been previously linked with early dropout in the literature. On the opposite, a factor that might be associated to the slightly higher completion rate compared with profiles 1 & 4 could be related to the age, as being older has been found to be associated with higher retention of therapy sessions (Fenger et al., 2010; Karyotaki et al., 2015; Hanevik et al., 2023). Therefore, this profile may represent older individuals who found the intervention less useful, potentially due to their symptomatology or their education level.

Profile 3 comprised of 12.8% of participants with a slightly below-average mean age (35.54 years). They reported high system usability scores (5.10) and average symptom levels, shown by the z-score of 0.05. This group stands out for their extensive engagement with the mental health intervention, completing an average of 6.40 modules, which is substantially higher than all other profiles. Their educational level remained high (mean of 4.00), with the average participant holding a bachelor's degree. These individuals appear to be proactive in addressing their mental health needs through high engagement with the intervention modules. Here, the combination of having low symptoms (Christensen et al., 2009) and a high educational degree (Hanevik et al., 2023; Karyotaki et al., 2015; Reinwand et al., 2015) might have acted as a buffer against early dropout.

Lastly, profile 4 represents 16.3% of participants and consists of the youngest individuals (average age 30.91 years). They reported high system usability scores (5.05) but also exhibited the highest symptom levels (2.23) among all profiles. Despite their elevated symptoms, they engaged minimally with the WBIs, completing approximately one module on average (0.96). Their academic level remained high with a mean of 3.88. This group appears to represent younger individuals experiencing significant symptoms who, despite finding the system design as intuitive, did not extensively engage with the intervention modules. Two of the characteristics found in this profile have oftentimes been linked to early dropout in the literature and might therefore explain this profile's low completion rate. Firstly, being young is consistently being reported as a driving factor for non-adherence in both WBIs (Karyotaki et al., 2015), as well as in face-to-face settings (Fenger et al., 2010, Hanevik et al., 2023). Furthermore, having high depression (Lippke et al., 2021), as well as anxiety symptoms were found to be strong predictors of premature dropout (Binnie & Boden, 2016). Thus, these two factors of age and symptom severity could help in explaining the low adherence of individuals who are part of profile 4.

To conclude, the four identified profiles clearly reveal different patterns of engagement with mental health interventions. The majority of participants (Profile 1) represent well-functioning individuals with minimal symptoms and intervention needs. Profile 2 identifies older participants with low academic achievement and high symptoms who may need additional support. Profile 3 is made up of highly engaged individuals who made extensive use of the WBIs. Profile 4 is made up of younger individuals who, despite having elevated symptoms, did not fully engage with the available mental health interventions.

These findings suggest targeted approaches may be necessary to address the varied needs across profiles, particularly for younger symptomatic participants who are not using available resources and older participants who may face both academic and usability challenges.

Furthermore, in line with previous findings (e.g. Binnie & Boden, 2016; Lippke et al., 2021), individuals belonging to profile 3, who were experiencing psychological symptoms, but whose symptom severity had not reached a clinically acute or overwhelming level were most likely to follow up multiple modules of the interventions. This suggests that WBIs may be particularly effective for those in the early to moderate stages of psychological distress, rather than for individuals requiring more intensive or specialised treatment.

In order to investigate the second research question, four hypotheses were tested. First, hypothesis 1 stated that greater usability indicated by higher SUS scores would be associated with higher intervention adherence, operationalised as the number of modules completed. Although a weak positive correlation was observed, it was not statistically significant. This result partly aligns with prior research suggesting that while usability is linked to engagement rates, its influence may be limited or indirect. For example, one study found that an optimised user interface (UI) based on UX design principles led to increased engagement in a WBI compared to a basic UI (Hentati et al., 2022). However, the overall self-rated usability or perceived treatment credibility did not differ between the two conditions in their study (Hentati et al., 2022). Furthermore, in a broader sense, Reinwand et al. (2015) found that how positive or negative participants evaluate a WBI does not predict their point of dropout. This supports the finding of the current study that self-reported levels of usability, as measured by tools like the SUS, may not fully capture factors that contribute to user engagement. It also highlights that other design features can promote engagement even when perceived usability remains the same. Thus, the non-significant correlation between SUS scores and adherence may reflect a broader complexity in how digital design impacts user behaviour, with usability being only one factor.

Next, hypothesis 2 investigated the relationship between participants' attitudes toward the intervention, as measured by the APOI scale, and adherence. However, the observed correlation was weakly negative and non-significant. The weak and non-significant correlation between participants' attitudes toward the intervention and adherence suggests that favourable perceptions alone may not be sufficient to drive engagement in WBIs. This finding aligns with the principles described in the Theory of Planned Behaviour (TPB), which emphasises that while attitudes contribute to the overall behavioural intention of a person, intention itself is made up of a multitude of factors, namely attitudes, perceived behavioural control, and subjective norms (Ajzen, 1991). Therefore, as the APOI only measures one factor making up an individual's intention, it is possible that key mediating factors, namely perceived behavioural control and subjective norm, were missing in the analysis, thereby weakening the observed link between attitude and adherence (Clough et al., 2019). Based on these insights, Clough et al. (2019) developed the e-Therapy Attitudes and Process (eTAP) questionnaire, which is grounded in principles of the TPB, to more accurately measure the factors influencing user engagement with WBIs. Consequently, the present finding further highlights the importance of moving past the measurement of attitudes alone and instead applying more comprehensive tools like the eTAP to capture the full range of motivational processes driving engagement in WBIs.

Further, hypothesis 3 investigated whether including users in the design process improves adherence by comparing dropout rates of interventions with and without UX design elements. Contrary to the hypothesised outcome, the non-UX group showed slightly higher module completion, although this difference was not statistically significant. While contrasting the finding that UIs grounded in UX-principles showed more engagement than simple UIs, (Hentati et al., 2022), considering the broader context in which WBIs are followed by participants could help explain the current finding. Here, Ikwunne et al. (2021) emphasise that user engagement is often weakened when so-called socio-technical factors such as cultural context and social dynamics are ignored in the design process of digital interventions. In their study they argue that approaches solely focusing on the technical aspects of an intervention, even when based on well-established user-centred design frameworks, often still suffer from high dropout because they fail to take into account the system in which users interact with WBIs (Ikwunne et al., 2021). This aligns with the current findings by suggesting that the inclusion of UX elements alone, without paying attention to users' social and technical environments, may not significantly enhance completion rates. Thus, future interventions could benefit from a more holistic, context-sensitive approach that goes beyond standard UX principles to engage users and support sustained participation meaningfully.

Lastly, hypothesis 4 explored whether usability scores moderate the relationship between UX design and module completion through a quantile regression analysis. However, the lack of significant main effects or interaction effects indicates that SUS scores did not influence the effectiveness of UX design in predicting adherence. This indicates that including users in the design process did not significantly impact how usable the system was perceived to be, as reflected by the number of modules participants were able to complete. Here, similar factors described for the previous hypotheses could explain the non-significant results.

Limitations

When interpreting the results of this study, a few important limitations must be considered. Firstly, there is a strong unequal distribution of participants among the three interventions. While Grief COVID provided 56 participants (64.3%), Mental Health COVID and Healthcare Workers COVID only provided 26 (29.8%) and 5 (5.7%) participants respectively. Consequently, as only a third of the participants were part of the non-UX group (29.8% of the sample), this unequal distribution could have potentially biased the comparison of UX- vs non-UX interventions.

Furthermore, a potentially even more impactful bias stemming from the low sample size is related to the latent profile analysis. While the sample used for this LPA included 86 participants, a study by Nylund et al. (2007, as cited in Spurk et al., 2020) states that a sample size of at least 500 participants is needed to assign latent profiles accurately. Therefore, the four profiles of dropout behaviour found in this study must be interpreted cautiously. Nonetheless, due to the exploratory nature of this approach, the current findings could still act as a starting point to inform further research and thereby aid in increasing user adherence.

Another important limitation concerning the sample is inherent to the nature of dropout itself. All participants in this study are individuals who, despite having dropped out of the main intervention, still responded to a follow-up questionnaire. Consequently, this non-response bias could indicate that the people who followed-up on the drop-out questionnaires are systematically different from the individuals who dropped-out entirely, thereby limiting the generalisability of the findings (Prince, 2012).

Next, a potential bias results from the different operationalisations applied by each of the three interventions. While they all share some commonalities in the form of the same questionnaires, they also show subtle differences that make the generalisation and comparison of the results difficult. Firstly, for measuring depression symptoms two of the three interventions made use of the CESD-R, while one applied the BDI-II. While Choi et al. (2014) created a combined scale called "PROMIS" allowing for comparison, the translation of the scores to a combined scale still potentially leads to a loss of precision in individual scores that could have biased the overall symptom-score.

Finally, across three of the questionnaires making up the symptom severity variable in the LPA (CESD-R, PSQI, and GAD-7), slight variations in question wording and response options were present. For example, the PSQI items on sleep and wake times differed between interventions: two used AM/PM formats, while the third allowed open responses on a 0–24 scale. Consequently, these differences required data adjustments to ensure comparability across interventions. As question wording and structure can affect self-reported measures, with more precise phrasing often reducing reported prevalence (Ekerljung et al., 2012), the adjustments made to the questionnaires may have introduced subtle biases into the analyses.

To conclude, although this study provides new insights into the driving factors of early dropout in WBIs, due to the previously identified limitations the findings should be interpreted with caution. Thus, these limitations constitute areas of improvement for future research.

Strengths

This study has several strengths that are worth mentioning. Firstly, to the best of the author's knowledge, this study is among the first to explore whether different user profiles are related to specific dropout patterns in WBIs. While previous research has examined general dropout rates and identified isolated factors (e.g. Baños et al., 2022; Karyotaki et al., 2015; Melville et al., 2010), limited attention has been given to how these factors combine to make up user profiles. By identifying potential user profiles, this study aimed to create a more nuanced understanding of user behaviour in WBIs, which could then inform the development of strategies to reduce dropout and thereby increase intervention effectiveness.

Furthermore, the inclusion of data from three different WBIs allowed for a broader sample and for comparative analyses across these interventions. This approach offers a strength of the study, as it addresses a common limitation in prior research, in which conclusions are often drawn from single interventions. Here, particularly the comparison between a UX-based design and a non-UX-based design was valuable, as it offered insights into how the inclusion of UX principles potentially influences user engagement and intervention completion. Therefore, this study contributes to closing a notable gap in the literature and provides more robust insights into user engagement and dropout behaviour.

Suggestions for Further Research

Given the exploratory nature of this study and its methodological limitations, several points for future research are recommended in the following section.

Firstly, the LPA could be replicated using a substantially larger and broader sample. While the current study offered initial insights into potential user subgroups based on dropout patterns, symptom severity, educational level, age, and usability perceptions, the relatively small sample size, particularly when divided across three interventions, limits the generalisability of the identified profiles. As stated by Nylund et al. (2007, cited in Spurk et al., 2020) an LPA typically requires a sample of at least 500 participants to reliably identify profiles. Therefore, repeating the analysis with a larger sample would increase the validity of the profile classifications and could potentially reveal more detailed patterns of engagement, thereby helping in tailoring intervention strategies to specific user types.

Second, future research should consider adopting the eTAP questionnaire instead of the APOI to more comprehensively assess factors related to engagement based on the TPB (Clough et al., 2019). While this study made use of the APOI to measure attitudes toward the intervention, it did not capture key TPB constructs such as subjective norms, and perceived behavioural control, which together predict behaviour more accurately. The eTAP offers a theoretically grounded and psychometrically validated tool to evaluate these dimensions, and its inclusion in future studies could therefore enable a more precise understanding of the motivational processes related to adherence in WBIs. This could help clarify the role of users' intentions in driving actual usage and could offer more factors for increasing engagement and reducing dropout.

Lastly, future research could explore the integration of socio-technical factors into the design of WBIs. Even when grounding an intervention in UX-principles, their effectiveness is often undermined when the broader socio-cultural and technical contexts in which users operate are not adequately taken into consideration (Ikwunne et al., 2021). Accordingly, future interventions could adopt a more holistic, context-sensitive approach that includes users' social environments, technological access, cultural norms, and perhaps even daily routines in the design process. Thus, by moving away from purely techno-centric UX approaches to more socio-technical designs, dropout rates of future interventions could perhaps be reduced.

Taken together, these recommendations highlight the need for both practical and theoretical refinement in future studies aimed at addressing early dropout in WBIs. By increasing sample size, using more comprehensive theoretical models of user intentions, and by embedding interventions in a broader socio-cultural context, future research can contribute to the development of more adaptive and user-sensitive WBIs.

Conclusion

This study investigated early dropout in WBIs by identifying different user profiles and examining whether implementing a UX-focused design could improve adherence. Four dropout profiles were identified, each differing in symptom severity, level of engagement, and user characteristics. These findings highlight the diversity of WBI users and suggest that more tailored approaches are necessary to address individual needs, especially for users experiencing severe symptoms, who are more likely to drop out early despite having a greater need for support, as well as individuals who potentially fall below the symptom threshold of feeling the need for therapy.

Contrary to expectations, incorporating UX principles did not significantly improve adherence rates. Neither usability scores nor positive attitudes toward the intervention were correlated with higher engagement. These results partly align with existing research suggesting that grounding interventions in UX-principles alone without considering broader socio-technical factors is not enough to increase adherence.

Despite limitations such as small sample size and inconsistencies in measurement tools, this study offers new insights due to its comparative approach. Future research should use larger samples for identifying latent profiles and embed interventions within users' social and cultural contexts to increase engagement rates.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika*, *52*(3), 317–332. https://doi.org/10.1007/bf02294359

Alqahtani, F., & Orji, R. (2020). Insights from user reviews to improve mental health apps. *Health Informatics Journal*, *26*(3), 2042–2066. https://doi.org/10.1177/1460458219896492

Arias, D., Saxena, S., & Verguet, S. (2022). Quantifying the global burden of mental disorders and their economic value. *EClinicalMedicine*, *54*, 101675. https://doi.org/10.1016/j.eclinm.2022.101675

Baños, R. M., Herrero, R., & Vara, M. D. (2022). What is the Current and Future Status of Digital Mental Health Interventions? *The Spanish Journal of Psychology*, *25*. https://doi.org/10.1017/sjp.2022.2

Beck, A. T., Steer, R. A., & Brown, G. (1996). Beck Depression Inventory–II. In *PsycTESTS Dataset*. https://doi.org/10.1037/t00742-000

Binnie, J., & Boden, Z. (2016). Non-attendance at psychological therapy appointments. *Mental Health Review Journal*, *21*(3), 231–248. https://doi.org/10.1108/mhrj-12-2015-0038

Botella, C., Quero, S., Serrano, B., Baños, R. M., & García-Palacios, A. (2009). Avances en los tratamientos psicológicos: la utilización de las nuevas tecnologías de la información y la comunicación. *Anuario de psicología*, *40*(2), 155-170. https://www.redalyc.org/pdf/970/97017660002.pdf

Boucher, E. M., & Raiker, J. S. (2024). Engagement and retention in digital mental health interventions: a narrative review. *BMC Digital Health*, *2*(1). https://doi.org/10.1186/s44247-024-00105-9

Brooke, J. (1996). SUS-A quick and dirty usability scale. *Usability evaluation in industry*, *189*(194), 4-7. https://www.taylorfrancis.com/chapters/edit/10.1201/9781498710411-35/sus-quick-dirty-usability-scale-john-brooke

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

Carolan, S., Harris, P. R., & Cavanagh, K. (2017). Improving Employee Well-Being and Effectiveness: Systematic review and Meta-Analysis of Web-Based psychological interventions delivered in the workplace. *Journal of Medical Internet Research*, *19*(7), e271. https://doi.org/10.2196/jmir.7583

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195–212. https://doi.org/10.1007/bf01246098

CESD-R: Center for Epidemiologic Studies Depression Scale Revised Online Depression Assessment. (n.d.). https://cesd-r.com/

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

Christensen, H., Griffiths, K. M., & Farrer, L. (2009). Adherence in internet interventions for anxiety and depression. *Journal of Medical Internet Research*, *11*(2), e13. https://doi.org/10.2196/jmir.1194

Ciharova, 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.invent.2023.100646

Clough, B. A., Eigeland, J. A., Madden, I. R., Rowland, D., & Casey, L. M. (2019). Development of the eTAP: A brief measure of attitudes and process in e-interventions for mental health. *Internet Interventions*, *18*, 100256. https://doi.org/10.1016/j.invent.2019.100256

Cowpertwait, L., & Clarke, D. (2013). Effectiveness of web-based Psychological Interventions for Depression: a Meta-analysis. *International Journal of Mental Health and Addiction*, *11*(2), 247–268. https://doi.org/10.1007/s11469-012-9416-z

Davies, E. B., Morriss, R., & Glazebrook, C. (2014). Computer-Delivered and Web-Based Interventions to Improve Depression, Anxiety, and Psychological Well-Being of University Students: A Systematic Review and Meta-Analysis. *Journal of Medical Internet Research*, *16*(5), e130. https://doi.org/10.2196/jmir.3142

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

Dominguez-Rodriguez, A., Martínez-Arriaga, R. J., Herdoiza-Arroyo, P. E., Bautista-Valerio, E., De La Rosa-Gómez, A., Vargas, R. O. C., Lacomba-Trejo, L., Mateu-Mollá, J., De Jesús Lupercio Ramírez, M., González, J. a. F., & Martínez, F. R. R. (2022). E-Health Psychological Intervention for COVID-19 Healthcare Workers: Protocol for its Implementation and Evaluation. *International Journal of Environmental Research and Public Health*, *19*(19), 12749. https://doi.org/10.3390/ijerph191912749

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

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

Control Trial (Preprint). *JMIR Formative Research*, *8*, e53767. https://doi.org/10.2196/53767

Ekerljung, L., Rönmark, E., Lötvall, J., Wennergren, G., Torén, K., & Lundbäck, B. (2012). Questionnaire layout and wording influence prevalence and risk estimates of respiratory symptoms in a population cohort. *The Clinical Respiratory Journal*, *7*(1), 53–63. https://doi.org/10.1111/j.1752-699x.2012.00281.x

Fenger, M., Mortensen, E. L., Poulsen, S., & Lau, M. (2010). No-shows, drop-outs and completers in psychotherapeutic treatment: Demographic and clinical predictors in a large sample of non-psychotic patients. *Nordic Journal of Psychiatry*, *65*(3), 183–191. https://doi.org/10.3109/08039488.2010.515687

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

Gili, M., Castro, A., García-Palacios, A., Garcia-Campayo, J., Mayoral-Cleries, F., Botella, C., Roca, M., Barceló-Soler, A., Hurtado, M. M., Navarro, M., Villena, A., Pérez-Ara, M. Á., Riera-Serra, P., & Baños, R. M. (2020). Efficacy of three Low-Intensity, Internet-Based Psychological interventions for the treatment of depression in primary Care: randomized controlled trial. *Journal of Medical Internet Research*, *22*(6), e15845. https://doi.org/10.2196/15845

González-Cantero, J. O., López-Torres, L. P., Alvarado-Avalos, I. R., López-Alcaraz, F., Gasca-Suarez, E., Cisneros-Hernández, A. A., Valadez, A., Macías-Espinoza, F., & Dominguez-Rodriguez, A. (2024). An internet-based self-help intervention for the reduction of consumption of ultra-processed products and increase of physical activity in Mexican university population: study protocol for a randomized controlled trial. *Frontiers in Nutrition*, *11*. https://doi.org/10.3389/fnut.2024.1325528

González, D. A., Reséndiz, A., & Reyes, I. (2015). Adaptation of the BDI–II in Mexico. *Salud Mental*, *38*(4), 237–244. https://doi.org/10.17711/sm.0185-3325.2015.033

González-Forteza, C., Jiménez-Tapia, J., Ramos-Lira, L., Wagner, F., Instituto Nacional de Psiquiatría Ramón de la Fuente, & Morgan State University. (2008). Aplicación de la Escala de Depresión del Center of Epidemiological Studies en adolescentes de la Ciudad de México. In *Salud Pública De México* (Vol. 50, Issue 4, pp. 292–299) [Journal-article]. https://www.scielosp.org/pdf/spm/v50n4/a07v50n4.pdf

Halfaker, D. A., Akeson, S. T., Hathcock, D. R., Mattson, C., & Wunderlich, T. L. (2011). Psychological aspects of pain. In *Elsevier eBooks* (pp. 13–22). https://doi.org/10.1016/b978-1-4160-3779-8.10003-x

Hanevik, E., Røvik, F. M. G., Bøe, T., Knapstad, M., & Smith, O. R. F. (2023). Client predictors of therapy dropout in a primary care setting: a prospective cohort study. *BMC Psychiatry*, *23*(1). https://doi.org/10.1186/s12888-023-04878-7

Hentati, A., Forsell, E., Ljótsson, B., Kaldo, V., Lindefors, N., & Kraepelien, M. (2022). Corrigendum to "The effect of user interface on treatment engagement in a self-guided digital problem-solving intervention: A randomized controlled trial" [Internet Interv. 26 (2021) 1-10/100448]. *Internet Interventions*, *29*, 100550. https://doi.org/10.1016/j.invent.2022.100550

Ikwunne, T. A., Hederman, L., & Wall, P. J. (2021). Designing mobile health for User Engagement: The Importance of Socio-Technical Approach. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2108.09786

Jabir, A. I., Lin, X., Martinengo, L., Sharp, G., Theng, Y., & Car, L. T. (2023). Attrition in Conversational Agent–Delivered Mental Health Interventions: Systematic Review and Meta-Analysis. *Journal of Medical Internet Research*, *26*, e48168. https://doi.org/10.2196/48168

Jurado, Samuel & Villegas, Ma.E. & Méndez, L. & Rodríguez, F. & Loperena, V. & Varela, R.(1998). Standarization of Beck's depression inventory for Mexico City inhabitants. Salud Mental. 21. 26-31. Retrieved from https://www.researchgate.net/publication/279618211_Standarization_of_Beck's_depression_inventory_for_Mexico_City_inhabitants

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

Khan, Q., Hickie, I. B., Loblay, V., Ekambareshwar, M., Zahed, I. U. M., Naderbagi, A., Song, Y. J., & LaMonica, H. M. (2025). Psychometric evaluation of the System Usability Scale in the context of a childrearing app co-designed for low- and middle-income countries. *Digital Health*, *11*. https://doi.org/10.1177/20552076251335413

Koelen, J., Vonk, A., Klein, A., De Koning, L., Vonk, P., De Vet, S., & Wiers, R. (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

Krämer, R., Köhne-Volland, L., Schumacher, A., & Köhler, S. (2022). Efficacy of a Web-Based Intervention for Depressive Disorders: Three-Arm randomized controlled trial comparing guided and unguided Self-Help with Waitlist control. *JMIR Formative Research*, *6*(4), e34330. https://doi.org/10.2196/34330

Lemon, C., Huckvale, K., Carswell, K., & Torous, J. (2020). A narrative review of methods for applying user experience in the design and assessment of mental health smartphone interventions. *International Journal of Technology Assessment in Health Care*, *36*(1), 64–70. https://doi.org/10.1017/s0266462319003507

Lippke, S., Gao, L., Keller, F. M., Becker, P., & Dahmen, A. (2021). Adherence With Online Therapy vs Face-to-Face Therapy and With Online Therapy vs Care as Usual: Secondary Analysis of Two Randomized Controlled Trials. *Journal of Medical Internet Research*, *23*(11), e31274. https://doi.org/10.2196/31274

McLachlan, G., & Peel, D. (2000). Finite mixture models. In *Wiley series in probability and statistics*. https://doi.org/10.1002/0471721182

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

Mollayeva, T., Thurairajah, P., Burton, K., Mollayeva, S., Shapiro, C. M., & Colantonio, A. (2015). The Pittsburgh sleep quality index as a screening tool for sleep dysfunction in clinical and non-clinical samples: A systematic review and meta-analysis. *Sleep Medicine Reviews*, *25*, 52–73. https://doi.org/10.1016/j.smrv.2015.01.009

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo Simulation study. *Structural Equation Modeling a Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Pelucio, L., Quagliato L. A., Nardi A. E. (2024). Therapist-Guided versus Self-Guided Cognitive-Behavioral therapy: A Systematic review. *Psychiatrist.com*. https://www.psychiatrist.com/pcc/therapist-guided-versus-self-guided-cognitive-behavioral-therapy-systematic-review/

Price, M., Gros, D. F., McCauley, J. L., Gros, K. S., & Ruggiero, K. J. (2012). Nonuse and dropout attrition for a Web-Based mental health intervention delivered in a Post-Disaster context. *Psychiatry*, *75*(3), 267–284. https://doi.org/10.1521/psyc.2012.75.3.267

Prince, M. (2012). Epidemiology. In *Elsevier eBooks* (pp. 115–129). https://doi.org/10.1016/b978-0-7020-3397-1.00009-4

Reinwand, D. A., Crutzen, R., Elfeddali, I., Schneider, F., Schulz, D. N., Stanczyk, N. E., Tange, H., Voncken-Brewster, V., Walthouwer, M. J. L., Hoving, C., & De Vries, H. (2015). Impact of educational level on study attrition and evaluation of Web-Based Computer-Tailored interventions: results from seven randomized controlled trials. *Journal of Medical Internet Research*, *17*(10), e228. https://doi.org/10.2196/jmir.4941

Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, *6*(2), 461–464. http://www.jstor.org/stable/2958889

Serrano-Ripoll, M. J., Zamanillo-Campos, R., Fiol-DeRoque, M. A., Castro, A., & Ricci-Cabello, I. (2021). Impact of Smartphone App–Based Psychological Interventions for reducing depressive symptoms in people with Depression: systematic literature review and meta-analysis of randomized controlled trials. *JMIR Mhealth and Uhealth*, *10*(1), e29621. https://doi.org/10.2196/29621

Sevilla-Llewellyn-Jones, J., Santesteban-Echarri, O., Pryor, I., McGorry, P., & Alvarez-Jimenez, M. (2018). Web-Based Mindfulness Interventions for Mental Health Treatment: Systematic Review and Meta-Analysis. *JMIR Mental Health*, *5*(3), e10278. https://doi.org/10.2196/10278

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

Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. *Journal of Vocational Behavior*, *120*, 103445. https://doi.org/10.1016/j.jvb.2020.103445

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

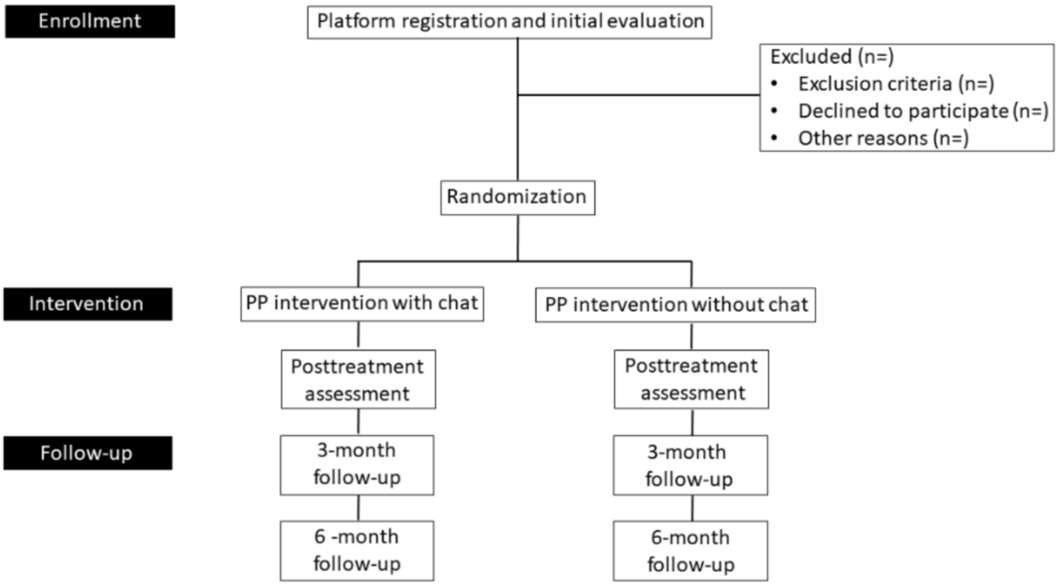
Vangrunderbeek, A., Raveel, A., Matheï, C., Claeys, H., Aertgeerts, B., & Bekkering, G. (2022). Effectiveness of guided and unguided online alcohol help: A real-life study. *Internet Interventions*, *28*, 100523. https://doi.org/10.1016/j.invent.2022.100523

White, V., Linardon, J., Stone, J. E., Holmes-Truscott, E., Olive, L., Mikocka-Walus, A., … Speight, J. (2022). Online psychological interventions to reduce symptoms of depression, anxiety, and general distress in those with chronic health conditions: a systematic review and meta-analysis of randomized controlled trials. *Psychological Medicine*, *52*(3), 548–573. doi:10.1017/S0033291720002251

Appendices

Appendix A

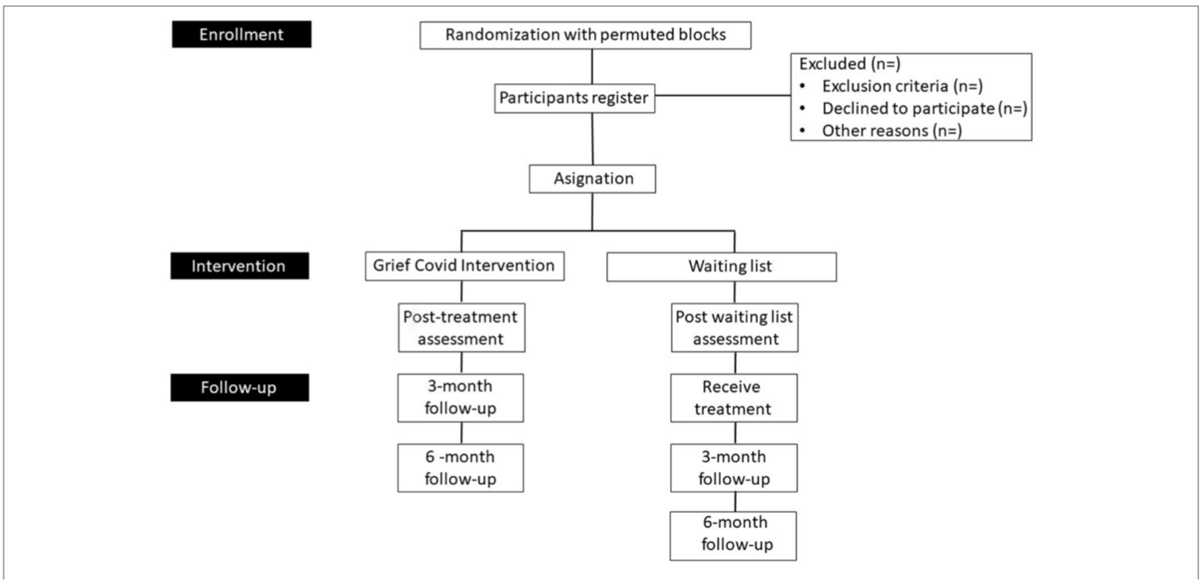
Flowchart of the Study Design for Mental Health COVID-19 Platform



Note. By Dominguez-Rodriguez et al. (2020), reprinted with permission.

Appendix B

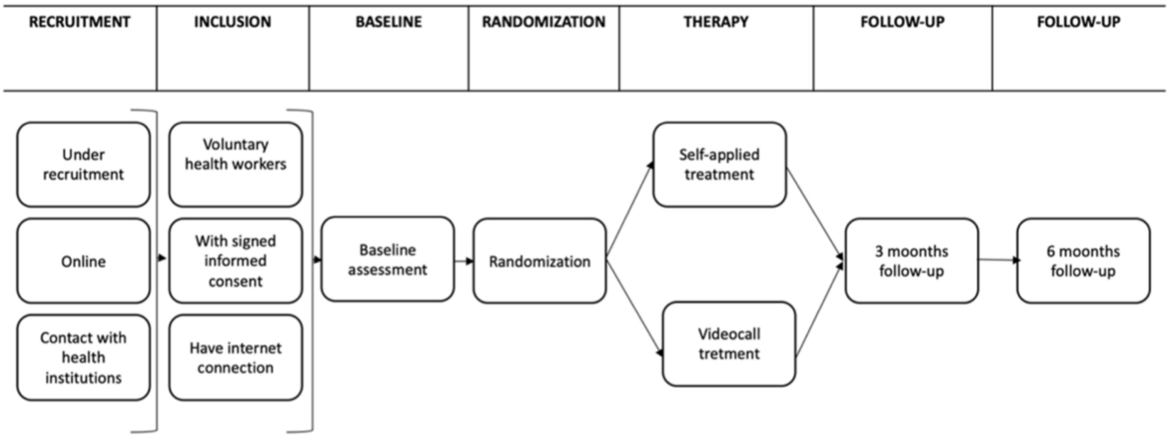
Flowchart of the Study Design for Grief-COVID Platform



Note. By Dominguez-Rodriguez et al. (2021), reprinted with permission.

Appendix C

Flowchart of the Study Design for Healthcare Workers COVID



Note. By Dominguez-Rodriguez et al. (2022), reprinted with permission.