Engagement in Digital Mental Health Intervention and its influence on the effectiveness of treatment outcomes

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Background: Engagement in digital mental health interventions can be an important factor when it comes to treatment outcomes and effectiveness of digital mental health interventions. However, due to various definitions of engagement in research and the complex nature of mental disorders, it can be hard to generalize the findings of current literature on other digital interventions. This research investigates to what extent engagement can predict treatment outcomes of individuals suffering from high burnout and stress. To continue, potential moderator variables and their effect on the relationship between engagement and treatment outcomes will be analyzed. **Aim:** This study investigates whether engagement in digital mental health interventions can predict the treatment outcome in individuals suffering from high stress and burnout and whether the relationship between engagement and treatment outcome is moderated by the variables of gender, age and treatment duration. **Methods:** For this quantitative study ($N = 4516$) individuals that participated in an unguided self-help module on the dutch eHealth platform "therapieland.nl" have been analyzed. Gender, age and treatment duration are captured by the platform itself after starting a module for burnout and high stress. The symptoms of high stress and burnout are captured by the dutch 4DKL questionnaire that utilizes four sub scales (Distress, Depression, Anxiety, Somatization) related to the complaints. Engagement was evaluated by the TWEETS questionnaire. The main analyses that answers the research questions utilize multiple regression analyses for the variable engagement and the four sub scales of Distress, Depression, Anxiety and Somatization at the end of the treatment, while also controlling for the beginning of the treatment. To continue, moderation analyses are used that investigate whether the variables of gender, age and treatment duration has a moderation effect on the relationship between engagement and treatment outcomes. **Results:** Engagement is able to significantly predict treatment outcomes in individuals suffering from burnout and high stress, with higher engagement leading to slightly better treatment outcomes in regards to all four sub scales. To continue, both gender and age have no moderation effect on the relationship between engagement and treatment outcomes. Only treatment duration has a moderating effect on the relationship between engagement and treatment outcomes for the sub scale Somatization, with a longer treatment duration minimally reducing the effectiveness of engagement on the treatment outcome of somatization. **Conclusion:** This study showed in accordance to previous literature, that engagement can predict treatment outcomes in a digital mental health intervention, while also generating new findings in regards to engagement being able to predict treatment outcomes for high stress and burnout. Moreover, only treatment duration seems to have a very minimal moderating effect on the relationship between engagement and treatment outcomes.

1. Background

1.1 The Rise of Mental Health Concerns

Worldwide, people are living with diverse mental health disorders, such as post-traumatic stress disorder, general anxiety disorders, and burnout. Over the years, the number of individuals living with mental health disorders has increased due to a variety of factors ("2020 was a record year", 2022). One potential factor is the psychological and social consequences of the COVID-19 pandemic. Due to government rules that required individuals to conduct social distancing and to rising insecurities about personal futures, the prevalence of mental health problems increased. To give an example, anxiety and depression disorders rose by 26% and 28%, respectively, one year after the beginning of the COVID-19 pandemic (WHO, 2022). Additionally, it has been estimated that 43% of people from over 100 countries in the year 2020 experienced burnout, compared to 38% in the year 2019 (Zeeburg, 2022). However, even before the start of the pandemic, the prevalence of mental health disorders was steadily rising. The total population that is suffering from mental health concerns rose from 924.44 million individuals in 2015 to 970.07 million individuals in 2019 (Dattani et al., 2021).

The consequences for individuals suffering from such disorders can present in a multitude of ways. For example, because of related physical conditions and problems that arise from these disorders, individuals affected by mental health disorders tend to die earlier than healthy individuals. Furthermore, the actual symptoms of the disorders are also issues that affect the individuals; for example, burnout can lead to exhaustion and depersonalization (Kowalski & Podlesny, 2000). Reduced professional efficacy, high cynicism, and a steady reduction of mental and physical resources are other factors that are prevalent in individuals who suffer from burnout (Ahola et al., 2014).

Due to the large and rising number of individuals with psychological problems, mental healthcare specialists, such as therapists, are reaching their maximum capacity in regards to patients and clients (Patel et al., 2020). As a consequence of long waiting times to receive adequate treatment, the symptoms and burdens of a disorder can increase over the duration of the wait. Moreover, due to limited financial and other resources, it can be hard to fulfill the increased demand for more mental and psychological treatment options. To respond to these concerns, digital mental health interventions have been utilized as scalable and cost-efficient solutions to the rising demand for more and better mental healthcare options. Through utilizing different digital platforms including websites and apps, interventions can be given to a wider population and with less therapist involvement (Hewitt et al., 2020). Moreover, digital interventions can be a viable and effective way to treat a variety of psychological problems with a high degree of quality (Murray et al., 2016).

1.2 Digital Mental Health Interventions and Engagement

Digital mental health interventions can be defined as psychological treatment that is delivered via electronic and digital components, including online treatment (Soobiah et al., 2020). Digital mental health interventions involve individuals interacting with digital content to advance therapeutical processes such as treatment, symptom reduction, and diagnosis in order to better handle aspects of their lives affected by mental disorders (Kowatsch et al., 2019). One example of a provider of digital mental health interventions is therapieland.nl, a website that offers psychological resources to clients and patients, while also giving tools to experts such as the ability to message their clients and to work with them through digital means such as assisted self-help modules. Digital mental health interventions can assist and advance existing healthcare services by providing tailored and accessible help (Murray et al., 2016). By identifying users' behavioural and psychological patterns, the system or an expert can adapt the content of an intervention according to the needs and preferences of the client (Ryan et al., 2019). In comparison to traditional face-to-face psychotherapy, digital mental health interventions have reduced costs and need fewer resources under the condition that care provider involvement stays low (Kambeitz-Ilankovic et al., 2022). When these digital interventions are distributed to a wide population, they can be applied to clients that are living too far away for physical treatment to be a feasible option (Kambeitz-Ilankovic et al., 2022).

While digital mental health interventions are more easily accessible than physical treatment, they can be modified and tailored to the personal needs and demands of clients in a similar manner to physical treatment (Center for Devices and Radiological Health, 2020). Digital mental health interventions have been proven to reduce client symptoms for some mental disorders, such as anxiety and depression (Hollis et al., 2017). There have been several meta-analyses that display the effectiveness of digital mental health interventions. A meta-analysis by Andersson et al. (2019) involved 29 Swedish studies with a total of 2866 participating individuals. Of these individuals, 65.6% were treatment responders and a third of these participants achieved remission, highlighting the effectiveness of digital mental health interventions. These interventions are most effective when they implement both individual tailoring and human support elements, such as messaging (Gan et al., 2022). Key to the success of the digital treatment process is the engagement of the target group with the corresponding digital mental health intervention (Gan et al., 2022).

Engagement has been hypothesized as being an important factor to a variety of treatment outcomes and effects. Previous research has shown that high user engagement can result in, for example, more physical activity in digital interventions that are aimed at promoting exercising (Edney et al., 2019). Moreover, engagement has been hypothesized to be related to the effectiveness of digital mental health interventions (Alkhaldi et al., 2017). A systematic review by Gan et al. (2021) has shown, that greater engagement with digital mental health intervention leads to a significant improvement in mental well-being in individuals suffering from different psychological disorders. As such, engagement could be seen as an indicator for a successful treatment outcome.

Engagement in the context of digital mental health interventions has been analysed in previous research in order to establish a definition and to gather an overview of the components that it entails. The term engagement has been viewed from different perspectives, and multiple explanations and definitions have been created. Fortuna et al. (2019) describe engagement as a process in which the psychosocial procedure that individuals undergo when working towards personal health combines cognitive, emotional, and behavioural aspects. Delaney et al. (2021) define engagement in terms of behaviour and usage: the duration, amount, and depth of usage when accessing digital mental health interventions and the perceived quality of maintaining interest and emotional effect. Similarly, but without the emotional component and from a more technical viewpoint, Chien et al. (2020) define engagement as whether an individual used a program and whether they used specific sections of the digital mental health intervention within a one-week timeframe. In addition to these definitions, some attempts have been made to capture and measure the construct of engagement in the form of a scale. For example, the user-engagement-scale (UES) is a 31-item questionnaire that attempts to measure engagement corresponding to digital media in a variety of settings such as education and information searches (O’Brien et al., 2018).

To summarize the view of the different view of the authors; While Fortuna et al. (2019) use human experience as the starting point for their definition, Chien et al. (2020) have a purely technical point that captures engagement as a statistic of whether certain sections have been accessed. A combination of both Fortuna et al. (2019) and Chien et al. (2020) can be seen in the definition of Delaney et al. (2021), where not only the data provided by usage, duration, and more is emphasized but also how they perceive the intervention.

For this study, a psychological combined with a slight technical meaning will be used to define engagement as this definition entails a variety of constructs that are definable and measurable. Since the dataset the study uses is built upon the TWente Engagement with eHealth Technologies Scale (TWEETS) by Kelders et al. (2020), the definition of Kelders et al. will be used here. Kelders et al. describe engagement in digital mental interventions as intensity of use and personal experience, and their definition includes components of attention, interest, and affect. The given definition has similarities to that of previous authors like Delaney et al. (2021), who use a more technical viewpoint that analyses data and usage, and Fortuna et al. (2019) who look more at behaviour and feelings. As such, the definition of Kelders et al. (2020) is able to both entail previous definitions and combine technological aspects with human components like cognition and emotions.

When it comes to influencing engagement in digital mental health interventions, there are a variety of components that can affect to what degree the user is interacting with the system and what quality the interaction experience has. Based on this, a systematic review by Borghouts et al. (2021) demonstrates that three components can alter user engagement. First, the characteristics of the user, such as personality, characteristics, and psychological well-being, are key factors that determine the amount of engagement a user has with a digital mental health intervention. In this context, the demographic components of age and gender are notable aspects for the concept of engagement. Due to their influence, these are factors that can be taken into account when designing and tailoring the content of an intervention to maximize effectiveness. Available research hypothesizes that being female is correlated with more engagement (Funk et al., 2010), and younger individuals are assumed to show less engagement with interventions (Geraghty et al., 2013). While current literature provides assumptions on the possible effects of demographics on engagement, the causes for these relationships have not yet been explained.

Second, the program and the digital intervention system itself in regards to content and how it is viewed by the user, as well as to what degree the program is able to establish social connections, are important variables to consider. In this context, including demonstration videos that show how to perform individual tasks and reminding users through aspects like notifications can help achieve and maintain high engagement (Escriva Boulley et al., 2018).

Third, both the system itself and the environment that it is used within are important for engagement. The way an intervention is implemented and how personal data and information is handled are some of the aspects that influence engagement in this context. Research has shown that including social support elements in the intervention can be an important predictor for high engagement (Escriva Boulley et al., 2018). It has also been found that a persuasive design, assistance from other individuals, and tailoring an intervention according to an individual user’s need and demands can be ways to ensure high engagement with a digital intervention (Yeager & Benight, 2018).

1.3 Significance of study

While engagement in digital mental health interventions is an important concept that has the potential to shape the way virtual mental healthcare can be delivered and tailored to the needs of clients, literature gaps as well as ambiguous research results are still prevalent and need to be addressed. As discussed in the previous section, there is a need for more research in the area of engagement and its relationship to outcomes. To continue, more research is needed to see whether user gender, age, and treatment duration can influence a possible relationship between engagement and a decrease in symptoms. As of now, no current studies exist that investigate gender and treatment duration as potential moderators for a relationship between engagement and treatment outcomes. Only age was investigated as a potential moderator variable in previous literature (Khan et al., 2022). In the study by Khan et al. (2022), it was analyzed whether the efficacy of engagement on tic disorders in children is moderated by the age of the participating children. Based on their results, age was not identified as a moderator variable for the relationship between engagement and an improvement in tic disorders in children (Khan et al.,2022). By investigating the possible influence of the variables gender, age and treatment duration, digital mental health interventions can make adjustments based on these factors depending on whether these variables have a positive or negative effect on the relationship between engagement and treatment outcomes. To give an example, if a longer treatment duration would negatively influence the effectiveness of engagement on treatment outcomes, adjustments to the length of the treatment could be made in order to ensure that engagement leads to significant reduction in symptoms. To continue, while it is widely assumed that a high degree of engagement can be an important factor for a successful digital mental health intervention, current literature still lacks further verification of this assumption. Overall, more research and verification is needed regarding what factors positively or negatively influence engagement in digital mental health interventions (Buckingham et al., 2019).

While other connections are also important, investigating whether engagement in digital mental health intervention can predict symptom reduction of participants suffering from high burnout and stress is one of the main focus of this study. Another focus of this study is to investigate whether the relationship between engagement and treatment outcome could be moderated by demographic (gender, age) and treatment-related (duration of treatment) variables. It is widely assumed that a high level of engagement may be a factor in successful digital mental health interventions as users who interact longer and more deeply with a system should be better able to achieve the goals that are prescribed in the digital mental health intervention (Delaney et al., 2021). By investigating to what extent engagement can predict the treatment outcome of patients with high stress and burnout and how this possible relationship is influenced by other variables, existing treatment can be adapted according to the findings. Through this investigation, the current literature gap in this area can be filled and a basis for future research (such as studying other target populations and mental disorders in the context of engagement) can be laid. Through determining to what degree engagement can predict treatment outcomes of digital mental health interventions aimed at individuals suffering from burnout and stress, the available resources for current and future development of digital mental health interventions can be distributed accordingly, resulting in more cost efficiency and less loss of resources.

1.4 Research questions

The following research question is proposed to address the above considerations: “To what extent can the level of engagement predict treatment outcomes in individuals suffering from high burnout and stress in regards to the symptom dimensions distress, depression, anxiety and somatization?” .The second, third and a fourth research sub-questions build upon this first research question and focus on demographic variables and treatment duration as potential moderators that influence the relationship between engagement and treatment outcomes. As such, the second research question is “To what extent is the relationship between level of engagement and treatment outcome of clients suffering from high stress and burnout moderated by age?” The third research question is “To what extent is the relationship between level of engagement and treatment outcome of clients suffering from high stress and burnout moderated by gender?” The fourth and final research question is “To what extent is the relationship between level of engagement and treatment outcome of clients suffering from high stress and burnout moderated by the treatment duration?”

In order to answer these research questions, real world data from the eHealth platform Therapieland will be utilized. As the real-world data contains a variety of datasets from different disorders, this study will focus on high stress and burnout.

2. Methods

2.1 Research design

This study utilized a quantitative design and was longitudinal in nature. Data from participants that used the therapieland.nl platform and participated in the Overspanning and Burnout (Stress and Burnout) module provided a real-world setting for this research. For this study, usage of the Overspanning & Burnout module on the Therapieland platform from the beginning of the treatment, till the completion of the module was taken as the basis for the dataset. These clients were seeking digital mental health services in the form of self-help modules with or without the help of a private therapist that would assist them in addition to the module. During the module, participants could fill out questionnaires about their symptoms that were then saved in a dataset if consent was given by the user.

2.2 Participants

Regarding recruitment, there have been a variety of ways on how participants are introduced to the Therapieland platform and the Overspanning and Burnout module, including ordinary methods such as Therapieland advertisements or finding the website through search engines or recommendations from friends and family. Some participants were also recommended the platform by their general practitioner or their therapist.

With an original sample of 45292 individuals, stricter inclusion and exclusion criteria were taken to later maximize the validity and reliability of the analyses. Only individuals who filled out their gender, age, and who filled out the corresponding engagement questionnaire were included. Only individuals who filled out at least the first and the last 4DKL questionnaire sufficiently and thus reported their symptoms both at the beginning and at the end of the treatment were included. Individuals with invalid data points (e.g., having an age of -481) were excluded from the dataset. Since this study focuses on burnout and stress, a minimum age of 18 was required to be included in this dataset, as this is the most common age when individuals work full- or part-time in a job. After having applied the inclusion and exclusion criteria, the original sample consisting of 45292 participants was reduced to a final dataset with 4516 participants. This also means that a group of 40776 participants was excluded.

2.3 Materials and Measures

2.3.1 Therapieland.nl and Demographics

The most important source used in this study was the digital mental health platform therapieland.nl. As previously mentioned, this website specializes in providing both clients and therapists with the necessary instruments to achieve their respective goals. As such, clients were able to choose from a variety of self-help modules and digital psycho-education that can be used either alone or in collaboration with their private therapist. For therapists, the website also provided a platform to work together and communicate with clients and to tailor modules according to the needs of their clients. During the treatment process, clients filled out demographic information about themselves such as age and gender.

2.3.2 Overspanning & Burnout module and 4DKL questionnaire

To continue, since the topic of burnout and stress was investigated, the "Overspanning & Burnout" module was used. This module consists of four session that contain lessons and psychoeducation about burnout and stress. In order to capture the degree to which the symptoms of high stress and burnout are present before and after treatment, the Dutch 4DKL questionnaire by Terluin et al. (2008) was used to obtain variables. The 4DKL questionnaire consists of 50 items and four subscales that ask about symptoms that have occurred in the past seven days (Terluin et al., 2008). The dimensions of depression, distress, anxiety, and somatization are the main constructs of this questionnaire. In the study of Terluin et al. (2006), it has been shown that the symptoms of individuals that suffer from high stress and burnout can be categorized into four distinctive dimension. The first dimension distress describes the degree of cognitive and physical problems that can interfere with the daily functioning of the individuals. Secondly, the dimension of depression contains gloomy and pessimistic thinking patterns, as well as the temporary inability to experience pleasure (Koutsimani et al., 2019). To continue, the anxiety component includes concerns and emotions of dread, while the final component of somatization describes the physical problems caused by psychological issues as well as increased awareness of ones own body and sensations (Terluin et al., 2006).

The dimension of Distress is measured by 16 items on a 5-Point Likert Scale, ranging from 0 ("No") to 4 ("Very often or constantly"). The score range for this dimension is 0-32. Individuals with scores between 0 and 10 are defined as having a "low" level of distress. To continue, scores between 11 and 20 mean that an individual has a "moderately elevated" level of distress. Moreover, an individual scoring between 21 and 32 has a "greatly increased" level of distress. An example item for this dimension is: "During the past week, did you feel tense?". The corresponding Cronbachs Alpha for this sub scale is 0.94.

To continue, the dimension of Depression is measured by 6 items on a 5-Point Likert Scale, ranging from 0 ("No") to 4 ("Very often or constantly"). Here, the score range is 0-12. Individuals scoring between 0 and 2 are defined as having a "low" level of depression. Furthermore, scores between 3 and 5 mean, that an individual has a "moderately elevated" level of depression. Furthermore, an individual scoring between 6 and 12 has a "greatly increased" level of depression. One example item for this dimension is: "During the past week, did you feel that you cant enjoy anything anymore?". The Cronbachs Alpha for this sub scale is 0.94.

The next dimension Anxiety is measured by 12 items on a 5-Point Likert Scale, ranging from 0 ("No") to 4 ("Very often or constantly"). The score range is 0-24. Scores between 0 and 3 mean, that an individual shows a "low" level of anxiety. To continue, individuals scoring between 4 and 9 are defined as having a "moderately elevated" level of anxiety. Moreover, scores between 10 and 24 mean, that an individual shows a "greatly increased" level of anxiety. An example item for this dimension is: "During the past week, were you afraid to travel on busses, trains or trams?". The corresponding Cronbachs Alpha for this sub scale is 0.88.

The last dimension Somatization is measured by 16 items on a 5-Point Likert Scale, ranging from 0 ("No") to 4 ("Very often or constantly"). The score range for this dimension is 0-32. Individuals scoring between 0 and 10 are defined as having "low" levels of somatization. Furthermore, an individual scoring between 11 and 20 has a "moderately elevated" level of somatization. To continue, scores between 21 and 32 mean, that an individual has a "greatly increased" level of somatization. An example item for this dimension is: "During the past week, did you suffer from palpitations?". The Cronbachs Alpha for this sub scale is 0.84.

Regarding the 4DKL questionnaire and its four sub scales, it is important to mention that while a 5-point Likert scale for each symptom dimension is used, the scoring process is different than usual. For the 5-point Likert scales of the symptom dimensions, answers could be given with “no”, “sometimes”, “regularly”, “often” or “very often or constantly”. To calculate the sum score of the corresponding sub scale, answers of “no” were coded as 0 and answers of “sometimes” as 1. All other answer categories were coded as 2 as instructed by the questionnaire. To continue, in order to calculate the difference score for the sub scales, the scores of timepoint T0 need to be subtracted from the timepoint T1. A summary of the four symptom dimensions in regards to score range, example question, number of items and cronbachs alpha can be found in Table 1.

Table 1.

Dutch 4DKL Questionnaire by Terluin et al. (2008)

Sub scale and Score Range	Distress (Score Range 0-32)	Depression (Score Range 0-12)	Anxiety (Score Range 0-24)	Somatization (Score Range 0-32)
Example Question	„During the past week, did you feel tense?„	„ During the past week, did you feel that you cant enjoy anything anymore? "	„During the past week, were you afraid to travel on busses, trains or trams?“	„During the past week, did you suf-fer from palpitati-ons?„
Number of items	16	6	12	16
Cronbachs Alpha	0.94	0.94	0.88	0.84

2.3.3 Treatment duration

The 4DKL questionnaire in the "Overspanning & Burnout" was first administered at the first session near the end. After the client has filled out and submitted the questionnaire, the tracking of the treatment duration started (timepoint also known as T0, beginning of treatment). To continue, when the client has filled out and submitted the 4DKL questionnaire for the third and last time at the end of the fourth session, the tracking of the treatment duration stopped (timepoint also known as T1, end of treatment) and the overall treatment duration can be calculated by investigating the timespan between the first and the third (last) submit of the 4DKL questionnaire. Based on this, the beginning and end point of the treatment can differ between participants depending on how fast they work through the "Overspanning & Burnout" module.

2.3.4 Engagement score as measured by the TWEETS questionnaire

To continue, the general engagement score was used. This measure indicates the amount of engagement the participant displayed while interacting with the digital mental health intervention by utilizing the TWEETS questionnaire from Kelders et al. (2020). This survey consists of nine items and three sub scales, namely behavioral engagement, cognitive engagement and affective engagement and asks questions from a 5-point Likert Scale ranging from 0 (Strongly disagree) to 4 (Strongly agree). Individuals with an overall engagement score between 0 and 12 were defined as low engaged, while those that had an overall engagement score between 13 and 22 were described as moderately engaged. To continue, individuals that scored between 23 and 36 were defined as high engaged. Each sub scale has three items. To calculate engagement, only the full scale will be used. The score range for the overall engagement score is 0-36. The Cronbachs Alpha value of the TWEETS questionnaire is .86 (Kelders et al., 2020). Table 2 displays an example question for the corresponding sub scale.

Table 2.

Example Questions from the TWEETS Engagement Questionnaire by Kelders et al. (2020)

	Behavioural Engagement	Cognitive Engagement	Affective Engagement
Example Question	“In thinking about using [this technology] in the past week, I feel that [this technology] is part of my daily routine.”	“Thinking about using [this technology] in the past week, I feel that [this technology] makes it easier for me to work on [my goal].”	“Thinking about using [this technology] in the past week, I feel that I enjoy seeing the progress I make in [this technology].”

2.4 Intervention

The eHealth platform "therapieland.nl" provides unguided self-help modules for a variety of mental disorders such as worrying, ADHD and the focus of this study, high stress and burnout ("Overspanning & Burnout" in dutch). The majority of these modules are in dutch, while some translations in English exist for some modules. Besides modules for mental issues, modules aimed at increasing resilience and improving well-being are also available.

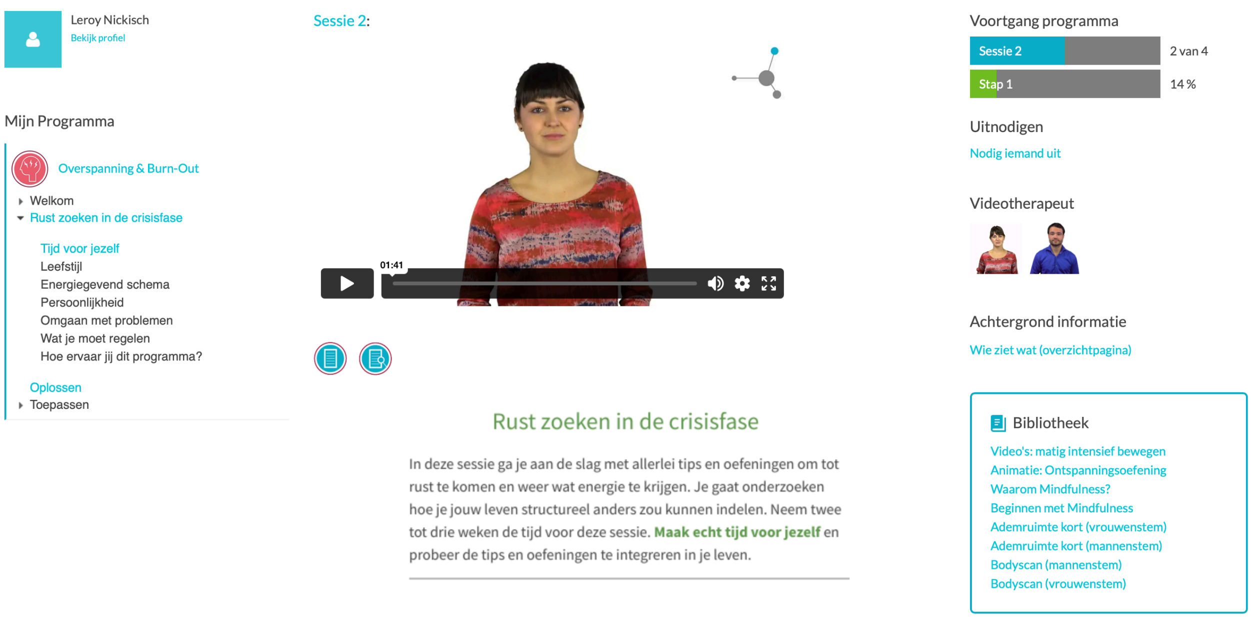
Within the Overspanning & Burnout module, clients received psychoeducation about their problems according to the three phases of a crisis. The three phases of a crisis concept, as described by Therapieland, helps provide a systematic approach to the Overspanning & Burnout module and to the problems of a client. In the context of high stress and burnout, the first phase is about the individual and how they experience an overload of stress. Next, the solution phase is about finding the cause and the correct interventions. The final phase explains how to apply the found solutions within the daily life of the client and how to prevent relapse by providing a corresponding plan. In addition to these concepts, clients learned different techniques for how to deal with relevant problems, such as getting social help or expressing emotions. This concept is also embedded in the structure of the module.

The Overspanning & Burnout module consists of four sessions that contain several sublessions. The first session starts with an introduction to the platform Therapieland and the module itself, while also giving an introduction about the symptoms of burnout and high stress. In the second phase, the module gives concrete advice and techniques on how to reduce the experienced stress, while also asking how the general experience with the program is in regards to engagement. The third session is about finding the causes for the complaints of the client and investigating what factors contribute to the symptomatic. The fourth and last session contains information about relapse prevention and how to proceed after the module is finished.

The client can access all content, video education, and slides at any given time. Therefore, a client who needs help with relapse prevention could directly access the corresponding section without going through the introduction and other prior content. To continue, the "Overspanning & Burnout" module is a self-guided module and as such, the client works without the assistance of a psychotherapist on their problems. However, clients can still privately seek a psychotherapist during working on the module if the client wants to do so. The module works mostly through explanatory videos that teach users how to apply their newfound knowledge. The user can change the gender of the videotherapist that explains the content within the videos. Graphics, a diary option, and text boxes where the client can write their personal experiences and answers are utilized. Additionally, a sidebar displays a box with links that serve as a library for relevant knowledge and to rehearse previous knowledge. Figure 1 is an image of the interface of the website for the Overspanning and Burnout module in Dutch.

Figure 1

Introduction to the module Overspanning and Burnout.



Notes. The image shows the introduction to the module after the client has filled out the 4DKL-questionnaire for the first time. The library sidebar ("Bibliotheek") is on the bottom right. The pictures on the right can be used to change the appearance of the therapist. On the top right, the progress and the number of sessions are displayed. Below the video, a summary text can be found that gives more information. The left side shows the profile of the user and below that, the menu to access the different sessions can be found.

2.4 Procedure

After the client made an account and signed up on therapieland.nl, they can choose from a variety of self-help modules. When the client opens the "Overspanning & Burnout" module, the client will see an overview about the module and the corresponding content. The first session explains how the e-Health platform therapieland.nl works, how to change technical settings and what kind of symptoms there are. At the end of the first session, the client was also asked to fill out the 4DKL questionnaire for the first time, indicating the beginning of the treatment for this study. The second phase continued with psychoeducation about how to relax and to calm down during a troubling time, as well as how to make a structure for ones everyday-life. Here, the client also learned about the role of the stress hormone cortisol and how the personality of a person can determine how they might behave. During the end of the second session, the client was asked to fill out the engagement questionnaire, also known as TWEETS (Twente Engagement with eHealth Technologies Scale) At the start of the third session, the client was asked to fill out the 4DKL questionnaire for the second time to see, whether there is an improvement in the mental-wellbeing of the client. The third session then continued with introspection and identifying the causes for the burnout or the constant stress. The fourth and last session was about finding ways to prevent relapse. At the end of the fourth session, the client was asked to fill out the 4DKL questionnaire a last time, indicating the end of the treatment process.

2.5 Statistical analyses

For the quantitative analyses, SPSS Version 25 was used and the significance level was set to $p < .05$ for all statistical tests. All tests were two-tailed.

The assumption of normality was checked by performing a Kolmogorov-Smirnoff test. The assumption of equal variance (homoscedasticity) was checked by investigating the scatterplots of the corresponding groups. Next, since the data of the groups was independently collected from the population, the assumption of independence was checked. For the last assumption, the absence of outliers, the corresponding box-plots were investigated.

The assumption of absence of outliers and the assumption of equal variance were not violated. However, all variables had skewness and kurtosis values under 2, except the variable treatment duration (skewness = 11.23, SD = 0.04 and kurtosis = 176.52, SD = 0.07) and the T1 depression score (skewness*s* = 1.76, SD = 0.04 and kurtosis = 2.70, SD = 0.07). For all variables, the Kolmogorov-Smirnoff test was significant at $p < .05$. The histograms were skewed left for T0 anxiety, T0 depression, T1 anxiety, T1 depression, T1 somatization, and treatment duration, and skewed right for T0 distress. Based on these results, non-parametric tests were used.

For the later regression analyses, the assumption of a linear relationship was investigated by scatterplots, while the assumption of independence of residuals was checked by the Durbin-Watson statistic. All Durbin-Watson values were above 1.5. and as such, independence of residuals was observed. To continue, no multicollinearity was found by the means of the VIF values. Homoscedasticity was observed by plotting the studentized residuals against the unstandardized predicted values.

Before starting with the main analyses, some preparatory analyses have been done. The statistical analyses started by investigating the descriptives first in order to describe the characteristics of the included participants. After that, the included participants (final dataset) were compared with the group of participants excluded due to the inclusion and exclusion criteria by utilizing Mann-Whitney U tests. This was in order to investigate, whether these two samples differed statistically from one another in terms of the four symptom dimensions (both T0 and T1), age, treatment duration and engagement score. By doing this, it can be seen whether precautions against a potential bias needs to be taken. Followed by that, Wilcoxon Signed Ranked tests between baseline and post-intervention have been utilized to see, whether the intervention Therapieland had a significant effect on the symptoms of the client. To continue, a spearman correlation analysis was used as a requirement for the later regression analyses, as well as to investigate whether there is a correlation between engagement and the baseline scores of the four sub scales. Followed by that, it was investigated whether a correlation between engagement and the difference scores exists to see, whether individuals with a high engagement would also show a high symptom reduction. Here, the difference score was used as for the spearman correlation analysis, it can be a slightly more accurate variable for treatment outcome. Moreover, as a basis for the later regression and moderation analyses, a Mann-Whitney U test between engagement score and gender, as well as spearman correlational analyses between engagement and age and treatment duration have been conducted.

After the preparatory analyses, the main analyses will start. In order to answer the research question: “To what extent can the level of engagement predict treatment outcomes in individuals suffering from high burnout and stress in regards to the symptom dimensions distress, depression, anxiety and somatization?”, four multiple regression analyses have been done with the "Stepwise" method. Here, the first step included the T0 sub scale as the independent variable and the T1 sub scale as the dependent variable. In the second step, engagement was added as the second independent variable in order to investigate the change in the adjusted explained variance by engagement. To continue, in order to answer the second to fourth research question regarding to what extent the relationship between level of engagement and treatment outcome of clients suffering from high stress and burnout is moderated by either age, gender or treatment duration, several moderation analyses have been done. Here, the SPSS application "PROCESS" Version 4.2 by Andrew F. Hayes will be used (2022). As such, the engagement score was used as the independent variable and the T1 sub scale as the dependent variable. Gender, age and treatment duration are the moderator variables in this part of the analyses. To control for the beginning of the treatment, T0 sub scales were used as a covariate.

3. Results

3.1 Preparatory analyses

3.1.1 Descriptive Statistics

The final dataset had a sample of 4516 participants. Of these participants, 61.7 % were female (2785) and 38.3 % were male (1731). The average age of participants was 43.6 years (N = 4516, SD = 11.83). The mean score for the engagement variable was 22.0 (N = 4516, SD = 4.35), indicating that the average participant was moderately engaged. For the baseline T0 values, distress had the highest score, followed by somatization, anxiety, and then depression. The same order was apparent in T1. The participants in the final dataset showed a high level of distress, and a moderate level of depression, anxiety and somatization based on the means at the beginning of treatment. To continue, the final dataset showed a moderate level of distress, anxiety, somatization and a low level of depression at the end of the treatment based on the means. The mean treatment duration was 47.82 days (N = 4516, SD = 87.45). Table 3 displays the descriptive statistics of mean scores, standard deviations, minimum scores, and maximum scores for age, engagement and the individual sub scales at the timepoints T0 (beginning of the treatment) and T1 (end of treatment), as well as the corresponding difference score.

Table 3

Descriptive Statistics for the variables for the final dataset (N= 4516)

Variable	Mean	Standard Deviation	Minimum Score in the Sample	Maximum Score in the Sample
Age	43.57	11.83	18	76
Engagement Score	21.97	4.35	4	36
Distress Score (T0)	22.88	6.63	0	32
Distress Score (T1)	15.72	8.20	0	32
Difference Score Distress	7.16	6.87	-15	31
Depression Score (T0)	3.66	3.21	0	12
Depression Score (T1)	1.93	2.71	0	12
Difference Score Depression	1.74	2.52	-10	12
Anxiety Score (T0)	7.11	5.46	0	12
Anxiety Score (T1)	4.34	4.84	0	24
Difference Score Anxiety	2.77	3.91	-14	22
Somatization Score (T0)	15.14	6.92	0	32
Somatization Score (T1)	10.52	6.74	0	32
Difference Score Somatization	4.62	5.50	-14	28

Notes. The score range for engagement is 0–36. The score range for T0/T1 distress is 0–32. The score range for T0/T1 depression is 0–12. The score range for T0/T1 anxiety is 0–24. The score range for T0/T1 somatization is 0–32. Difference Score calculated by T0 - T1.

3.1.2 Differences between the group of excluded participants and final dataset

It is also important to examine the group of participants that have been deleted from the final dataset due to the exclusion and inclusion criteria. By doing this, it can be seen whether the excluded participants (*N* = 40776) and the final dataset (*N* = 4516) have statistically different data and characteristics and whether precautions against potential bias needs to be taken. As such, several Mann-Whitney U Tests were conducted comparing the final dataset and the group of excluded participants in terms of engagement, age, treatment duration, T0 subscales, and T1 subscales. Based on the results, it can be seen that the final dataset shows a significant higher score for engagement compared to the group of excluded participants. To continue, the final dataset shows a significant lower score in treatment duration and all symptom dimensions for both T0 and T1. The only variable where both groups show no significant difference is the age variable. The results are displayed in Table 4.

Table 4

Mann-Whitney U tests between the group of excluded participants (N = 40776) and the final data-set (N = 4516)

Variable	Mean Final Dataset	Mean Group of excluded participants	Significance (*p*)	Z-Statistic (*Z*)	Effect Size
Age	43.57	43.28	.11	-1.58	< -.01
Treatment Duration	47.82	47.94	< .01	-3.17	- .02
Engagement Score	21.97	21.55	< .01	-8.93	-.01
Distress Score (T0)	22.88	23.03	< .01	-2.64	- .01
Depression Score (T0)	3.66	3.81	.03	-2.12	- .01
Anxiety Score (T0)	7.11	7.52	< .01	-3.82	- .02
Somatization Score (T0)	15.14	15.76	< .01	-6.01	- .03
Distress Score (T1)	15.72	16.42	< .01	-6.64	- .05
Depression Score (T1)	1.93	2.10	< .01	-4.24	- .03
Anxiety Scores (T1)	4.34	4.74	< .01	-5.39	- .04
Somatization Scores (T1)	10.52	11.11	< .01	-5.81	- .05

Note. Effect size was calculated according to Rosenthal et al. (1994).

As some of the excluded participants did not fill out all necessary information, the total number of individuals (*N*) per variable varies. The mean age for the group of excluded participants was 43.53 years (*N* = 33312, *SD* = 11.89). To continue, 58.4 % were female (26384), 35.4 % were male (16010), and 6.1 % did not state their genders (2774). When it comes to the four subscales in the context of the baseline outcomes, distress was the highest, followed by somatization, then anxiety, and lastly depression. The same order also applied to treatment outcome T1. To continue, the group of excluded participants showed a greatly elevated level of distress and a moderate level of depression, anxiety and somatization for the beginning of the treatment according to the mean scores. Moreover, the group of excluded participants showed a moderate level of distress, depression, anxiety and somatization at the end of the treatment based on the mean scores. The average duration for using the module was 48 days (N = 16678, SD = 89.13). The mean engagement score for the group of excluded participants was 21.55 (N = 7626, SD = 4.52), indicating that the average excluded participant was moderately engaged.

3.1.3 Difference between baseline and post-intervention

All following analyses have been done with the final dataset (N = 4516). Wilcoxon signed-rank tests were performed to investigate potential differences between baseline and post-intervention scores, as well as to indicate the effect size r based on Rosenthal et al. (1994). Overall, the results show that participants improved significantly on the symptoms of distress (Z = -50.79, p = < .05, r = -.78), depression (Z = -40.36, p = < .05, r = -.62), anxiety (Z = -41.53, p = < .05, r = -.64), and somatization (Z = -45.56, p = < .05, r = -.70).

3.1.4 Spearman correlation analyses of engagement and T0 subscales

Whether engagement was correlated with the subscales of the baseline outcome (timepoint T0) was analyzed next. The results indicate that engagement is negatively correlated with distress (r = -.09, p = < .01, N = 4516), depression (r = -.11, p = < .01, N = 4516), anxiety (r = -.04, p = .01, N = 4516), and somatization (r = -.06, p = < .01, N = 4516). Table 5 displays the data of the correlation analyses.

Table 5

Relationship between engagement and the subscales of baseline outcome T0 (N = 4516)

Engagement and …	Degree of Correlation (*r*)	Significance Level (*p*)
Distress (T0)	- .09	< .01
Depression (T0)	- .11	< .01
Anxiety (T0)	- .04	.01
Somatization (T0)	- .06	< .01

3.1.5 Spearman correlation analyses of engagement and difference scores (T0–T1)

Whether the engagement score and the difference scores were correlated was investigated next. After conducting the spearman correlation analysis, it was apparent that all the difference scores are weakly correlated with the engagement scores of the participants. As such, engagement is positively correlated with the distress difference score ($r = .20$, $p = < .01$, $N = 4516$), the depression difference score ($r = .07$, $p = < .01$, $N = 4516$), the anxiety difference score ($r = .11$, $p = < .01$, $N = 4516$), and the somatization difference score ($r = .15$, $p = < .01$, $N = 4516$).

3.1.6 Mann-Whitney U Test for engagement and gender

To investigate whether one gender shows more engagement than the other and as a requirement for the later moderation analysis, a Mann-Whitney U test was applied. The engagement score is not statistically different for either male or female individuals ($N = 4516$, $Z = -0.69$, $p = .49$, $r = -.01$, $p = .50$).

3.1.7 Spearman correlation analyses of age and treatment duration

As a basis for the later moderation analyses, some additional spearman correlation analyses were computed to investigate whether there is a correlation between engagement, age, and treatment duration. A significant correlation was found between engagement and participant age ($r = .06$, $p = < .01$, $N = 4516$). A significant correlation between engagement and treatment duration was also found ($r = .07$, $p = < .01$, $N = 4516$).

3.2 Main analyses

3.2.1 Multiple regression analysis for engagement and T1 (First research question)

In order to answer the first research question: To what extent can the level of engagement predict treatment outcomes in individuals suffering from high burnout and stress in regards to the symptom dimensions distress, depression, anxiety and somatization?", multiple regression analyses have been conducted.

The first step of the first model included the distress score at the end of treatment (T1) as the dependent variable and the distress score at the beginning (T0) as the independent variable: F (1, 4514) = 2404, p = < .01, adj. R2 = .35. In the second step, engagement was added as the second independent variable. The last step of the regression model significantly predicted distress at the end of treatment (T1): F (2, 4513) = 1403 , p = < .01, adj. R2 = .38. Both T0 distress (B = 0.71, SD = .02, Beta = .57, T = 48.91, p = < .01) and engagement (B = -0.358, SD = .02, $Beta$ = -0.19, T = -16.19, p = < .01) were significant predictors for the last step of this model. Table 6 displays the results of this regression analysis for distress.

Table 6

Significant predictors and coefficients for the regression model Distress (N = 4513)

	Regression Coefficient (*B*)	Standardized Coefficient (*Beta*)	Standard Error (*SD B*)	Significance (*p*)
Step 1				
Constant	-.959	-	.354	< .01
Distress (T0)	.729	.590	.015	< .01
Step 2				
Constant	7.351	-	.618	< .01
Distress (T0)	.709	.574	.015	< .01
Engagement	-.358	-.190	.022	< .01

Notes. Adj. R2 = .347 for step 1 (p = < .01); Δ Adj. R2 = .036 for step 2 (p = < .01).

The first step of the second model included the depression score at the end of treatment (T1) as the dependent variable and the depression score in the beginning (T0) as the independent variable: *F* (1, 4514) = 3302, *p* = < .05, adj. R2 = .42 . In the second step, engagement was added as the second independent variable. The last step of the regression model significantly predicted a depressive symptom at the end of the treatment (T1): *F* (2, 4513) = 1768 , *p* = < .01, adj. R2 = .44. Both T0 depression (*B* = 0.54, *SD* = .01, *Beta* = 0.64, *T* = 56.96, *p* = < .01) and engagement (*B* = -0.08, *SD* = .01, *Beta* = -0.13, *T* = -11.63, *p* = < .01) were significant predictors for the last step of this model. Table 7 displays the results of the regression analysis for depression.

Table 7

Significant predictors and coefficients for the regression model Depression (N = 4513)

	Regression Coefficient (*B*)	Standardized Coefficient (*Beta*)	Standard Error (*SD B*)	Significance (*p*)
Step 1				
Constant	-.084	-	.047	.072
Depression (T0)	.549	.650	.010	< .01
Step 2				
Constant	1.737	-	.163	< .01
Depression (T0)	.539	.638	.009	< .01
Engagement	-.081	-.130	.007	< .01

Notes. Adj. R2 = .422 for step 1 (p = < .01); Δ Adj. R2 = .017 for step 2 (p = < .01).

The first step of the third regression model used the anxiety score at the end of treatment (T1) as the dependent variable and the anxiety score at the beginning of the treatment (T0) as the independent variable: *F* (1, 4514) = 4813, *p* = < .01, adj. R2 = .52. In the second step, engagement was added as the second independent variable. Here, the regression model significantly predicted anxiety scores at the end of the treatment (T1): *F* (2, 4513) = 2516 , *p* = < .01, adj. R2 = .53. Both T0 anxiety (*B* = 0.63, *SD* = .01, *Beta* = 0.71, *T* = 69.59, *p* = < .05) and engagement (*B* = -0.12, *SD* = .01, *Beta* = -0.11, *T* = -10.35, *p* = < .01) were significant predictors for the last step of this model. Table 8 displays the results of the regression analysis for anxiety.

Table 8

Significant predictors and coefficients for the regression model Anxiety (N = 4513)

	Regression Coefficient (*B*)	Standardized Coefficient (*Beta*)	Standard Error (*SD B*)	Significance (*p*)
Step 1				
Constant	-.183	-	.082	.026
Anxiety (T0)	.637	.718	.009	< .01
Step 2				
Constant	2.442	-	.266	< .01
Anxiety (T0)	.632	.713	.009	< .01
Engagement	-.118	-.106	.011	< .01

Notes. Adj. R2 = .516 for step 1 (p = < .01); Δ Adj. R2 = .011 for step 2 (p = < .01).

Finally, the first step of the fourth model used the somatization score at the end of treatment (T1) as the dependent variable and the somatization score at the beginning of treatment (T0) as the independent variable: F (1, 4514) = 3811, p = < .01, adj. R2 = .46. For the second step, engagement was added as the second independent variable. This model significantly predicted the somatization scores at the end of treatment (T1): F (2, 4513) = 2072 , p = < .01, adj. R2 = .48. Both T0 somatization (B = 0.65, SD = .01, $Beta$ = 0.67, T = 62.10, p = < .01) and engagement (B = -0.23, SD = .02, $Beta$ = -0.15, T = -13.47, p = < .01) were significant predictors for the final step of this model. Table 9 displays the results of the regression analysis for somatization.

Table 9

Significant predictors and coefficients for the regression model Somatization (N = 4513)

	Regression Coefficient (*B*)	Standardized Coefficient (*Beta*)	Standard Error (*SD B*)	Significance (*p*)
Step 1				
Constant	.533	-	.178	< .01
Somatization (T0)	.659	.677	.011	< .01
Step 2				
Constant	5.588	-	.414	< .01
Somatization (T0)	.652	.668	.010	< .01
Engagement	-.225	-.145	.017	< .01

Notes. Adj. R2 = .458 for step 1 (p = < .01); Δ Adj. R2 = .021 for step 2 (p = < .01).

3.2.2 Moderation analyses (Second to fourth research questions)

To continue, moderation analyses were conducted next in order to investigate the second to fourth research questions on whether gender, age and treatment duration have a moderating effect on the relationship between engagement and treatment outcome on individuals suffering from burnout and depression. These analyses investigated whether the relationship between the engagement score and the four subscales at the end of treatment (T1) was influenced by participant age and treatment duration, while also controlling for the corresponding baseline outcome T0.

As no statistical difference was found after conducting the Mann-Whitney U test for gender, no moderation analysis was done for a potential interaction between engagement and gender.

The interaction term of engagement and age was not significant for distress (B = -.0018, 95% CI [-.0053, .0018], t (4516) = -0.98, p = .33), depression (B = .0006, 95% CI [-.0005, .0017], t (4516) = 1.07, p = .28), anxiety (B = -.0005, 95% CI [-.0024, .0013], t (4516) = -0.54, p = .59), or somatization (B = .0007, 95% CI [-.0020, .0034], t (4516) = 0.51, p = .61), meaning that the relationship between engagement and treatment outcomes is not moderated by age for any of the four symptom dimensions.

The interaction term of engagement and treatment duration was not significant for distress (B = -.0004, 95% CI [-.0007, .0000], t (4516) = -1.90, p = .06), depression (B = 0000, 95% CI [-.0002, .0001], t (4516) = -.75, p = .45), or anxiety (B = .0000, 95% CI [-.0002, .0002], t (4516) = -0.12, p = .93). However, the interaction term of engagement and treatment duration was significant for somatization (B = -.0004, 95% CI [-.0007, -.0001], t (4516) = -2.92, p = < .05). This means that a longer treatment duration can reduce the effect of engagement on the symptom dimension somatization for individuals suffering from burnout and high stress.

4. Discussion

4.1 Findings of the preparatory analyses

4.1.1 Influence of therapieland.nl on the symptoms of the client

Before discussing and answering the research questions, it is important to have a look at the results of the preparatory analyses that were needed in order to gather more information from the final dataset and to conduct the later regression and moderation analyses. As such, it was first investigated whether the digital mental health intervention Therapieland had an influence on the symptoms of the participants. Here, it can be seen that there is a significant reduction of the symptoms for all four sub scales (Distress, Depression, Anxiety, Somatization) when comparing the beginning of the treatment with the end of the treatment.

These findings are congruent with that of other research projects. To give an example, a study of Bull-Beddows (2020) has shown, that a digital self-help application (named "Headspace") for smartphones was capable of significantly reducing burnout in teachers. Here, the participants in this study used the intervention for 2 months. To continue, the participants were mostly female and only teachers from Wales and England were participating in this research. Burnout was measured by the Maslach Burnout Inventory - Educator Survey, a questionnaire that uses emotional exhaustion, depersonalization and personal accomplishment as its main scales. The self-help application has different features such as psychoeducation, unguided meditation sessions and general tips on how to improve their mental health with mindfulness. The study by Bull-Beddows (2020) has similarities to that of the current study. As such, both studies investigated symptom reduction on burnout. To continue, both interventions are based on the concept of self-help and demonstrate, that digital mental health interventions have the potential to reduce burnout and high stress in individuals.

4.1.2 Discussing the results of the correlational analyses in regards to difference scores

To continue, a set of correlational analyses have been done in preparation for the later regression and moderation analyses. First, engagement was positively correlated with the difference scores of the four sub scales. However, these correlations range from negligible (e.g., depression sub scale with r = .07) to weak (e.g. distress sub scale with r = .20).

Literature has shown similar results to that of the current study. The study of Ring et al., (2015) has investigated whether engagement with a conversational agent (i.e., a chatbot) is correlated with a reduction in loneliness for older individuals. Engagement in the study of Ring et al., (2015) was defined as the time spent with the conversational agent and as such, a more technical definition of engagement was used there. The sample in this study consisted mostly of older individuals over the age of 55 years that displayed sub-clinical complaints of loneliness and depression. The results of the study display, that engagement with the conversational agent was highly positively correlated with a reduction in loneliness (r = .70, p = < .05). However, since the study of Ring et al. (2015) investigated a different mental complaint and used a different definition of engagement than that of the current study, the comparison of these two studies needs to be taken cautiously.

4.1.3 Correlation of engagement and age and treatment duration

Starting with engagement and age, the results of this study show, that there is a positive correlation between engagement and the age of the participant, although this correlation is almost non-existent (r = .06, p = < .01). In a similar way, there exists a very weak positive correlation between engagement and treatment duration (r = .07, p = < .01).

When it comes to age, research project exists that display similar results to that of the current study. For example, a study by Lavikainen et al. (2022) has shown, that in a digital intervention aimed at encouraging living a healthier lifestyle to prevent Type 2 Diabetes, engagement was correlated with older age (correlation ranging from 0.14 to 0.21). In their study, engagement was measured with the eTAP questionnaire, a survey that asks questions about the intention and attitude towards digital mental health intervention. As such, the definition of engagement that was used in the study of Lavikainen et al. (2022) is more psychological and aimed at behaviour, leaving out technical statistics like logins or duration of usage.

However, there are also studies that identified older age as a barrier for higher engagement. A study by Borghouts et al. (2023) hypothesized that older age could be associated with less engagement due to low experience with technology and confidence in utilizing digital tools. One example why higher age was still associated with higher engagement in this study could be within the design of the intervention. The aforementioned barriers could be eliminated for example by having clear instructions and a good interface in order to give individuals with low digital literacy and technological expertise the opportunity to properly engage with the intervention and its exercises.

4.2 Discussion regarding the main analyses and research questions

4.2.1 Predicting treatment outcomes in clients with burnout with engagement

The first research question was: “To what extent can the level of engagement predict treatment outcomes in individuals suffering from high burnout and stress in regards to the symptom dimensions distress, depression, anxiety and somatization?”. Here, the results of the corresponding multiple regression analyses show that engagement is only able to predict the four sub scales for T1 to a very small degree. As such, participants that were highly engaged showed a higher symptom reduction. To continue, for all regression models, the adjusted R2 value increased only by a small amount when entering the variable of engagement on the second step. As such, the majority of the explained variance in the models are due to the baseline values, also known as T0 in this study. Given these points, it is debatable, whether engagement can be interpreted as being a reliable predictor for a general better treatment outcome.

One study that can be compared and used to discuss these findings is that of van der Linden (2021). Here, it was investigated whether the eHealth platform therapieland.nl can reduce symptoms of participants suffering from worry, panic, burnout and depression by the means of a guided digital behaviour change intervention. Similar to the current study, engagement was measured by the TWEETS questionnaire (Kelders et al., 2020), while burnout was measured by the 4DKL questionnaire in an English version. The results of the study by van der Linden (2021) show, that engagement is an important variable when it comes to symptom reduction in clients with burnout. This means that engagement can significantly reduce the symptoms of individuals with burnout based on the four sub scales. The effect sizes that have been found in the study from van der Linden (2021) are generally higher than found in the current study. One explanation of why these effect sizes are different could be found in the way how the digital mental health intervention is delivered and applied to the client. As such, the participants in the study of van der Linden (2021) could have received more intensive care from psychotherapists, staff or similar. The increased component of human support may increase the engagement towards digital mental health intervention.

The assumption in regards to the effect of human support has also been analyzed in literature. The study of Mohr et al. (2011) found out, that engagement can be increased by adding elements of human support such as communicating with a therapist or expert via chatrooms, telephone or other media. Here, engagement was also called adherence and was defined by the technical usage of the digital intervention by the client in terms of logins, completed modules and more. The reason why human support can increase adherence in digital mental health intervention by a variety of factors. First, the client can receive clear expectations about the behavioral change and a logical reasoning of why this behavioral change is beneficial to the mental health of the client. Additionally the progress of the client regarding the digital intervention can be supervised by the expert and corresponding and tailored feedback can be given to the client, further enhancing adherence.

Moreover, it is important to take a look at the symptomatic of burnout and stress when trying to interpret the results of whether engagement can predict treatment outcomes. Besides physical problems such as sleep problems, mental problems like fatigue, a depressive mood and a high negative evaluation of ones self can be a part of these disorders (Ekstedt et al., 2006). Participants might have been interested in the module, but may not have had the necessary strength to apply the new knowledge and techniques in their daily life. These individuals could have had a high amount of engagement but the corresponding effectiveness of said engagement could have been diminished. The aforementioned assumption can also be supported by other research projects. As such, a systematic review by Tunvirachaisakul et al. (2018) found out, that baseline depression severity is a predictor for the later treatment outcomes, with higher depression severity leading to worse treatment outcomes. The systematic review analyzed mostly depression and other similar constructs such as co-morbid anxiety and as such, the effect of baseline burnout and high stress levels on treatment outcomes needs to be further researched. To give an example, correlational and regression analyses between T0 symptoms and T1 symptoms in the context of individuals suffering from burnout and high stress could be done to see, whether the aforementioned hypothesis holds true.

The implications of these comparisons mean, that digital mental health intervention could benefit from adding elements of human support in order to increase engagement of the clients. However, given the limited resources regarding available experts and therapists, human support must be implemented in such a way, that it is still resource-efficient for the providers of the digital mental health intervention, while still providing the majority of the clients with a form of human interaction. Moreover, it could be beneficial to adapt digital mental health interventions based on what symptoms could hinder engagement with the corresponding intervention (e.g., depression). One potential idea on how to implement this suggestion could be to add positive psychological exercises early in the intervention, as these have been proven in literature to alleviate depressive symptoms (Sin & Lyubomirsky, 2009).

4.2.2 Gender, Age and Treatment Duration and their influence on the relationship between engagement and treatment outcomes

The second to fourth research question was about whether gender, age and treatment duration have a moderating influence on the relationship between engagement and treatment outcome in clients that suffer from burnout and high stress. Starting with gender, the Mann-Whitney U Test showed, that no gender showed significantly more engagement than the counterpart and as such, no moderation analysis was done for this variable. To continue with age, the results show that this variable does not moderate the relationship between engagement and treatment outcome for any of the four sub scales. For treatment duration, no moderation effects have been observed when it comes to the relationship between engagement and treatment outcomes for the sub scales Distress, Depression and Anxiety. Only somatization had a very minimal moderation effect, in where the effectiveness of engagement on treatment outcomes was negatively influenced.

The literature on potential moderator variables in regards to the relationship between engagement and treatment outcomes is scarce. However, some research exists that can partially support the findings of the current studies moderation analyses. The study of Khan et al. (2022) investigated whether variables such as medication use, comorbidity and most importantly age can moderate the relationship between engagement and treatment outcome in children suffering from tic disorders. Here, the engagement towards the digital intervention was measured in technical statistics such as logins or completion rate of the content. The results of the study of Khan et al. (2022) show, that the relationship between child engagement and treatment outcome in regards to tic disorders is not moderated by the variable age. However, since the definition of engagement and the chosen disorder are different, the generalization and comparison to the topic of burnout and high stress need to be taken cautiously. Moreover, when taking the results of the current study and the first research question into account, namely that engagement can only predict treatment outcome of clients suffering from burnout and high stress to a small degree, it is not surprising, that the results of the moderation analyses range from non-significant to almost negligible (depending on what variable and sub scale is investigated).

The findings of the moderation analyses can be interpreted in different ways. As such, it can be positive that except for somatization for the treatment duration variable, no variable has a negative influence on the relationship between engagement and the treatment outcome. This means that the digital mental health intervention and its usage of engagement does not lose effectiveness when delivered to a diverse population in regards to age and gender. The current study is one of the first to investigate how the relationship between engagement and treatment outcome is influenced by other variables when it comes to individuals suffering from high burnout and stress. As such, the findings of this study need to be taken cautiously as more research is needed to verify the findings.

4.3 Strengths and limitations

This study utilized data from a platform that specializes in providing digital mental health interventions to individuals for their psychological symptoms such as, in this study, stress and burnout. Using statistics and information from a real-world population and setting can lead to new information on how to design, build, and improve available digital mental health interventions.

A strength of this study is the implementation and investigation of four subscales: distress, depression, anxiety, and somatization. By placing an increased focus on these four subscales and their relationships with engagement, the problems of burnout and stress and how they are affected by engagement could be investigated extensively. Engagement with digital mental health interventions was not only examined in the broad context of burnout and stress, but also in its individual components. Burnout is a complex disorder that can lead to various symptoms (Terluin et al., 2008), but by looking into each individual dimension and how it relates to engagement, new knowledge can be gathered that can help to build refined digital mental health interventions tailored specifically for individuals with their own problems regarding burnout and stress.

The first limitation could arise from the context of the target population. This study only investigated the effect of engagement in a digital mental health intervention for participants that suffer from burnout and stress. Even though the subscales give some insight into other mental constructs (e.g., anxiety), that could be related to other psychological disorders (e.g., panic disorders) it is not sufficient to be able to predict other psychological disorders based on the results of this study. As such, it could be difficult to investigate what the effect of engagement on individuals with other mental health disorders could be and to generalize the results to a different target population.

Moreover, a form of sampling bias could have influenced the results of this study. Within this study, only individuals who fully completed their data (including all the necessary demographics, 4DKl-questionnaire, and TWEETS engagement questionnaire) were included in this study. As such, the original sample with a participant number of 45292 individuals was reduced to a final dataset of 4516 individuals. After conducting several Mann-Whitney U Tests to investigate potential complications, it can be seen that the final dataset shows a significant higher score in the areas of engagement compared to the group of excluded participants. To continue, the final dataset shows a significantly lower score in treatment duration and all symptom dimensions for both T0 and T1. The only variable where both groups show no significant difference is the age variable. Based on this, it could be that mostly individuals with certain characteristics have been included in the study and as such, the generalizability of the findings may be limited.

To continue, the issues of working with real-life data needs to be addressed for this study. To give an example, as it was mentioned in the methods section, the starting and end point for the treatment can be different for the participants, as depending on how fast they work through the sessions, the participants can arrive at different times at when they are asked the 4DKL questionnaire. As such, it can be harder to replicate the findings of this study and to generalize the results to other populations. Moreover, since one of the inclusion and exclusion criteria for this study was to have filled out the 4DKL questionnaire as a minimum the first and the last time, individuals that have dropped out of the intervention early due to low engagement could have been unintentionally left out of the final dataset. This means that the results such as the correlation and regression analyses between engagement and treatment outcomes could have been different.

4.4 Recommendations for future research

First, it could be beneficial to investigate whether engagement in the context of digital mental health interventions has an influence on symptoms for other target populations. This study only investigated individuals that suffered from burnout and stress. These participants could have had trouble engaging with the application. Current literature indicates that fatigue-related and depression symptoms can be obstacles when it comes to feeling engaged with an application (Borghouts et al., 2021). Further research could investigate what other psychological issues could be a problem for successful engagement with a digital mental health intervention. What other forms of content delivery (e.g., smart-watches, mobile phone applications, or forums) could be best suitable for individuals with specific disorders or problems should also be investigated.

A good addition to existing literature could be a further investigation of the concept of engagement. As seen in the introduction, there is no uniform definition for engagement and past research projects have had different views and conceptualizations, ranging from entirely technical, psychological and mixed definitions. By having a standardized definition for engagement and applying this to see whether participants were engaged to an intervention, it would be possible to compare studies and intervention more easily as there would be a shared understanding of how engagement was measured and what high or low engagement would look like.

Another recommendation for the future could be to use qualitative research methods when investigating the topic of engagement and either burnout or other mental disorders. By investigating the emotions and attitudes clients have towards the corresponding digital mental health intervention, more insight into how their disorder is affecting their experience and engagement with the intervention can be analyzed. To give an example, while they have not been statistically analyzed, the participants in this study were also able to state a comment at the end of the treatment regarding their experience and possible points of improvement. These ranged from positive (e.g., "It has helped me see things I enjoy doing again, has given me more insight into how and why I felt the way I did. ") to neutral (e.g., "It contains a number of exercises that provide insight, but there are many open doors in between.") to negative expressions (e.g., "Not really focused on my problem."). Depending on the content of the comments or experiences, the digital mental health intervention can be adapted accordingly and tailor the intervention in such a way, that is is beneficial for the mental health and engagement of the client.

At last, the results of the research question on the potential moderating effect of age, gender and treatment duration on the relationship between engagement and treatment outcomes could be further investigated and other variables could be analyzed. As mentioned previously, Borghouts et al. (2021) found out in a systematic review, that the symptoms of the client can hinder proper engagement with the digital mental health intervention. It can be beneficial for further studies to investigate symptoms, especially those that are depressive related, and how they affect the effectiveness of engagement on digital mental health interventions. Depending on the results, corresponding actions can be taken in order to prevent early-dropout of the intervention and to achieve higher and more effective engagement.

4.5 Conclusion

The results of this study indicate that engagement can predict the four subscales of distress, depression, anxiety, and somatization for the treatment outcome of individuals suffering from burnout and high stress, with higher engagement leading to better symptom reduction. However, the corresponding effect ranges from particularly small to weak and it is therefore debatable whether an effect this negligible can be seen as a reliable prediction indicator. No moderation effect in regards to the variables gender and age was observed for the relationship between engagement and treatment outcome. Only the variable treatment duration had a moderation effect when it comes to the symptom dimension somatization. However, this effect is almost non-existent.

While current research has demonstrated similar results when it comes to engagement and whether it can predict the treatment outcome, more research is needed to see what potential factors could explain these results and how engagement can differ when it comes to various psychological problems. Particularly, not much literature exists that investigates potential moderating variables when it comes to the relationship between engagement and treatment outcomes Overall, replication research with a focus on correlation, regression, and moderation analyses on engagement and participant demographics could help to assist current technological research in finding new ways of applying digital mental health interventions for the public. By utilizing a questionnaire containing four subscales of pathology, more information about the influence of engagement on different complaints can be gathered. However, the issues of working with real-life data and the sole focus on burnout and stress could be obstacles for generalizing the results to other target populations. Future research on the construct of engagement and what components can encourage individual engagement in digital health interventions, as well as more analyses on the relationship between engagement and treatment outcomes and what variables could be potential moderators can help to make a fundament for future research in the field digital mental health interventions and engagement.

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