Engagement in Digital Health Interventions

Using engagement measures extracted from log data to predict subjective engagement and therapy outcomes

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Abstract

Background: Digital Health Interventions (DHI) have been proposed as a valid method to offer low intensity, accessible and effective support to people seeking mental health help. Though promising, these DHIs are troubled by high attrition and low adherence. The improvement of engagement is often used to address these problems. Log data, which are anonymous records of real-time actions performed within a digital program, are a popular method to measure engagement. Unfortunately, it is not yet clear if variables created from the log data can be considered related to and even predictive of engagement or therapy outcomes.

Aim: The goal for this study is to determine whether the engagement variables extracted from log data can predict subjective engagement and therapy outcomes.

Methods: A quantitative correlational research design was used. Real-world data was collected on the use of a rumination intervention program. N = 94 respondents were included in the study. The objective engagement variables extracted from the log data were the number of visits to the intervention (Frequency), average number of actions per visit (Intensity), the number of messages sent and received through the chat with therapist function (Type) and the total number of minutes spent in the intervention (Time). To measure subjective engagement the TWEETS questionnaire was used and for therapy outcomes scores from the PSWQ were used. Linear regressions between these variables were performed.

Results: A significant difference on rumination scores was found between start (T0) and end (T1) of program participation. Rumination at T0 was able to predict rumination at T1. Neither subjective engagement, nor the FITT measures for objective engagement showed an additional predictive quality on rumination at T1. Only the objective engagement variable of Time predicted subjective engagement.

Conclusion: No direct relation was found between log data objective engagement measures and subjective engagement nor therapy outcomes. This could have been the result of having used raw data for the objective engagement measures. For the working mechanisms of the DHI to be effective, the intended use of the program needs to be accounted for when constructing and interpreting these engagement variables. Having used derived variables that account for the intended use instead of raw data variables might therefor have yielded different results. Future research into the topic of engagement from log data is advised to consider the goals and intentions of users, developers and therapists when attempting to predict therapeutic outcomes.

Introduction

As concluded by the World Health Organization, one in eight people around the world, or 12.5%, was suffering from a mental health disorder in 2019 (World Health Organization, 2020). Most prevalent among these disorders are anxiety disorders and depression. These respectively represent 301 million and 290 million individuals annually, which accounts for about 60% of the total sum suffering from a mental health disorder. Due to the COVID-19 pandemic even more people than before are now experiencing significant psychological distress with initial estimates of an increase of around 26% for both anxiety disorders and depression (World Health Organization, 2020). A study in the Netherlands confirmed that the pandemic increased mental health disorder symptom levels among people previously undiagnosed, although these symptom levels had remained stable for individuals that were already diagnosed (Pan et al., 2021). The fact that such a large amount of the world population is suffering from mental health disorders implies this is more than a problem on the micro- or individual level. A meta-analysis conducted in 2017 (Doran & Kinchin) reviewed the impact of mental illness on society. This showed a wide range of negative consequences, including an increase in academic drop-out, a decreased probability of finding and maintaining full-time employment, an overall reduced quality of life and a very significant economic impact which is only expected to increase many fold over the coming decades.

Worldwide, This increase of people suffering from mental health problems is met with a serious intent to improve current mental health care services. Many different effective treatments are already available to help those individuals suffering, but the current quantity of demand exceeds the amount of professional help available to give these treatments. This has also become the case in the Netherlands where the rise in demand for therapeutic help has led the waiting lists to become longer in recent years (NZA, 2021). To warrant timely help, the Netherlands have put in place a national target for maximum wait listing of three weeks for intake, and 14 weeks for treatment. The time that applicants are waitlisted for intake strongly varies depending on diagnosis and severity, but from recent studies averages around 10 weeks (Vektis, 2022) which is significantly higher than the national target. Additionally, for most diagnosis the target total waiting time of 14 weeks is not met either (Vektis, 2022). Waiting times are more than an inconvenience to those suffering. Examples of negative consequences include a decline in ability to function, an increase of negative beliefs and emotions (Punton, 2022) and even an increased risk for suicide (Williams, 2008).

Consequences are found to be especially severe for those waiting for more than three months (Reichert & Jacobs, 2018), which is on average the case in the Netherlands.

A possible solution to the issue of long waiting lists comes in the form of digital health interventions (DHIs). The key characteristic of DHIs is that these aim to teach their participants about concepts and skills relevant to their condition without them seeing a health care professional (Ong, 2021). This definition encompasses many different types of interventions. In order to label, define and categorize them, Barak and colleagues (2009) have found two main dimensions on which these DHI can be distinguished from each other. The first dimension is the degree to which the program content requires active participation. This can range from psycho-education, to content which actively attempts to change behavior. The second dimension is the level of support. This can range from self-help programs to interventions that integrate regular direct human support. Blended-care is an example of this last type of intervention, where participation to the DHI is combined with face-to-face treatment (Wentzel et al., 2016). These two dimensions offer a large variety of differing types of DHIs, with each a slight difference in the goal they are meant to achieve. In general, DHIs that require less active participation and offer less support features aim to raise awareness among a larger target group, whereas those that are more investment intensive from both the user as well as the intervention developers and collaborators focus their efforts on behavior change among individuals. Another study points to a third element to contrast DHIs, which is whether the intervention is offered through a platform with accounts or through an open access website (Christensen, 2009). Given the lower level of personalization, interventions offered through open access websites usually elicit less commitment, leading to significantly higher dropout rates than for interventions on digital platforms (Christensen, 2009).

Since their introduction, a lot of interest, resources and research has been dedicated to different versions of DHIs. These interventions have been shown to not only be effective in improving treatment outcomes compared to waitlisted patients (Aardom, 2013), but also show similar results as traditional face-to-face treatment (Andersson, 2014; mohr, 2019). Besides their possible effectiveness, a large part of their appeal can be assigned to these interventions being of relative low intensity for their users and being highly accessible to anyone with an internet connection. As such, DHI are used in many health care domains, from prevention through after treatment care. Considering mental health care in particular, these interventions match up well with the widely implemented stepped-care approach. This approach aims to optimally manage mental health care resources, by offering clients low intensity and low cost interventions first, scaling up to more rigorous treatments when needed (Meeuwissen, 2018). Given the aforementioned advantages and scalability of self-help interventions, most of the diagnoses have online self-help as one of the initial steps (National Institute for Health and Care Excellence, 2023). In other words, this approach advises mental health care professionals to consider the use DHIs even before signing clients up for face-to-face treatment where they would be placed at the back of the aforementioned long waiting lists. Another benefit of DHIs is that they can address inter-diagnosis issues people experience, such as worrying or ruminating, without requiring an official diagnosis first. Rumination is for example linked to disorders such as depression and generalized anxiety disorder, but also with burn-out and is often found among those suffering without matching with sufficient criteria to obtain a diagnosis. The mental health care field is increasingly acknowledging these inter-diagnosis or transdiagnostic factors as key to understanding mental disorders, which has resulted in the incorporation of a transdiagnostic system within the newest version of the Diagnostic and Statisti?cal Manual (Krueger & Eaton, 2015). Implementing a DHI which targets transdiagnostic factors such as rumination, could firstly offer a valid alternative to waitlisting for people awaiting treatment for a variety of different diagnoses. Especially in those cases where the transdiagnostic factor is the primary cause of suffering, can participants to the DHI get an effective head start on their eventual face-to-face treatment. In the aggregate, the number of people requiring more intensive face-to-face treatment could even be lowered as a consequence. Also for those individuals that suffer from a transdiagnostic factor that is not part of their primary diagnosis can such a DHI be of value. Since the face-to-face treatment for their primary diagnosis would not target this factor, participation to a DHI can broaden the scope of treatment without it having to interfere with the work of the psychologist.

Even though results from studies on effectiveness and efficacy of DHIs are promising (Luo et al., 2020), there are still challenges when considering their use in practice. DHIs are offered through a wide variety of online platforms such as websites or through mobile phone applications. Additionally, DHI pricing can vary from completely free, reimbursed by health insurance or by a fee or monthly subscription. As a result, many thousands of mental health apps are available to the average person with an internet connection, making it difficult for someone seeking real help to find the correct DHI of high quality. A recent meta-review showed that almost none of the apps within the research had been subjected to randomized control trials and the majority of them had not been developed in consultation with a health care professional, let alone one specialized in mental health (Grundy, 2022). In the context of individuals that have already reached out to mental health care providers, quality can be assured when these providers work together with, or use services from, established digital health care platforms such as Therapieland.nl or Gezondeboel.nl. These platforms collaborate with internal and external experts to translate existing face-to-face treatment methods such as cognitive behavioral therapy into online programs. Therapieland.nl focuses on blended care, offering a platform where professionals extend their services online to their clients or patients. This means clients can both follow the aforementioned programs picked out by their health care professional, but also communicate with them through video calls and fill in validated questionnaires. Gezondeboel.nl on the other hand focuses on prevention by offering trainings that stimulate psychological resilience.

Regardless of the form or source of the DHI, the most significant challenge that DHI platforms face is that of high attrition and low adherence (Van Ballegooijen et al., 2014; Yardley et al., 2016). These two concepts both refer to the degree a participant is still engaged with the treatment. A distinction can be made as to what participants engage with. For attrition, the degree to which the participant actually participates in (all elements of) treatment is addressed. High attrition in this sense means that people do not participate or do not complete the DHI (Yardley et al., 2016; Short et al., 2018). For adherence, this can reflect on the degree to which the participant uses the intervention as intended. This can mean both the use of the material offered, as well as applying the knowledge and skills taught in one’s personal life. In the case of high attrition and low adherence the expected effectiveness of the intervention to change behavior is greatly reduced (Yardley et al., 2016). Platforms such as Therapieland.nl aim to improve these rates by making their content as engaging as possible. Unfortunately, there is no clear consensus on what engagement refers to, encompasses and how this could most effectively be measured (Perski et al., 2017).

A systematic review of existing research was done on engagement within the context of DHIs (Perski et al, 2017). The aim for their review was to map out the known factors associated with engagement and its interactions. It was concluded that engagement can refer to two constructs, these being engagement as a subjective experience and engagement as a behavior. The behavioral construct is proposed as objectively measurable. It can be studied using the concepts of attrition and adherence by using automatic program-use patterns tracking or by using more hands-on methods in the form of physiological measures such as cardiac activity, or psychophysical measures such as eye movement tracking. The subjective experiential construct in turn refers to emotional, as well as cognitive states such as attention, interest and affect during the use of the DHI. In a later paper, Perski and colleagues (2020) operationalized both of these facets of engagement into a self-report questionnaire. Unfortunately, the constructed scale did not correlate with or was able to predict future objective measures of engaged behavior, such as total amount of logins. The researchers hypothesized that their scale was not able to predict objective engagement, because it was missing another element of subjective engagement which pertains to the motivation to change and the perceived personal relevance of the DHI to the user or the degree to which the person expects completing the intervention will help them attain their goal. Another paper from 2020 did incorporate this aspect in their TWEETS questionnaire as an aspect of cognitive engagement (Kelders et al, 2020). Although the expected division into the three constructs of behavioral, cognitive and affective engagement was not confirmed, this questionnaire did show a capability to predict behavior change outcomes. Regardless of which precise concepts are used, a significant downside to the use of questionnaires in determining levels of engagement among participants to DHIs is the low response rate (Perski et al, 2020). As a result, their usefulness in the realm of research is not easily converted to real-world settings.

A benefit of DHI is that the platforms these interventions are made available on can automatically and autonomously collect log data. Log data are anonymous records of real-time actions performed by each user within a digital program (Sieverink et al., 2017). It has become a common undertaking for digital intervention developers, as well as app developers in general, to use log data (or usage data) to get a sense of the level of engagement their app users have (Nelson et al., 2016). Unfortunately, similar to the general discussion on how to measure behavioral engagement, there is no consensus yet on what log data serve best to measure engagement (Miller et al., 2019). This in part is caused by the wide variety of types of apps and fields of expertise that have differing perspectives on the matter which results in diverging methods of approach. Short and colleagues (2018) have assessed these different methods previously used and compiled options to consider for future engagement research. On the level of usage data they propose the use of a preexisting categorization used within physical activity research under the acronym FITT which refers to the elements frequency, intensity, type and time (Barasic et al, 2011). **Frequency** refers to the number of times a user has visited the intervention. **Intensity** in turn refers to the number of times available features the user has employed. **Type** is very dependent on the content that the user interacts with which can elicit different types of engagement, ranging from very passive where no interaction is needed to very active where a lot of interaction is needed. Lastly, **time** refers to the amount of time the user has spent within the app or intervention either in total or more specifically during a visit.

In summary, Digital Health Interventions (DHI), with topics of treatment such as rumination, are proposed as a valid method to offer low intensity, accessible and effective treatment to people seeking mental health help. Though promising, these DHIs are troubled by high attrition and low adherence percentages. The improvement of engagement is often used to address these problems. No consensus exists on what the best way is to measure engagement. Self-report questionnaires such as the TWEETS have been shown capable of measuring subjective engagement, but are less practical for structural implementation due to low response rates. Usage data, which can automatically be collected from DHI platforms, are typically generated in high quantities for each user and as a result don't suffer the same downside. It is not yet clear though if variables created from the usage data can be considered related to and even predictive of engagement as we currently understand it and if these variables are related to actual therapeutic effects. The goal for this research is to answer these questions.

Firstly, the assumption that subjective engagement measured through the TWEETS self-report questionnaire predicts therapy outcomes is tested, as this provides the fundament for the usefulness of measuring such a concept. Secondly, engagement variables extracted from usage data are analyzed to see if they predict subjective engagement. The previously discussed measures constituting the acronym FITT will function as the objective engagement variables. To measure the Frequency of use, the number of visits to the intervention is used. To measure the Intensity, the average number of actions per visit is used. Given that the intervention contains the same elements for each user, the same active type of engagement is elicited from each user. One aspect that can vary between users however is the degree to which they have made use of the chat with therapist function on the platform. As guided support is known to significantly influence engagement, as well as treatment outcomes (Barello, et al., 2016), and it can be considered an element that elicits an increased level of active engagement, it is used as the variable measuring Type extracted from usage data. To measure the element of time, the total amount of time spent in the intervention is used. Thirdly, the usage data variables mentioned above are analyzed to see if they can predict subjective engagement. Finally, the last question aims to answer whether the engagement variables extracted from usage data predict therapy outcomes.

1. Does subjective engagement to the Therapieland.nl program predict therapy outcomes?
2. Do usage data indicators of app engagement of the Therapieland.nl program predict subjective engagement?
    a. Does the number of visits predict subjective engagement?
    b. Does the average number of interactions per visit predict subjective engagement?
    c. Does the number of guidance support interactions during the program predict subjective engagement?
    d. Does the total amount of time spent logged in predict subjective engagement?
3. Do usage data indicators of app engagement of the Therapieland.nl program predict therapy outcomes?
    a. Does the number of visits predict therapy outcomes?
    b. Does the average number of interactions per visit predict therapy outcomes?
    c. Does the number of guidance support interactions during the program predict therapy outcomes?
    d. Does the total amount of time spent logged in predict therapy outcomes?

Method

Research design

In order to answer the research questions, a quantitative correlational research design was used. Real-world data has been collected by Therapieland.nl over the period from April 2018 to December 2022 on the use of the rumination program, which is called “Piekeren” in Dutch. This means that individuals who’s data were collected used the program and platform as intended for regular use, rather than participating in an experimental setting. They were all made aware that both the data which was automatically generated and that which was requested through online questionnaires could be used for research, at which point they had the option to decline the use of their data for this purpose.

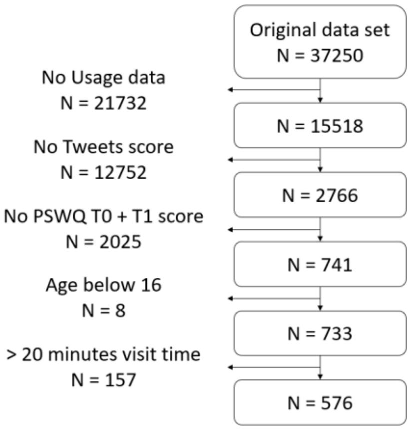
Participants

The people whose data was used for this had participated to the rumination program, which was available through the main platform of Therapieland.nl, as well as their secondary platform called Gezondeboel.nl. While individuals that took part through Therapieland.nl can largely be considered clients of mental health care, those that accessed the DHI through Gezondeboel.nl often did so through a larger organization such as their employer or their education. Among them are people that signed up themselves, but most got signed up by a therapist from whom they also received face-to-face treatment.

The original dataset received from Therapieland contained 37250 participants to their rumination program. No filtering of the data was done on their end prior to sending the data. To improve validity of the analyses, exclusion criteria have been applied, see Figure 1. Respondents that did not have usage data and did not have TWEETS or PSWQ scores were excluded from the research. Participants aged below 16 were not included. Although in the Netherlands children from the age of 12 can consent, their parents also need to consent (Kind en Onderzoek, n.d.). This was not possible for Therapieland. Respondents with less than 20 minutes total visit time were also excluded to ensure a minimum level of actual participation. Lastly, Therapieland was unable to guarantee the usage data only concerned participation to the rumination program. Since 83.7% of the remaining respondents were known to have participated in more than one online program, these were filtered out. Of the remaining 94 respondents 48 (51.1%) reported being female, 37 (39.4%) being male, with 9 (9.6%) of the respondents not having filled in their gender. The average age of the respondents was 42.46 years old, with the oldest person reporting an age of 77 years.

Figure 1

Data preparation flow



Measures and variables

Therapieland requested the users of their programs to fill in questionnaires at different stages of program completion. Additionally, usage data was automatically generated by the platform itself. To answer the research questions for this study a combination of constructs was used, measured through the questionnaires as well as extracted from the usage data.

Firstly, to measure subjective engagement, the TWente Engagement with Ehealth Technologies Scale (TWEETS) questionnaire was used (Appendix A). From psychometric analysis, the TWEETS was found to be both reliable and valid with an ability to predict perceived behavior change at a later stage. This questionnaire consists of nine items. For each item respondents are requested to answer through a five-point Likert scale if they agree with a given statement, running from “strongly disagree, to “strongly agree”. Three statements are dedicated to the behavioral component of engagement, three to the cognitive component and three to the affective component. The scores of all nine items are added up to a total score which can range from 0 to 36. The higher the score, the more subjective engagement with the rumination program the respondent has experienced over the past week.

Secondly, to measure therapy outcomes, the Penn State Worry Questionnaire (PSWQ) was used. This validated questionnaire measures the concept of excessive worrying or ruminating through 16 items (Meyer et al., 1990). Each item is a statement to which the respondent can answer to which degree the referred experience is typical to them by way of a five-point Likert scale, ranging from “not at all typical of me” to “very typical of me”. The total score on the PSWQ can range from 16 to 80, with higher scores indicating greater levels of worry. The questionnaire takes into account the generality, intensity, and uncontrollability of the worrying. The PSWQ has demonstrated good convergent and discriminant validity and being an overall reliable and valid tool for assessing the trait of worry in both clinical and non-clinical settings (Meyer et al., 1990).

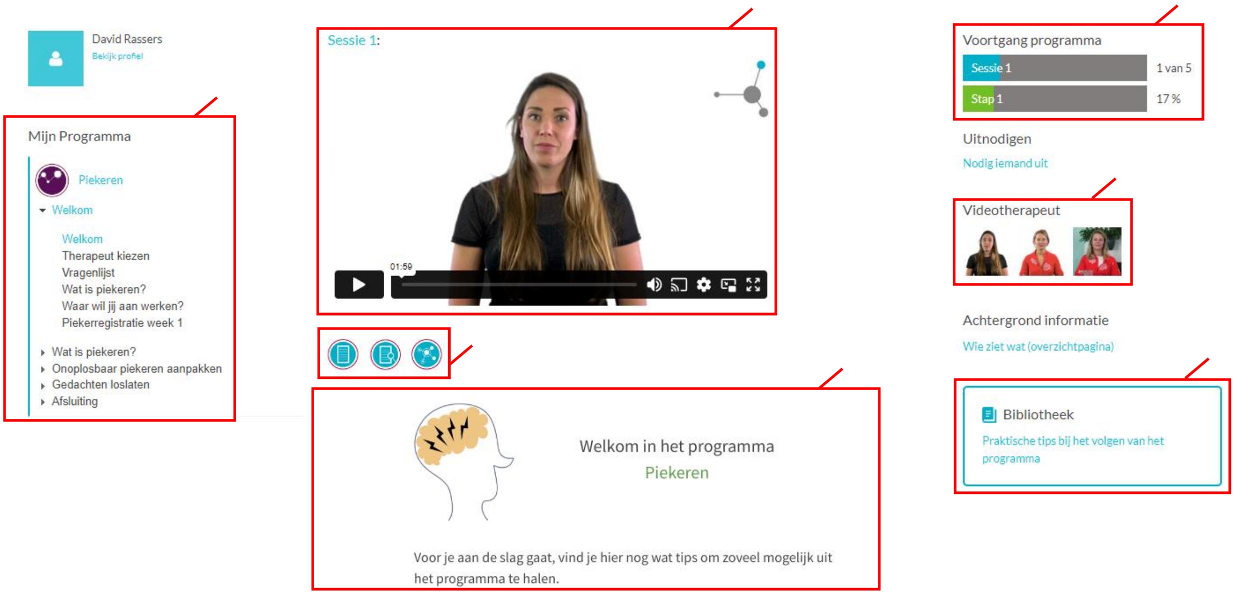
Thirdly, to measure app engagement, Therapieland used data that was automatically generated by the users of their platform. For the collection and storing of the data they used the computer program Matomo. As mentioned before, four variables have been extracted from the dataset as indicators of engagement. These are the number of times the rumination program was accessed by a user (Frequency), the number of interactions per visit of the program (Intensity), the number of guidance support interactions a user had (Type) and the amount of time in seconds in total he or she has spent in the program (Time).

The intervention and procedure

The rumination program can be accessed through the Therapieland and Gezondeboel platforms. When entering the platform for the first time, a participant is requested to give information such as their name to complete their digital account and to are asked for consent to use their data for research and development purposes. Once this is completed they are prompted to go to the rumination program, as this has already been assigned to them by their therapist. The content of the program is divided into 5 sessions, which is each divided into multiple pages, which are referred to as steps (See Appendix B). Although participants were not functionally limited in the amount of content they could go through during each visit, the program requested to complete no more than one session per week to ensure enough time to try out what they have learned. The rumination program structurally had seven functional elements on each page (See image 1).

Image 1

Rumination program interface



Firstly, to the left, a navigation pane was visible which allowed users to skip forward or move back to other steps or review previously completed sessions. In the top middle, a video player was visible. Video's displayed here explained the content and/or assignment of the step. Bellow the video player a set of different clickable icons were available that allowed participants to process the information given in the video in different ways. This included the option for a personal diary entry and a chat with therapist option. Below these icons the main content of the step was available which often contained additional information and exercises. To the top right a progress bar for the program and for the current session was visible. Below this was the option to select a different therapist that presented the video's throughout the program. Lastly, below this, the participant could find a library with additional content that could be helpful for the current step. Examples are tips for additional literature to read up on, more exercises or other background information.

Session one was an introduction to the program. After participants chose their preferred therapist to present the information video's, they were requested to fill in the PSWQ for the first time (Rumination T0). They then got a first explanation of the concept of rumination, after which they were prompted to define the goals they wanted to achieve by completing the program. Lastly, they filled in a rumination registration journal. The second session focused on what rumination looks like for the participant. Steps were aimed at understanding why they ruminate, how to differentiate between solvable and unsolvable thoughts and learning to think solvable thoughts. After this session's rumination journal, users were requested to fill in the first TWEETS questionnaire. The third session aimed to teach users techniques to apply when they had unsolvable thoughts. This included finding distraction, evaluating likelihood and severity of the worrisome scenario and choosing a designated time and place to ruminate. The session ended with a rumination journal. The fourth session focused on methods participants could employ to sooth themselves when ruminating. The first step asked participants to evaluate the degree to which they were reaching their previously set goals. The following steps were dedicated to methods such as adopting a different attitude towards the worrying scenario and mindfulness and relaxation exercises. To finish up, participants filled in their rumination journal and the TWEETS questionnaire for the second time. The fifth and final session had no additional informative content. This sessions contained three evaluations. The second PSWQ (Rumination T1), the final evaluation of the user's personal goal and an evaluation of the program. A closing video was included congratulating the participants on completing the program.

Data analysis

In order to answer the research questions, statistical tests were performed with the use of SPSS Version 28. All tests were two-tailed. A significance value of $p = .05$ was used for all tests. Firstly, descriptive analyses were performed to get an understanding on how participants are distributed along the independent variables. To be capable of making statements on the effect of participation to the program a repeated measures ANOVA was done. A significant difference between start and end of treatment rumination scores would indicate a shift in reported worrying among the participants and consequently suggest participation to the program had an effect. By indicating the effectiveness, research questions about its predictability are warranted.

To answer whether subjective engagement can predict therapy outcomes, a two-step approach is used. Firstly a Pearson correlation analysis was conducted between subjective engagement scores and the rumination scores at start and end of treatment, to verify if findings from previous research are replicated in this study and determine if subjective engagement relates differently at start of treatment to end of treatment rumination. Secondly, a linear regression was performed to measure if subjective engagement could actually predict post-intervention rumination scores. If at the correlational analysis a significant relation was found between rumination scores at start of treatment and at end of treatment, the linear regression would include an additional model which accounts for the effect start of treatment rumination has on end of treatment rumination. To answer the second research question, a linear regression analysis was performed to measure if the objective engagement measures of Frequency, Intensity, Type and Time could predict subjective engagement, both combined as well as considered as separate coefficients. In the scenario where no significance was found, plots were generated to visualize if any type of relationship between the objective engagement measures and subjective engagement was present. Lastly, to answer the third research question, a linear regression was performed to determine if the four objective engagement measures could predict rumination scores at the end of treatment. When no significant predictability was found, plots were also generated for this analysis to visualize a possible relationship between the objective measures and rumination scores.

Results

Descriptive analyses (see Table 1) have shown that the objective engagement variables had a kurtosis and/or skewness value above 2, resulting in the use of the median score instead of the mean score for these variables and leaving out the standard deviations. The average subjective engagement score was 21.71. Considering this represents the total score of each respondent on the 9 TWEETS items, the average score for each respondent per item would be 2.41. This represents an on average neutral level of subjective engagement. The rumination scores have on average decreased by 5.67 from 59.81 to 54.14. Consulting Dutch normative data (van der Heiden, et. al, 2008), which includes both clinical and non-clinical samples, these scores can be considered having gone from a very high score to a high score, with the T0 average being comparable to the lower percentiles of clinical patients with a generalized anxiety disorder and the T1 average being comparable to the higher percentiles of the non-clinical sample.

Table 1

Descriptive statistics.

Variable	Mean	Standard deviation	Minimum	Maximum
Age	42.46	17.94	16	77
Subjective engagement	21.71	5.7	2	35
Rumination				
Start of treatment T0	59.81	6.94	43	76
End of treatment T1	54.14	8.69	36	79
T0 – T1 difference	-5.67	7.13	-27	12
Objective engagement				
Frequency	7.5*	-	1	55
Intensity	56.5*	-	9	396
Type	0*	-	0	16
Time	4711*	-	1301	31801

*Median

To indicate if participation to the program is effective, a one-way repeated measures ANOVA was performed to determine if the mean rumination score of respondents was different between start and end of the intervention. The one-way repeated measures ANOVA revealed that time does lead to statistically significant differences in rumination scores ($F = 59.463$, $p < 0.01$) with scores at the end of the program on average being lower than scores at start of the program.

To answer the first research question, a correlation analysis was performed between subjective engagement, rumination scores at start of treatment and rumination scores at end of treatment. Subjective engagement did not correlate to either rumination at start nor end of treatment, but rumination at start of treatment did correlate with rumination at end of treatment (*r*(92) = .60, p < .001).

A linear regression was then performed to analyze if subjective engagement was able to predict the rumination score at end of treatment (Table 2). Given the correlation found between start and end of treatment rumination, two models were compared in this linear regression. The first model showed that rumination at start of treatment could predict rumination at end of treatment (F (1,93) = 7.27, p = <.01), with 36% of the variance in rumination at end of treatment being explained by rumination at start of treatment. The second model showed what additional predictive value subjective engagement has on rumination at end of treatment, considering the rumination at start of treatment already showed a significant level of predictability. This was found to not be significant (p = .24).

Table 2

Linear Regression predicting Rumination at T1 using Rumination at T0 and Subjective Engagement

Model	Variable	B (SE)	Beta	p
1	Constant	8.92 (6.27)		.158
	Rumination T0	-0.14 (0.16)	.60	< .001
2	Constant	12.06 (6.79)		.076
	Rumination T0	0.76 (0.14)	.61	< .001
	Subjective Engagement	-.015 (0.13)	-.10	.242

Note Model 1: R^2 = .37, adjusted R^2 = .36.

To answer the second research question, a linear regression was performed to analyze if the objective engagement variables Frequency, Intensity, Type and Time could predict subjective engagement. The independent variables do not significantly predict subjective engagement (F (4, 89) =1.97, p = .11) which indicates that the four factors combined do not significantly impact subjective engagement for the rumination DHI.

Additionally, coefficients were assessed to determine the influence of each of the individual factors on subjective engagement. The results revealed that chats performed (type) does show significant negative impact on subjective engagement (B = -.63, t = -2.06, p =

0.042). The other factors did not have a significant impact on subjective engagement. See table 3.

Table 3

Linear Regression predicting Subjective Engagement using Objective Engagement variables.

Independent variables	B	B SE	β	p
Frequency	.09	.14	.14	.518
Intensity	.15	.03	.17	.547
Type	-.63	.31	-.21*	.042
Time	0	0	-.11	.632

* $p < .05$

To explore whether there might be a different type of relationship (non-linear) between each usage data factor and subjective engagement their simple scatter plots were generated and visually inspected. As seen in Appendix C no discernable relationship is apparent from the scatter plots.

For the third and final research question, the dependent variable (rumination score at T1) was regressed on predicting variables Frequency, Intensity, Type and Time . Similarly as for the first research question, two models were compared. The first model once again showed the predictability of rumination at T1 by rumination at T0. The second model showed what additional predictive value subjective engagement has on rumination at end of treatment. The independent variables did not significantly predict the rumination score at T1, $F(4, 89) = 1.87$, $p = .12$, which indicates that the four factors combined do not significantly impact therapy outcomes of the rumination DHI.

Additionally, coefficients were assessed to determine the influence of each of the individual factors on the rumination score at the end of the program. The results revealed that none of the factors had a significant impact on therapy outcomes (Table 4).

Table 4

Linear Regression predicting Rumination at T1 using Rumination at T0 and Objective Engagement variables

Model	Variable	B (SE)	Beta	p
1	Constant	8.92 (6.27)		.16
	Rumination T0	-.14 (.16)	.6	< .01
2	Constant	12.06 (6.79)		.08
	Frequency	.01 (.18)	.01	.97
	Intensity	-.03 (.03)	-.21	.38
	Type	-.58 (.39)	-.13	.14
	Time	0 (0)	.23	.23

Note Model 1: R^2 = .37, adjusted R^2 = .36.

To explore for other relationships between each usage data factor and therapy outcomes their simple scatter plots were generated. In order to adequately visualize the data a T0-T1 rumination difference score is used for therapy outcomes instead of the T1 rumination score. As seen in Appendix D, no discernable relationship is apparent from these scatter plots.

Discussion

Key Findings

This study examined whether log data generated by DHIs can be used as a measure of objective engagement to predict subjective engagement and therapy outcomes. The first research question aimed to verify if subjective could predict therapy outcomes to a DHI. The study found that whether a respondent reported high or low subjective engagement, this did not predict their eventual rumination score at T1, including having accounted for the predictive capacity the rumination score at T0 had on scores at T1. This suggests that feeling engaged does not impact actual therapy outcomes, which is contrary to previous findings (Donkin & Glozier, 2012; Kelders et al., 2020). Given that multiple of the TWEETS items contain an implicit expectation of goal attainment (Appendix B), it means that people that score high on this questionnaire do themselves expect that participation to the program will significantly enable them to reach their goal, but this was not reflected in the rumination scores. A first possibility for this is that, given the TWEETS questionnaire was administered near the start of the intervention, it is possible that those participants that had initial positive expectations of the program did not have these expectations met at the end. Another possible explanation comes from the fact that a real-life dataset was used, consisting of respondents that had been assigned to the rumination program by a therapist. This means it is likely for them to receive psychological treatment from this therapist alongside following the rumination program. It is possible that subjective engagement to the program is less relevant to rumination scores when it is not participation to the program but following this face-to-face treatment which impacts it more. Previous research has indicated that mostly, or even only participants that had weekly contact with a professional alongside the digital intervention improved on their therapeutic goals (Kleiboer et al., 2015; Richards & Richardson, 2012). This suggests that the effect on therapeutic goals could best be attributed to the face-to-face element of the blended therapy. Another potential explanation for the incongruence might be that the goals participants defined for themselves do not significantly relate to rumination as measured by the PSWQ. Respondents most likely all participated in face-to-face treatment during DHI participation. In order for someone to be treated, a diagnosis is required which should only be given when sufficient criteria of a disorder are met. Rumination is, as previously mentioned, a transdiagnostic characteristic. As a result, rumination or excessive worrying can both be at the core of the disorder, such as for generalized anxiety disorder and illness anxiety disorder (American Psychiatric Association, 2013) or not be part of the primary diagnosis yet impacting the life of the individual significantly. Having excluded respondents from this study that had participated to more than one DHI, did not mean that all respondents prioritized rumination when defining their goals.

The second research question was whether objective engagement measures, extracted from usage data of the Therapieland platform, could predict subjective engagement. From this study, we can conclude that frequency of DHI use, intensity of DHI use and amount of time spent in the program do not significantly predict subjective engagement. This means that a participant that made frequent and longer visits to the DHI and actively clicked through the content on the program pages, did not report higher subjective engagement to the program than those that seemed less engaged with the program from the usage data. A possible explanation for these findings is that the factors used from the usage data do not sufficiently measure objective engagement. As previously mentioned, high attrition and low adherence are problems that often arise for DHIs (Van Ballegooijen et al., 2014; Yardley et al., 2016), which is the main reason developers seek to improve and the measure engagement as their antithesis. In order to measure engagement, especially objective engagement, both these concepts need to be considered. Given that adherence is about the degree to which a participant used the program content, knowledge and skills as intended, the variables that measure adherence, and consequently engagement, need to reflect this intended use. The four factors used did not do so. Although attrition can benefit from an understanding of intended use, such as in the determination of a range of optimal use, a more static approach to its definition and interpretation can be used. This has been the case within this study. It is possible that objective engagement was not able to predict subjective engagement, because it is not as much attrition but adherence which relates to it.

Of the four objective engagement measures used within this study, only the variable Type (amount of chat messages) was found to predict subjective engagement. The relation is negative though, meaning that an increase in chat messages predicts a decrease in subjective engagement. A possible explanation is that the chat functionality might most often be used when an issue arises, either on a practical or content level. Previous research has indicated that guided support during the participation in a DHI has positive effects (Barello et al., 2016; Werntz et al., 2023). This support is often in the form of encouragement and progress evaluation throughout participation (Werntz et al., 2023). The fact that most respondents for this study didn’t have any chat activity, implies that this functionality is not a structural feature of the intervention and is most likely only used incidentally. This means the chat function isn’t used in the form of guided-support. To the contrary, using the chat implies that the respondent found the intervention less intuitive than was intended. Since the TWEETS questionnaire includes ease of use as an aspect of subjective engagement, this could explain why higher chat use predicted lower subjective engagement.

The third research question was whether the objective engagement measures could predict therapy outcomes. This study concludes that, similarly as for subjective engagement, frequency of DHI use, intensity of DHI use and amount of time spent in the program do not significantly predict therapy outcomes, nor does type of DHI use or chat use. This finding matches up with previous research done. In a meta-analysis of 33 DHIs (Donkin et al., 2011) it was found that engagement measures extracted from usage data varied a lot on their relation to treatment outcomes depending on the program topic, with DHIs specifically targeting mental health showing no association between these objective engagement factors also used in this study and treatment effects. As discussed above for the second research question, it is possible that these objective engagement measures do not sufficiently represent the aspect of adherence. As indicated by Sieverink and colleagues (2017) when reviewing 62 articles that studied the relation between technology use and intended outcomes, research often doesn’t sufficiently include an understanding of intended use when attempting to find predictability from usage data on outcomes.

Limitations

At the start of this study, a higher amount of participants was expected to be included in this research, which is why this program has specifically been selected. Unfortunately, the eventual data set did not contain this amount, without a clear reason as to why this was the case. As a result, it is possible that a smaller selection of the actual respondents consenting to this study were analyzed leading to different outcomes.

An additional limitation of this study is that the actual number of participants to the rumination DHI that had experienced low engagement could have been significantly larger than the one included in this study. Only those that had filled in all the questionnaires that are part of the intervention program were selected, which is roughly 5%. Assuming that this can’t only be attributed to computer system issues on the platform end or the participant’s end, this suggests that many of the individuals that started the program did not complete the intervention as intended and could be considered low on engagement. These have nevertheless not been included in this study since for most no therapy outcome scores were available, nor was it possible to determine what the true reason was for this missing information.

Future research

When considering future research into using usage data from DHIs, it is advised to integrate a better understanding of intended use of the program when defining objective engagement measures, as to ensure they also represent adherence. Looking at the measures used within this study (Frequency of DHI use, Intensity of DHI use and Time spend logged into the DHI) ranges could be defined for insufficient quantities, suboptimal quantities and perhaps optimal quantities. These quantities could be interrelated as well. For example, you might expect that a single visit to the DHI, within which all sessions are completed, would not give the user sufficient time between sessions to apply the knowledge and skills in their personal lives. This could be considered an insufficient quantity on the variable Frequency. If the user would have made more than 30 visits to the DHI, but had a moderately low amount of interactions per visit, this in turn could be considered sufficient, yet suboptimal on the variable Frequency. These adherence ranges need to be defined in consultation with the DHI developers and mental health care professionals to ensure they are based on an understanding of the working mechanisms within the intervention. Additionally, adherence could be measured using new concepts different from frequency, intensity, type and time. An example would be to analyze open text field inputs the users have written as answers to tasks in the DHI. Perhaps the length or structure of their text inputs could suggest the degree to which users took the tasks seriously, signaling the more interactive elements of the DHI were used as intended.

Most of the participants to the rumination program did not fill in sufficient information to be included in this research. This can be considered very high attrition, meaning that most people that had been assigned the rumination program had a very low level of engagement to the DHI. Developers of DHI's want to know how specifically this group of people can remain engaged. It is therefore advised to consider other methods to reach this group. Examples can be follow-up calls, or requesting therapists that assigned someone that dropped out to report on the reason for this drop out.

Another advise for future researchers into using usage data to determine objective engagement is to control for the effects caused by receiving treatment from a psychologist on outcomes of DHI participation. This could be done by using self-report items for both respondent and therapist, or by changing the research design to include the two additional conditions of face-to-face treatment and stand-alone program participation alongside blended treatment.

In intervention programs such as the ones offered by Therapieland.nl where participants are requested to define their own change goals and where subjective engagement is also measured, it is important to include a qualitative analysis of these personal goals. Subjective engagement often relates to expectations of achieving goals through participation (Kelders et al., 2020). If these user specific goals are not aligned with the intended and possibly even proven effects of the intervention, no predictive relation can be expected between subjective engagement and intervention outcomes. The qualitative analysis of the personal goals helps determine whether they are aligned with the intended intervention outcomes.

Lastly, it is advised to check chat logs of the respondents that used to chat with therapist function to understand in what way it is used. If it is mainly used when there is an issue with the practical aspects of the intervention or when the participant has trouble understanding content, this would imply a lower level of subjective engagement. On the other hand, if the chat function is used to offer guidance and motivation to the user a higher level of subjective engagement is expected. Additionally, it would be valuable to understand what expectations the therapists have of the program and what instructions they give their patients for using the chat function specifically or the program in general, as this could create variance in what adherence to the program means for different users.

Conclusion

Although DHI's seem promising as a method to offer effective, easily accessible and affordable mental health support, it remains uncertain how to approach the issue these programs have of high attrition and low adherence. The proposed method of using log data to interpret levels of engagement that can predict a user's subjective engagement and eventual therapy outcomes was not found to be effective. Based on these findings and existing literature, alternative methods to use log data to determine the degree of engagement are theorized which are expected to yield better predictive value for the effectiveness of DHI's.

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Appendix A

The Twente Engagement with Ehealth Technologies Scale (TWEETS).

Item	Thinking about using [the technology] the last week, I feel that:	Construct
1	[this technology] is part of my daily routine	Behavior
2	[this technology] takes me little effort to use	Behavior
3	I'm able to use [this technology] as often as needed (to achieve my goals)	Behavior
4	[this technology] makes it easier for me to work on [my goal]	Cognition
5	[this technology] motivates me to [reach my goal]	Cognition
6	[this technology] helps me to get more insight into [my behavior relating to the goal]	Cognition
7	I enjoy using [this technology]	Affect
8	I enjoy seeing the progress I make in [this technology]	Affect
9	[This technology] fits me as a person	Affect

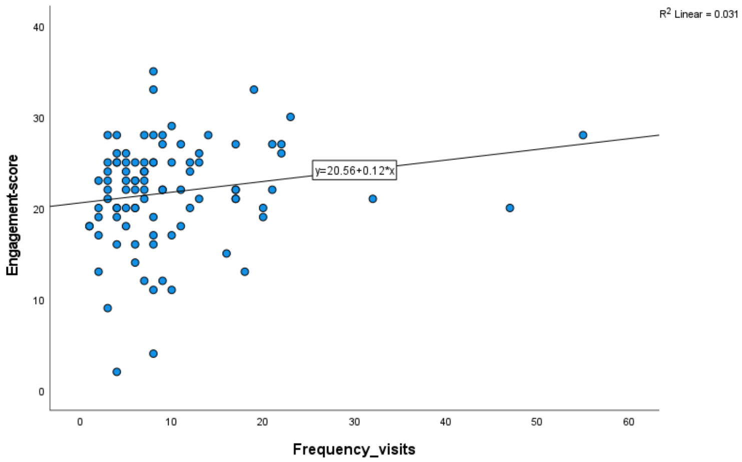
Appendix B

Structure of the Therapieland.nl Rumination program

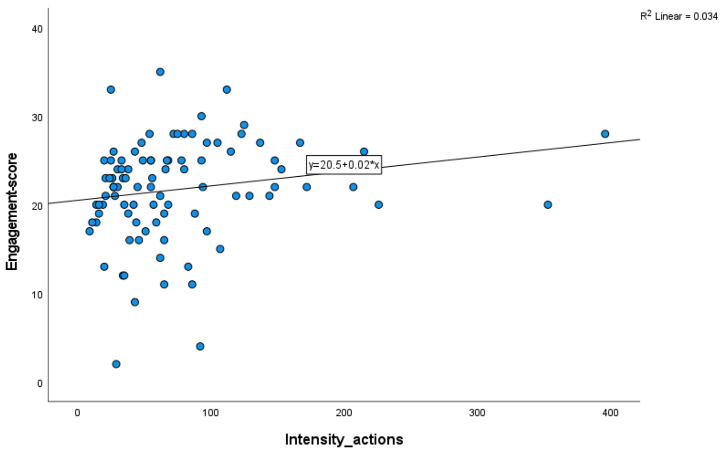
Sessie 1 Welkom	
Stap 1 Welkom	ca. 10 minuten
Stap 2 Therapeut kiezen	ca. 5 minuten
Stap 3 Vragenlijst	ca. 15 minuten
Stap 4 Wat is piekeren?	ca. 20 minuten
Stap 5 Waar wil jij aan werken?	ca. 10 minuten
Stap 6 Piekerregistratie week 1	ca. 10 minuten
	ca. 70 minuten totaal
Sessie 2 Wat is piekeren?	
Stap 1 Waarom pieker jij?	ca. 10 minuten
Stap 2 Oplosbaar of onoplosbaar?	ca. 15 minuten
Stap 3 Oplossingsgericht denken	ca. 20 minuten
Stap 4 Piekerregistratie week 2	ca. 10 minuten
Stap 5 Hoe ervaar jij dit programma?	ca. 10 minuten
	ca. 65 minuten totaal
Sessie 3 Onoplosbaar piekeren aanpakken	
Stap 1 Afleiding zoeken	ca. 10 minuten
Stap 2 Rampscenario's	ca. 10 minuten
Stap 3 Piekerkwartier	ca. 10 minuten
Stap 4 Piekeren in bed	ca. 15 minuten
Stap 5 Piekerregistratie week 3	ca. 10 minuten
	ca. 55 minuten totaal
Sessie 4 Gedachten loslaten	
Stap 1 Waar sta je nu?	ca. 5 minuten
Stap 2 Accepteren en loslaten	ca. 15 minuten
Stap 3 Mindfulness	ca. 25 minuten
Stap 4 Ontspanningsoefeningen	ca. 30 minuten
Stap 5 Piekerregistratie week 4	ca. 10 minuten
Stap 6 Hoe ervaar jij het programma?	ca. 10 minuten
	ca. 95 minuten totaal
Sessie 5 Afsluiting	
Stap 1 Vragenlijst	ca. 10 minuten
Stap 2 Doelen evalueren	ca. 5 minuten
Stap 3 Tot ziens	ca. 1 minuut
	ca. 16 minuten totaal

Appendix C

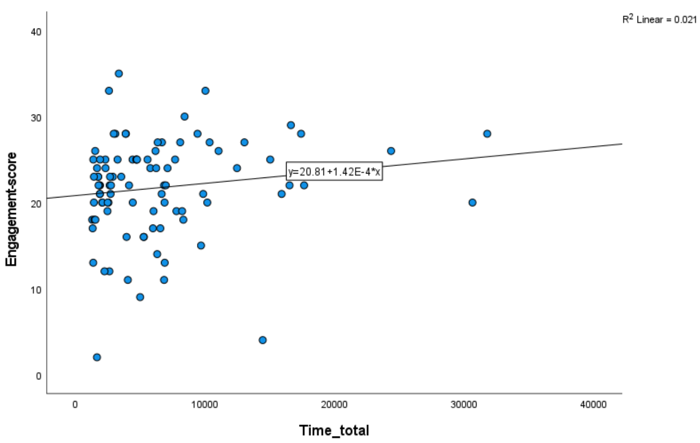
Scatterplot of Frequency and Subjective Engagement.



Scatterplot of Intensity and Subjective Engagement.

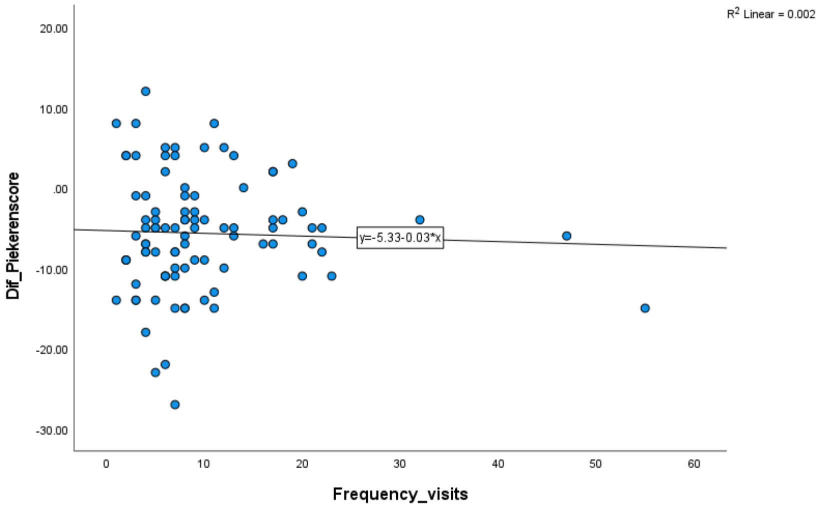


Scatterplot of Time and Subjective Engagement.

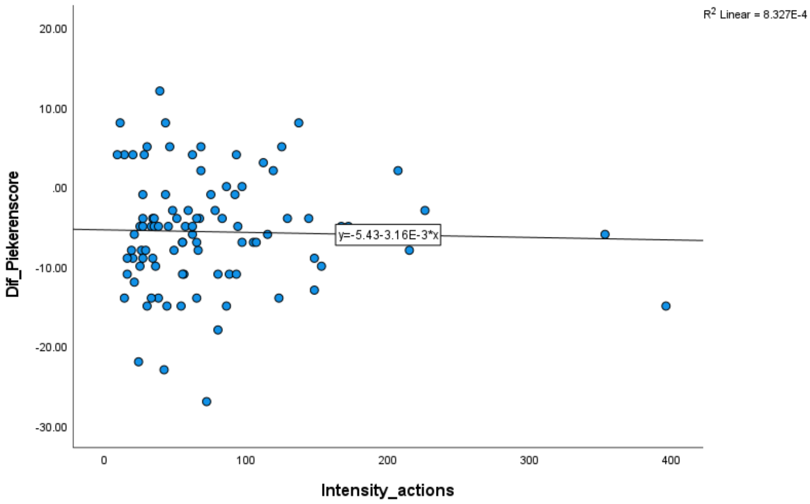


Appendix D

Scatterplot of Frequency and Rumination T0-T1 Difference score.



Scatterplot of Intensity and Rumination T0-T1 Difference score.



Scatterplot of Time and Rumination T0-T1 Difference score.