It's All About Perspective: Introducing PsySys as a Digital Network-Informed Psychoeducation for Depression

Emily J. Campos Sindermann

Master Thesis in the Research Master Psychology

University of Amsterdam

Supervisor: Prof. Dr. Denny Borsboom

Second Assessor: Dr. Marie Deserno

Collaborators: Julian Burger (M.Sc.); Prof. Dr. Lars Klintwall; Dr. Tessa Blanken

Abstract

Major depressive disorder remains among the most prevalent mental disorders worldwide. Previous studies suggest that internal illness representations are critical to the trajectory and treatment effectiveness of depression. Thus, shifting individuals' perspectives on their depressive complaints might be a promising strategy to enhance treatment outcome. The present study aims to do this by introducing PsySys, the first digital psychoeducation for depression rooted in the network approach of psychopathology. In a 20-30 minute session, PsySys is designed to convey the conceptual foundations of the network approach through explanatory videos and help participants internalize and apply them in practical exercises. After participating in a single PsySys session, participants showed less prognostic pessimism and an increase in perceived personal control, and understanding of their complaints. PsySys was generally well received and participants provided valuable insights to inform future work. Overall, our findings indicate that a brief network-informed psychoeducation may serve to improve people's attitudes towards their depressive complaints, and thereby increase their motivation and susceptibility to treatment.

Keywords: depression, illness representations, network approach, psychoeducation

It's All About Perspective: Introducing PsySys as a Digital Network-Informed Psychoeducation for Depression

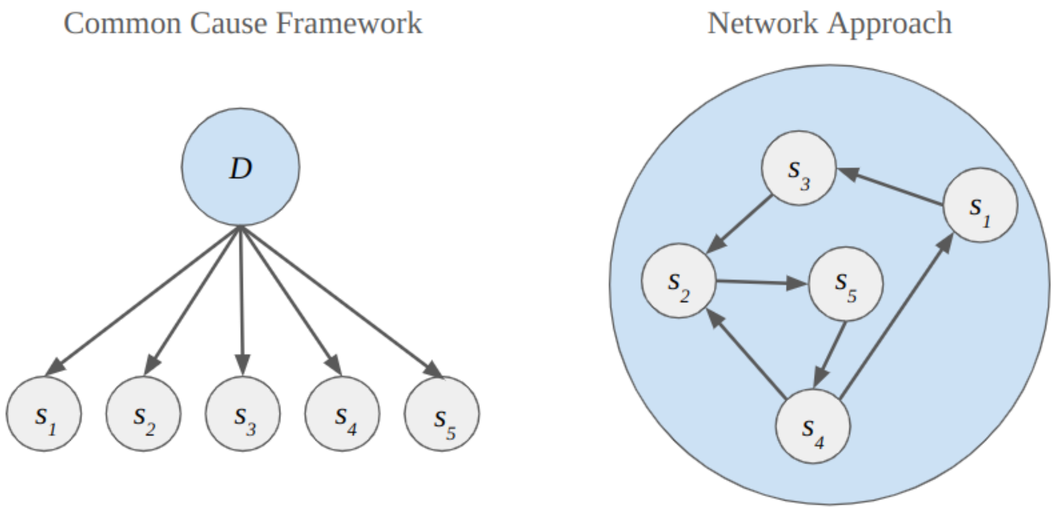
For over three decades Major Depressive Disorder (hereinafter: depression) has remained among the leading causes of disability worldwide (Ormel et al., 2022). Thereby, it not only causes substantial personal suffering, but also carries debilitating societal impact (Richards, 2011). Paradoxically, increased efforts to provide evidence-based treatments have failed to address the burden of depression (Patten et al., 2016). This apparent stagnancy might be traced back to the predominant categorical perspective on mental disorders that has guided scientific progress, and might have failed to fully grasp the nature of depression after all (Fried, 2015).

In the quest to explain, diagnose and treat observable symptoms, the field has relied on the search for *common causes* (Borsboom, 2017). Thereby, symptoms are viewed as interchangeable and causally independent entities stemming from an underlying cause and can therefore be neatly assigned to their corresponding disorder categories (Borsboom, 2008). The resulting hard boundaries between disorders, however, do not account for the observed heterogeneity as well as comorbidity found in depression, indicating a rather fuzzy structure of the disorder (Fried, 2015).

In recent years, the study of depression has increasingly taken on a network perspective, which offers an alternative way to conceptualize mental disorders (Fried, 2017). In contrast to the predominant common cause framework that assumes that mental disorders cause certain sets of symptoms (see Figure 1), the network theory posits that the underlying symptom dynamics give rise to, and maintain, the disorder (Borsboom, 2008). Consequently, symptoms are not seen as mere passive indicators of an underlying cause, but rather as active interconnected elements within a disorder network. This conceptual level is complemented by the network methodology, providing statistical tools to quantify these disorder dynamics (Epskamp et al., 2018).

Figure 1

Models of Mental Disorders



Note. While the common cause framework assumes that a mental disorder D causes a set of observable symptoms S, the network approach posits that the underlying symptom dynamics give rise to D. Here, nodes within the network represent the symptoms, while the directed edges represent the causal relations between them.

Since its introduction in 2008, the network approach has left an astonishing mark in the scientific landscape, reflected by the vast increase of network papers in clinical research (Robinaugh et al., 2020). Efforts to explore the practical utility of the approach have mainly focused on using networks to reveal how personalized symptom dynamics unfold over time (Bringmann & Eronen, 2018). Naturally, the aim to estimate "true" person-specific networks bears the promise of contributing a great deal toward more personalized therapy. Not only would the integration of personalized networks in practice allow for more informed treatment decisions, but optimally even enable mood predictions, and could therefore provide early warning signals for e.g. the onset of depressive episodes.

However, how successful these network models are in capturing the "truth", is certainly up for debate (Haslbeck et al., 2022), and flexibility in the choice of model and structure might overshadow the replicability of network findings (Forbes et al., 2017). The adoption of personalized networks in practice is further hampered by concerns about feasibility, mostly linked to the extensive necessary data collection, creating significant participant burden (Contreras et al., 2019). Furthermore, already established methods such as case conceptualization, are also directed at identifying symptom relations (Kuyken et al., 2008), leading practitioners to question the added benefit of estimating networks (Frumkin et al., 2021). These drawbacks have resulted in a gap between research and practice, leaving the exact clinical utility of the network approach unclear.

Drifting away from the conceptual roots of the network approach, the scientific literature has been focussing on its methodological application. However, as Bringmann and Eronen (2018) put, the network approach does not propose any novel models per se, rather, its strength lies in providing a new window into the study of mental disorders. Thus, in essence, the “unique selling point” of the network approach is not that it introduces statistical models, but that it breaks down the notion of mental disorders and represents it in a new light – it provides a new *perspective*.

Recent efforts have explored alternative applications of this perspective. For instance, Klintwall et al. (2021) introduced PECAN, a method in which patients themselves iteratively build their network, by indicating the perceived causal relations between their complaints. Thereby, PECAN not only circumvents the statistical estimation of networks, and the related limitations thereof but also integrates the patients’ perception.

Taking one step further, Meier et al. (2022) disregarded the use of personalized networks altogether, and suggested that simply conveying the network perspective might prove clinically useful. They found that a brief network explanation of eating disorders led to a decrease in self-blame, and improvements in prognostic pessimism, perceived agency, and understanding of present complaints. Such perceptions, that individuals hold of their health conditions, are likely to influence coping behavior and treatment adherence, ultimately shaping individuals’ response to treatment (Manber et al., 2003).

Individuals' beliefs and expectations about their health conditions are also known as illness representations[1], which are commonly divided into well-defined dimensions as follows (Leventhal et al., 1980). *Identity* representations embody the labels (e.g. depression) and symptoms (e.g. feelings of sadness) that individuals associate with their condition. *Causal* representations refer to what individuals believe to have triggered their condition (e.g. past traumatic experience). Representations about *consequences* relate to the perceived impact of the condition on a person's everyday life (e.g. stigma). *Timeline* representations encompass the perceived course and duration of a condition (e.g. whether it is perceived as permanent or temporary). Representations of *control* cover expectations about whether the condition can be tackled either by the individual themselves (personal control) or by a professional. Finally, representations of *illness coherence* refer to the extent to which individuals understand their condition, and *emotional* representations relate to individuals' emotional response to their complaints and diagnosis.

In their systematic review, Mavroeides and Koutra (2021) showed that longer duration expectancies, as well as a lower sense of personal control and illness coherence, were linked to poorer treatment adherence and depression outcomes. Thus, a patient expecting their depression to last forever, who thinks it is a "lost cause", and who lacks an overall understanding of their complaints, would be less likely to engage in therapy or take their medication as recommended. In contrast, a patient who sees their depression as temporary and believes there to be promising treatments and helpful lifestyle changes, would more readily go to therapy and follow their treatment plan. Ultimately, the latter case would be more likely to show an improvement in their symptoms, as well as overall quality of life (Cannon et al., 2022). However, although patients' illness representations appear critical to the course of treatment, thus far, no initiatives have been taken to integrate them into therapeutic interventions for depression (Mavroeides & Koutra, 2021).

[1] In line with other studies on *illness representations* in mental disorders, we will adopt this terminology. Note, however, that *disorder representations* might be more appropriate in the context of mental health.

Within the present study, we introduce PsySys – Psychological Systems Education – the first digital, self-guided, and network-informed psychoeducation for depression, that aims to target and improve participants' illness representations. Building on the study by Meier et al. (2022), who created brief psychoeducational videos focussing on eating disorders, we translate the network rationale to another disorder domain, improve its theoretical scope and effective communication, and augment the learning experience with practical exercises. Thereby, we strive to further explore the clinical applicability of the network theory. Moreover, we aim to create a format that can be easily expanded and utilized for both research and practical purposes in the future.

To provide a first evaluation of the clinical utility of PsySys, our study examines participants' change in illness representations after engaging in a PsySys session. Thereby, we focus on participants' expected duration of their complaints, as well as their sense of personal control over and understanding of their condition. To investigate who might benefit the most from a PsySys session, we examine education-level and depression severity as possible influencing factors. Finally, we collect insights regarding participants' perceived educational and practical value of PsySys, to identify possible points for improvement.

In line with the findings by Meier et al. (2022), who found their network explanation to improve *timeline*, *personal control*, and *illness coherence* representations of eating disorders, we expect participants to show shorter duration expectancies, and higher personal control and understanding in regard to their depressive complaints. Considering the influence of education-level on this improvement, we do not have precise predictions as it is unclear how education-level might influence the participants' ability to understand the content of PsySys. Furthermore, we do not pose any expectations regarding the influence of depression severity, as previous studies do not indicate a clear trend. While Moss-Morris et al. (2002) suggested that depression severity might impede changes in illness representations altogether, Meier et al. (2022) indicated that depression severity might enhance improvements in illness coherence, specifically.

In the following, we first elaborate on the creation, content, and implementation of PsySys. Then, we move on to present our study where we first outline the methods we used and subsequently show our results. Finally, we delve into the implications of our findings within the broader scientific context and put forth directions for future work.

PsySys – Psychological Systems Education

PsySys was conceptualized in a collaborative effort to create a psychoeducative tool that is based on the concepts of the network approach and provides a clear and simple content delivery to allow for a stand-alone and self-guided learning experience. To this end, we invited experts in the field to participate in two informal brainstorming sessions. The first session (28.02.23) focused on discussing the key elements of PsySys. Therefore, we were joined by experts in the network research field from the University of Amsterdam, University of Groningen, University of Münster, Leiden University, and Northeastern University ($N = 7$). Once the PsySys elements were identified, the second session (08.03.23) focused on their clinical communication, for which we invited clinical researchers from the University of Amsterdam, Osnabrück University, and RPTU Kaiserslautern- Landau, as well as experts from industry ($N = 8$). During March 2023 we created PsySys in script format which was then translated into videos over the course of April 2023. For the video creation, we used the software VideoScribe. The final version of PsySys consisted of one introductory video followed by four blocks each consisting of an explanatory video and a practical exercise, encouraging participants to reflect upon the learned concepts and apply them to themselves. We also included optional *draw-along* instructions to help interested participants represent their perceived network structure. The script and videos can be found on Google Drive. In the following, we summarize the content of each PsySys block.

First PsySys Block – Everybody Struggles from Time to Time

Within the first PsySys block participants learn about the heterogeneity of mental problems, commonly stressed within the depression literature (Fried, 2017), and are encouraged to think about the mental distress they are currently dealing with. We deliberately decided not to use phrasing implying a categorical structure of mental health such as “mental disorders” and “depression”. Instead, we referred to mental health problems as *mental distress*, as we felt as though this would circumvent the use of clear disorder categories as well as increase the accessibility of the PsySys content in general. Furthermore, mental distress is regarded as being manifested through *personal factors*. This should not only emphasize the individuality underlying mental distress but also intuitively allow the distinction between *internal* and *external* factors made within the network approach (see Borsboom and Cramer (2013)). Here, we aimed to include more transient symptoms and influenceable behaviors, rather than biological factors.

Within the 04:46 minutes video (see Figure 2), we introduce the examples of *Sarah, John* and *Linda*, that differ considerably in age, gender, and life circumstances, and are supposed to demonstrate the variability within people struggling from mental distress (see Table 1). Furthermore, these diverse examples should serve the purpose of allowing various possible anchors of identification to facilitate the participant’s engagement with the content at hand. Within the exercise, participants are asked to choose their personal factors from a list. The factors that can be chosen are: *Loss of interest, Feeling down, Stress, Worrying a lot, Overthinking, Sleep problems, Changes in appetite, Self-blame, Trouble concentrating, Experiencing a break-up, Problems at work, Interpersonal issues.*

Figure 2

Video Screenshots Showing the Case of Linda and Exemplifying Different Coping Strategies

Table 1

PsySys Cases

Case Description
Meet Sarah. Sarah has been *feeling sad* for the past few months. She has *lost interest* in the little things that used to bring her joy, like going to the gym or meeting up with her friends. She's been struggling with *sleep problems*, and can sometimes find *no motivation* to get out of bed in the morning. It feels like there's a heavy weight on her shoulders that she just can't lift by herself.
Meet John. John has recently *retired* from his job at an insurance company. His newfound freedom quickly turns into boredom and John *starts drinking* as he doesn't really know what else to do. When his wife tries to help him, he gets annoyed and shuts off. Little discussions turn into full-fledged arguments, which takes a *toll on their marriage*. When John looks into the mirror he doesn't recognize himself anymore, when did he become so old? Where is the strong, young man he once was? He's *ashamed* and refuses to talk to anyone about his feelings.
Meet Linda. Linda is a university student. Recently, she *can't focus* on her studies and *procrastinates* most of the day scrolling through Instagram. Seeing the work piling up in front of her only increases her *stress*, and makes her feel *ashamed* for not doing enough. She feels overwhelmed and wishes she could "just snap out of it" – but she can't. She feels as though she's become a burden to her family. Linda directs all her anger toward herself and goes as far as *physically hurting herself* sometimes.

Note. The personal factors they are dealing with are marked in italic.

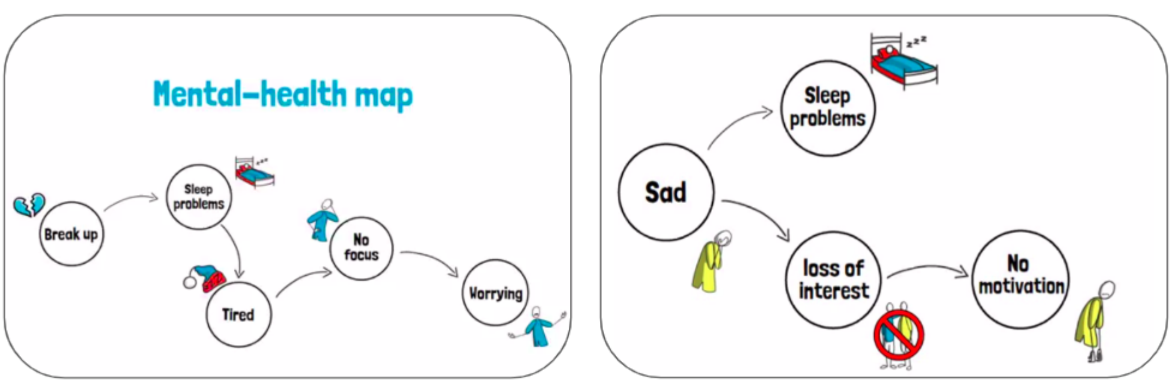
Second PsySys Block – Seeing the Connections

Within the second video (03:14 minutes), PsySys introduces the idea of psychological networks via the concept of *mental-health maps* (see Figure 3). These personalized mental-health maps consist of the factors the person is currently dealing with (i.e. nodes) and the causal relations between them (i.e. directed edges). Here, the aim is to direct the participant away from the notion of one single cause underlying personal factors, and towards the idea that these factors influence each other and thereby form a person's current state of *mental well-being*.

To emphasize the dynamic nature of mental-health maps, we differentiate between stable and variable connections between personal factors. While stable connections are always present in the map (e.g. *Sleep problems* → *Tiredness*), variable connections might arise and vary in response to certain life circumstances (e.g. the connection *Trouble concentrating* → *Worrying* might arise when facing an important deadline for work). Within the exercise, participants are presented with the initial factor list and are asked to indicate two causal chains that they find plausible or have been struggling with themselves. For this, we use a drag-and-drop answering format. In general, we make use of different answering styles throughout the PsySys session to create a more engaging user experience.

Figure 3

Video Screenshots Introducing Mental-health Maps and Showing the Map of Sarah's Case

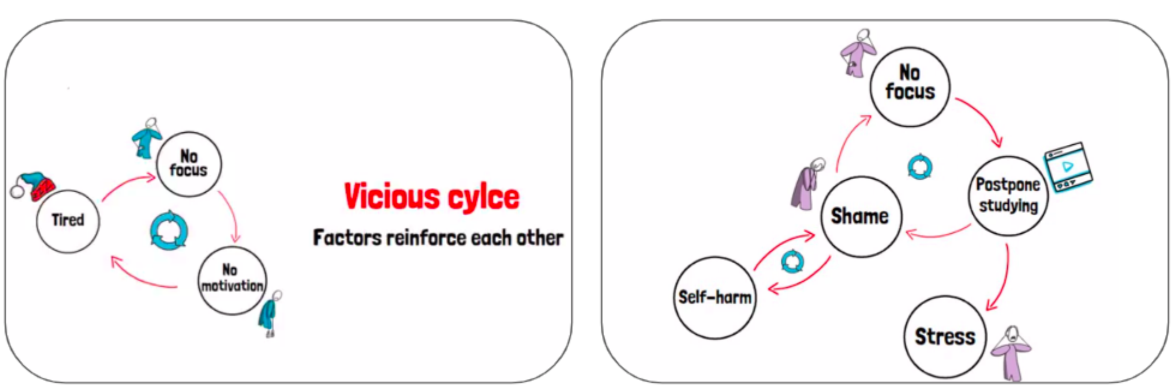


Third PsySys Block – Vicious Cycles

The third video (04:34 minutes) focuses on feedback loops, which are thought to be the key structure to drive psychological networks into a prolonged state of symptom activation, or into "mental disorders" in classical terms (Borsboom, 2017). A feedback loop occurs when factors in the network form a closed causal cycle (e.g. *Fear* ↔ *Avoidance*). Whether we classify a feedback loop as "good" or "bad" depends on the nature of the factors and connections contained therein. Thus, we introduce the distinction between *negative* factors (e.g. hurtful breakup) and *positive* factors (e.g. exercising regularly), as well as *amplifying* and *relieving* connections. While an amplifier from factors f_1 to f_2 would cause an increase in f_1 to further increase f_2 (i.e. a strengthening edge), a reliever would lead to a decrease in f_2 in the same scenario (i.e. a weakening edge). Thus, if a feedback loop consists of negative factors that are connected by amplifiers, it can form a *vicious cycle* in which the factors keep reinforcing each other. This can render harmful dynamics self-sustaining and ultimately lead to the person becoming stuck in a *downward spiral*. This block aims to help participants to better understand how mental distress can come about and why they might feel *stuck* sometimes. In the corresponding exercise, participants are presented with six examples of vicious cycles (e.g. Anxiety ↔ Worry) and asked to indicate which of them apply to their own experience.

Figure 4

Video Screenshots Introducing Vicious Cycles and Showing Linda's Case



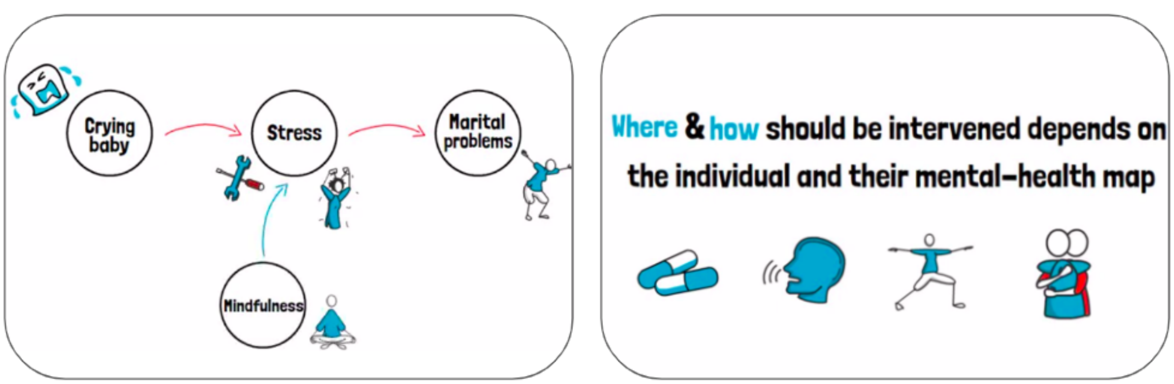
Fourth PsySys Block – Breaking Out of the Cycle

The fourth and final PsySys video (04:55 minutes) tackles the question of how to escape these vicious cycles and improve one's state of mental well-being (see Figure 5). Therefore, it explains how the inherent network properties, namely the factors' connectedness, that can drive it into an undesirable state, to begin with, can also be used to efficiently improve it. Participants should understand that the links between factors cause them to become dependent on each other and that targeting a given factor or specific connection can have a positive effect on other connected factors as well. More specifically, we stress that promising treatment strategies might comprise targeting factors and connections that are part of vicious cycles. Thereby, the reinforcing dynamics could provide opportunities for efficient treatment applications. We thereby also aim to underline the importance of individualized treatment strategies which vary dependent on the personalized mental-health map structures.

For the final exercise, participants are encouraged to reflect on the learned concepts by selecting promising treatment strategies for *John's* mental-health map. For a description of *John's* case, we refer the reader to Table 1. The choice of interventions includes e.g. *practicing mindfulness, going to marriage counseling,* or *meeting friends at a bar.*

Figure 5

Video Screenshots Explaining How Mental-Health Maps Can Inform Treatment



Method

Participants

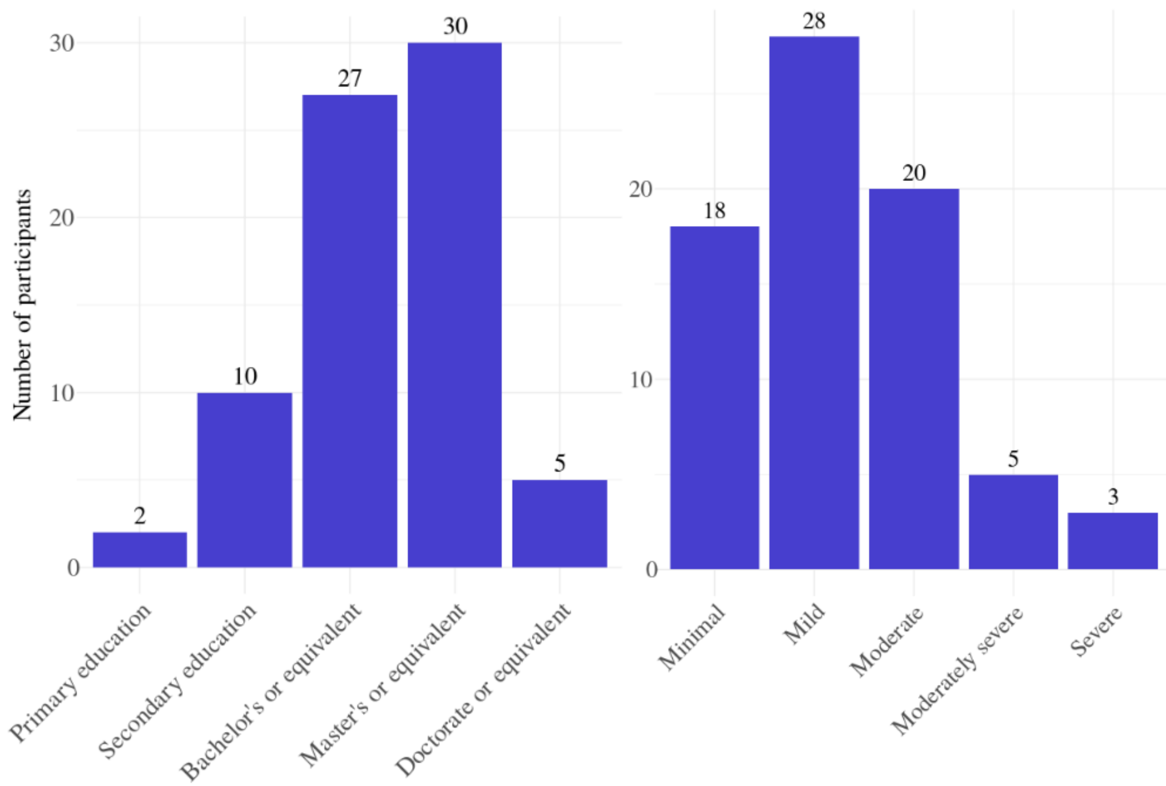
The present study was promoted via various media. While we advertised it directly at the Universities of Amsterdam and Osnabrück via posters and mailing lists, the big bulk of recruitment was done on social media platforms. We posted adverts in 89 Facebook groups, 13 sub-Reddits, and three Telegram channels related to mental-health. Furthermore, we placed paid advertisements on Facebook and Instagram and showed continuous online presence on Instagram, TikTok, and Twitter. Data was collected over one month (10.05 - 13.06.23), and participation was non-remunerated.

Initially, 215 individuals entered the survey, from which 139 terminated their participation before completion. Most dropouts were at the beginning of the study either right at the consent ($N = 47$) or at the descriptives ($N = 31$). A total of $N = 45$ participants dropped out during the pre- PsySys questionnaires, and $N = 16$ left the study during the PsySys session (see Figure B1). Since all study adverts were in English and specifically targeted individuals experiencing some type of mental distress (refer to Figure A1 in Appendix A), we chose not to exclude participants based on their English proficiency level or depression severity, to maintain a sufficient sample size.

In the following we describe the sample characteristics of the resulting $N = 74$ completed responses, we did however include duration cut-offs for our main analysis (see Data Analysis section). Our final sample consisted of 74 respondents (55.41% female, 36.49% male, 6.76% non-binary, and 1.35% undisclosed) with a mean age of 33.51 years ($SD = 15.08$), of which 83.78% held a university degree (see Figure 6). Participants predominantly reported becoming aware of PsySys through recommendations (48.65%) and took on average 169.52 minutes for completion. On average, participants scored 8.23 ($SD = 5.24$) on the depression questionnaire, indicating mild depression (see Figure 6). For a visualization of dropouts and a recruitment summary, we refer the reader to Appendix A and Appendix B.

Figure 6

Education-Level (Left) and Depression Severity (Right) of Completed Responses (N = 74)



Note. For consistent presentation, we show both the education-level and the categorized depression scores within a barplot. For a clearer visualization of the distribution of depression scores within the sample, we refer the reader to Appendix B Figure B2.

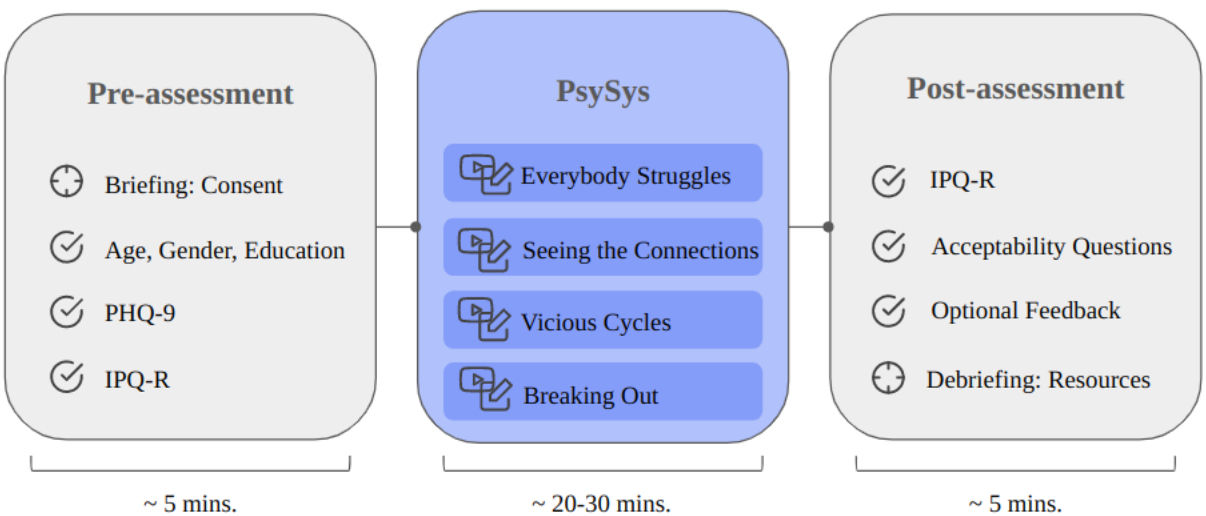
Procedure

The entire study was implemented in Qualtrics, an online survey platform. Upon entering the study link, participants were informed about the study procedure and had to give consent. Then, participants were asked to provide demographic information and were assessed on depression severity as well as their attitudes towards (their) mental health (i.e. illness representations). Participants then entered the PsySys session, consisting of a short introductory video followed by four blocks each including one explanatory video and a practical exercise. The entire PsySys session took a total of approximately 20-30 minutes.

After completing the session, participants had to repeat the questions on illness representations, answer questions on the acceptability of PsySys and were given the opportunity to give open-text feedback. At the end of the study, participants were provided with a short elaboration on the science behind PsySys as well as a list of mental health resources. The entire study was planned to take approximately 30-40 minutes. In an effort to keep it as short as possible, we decided not to include additional manipulation and understanding checks. For a procedure visualization, we refer the reader to Figure 7.

Figure 7

Study Procedure



Materials

We used PsySys as stimulus material for the present study. In the following, we describe the additional questionnaires that were used. All corresponding questionnaire items can be found in Appendix C.

The Patient Health Questionnaire – 9 (PHQ-9)

To assess depression, we used the depression module of the Patient Health Questionnaire (Kroenke et al., 2001). On a 4-point Likert scale (*not at all - nearly every day*) it evaluates the extent to which the nine DSM-IV depression criteria were experienced over the past two weeks (see Table C1). The scores reflecting severity are interpreted as follows: 0-4 *minimal*, 5-9 *mild*, 10-14 *moderate*, 15-19 *moderately severe*, and 20-27 *severe*. At a cutoff of 10 the PHQ-9 has been reported to have a sensitivity (true positive rate) and specificity (true negative rate) of 88% for depression (Kroenke et al., 2001).

The Illness Perception Questionnaire – Revised (IPQ-R)

To assess illness representations, we used the IPQ-R (Moss-Morris et al., 2002), focusing on the subscales *timeline, personal control*, and *illness coherence* (see Table C2). It assesses items on a 5-point Likert scale (*strongly disagree* - *strongly agree*). Meier et al. (2022) reported a good internal consistency for *timeline* ($\alpha = 0.88$ – *baseline*, $\alpha = 0.86$ – *post*), and *personal control* ($\alpha = 0.88$ – *baseline*, $\alpha = 0.86$ – *post*). For *illness coherence* the internal consistency was excellent ($\alpha = 0.94$ – *baseline*, $\alpha = 0.91$ – *post*). As we did not exclude participants based on depression severity, and felt the wording “illness” to be unfitting in the context of mental health, we changed it to “mental distress”.

Acceptability Questionnaire

To assess the acceptability of PsySys we created 10 items to cover the *explainability, scope, length*, and *perceived utility* of PsySys (see Table C3). These items were assessed on a 5-point Likert scale (*strongly disagree* - *strongly agree*).

Data Analysis

To examine the change in illness representations as well as the possible influence of education-level and depression severity, we performed both a frequentist analysis (R version 4.3.0) and corresponding Bayesian analysis (JASP version 0.17.2.1) with the default uniform priors. While we planned the entire survey to take approximately 30-40 minutes, responses outside of this time frame do not necessarily indicate that participants did not complete the PsySys session. Possible reasons for shorter completion times could be that participants chose to watch the videos at an accelerated pace or skip exercises, while longer completion times might be due to participants accidentally leaving the browser open. As we wanted to avoid preemptively excluding participants based on completion times, we ran the analyses with different duration cut-offs (in minutes). This resulted in five data sets with (1) all completed responses ($N = 74$), (2) $duration > 15$ ($N = 61$), (3) $15 < duration < 90$ ($N = 52$), (4) $duration > 30$ ($N = 50$), and (5) $30 < duration < 90$ ($N = 41$).

To analyze whether there was an improvement in illness representations after the PsySys session, we performed a one-sided paired t-test for each subscale. We, therefore, flipped all IPQ-R items that associated higher scoring on the Likert scale with longer *timeline* or lower *personal control* and *illness coherence* representations (I2, I3, I5, I10, I12-I16). Hence, a positive change score from pre- to post-PsySys measurement indicated an improvement in illness representations (i.e. shorter *timeline*, and an increase in *personal control* and *illness coherence* representations). Thus, our null hypothesis postulated that there was no difference between pre- and post-PsySys scores, whereas the alternative hypothesis stated there was a positive change from pre- to post-PsySys scores.

To investigate the potential influence of education-level and depression severity on the improvement in illness representations, we included them as covariates in repeated measures ANOVA models for each subscale. For the frequentist tests, we used a standard significance level of $\alpha = .05$ to reject the null hypothesis and applied false discovery rate (FDR) correction to all p-values to adjust for multiple testing (Benjamini & Hochberg, 1995). Within-group effect sizes were calculated by dividing the mean change scores by their standard deviation (Cohen's d, hereinafter: d). We interpreted the Bayesian results using the Bayes factor, which indicates the strength of evidence for either hypothesis, following the guidelines provided in Wagenmakers et al. (2018).

Lastly, we analyzed the acceptability of PsySys descriptively. As we used an ad-hoc acceptability questionnaire, we calculated Cronbach's alpha as a measure of reliability. Regarding the open-text feedback, we identified the main points and categorized them into either positive feedback, negative feedback, or suggestions. The analysis R script alongside all figures included in this report can be found in the project GitHub repository.

Results

The presented patterns were replicated across all duration cut-offs. Here, we report the results for our most conservative data set (5) $30 < duration < 90$ ($N = 41$). For a full description of the remaining analyses, we refer the reader to Appendix D.

The Change in Illness Representations

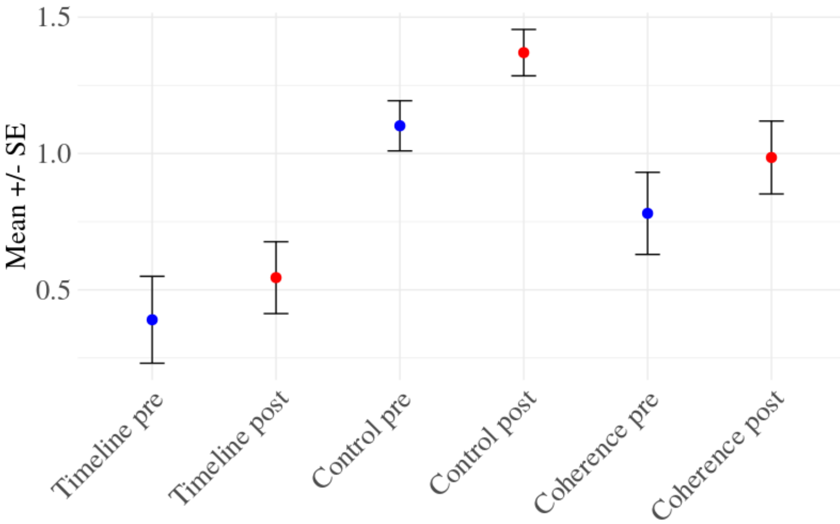
In line with our expectations, there was a significant improvement in all of the included illness representation subscales from pre- to post-PsySys assessment, which was mostly supported by our Bayesian analyses (see Table D8). Moreover, our effect sizes (d) exceeded the ones reported by Meier et al. (2022) by more than two to three times, except for the effect in *timeline*. Within the *timeline* subscale we found a significant change towards shorter *timeline* representations ($t(40) = 1.78$, $p = .04$, $d = 0.34$), with the Bayes factor providing inconclusive support for this change ($BF_{10} = 1.36$). The strongest effect was found for *perceived control* ($t(40) = 4.28$, $p < .001$, $d = 0.52$), which was heavily supported by the corresponding Bayes factor ($BF_{10} = 433.82$). Finally, we also found a significant improvement in *illness coherence* ($t(40) = 2.47$, $p = .01$, $d = 0.41$), which was moderately supported by the Bayes factor ($BF_{10} = 4.85$).

As the assumption of normality was violated for the *personal control* and *illness coherence* measures, which were all slightly left-skewed, we decided to additionally include a non-parametric alternative for these variables. We performed a Wilcoxon signed-rank test for each subscale which confirmed the significant t-test results for *personal control* ($V = 537$, $p < .001$), and *illness coherence* ($V = 321.5$, $p = .01$).

On an item level, we found that all items but I2 (*"My mental distress is likely to be permanent rather than temporary"*), which showed no change across participants, improved from pre- to post-PsySys assessment. The items that improved the most on a group level (change scores > 0.25) were I7 (*"There is a lot which I can do to control my symptoms"*), I8 (*"What I do can determine whether my mental distress gets better or worse"*), and I13 (*"The symptoms of my condition are puzzling to me"*) (see Figure D1 & Table D8).

Figure 8

Pre- (Blue) and Post- (Red) PsySys Mean Per Illness Representation Subscale



Note. *SE denotes the standard error.*

Figure 9

Pre- (Blue) and Post- (Red) PsySys Densities Per Illness Representation Subscale

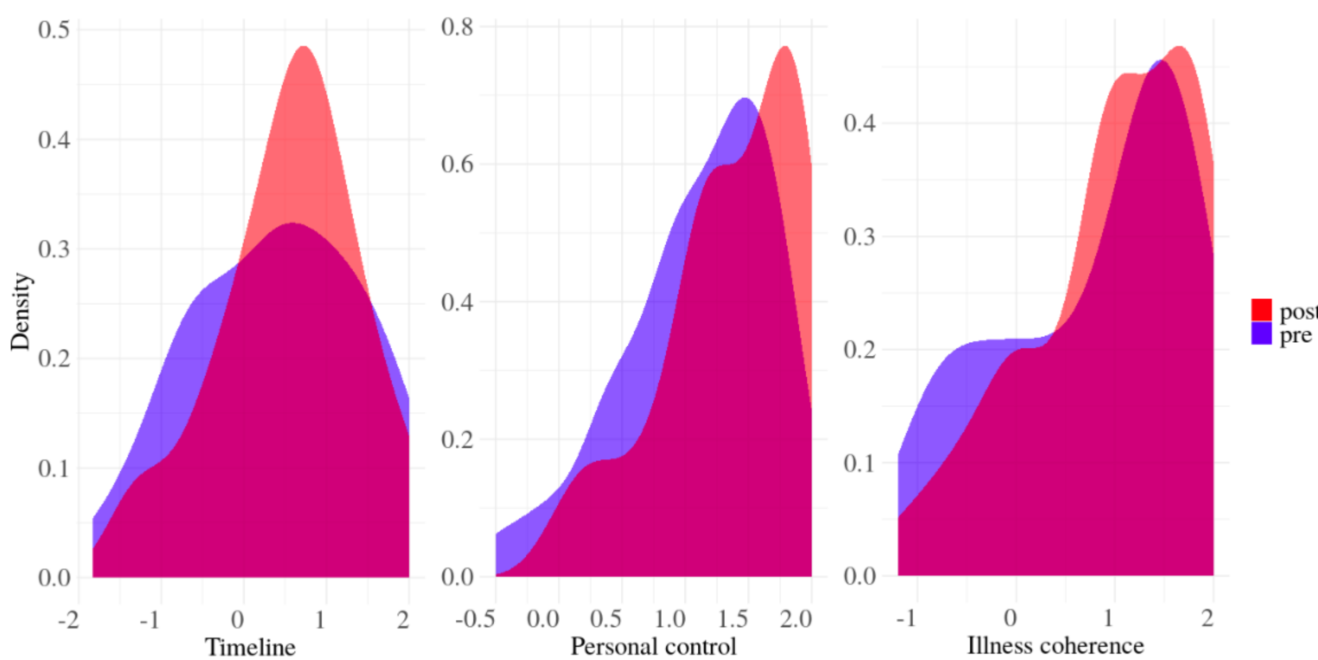


Table 2

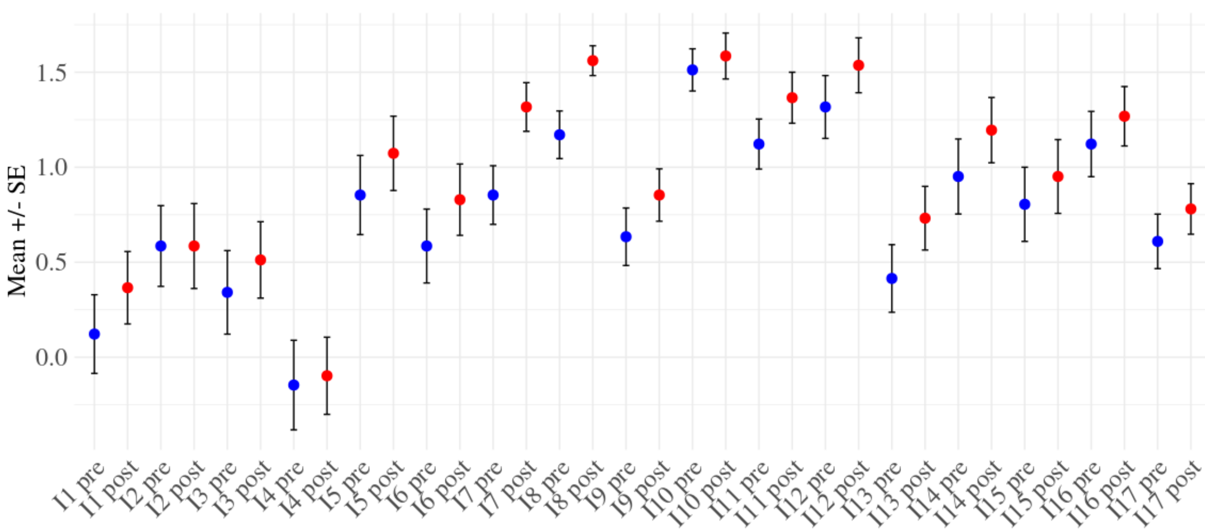
Frequentist and Bayesian T-test Results

	Frequentist						Bayesian
	T-test				Wilcoxon		
Subscale	*t*	*df*	*p*	*d*	*V*	*p*	BF_{10}
Timeline	1.78	40	.04*	0.28			1.36
Personal control	4.28	40	< .001***	0.67	537	< .001***	433.83
Illness coherence	2.47	40	.01*	0.39	321.50	.01*	4.85

Note. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Figure 10

Results. *Pre- (Blue) and Post- (Red) PsySys Means Per Illness Representation Item*



Note. *Items 1-6 pertain to the timeline, items 7-12 to the personal control, and items 13-17 to the illness coherence subscale.*

The Influence of Depression Severity and Education-Level

To examine depression severity and education-level as potential indicators for the efficacy of PsySys, we first performed spearman correlations between PHQ-9 as well as education scores and *timeline (T), personal control (PC)* and *illness coherence (IC)* change scores. While we found a moderate association between PHQ-9 scores and the change in *timeline* ($r_s = 0.42$), there were only weak associations for the other subscales ($r_{s_{PC}} = 0.04$; $r_{s_{IC}} = 0.10$). Education-level did not correlate with any of the change scores ($r_{s_T} = -0.10$; $r_{s_{PC}} = -0.04$; $r_{s_{IC}} = -0.01$). We additionally examined the relationship between PHQ-9 and education scores and the baseline illness representation assessments. While we found medium to moderate associations for PHQ-9 scores ($r_{s_T} = -0.56$; $r_{s_{PC}} = -0.29$; $r_{s_{IC}} = -0.34$), education-level did not appear to influence initial illness representations ($r_{s_T} = -0.09$; $r_{s_{PC}} = 0.02$; $r_{s_{IC}} = -0.10$).

Finally we present the results of our repeated measures ANOVA analysis (see Table D9). For *timeline* neither the main effect of the time points ($F(1, 38) = 0.03$, $p = .87$, $\eta_p^2 < 0.001$), nor the main effects of the covariates (PHQ-9: $F(1, 38) = 1.92$, $p = .17$, $\eta_p^2 = 0.05$; Education: $F(1, 38) = 0.21$, $p = .65$, $\eta_p^2 = 0.01$) was statistically significant. In contrast, while the Bayes factor confirmed our findings for the main effect of the time points ($BF_{incl} = 0.85$) and education-level ($BF_{incl} = 0.60$), it provided strong evidence for the influence of PHQ-9 scores ($BF_{incl} = 29.38$). For *personal control*, we also did not find any statistically significant results for both the main effect of the time points ($F(1, 38) = 3.58$, $p = .07$, $\eta_p^2 = 0.09$), as well as the main effects of the covariates (PHQ-9: $F(1, 38) = 0.17$, $p = .68$, $\eta_p^2 = 0.00$; Education: $F(1, 38) = 0.42$, $p = .52$, $\eta_p^2 = 0.01$). While the Bayes factor provided strong evidence for including the time points ($BF_{incl} = 190.67$), the finding for the covariates were further supported (PHQ-9: $BF_{incl} = 1.20$; Education: $BF_{incl} = 0.50$). Lastly, for *illness coherence* we also did not find statistical significance, neither for the main effect of the time points ($F(1, 38) = 0.21$, $p = .65$, $\eta_p^2 = 0.01$) nor for the covariates (PHQ-9: $F(1, 38) = 1.23$, $p = .28$, $\eta_p^2 = 0.03$; Education: $F(1, 38) = 0.17$,

$p = .69$, $\eta_p^2 = 0.00$). The Bayes factor provided anecdotal support for including time points ($BF_{incl} = 2.76$) and PHQ-9 scores ($BF_{incl} = 2.83$), and none for including education-level as a predictor ($BF_{incl} = 0.61$).

Overall, these results are mixed. The frequentist analysis indicates that depression severity and education-level did not influence the change in illness representations in the present sample. In contrast, the Bayes factor provides evidence indicating that there might be an influence of depression severity, especially for the change in *timeline* representations.

Table 3

Frequentist and Bayesian Repeated Measures ANOVA Results

	Frequentist				Bayesian
Factor	*df*	*F*	*p*	η_p^2	BF_{incl}
Timeline	1	0.03	.87	< 0.001	0.85
Timeline * PHQ-9	1	1.92	.17	0.05	29.38
Timeline * Education	1	0.21	.65	0.01	0.60
Personal control	1	3.58	.07	0.09	190.67
Personal control * PHQ-9	1	0.17	.68	0.00	1.20
Personal control * Education	1	0.42	.52	0.01	0.50
Illness coherence	1	0.21	.65	0.01	2.76
Illness coherence * PHQ-9	1	1.23	.28	0.03	2.83
Illness coherence * Education	1	0.17	.69	0.00	0.61

Note. BF_{incl} *can be interpreted as the evidence for including an effect.*

The Acceptability of PsySys

Of the current sample ($N = 41$), $N = 40$ participants completed the acceptability questionnaire. All items had a positive mean translating to an overall high acceptability (see Table 4). On a group-level participants agreed most strongly with A1 (*"The concepts were clearly explained"*; $M = 1.8$), A2 (*"The PsySys exercises were clear and I could follow them"*; $M = 1.7$), A5 (*"The PsySys videos and exercises complemented each other"*; $M = 1.7$), A3 (*"The amount of information within the PsySys videos was reasonable"*; $M = 1.6$), and A9 (*"I like how the PsySys session was structured (small videos + short exercises)"*; $M = 1.5$), all of which covered mainly the design aspect of PsySys. The item with the lowest mean, although still positive, was A7 (*"The PsySys session gave me a clearer understanding of my own mental health"*; $M = 0.7$). To determine internal consistency of our ad-hoc questionnaire, we calculated Cronbach's alpha values including all items, which ranged from 0.6 to 0.7 indicating acceptable internal consistency.

Table 4

Mean and Standard Deviation of Acceptability Items

Item	*M*	*SD*
"The concepts were clearly explained"	1.8	0.5
"The PsySys exercises were clear and I could follow them"	1.7	0.5
"The amount of information within the PsySys videos was reasonable"	1.6	0.6
"The amount of practical exercises was reasonable"	1.4	0.8
"The PsySys videos and exercises complemented each other"	1.7	0.7
"I think the time to engage in the PsySys session was reasonable"	1.1	1.0
"The PsySys session gave me a clearer understanding of my own mental health"	0.7	1.0
"Participating in the PsySys session was worth my time"	1.0	1.0
"I like how the PsySys session was structured (small videos + short exercises)"	1.5	0.6
"I think it would be nice to apply these concepts to my own mental-health map"	1.3	0.8

Note. M denotes the mean, while SD stands for the standard deviation. The values ranged from -2 (strongly disagree) to 2 (strongly agree) with 0 indicating neutrality.

Open Feedback

We received feedback from $N = 22$ participants. Although eight responses did not meet the duration cut-offs used in our main analysis, we present all available feedback.

Positive Feedback. Positive points that were raised considered the introduction of the mental-health map (i.e. network) concept and the design and implementation of PsySys especially in regard to its interactive structure and the quality of educational videos.

Negative Feedback. Negative feedback mainly focused on the content and following solutions being too simple and criticized the missing emphasis on the role of professional help in identifying and targeting mental health problems. Possibly rooted in the critique of missing complexity, one participant mentioned that the PsySys content could not help them acquire any new knowledge on (their own) mental health.

Suggestions. While we received some content-specific suggestions such as including a node for “intrusive thoughts”, putting more emphasis on external factors such as trauma and physical conditions, and mentioning the concept of comorbidity, other suggestions focused more generally on more (visual) emphasis on the dynamic nature of mental-health maps, and on referring the learned content back to familiar disorder patterns (e.g. ADHD, Anxiety). Regarding the exercises, we received the suggestion to include more practical exercises with examples as well as to provide feedback to the participants as to whether they solved the exercises correctly. More specifically, we received the suggestion of including more chain options for the second exercise as well as more guidance on how to select promising treatment strategies in exercise four. One further important point that was raised was to increase the accessibility of PsySys by including e.g. sign language, subtitles, and audio description. As expected, one recurring issue surrounded the creation of a personalized mental-health map, by either enabling its digital creation within PsySys or simply providing access to the PsySys resources to help participants draw it themselves at a later point in time. Finally, one participant also voiced their interest in subsequently discussing their resulting map with a professional.

Discussion

In line with our expectations, participants showed an improvement on all illness representation subscales after a PsySys session. This was reflected in a shift towards shorter *timeline* representations, and higher perceived *personal control* and *illness coherence*, with the effect being most pronounced for *personal control*. Replicated across different duration cut-offs, our results provide compelling insights into the potential clinical utility of PsySys. Given that the examined outcome measures have been linked to treatment efficacy in depression (Mavroeides & Koutra, 2021), these findings form a promising basis to further explore PsySys as a potential additional therapeutic measure to enhance treatment outcome. Furthermore, our findings extend the results by Meier et al. (2022) to another disorder domain, and therefore advocate for the network perspective as a possible transdiagnostic tool to improve illness representations across disorders.

Our analysis of depression severity and education-level as possible influencing factors for the observed change in illness representations provided mixed results. More specifically, we found strong evidence for the influence of depression severity on *timeline* representations in our Bayesian analysis, while our frequentist pendant was not significant. Apart from this, our results did not indicate either of our covariate variables to affect the improvement in participants' illness representations. While this could support the idea of PsySys being a viable tool for the general population, the current sample only showed little variability in educational background, raising doubts about the generalizability of our results.

In general, PsySys was met with approval shown by the high mean acceptability concerning its perceived explainability, scope, length, and utility. Participants scored highest on acceptability items that mostly covered the structure of PsySys, which was also reflected by the open feedback. While on average still positively viewed, participants showed most disagreement regarding the duration and informational depth of PsySys. Taken together, this suggests that while the implementation of PsySys in terms of design was well received, there is still room for improvement considering its delivery and content.

Limitations

The most evident drawback of the present study lies in its design which did not include a control group. The reason behind this was to allocate as much time as possible to the creation of PsySys without having to find an appropriate control condition, let alone create one. Furthermore, we wanted to maximize data on the acceptability of PsySys, as we felt these insights to be crucial to inform future studies.

This choice, however, introduced considerable limitations affecting the interpretation of our results. Firstly, the absence of a control group prevents us to draw any conclusions on the direct causal role of PsySys in the observed improvement in illness representations. To decipher whether it was the PsySys session itself, or even more specifically the included network elements, that caused this change, future studies will need to be controlled.

Secondly, the resulting within-subjects design further increased study duration. In total, our study took approximately 30-40 minutes which is a rather long duration for web-based surveys and therefore likely affected our sample size. This could explain the high dropout rates at the beginning of the study, as Galesic and Bosnjak (2009) also found that longer announced survey length raises subjects' barrier to start participation. What might further explain the dropout rates could be that we did not offer any compensation, which could have also prevented individuals to click on the study link to begin with.

Taken together, the long duration and lack of compensation might have had an impact on the characteristics of the current sample. As one can see in Figure B1 (Appendix B), most participants who completed the study indicated that they became aware of it because someone suggested it to them. While we cannot clearly break down what exactly falls under this category, it is not unreasonable to assume that participants who heard about the study from someone else, were more likely to be acquainted with the first author in some way. Furthermore, the repeated measures set up naturally indicated what the study was set out to examine, and therefore provided cues about the effect we expected to find. These cues, also known as demand characteristics, have been hypothesized to affect participants' behaviors to perform well in a study in order to contribute to the research purpose (Orne, 1962). Consequently, our participants' responses might have been biased, leading to the unusually large effect sizes, and thereby posing a threat to the generalizability of the present results.

More generally, our chosen online recruitment strategy might not have been ideal to reach our target audience. In an effort to retain an adequate sample size, we did not exclude participants based on their depression scores which caused our study population to not properly reflect a clinically depressed sample. While our initial aim was to adapt PsySys for depression, it is unclear how well our findings generalize to depressed patients.

Future Directions

We intend to guide future endeavors concerning PsySys along three main avenues. Hereby, we would like to focus on the improvement of the *study design* to replicate the present findings, the extension of the PsySys *content*, and the advancement of its *implementation*. In the following, we elaborate on the aforementioned directions.

Study Design

While promising, the present work only lays the groundwork for future studies to further refine PsySys and explore its possible clinical value. First and foremost, follow-up studies should incorporate control conditions to compare PsySys to alternative psychoeducations and to disentangle the possible effects of different network elements. Additionally, given its surprisingly high effect size and evidence from our Bayesian analysis, future studies should look into the possible role of *personal control* as mediating the effect of PsySys on the remaining illness representation subscales. Furthermore, while the end goal might be to accommodate PsySys in an online environment for easy access, testing its efficacy might be more fruitful in a clinical setting. Not only would this provide direct access to the study population of interest, and thereby enable a closer look into differing levels of severity within and across disorders, but also allow to provide professional help during the PsySys session.

PsySys Content

One key future avenue should explore how much PsySys can be extended content-wise, as some participants criticized the explained concepts and following solutions to be too simplified. These comments included that either the concepts were already known, or that the proposed solutions were too self-help-oriented or ignored additional barriers that might influence help-seeking behavior. Due to the realization of PsySys in a self-guided format, the question arises of how far we can extend its content while still remaining beneficial to a general audience.

This perceived benefit could be conceptualized as relying on three main pillars, namely the extent of *identification* with the presented problems, the *accessibility* of the learned content, and the *applicability* of the proposed solutions. These pillars might vary especially in regard to perceived mental distress and prior knowledge of the matter. In terms of *identification*, we tried to keep the current version of PsySys as generic as possible. Alternatively, future studies could explore the additional value of disorder-specific modules, which could include tailored examples and provide more informed treatment suggestions.

Regarding the *accessibility* of the learned concepts, future studies should explore the optimal level of complexity of the network content. For instance, more emphasis could be put on the underlying dynamics of the system, namely the alteration between stable states, and corresponding notions of phase transitions and hysteresis (see Cramer et al. (2016) for an overview). More effort should then be placed on referring these abstract concepts back to more familiar psychological characteristics such as vulnerability and resilience. As perceived complexity might differ not only based on prior knowledge but also more generally on education-level and preferred learning styles, finding a “sweet spot” regarding content depth might be challenging. Thus, future versions should at least offer participants supplementary materials and exercises for those who are interested.

Lastly, effort should be allocated towards increasing the *applicability* of the proposed treatment strategies. Instead of focussing on self-help strategies, future PsySys versions could for instance differentiate between factors that require professional attention and the ones that can be tackled by oneself through e.g. lifestyle changes. Not only could this put more emphasis on the role of professional help in recovery, but also help participants learn to identify factors that they might be able to overcome alone. Ultimately, we believe that acknowledging that solutions often go beyond self-help strategies, is especially important to avoid possible frustration among participants.

PsySys Implementation

Overall, we believe it is important to work towards a stand-alone application of PsySys. Although the current implementation through Qualtrics was convenient to host the entire study on the same platform, it restricted our ability to customize PsySys. In particular, we were unable to create the personalized user experience we initially envisioned. This was due to limitations in design choices as well as the extent to which we could dynamically adapt the exercises based on user input.

Furthermore, based on the feedback we gathered, a key additional feature should be a personalized mental-health map. While exploring the prospects of a purely conceptual network-based approach to psychoeducation is certainly interesting from a research standpoint, we should not underestimate the potential of using personalized network representations in practice. First of all, Morrison (2015) stressed the power of visual representations to make abstract concepts of internal states more graspable, and thereby, manageable. Here, the network perspective could be particularly promising as it provides a simplified account of how different personal factors relate to each other. Second of all, structuring the PsySys session around creating a personalized map, could increase the users' motivation to complete the exercises by objectifying a goal they are working towards.

Therefore, the first author has implemented a first working version of a PsySys app which enables a more personalized learning experience. The adapted exercises are structured to iteratively build and augment the user's personalized mental-health map (see Figure E1). Throughout the exercises, users get to select their personal factors and specify their causal chains and vicious cycles. Afterward, the user can customize their map by adding and removing elements. The map dynamically changes in response to the user input, providing direct visual feedback on their progress. This app was implemented using R shiny and is available online (https://psysys.shinyapps.io/psysysdeploy/)[2]. A short demo video explaining the app usage, can be found on Google Drive. The app in its current design and functionality is very basic. Future versions should therefore focus on improving the general user experience. Here, a promising avenue could be to explore gamification elements to create a more engaging user interface.

On a broader scale, we would like to emphasize not only the potential but the evident necessity associated with directing research efforts toward the development and assessment of digital tools for clinical practice. The digital revolution is moving at an astonishing pace and infiltrating all aspects of human life. In Psychology, digital systems offer novel prospects for accessible and cost-effective personalized care, and will increasingly drive mental health service reform (Bucci et al., 2019). Therefore, it is key for research to guide this change and actively contribute to the development of high-quality applications. This is especially important in light of the proliferation of unregulated online information and the abundance of non-evidence-based mobile health apps (Van Ameringen et al., 2017).

It is important to note that the potential of digital platforms to advance personalized care does not only lie in facilitating self-management and monitoring. A crucial aspect is that they can create collaborative spaces to foster seamless knowledge transmission (Bucci et al., 2019). This not only enables joint treatment decision-making between patients and practitioners but could also form continuous feedback systems between research and practice. This symbiotic knowledge stream could nurture the continual improvement of digital health applications, increase their acceptability and subsequent uptake in practice, and ultimately narrow the gap between the two realms.

[2] Note: If accessed on a computer we recommend adjusting the screen width to fit about half of the usual screen. If used on a smartphone we recommend using a horizontal format.

Conclusion

The present study introduced PsySys, a network-informed digital psychoeducation designed to improve individuals' perspectives on their depressive complaints. To test whether PsySys might be a promising treatment add-on, we examined the subsequent change in illness representations, which have been linked to treatment-relevant outcome measures. The results demonstrated that upon a single PsySys session, participants showed less prognostic pessimism, and perceived to be more in control over, and have a better understanding of, their mental health. Furthermore, we observed positive resonance among participants in regard to the implementation and educational value of PsySys and gathered valuable feedback to inform future work.

While we cannot infer the direct causal role of PsySys in the observed improvement, the current study provides multiple anchor points for further exploration. Ultimately, our findings suggest that a brief digital psychoeducation conveying a network perspective might be able to improve patients' illness representations and could therefore increase patients' susceptibility and adherence to treatment. Thereby, the broad scientific implications of the present study are twofold. Firstly, our work illustrates the promising use of digital applications in psychological healthcare to aid patients on a larger scale. Secondly, it adds to a growing body of evidence demonstrating that possible clinical applications of the network approach go beyond the data-hungry estimation of personalized networks. Thereby, our findings could serve as an incentive to the research community, to take a step back, and recognize the potential that lies within the theoretical network perspective.

References

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, *57*(1), 289–300.

Borsboom, D. (2008). Psychometric perspectives on diagnostic systems. *Journal of Clinical Psychology*, *64*(9), 1089–1108.

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13.

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, *9*, 91–121.

Bringmann, L. F., & Eronen, M. I. (2018). Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological Review*, *125*(4), 606.

Bucci, S., Schwannauer, M., & Berry, N. (2019). The digital revolution and its impact on mental health care. *Psychology and Psychotherapy: Theory, Research and Practice*, *92*(2), 277–297.

Cannon, M., Credé, M., Kimber, J. M., Brunkow, A., Nelson, R., & McAndrew, L. M. (2022). The common-sense model and mental illness outcomes: A meta-analysis. *Clinical Psychology & Psychotherapy*, *29*(4), 1186–1202.

Contreras, A., Nieto, I., Valiente, C., Espinosa, R., & Vazquez, C. (2019). The study of psychopathology from the network analysis perspective: A systematic review. *Psychotherapy and Psychosomatics*, *88*(2), 71–83.

Cramer, A. O., Van Borkulo, C. D., Giltay, E. J., Van Der Maas, H. L., Kendler, K. S., Scheffer, M., & Borsboom, D. (2016). Major depression as a complex dynamic system. *PloS One*, *11*(12), e0167490.

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*, 195–212.

Forbes, M. K., Wright, A. G., Markon, K. E., & Krueger, R. F. (2017). Evidence that psychopathology symptom networks have limited replicability. *Journal of Abnormal Psychology*, *126*(7), 969.

Fried, E. I. (2015). Problematic assumptions have slowed down depression research: Why symptoms, not syndromes are the way forward. *Frontiers in Psychology*, *6*, 309.

Fried, E. I. (2017). Moving forward: How depression heterogeneity hinders progress in treatment and research. *Expert Review of Neurotherapeutics*, *17*(5), 423–425.

Frumkin, M. R., Piccirillo, M. L., Beck, E. D., Grossman, J. T., & Rodebaugh, T. L. (2021). Feasibility and utility of idiographic models in the clinic: A pilot study. *Psychotherapy Research*, *31*(4), 520–534.

Galesic, M., & Bosnjak, M. (2009). Effects of questionnaire length on participation and indicators of response quality in a web survey. *Public Opinion Quarterly*, *73*(2), 349–360.

Haslbeck, J., Ryan, O., Robinaugh, D. J., Waldorp, L. J., & Borsboom, D. (2022). Modeling psychopathology: From data models to formal theories. *Psychological Methods*, *27*(6), 930.

Klintwall, L., Bellander, M., & Cervin, M. (2021). Perceived causal problem networks: Reliability, central problems, and clinical utility for depression. *Assessment*, *30*(1), 73–83.

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613.

Kuyken, W., Padesky, C. A., & Dudley, R. (2008). The science and practice of case conceptualization. *Behavioural and Cognitive Psychotherapy*, *36*(6), 757–768.

Leventhal, H., Meyer, D., & Nerenz, D. (1980). The common sense representation of illness danger. *Contributions to Medical Psychology*, *2*, 7–30.

Manber, R., Chambers, A. S., Hitt, S. K., McGahuey, C., Delgado, P., & Allen, J. J. (2003). Patients' perception of their depressive illness. *Journal of Psychiatric Research*, *37*(4), 335–343.

Mavroeides, G., & Koutra, K. (2021). Illness representations in depression and their association with clinical and treatment outcomes: A systematic review of the literature. *Journal of Affective Disorders Reports*, *4*, 100099.

Meier, M., Jansen, K., Summers, B. J., Dreier, M. J., Farrell, N. R., & Buhlmann, U. (2022). Using network theory for psychoeducation in eating disorders. *Cognitive Therapy and Research*, 1–13.

Morrison, L. G. (2015). Theory-based strategies for enhancing the impact and usage of digital health behaviour change interventions: A review. *Digital Health*, *1*, 2055207615595335.

Moss-Morris, R., Weinman, J., Petrie, K., Horne, R., Cameron, L., & Buick, D. (2002). The revised illness perception questionnaire (IPQ-R). *Psychology and Health*, *17*(1), 1–16.

Ormel, J., Hollon, S. D., Kessler, R. C., Cuijpers, P., & Monroe, S. M. (2022). More treatment but no less depression: The treatment-prevalence paradox. *Clinical Psychology Review*, *91*, 102111.

Orne, M. T. (1962). On the social psychology of the psychological experiment: With particular reference to demand characteristics and their implications. *American Psychologist*, *17*(11), 776.

Patten, S. B., Williams, J. V., Lavorato, D. H., Bulloch, A. G., Wiens, K., & Wang, J. (2016). Why is major depression prevalence not changing? *Journal of Affective Disorders*, *190*, 93–97.

Richards, D. (2011). Prevalence and clinical course of depression: A review. *Clinical Psychology Review*, *31*(7), 1117–1125.

Robinaugh, D. J., Hoekstra, R. H., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine*, *50*(3), 353–366.

Van Ameringen, M., et al. (2017). There is an app for that! The current state of mobile applications (apps) for dsm-5 obsessive-compulsive disorder, posttraumatic stress disorder, anxiety and mood disorders. *Depression and Anxiety*, *34*(6), 526–539.

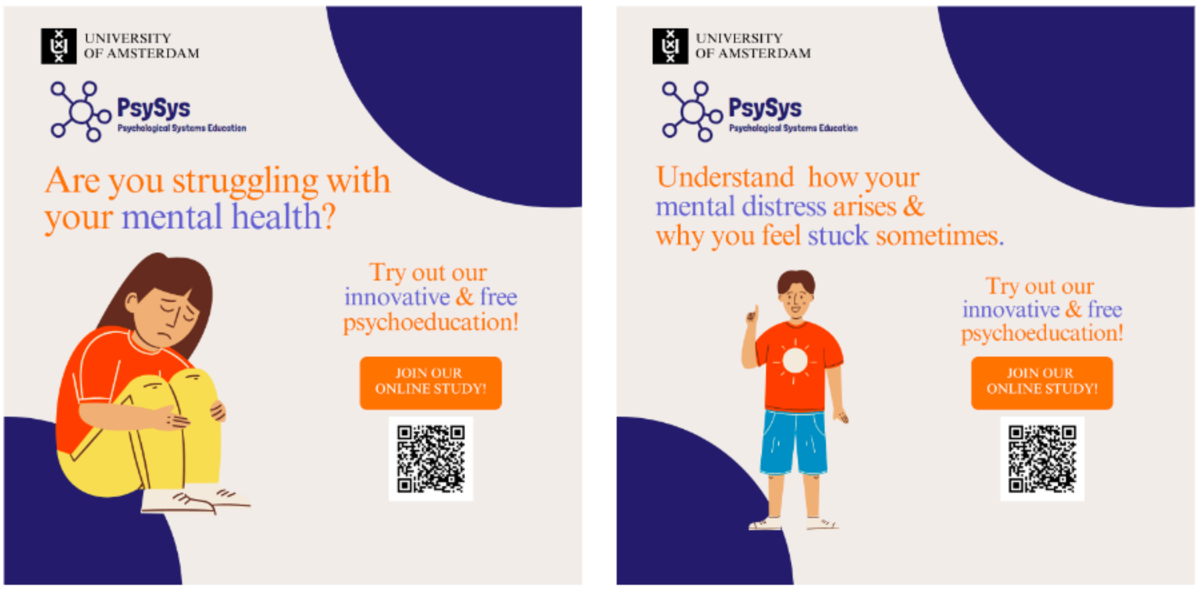
Wagenmakers, E. J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau, Q. F., Dropmann, D., Boutin, B., et al. (2018). Bayesian inference for psychology. part ii: Example applications with jasp. *Psychonomic Bulletin & Review*, *25*, 58–76.

Appendix A

Recruitment Details

Figure A1

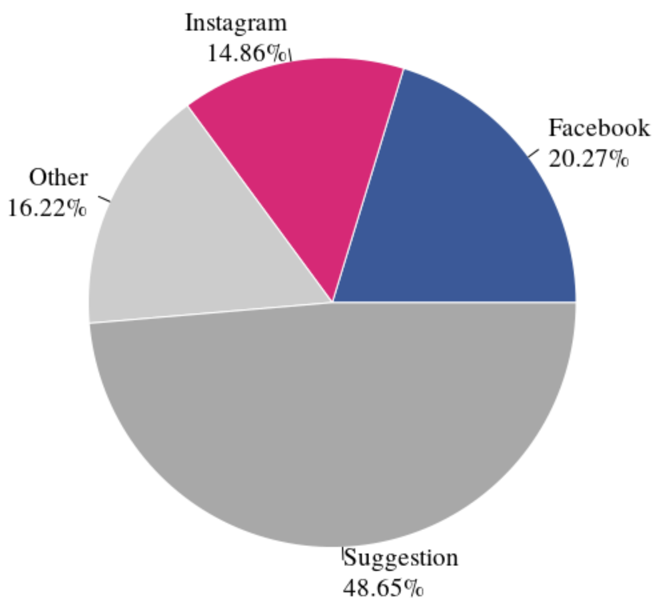
Recruitment Posters



Note. *Example recruitment text for Facebook groups: "Hello everyone, we, a research group at the University of Amsterdam have created a new short digital intervention - PsySys - that aims to help you better understand your mental health. Participate in our study and be among the first people to try out PsySys. The session is free and takes about 30 minutes. Sign up, get better, and help us shape the future of mental healthcare."*

Figure A2

Recruitment Summary of Completed Responses (N = 74)



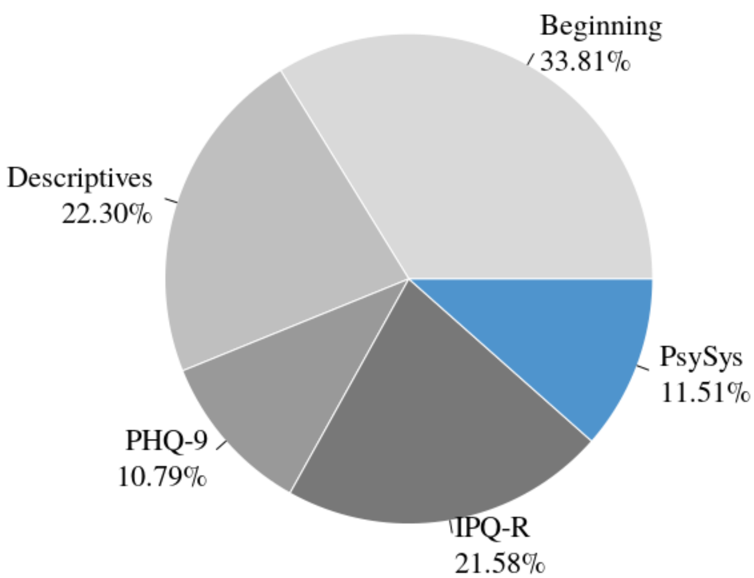
Note. The percentages translate to $N = 11$ hearing about the study on Instagram and $N = 15$ on Facebook, $N = 36$ indicated that someone suggested the study to them, and $N = 12$ became aware of the study by other means.

Appendix B

Descriptives

Figure B1

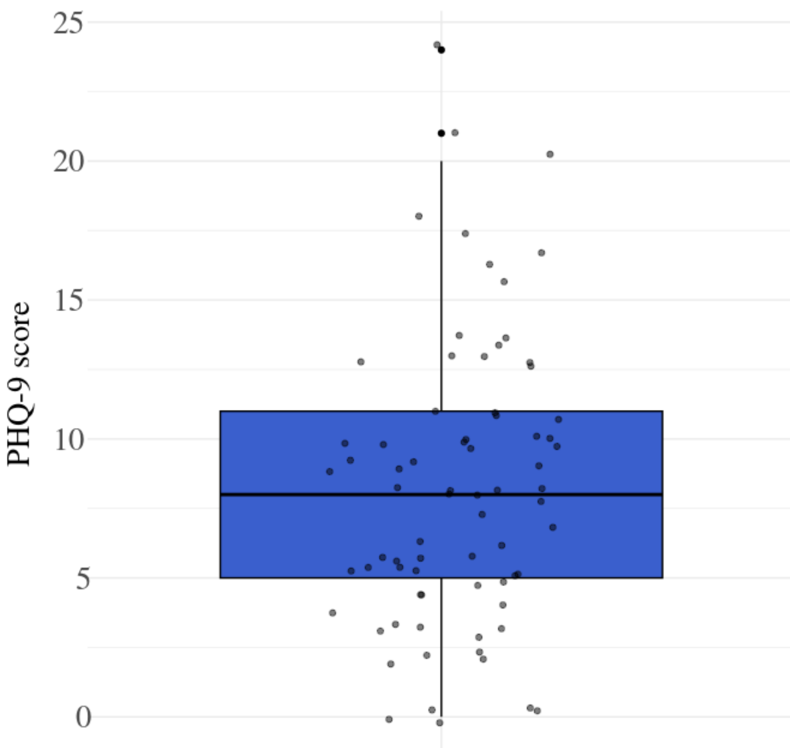
Dropout Percentages per Study Stage



Note. *The percentages translate to* $N = 47$ *at the beginning,* $N = 31$ *at the descriptives,* $N = 15$ *during the PHQ-9 questionnaire,* $N = 30$ *during the IPQ-R questionnaire, and* $N = 16$ *during the PsySys session. In total,* $N = 139$ *participants dropped out of the study.*

Figure B2

Depression Severity (PHQ-9) Scores (N = 74)



Appendix C

Materials

Table C1

PHQ-9 Items

Item	Description
P1	“Little interest or pleasure in doing things”
P2	“Feeling down, depressed, or hopeless”
P3	“Trouble falling, or staying asleep, or sleeping too much”
P4	“Feeling tired, or having little energy”
P5	“Poor appetite or overeating”
P6	“Feeling bad about yourself/like a failure/you have let yourself or family down”
P7	“Trouble concentrating on things, e.g. reading the newspaper/watching television”
P8	“Moving/speaking so slowly/fidgety/restless that other people could have noticed”
P9	“Thoughts that you would be better off dead, or of hurting yourself in some way”

Table C2

IPQ-R Items

Subscale	Item	Description
Timeline	I1	“My mental distress will last a short time”
	I2	“My mental distress is likely to be permanent rather than temporary”
	I3	“My mental distress will last for a long time”
	I4	“This mental distress will pass quickly”
	I5	“I expect to have this mental distress for the rest of my life”
	I6	“My mental distress will improve in time”
Control	I7	“There is a lot which I can do to control my symptoms”
	I8	“What I do can determine whether my mental distress gets better or worse”
	I9	“The course of my mental distress depends on me”
	I10	“Nothing I do will affect my mental distress”
	I11	“I have the power to influence my mental distress”
	I12	“My actions will have no effect on the outcome of my mental distress”
Coherence	I13	“The symptoms of my condition are puzzling to me”
	I14	“My mental distress is a mystery to me”
	I15	“I don’t understand my mental distress”
	I16	“My mental distress doesn’t make any sense to me”
	I17	“I have a clear picture or understanding of my mental distress”

Note. As the IPQ-R questions are directed towards the respondents own “mental distress”, we noted that if participants felt they did not struggle with some form of mental distress at the moment, they should indicate their general attitudes towards mental health (i.e. translate the questions to a hypothetical scenario).

Table C3

Acceptability Items

Item	Description
A1	"The concepts were clearly explained"
A2	"The PsySys exercises were clear and I could follow them"
A3	"The amount of information within the PsySys videos was reasonable"
A4	"The amount of practical exercises was reasonable"
A5	"The PsySys videos and exercises complemented each other"
A6	"I think the time to engage in the PsySys session was reasonable"
A7	"The PsySys session gave me a clearer understanding of my own mental health"
A8	"Participating in the PsySys session was worth my time"
A9	"I like how PsySys was structured with the short videos followed by small exercises"
A10	"I would like to have a look at, and apply these concepts to, my own mental-health map"

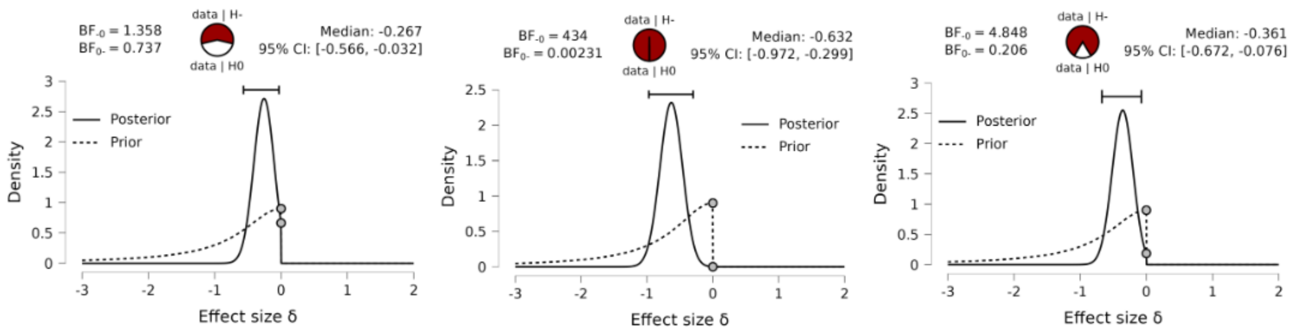
Note. Items A1 and A2 covered the explainability, items A3-A5 the scope, item A6 the length, and A7-A10 the utility of PsySys.

Appendix D

Analysis Supplements

Figure D1

Priors and Posteriors of Bayesian T-test



Note. *The plots are ordered as follows: Timeline, Personal Control, Illness Coherence.*

Table D1

Pre- and Post-PsySys Mean and Standard Deviation per Illness Representation Item

Item	Pre *M(SD)*	Post *M(SD)*
“My illness will last a short time”	0.1 (1.3)	0.4 (1.2)
“My illness is likely to be permanent rather than temporary”	0.6 (1.4)	0.6 (1.4)
“My illness will last for a long time”	0.3 (1.4)	0.512 (1.3)
“This illness will pass quickly”	-0.2 (1.5)	-0.1 (1.3)
“I expect to have this illness for the rest of my life”	0.9 (1.3)	1.1 (1.3)
“My illness will improve in time”	0.6 (1.3)	0.8 (1.2)
“There is a lot which I can do to control my symptoms”	0.9 (1.0)	1.3 (0.8)
“What I do can determine whether my illness gets better or worse”	1.2 (0.8)	1.6 (0.5)
“The course of my illness depends on me”	0.6 (1.0)	0.9 (0.9)
“Nothing I do will affect my illness”	1.5 (0.7)	1.6 (0.8)
“I have the power to influence my illness”	1.1 (0.8)	1.4 (0.9)
“My actions will have no effect on the outcome of my illness”	1.3 (1.1)	1.5 (0.9)
“The symptoms of my condition are puzzling to me”	0.4 (1.1)	0.7 (1.1)
“My illness is a mystery to me”	1.0 (1.3)	1.2 (1.1)
“I don’t understand my illness”	0.8 (1.3)	1.0 (1.2)
“My illness doesn’t make any sense to me”	1.1 (1.1)	1.3 (1.0)
“I have a clear picture or understanding of my illness”	0.6 (0.9)	0.8 (0.9)

Note. M denotes mean and SD standard deviation. Items I1-I6 pertain to the timeline, I7-I12 to the personal control, and I13-I17 to the illness coherence subscale. The values range from -2 to 2. Negative values correspond to longer timeline, as well as lower personal control and illness coherence representations. Positive values correspond to shorter timeline, as well as higher personal control and illness coherence representations.

Table D2

Frequentist and Bayesian T-test Results for the Full Data Set ($N = 74$)

	Frequentist						Bayesian
	T-test				Wilcoxon		
Subscale	t	df	p	d	V	p	BF_{-0}
Timeline	2.39	73	.02*	0.28			3.60
Personal control	3.65	73	$< .001$***	0.42	1329.50	$< .001$***	94.71
Illness coherence	2.18	73	.02*	0.25	858	.02*	2.32

Note. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. *There is a significant effect for all subscales.*

Table D3

Frequentist and Bayesian Repeated Measures ANOVA Results for $N = 74$

	Frequentist				Bayesian
Factor	df	F	p	η_p^2	BF_{incl}
Timeline	1	0.26	.61	0.00	2.17
Timeline * PHQ-9	1	1.51	.22	0.02	9.10
Timeline * Education	1	0.21	.65	0.01	0.41
Personal control	1	1.88	.18	0.03	49.91
Personal control * PHQ-9	1	2.12	.15	0.03	1.84
Personal control * Education	1	2.01	.16	0.03	0.54
Illness coherence	1	0.74	.39	0.01	1.53
Illness coherence * PHQ-9	1	1.11	.75	0.00	2.03
Illness coherence * Education	1	0.37	.55	0.01	0.45

Note. There is moderate evidence to include PHQ-9 as a predictor within the timeline subscale.

Table D4

Frequentist and Bayesian T-test Results for Duration > 15 Minutes (N = 61)

	Frequentist						Bayesian
	T-test				Wilcoxon		
Subscale	t	df	p	d	V	p	BF_{-0}
Timeline	2.64	60	.01*	0.34			6.58
Personal control	4.07	60	< .001***	0.52	1038	< .001***	314.18
Illness coherence	3.24	60	.00**	0.41	702	< .001***	28.98

Note. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. *There is a significant effect for all subscales.*

Table D5

Frequentist and Bayesian Repeated Measures ANOVA Results for N = 61

	Frequentist				Bayesian
Factor	df	F	p	η_p^2	BF_{incl}
Timeline	1	1.29	.26	0.02	3.64
Timeline * PHQ-9	1	0.42	.52	0.01	4.15
Timeline * Education	1	0.86	.36	0.02	0.49
Personal control	1	1.66	.20	0.03	158.07
Personal control * PHQ-9	1	0.7	.39	0.01	1.21
Personal control * Education	1	0.59	.45	0.01	0.47
Illness coherence	1	0.56	.46	0.01	15.49
Illness coherence * PHQ-9	1	0.09	.76	0.00	0.94
Illness coherence * Education	1	0.00	.97	< 0.001	0.57

Note. There is moderate evidence to include PHQ-9 as a predictor within the timeline subscale.

Table D6

Frequentist and Bayesian T-test Results for 15 < Duration < 90 Minutes (N = 52)

	Frequentist						Bayesian
	T-test				Wilcoxon		
Subscale	t	df	p	d	V	p	BF_{-0}
Timeline	2.24	51	.02*	0.31			2.93
Personal control	4.16	51	< .001***	0.58	805	< .001***	380.72
Illness coherence	2.70	51	.01*	0.38	557	.00**	7.84

Note. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. *There is a significant effect for all subscales.*

Table D7

Frequentist and Bayesian Repeated Measures ANOVA Results for N = 52

	Frequentist				Bayesian
Factor	df	F	p	η_p^2	BF_{incl}
Timeline	1	0.63	.43	0.01	2.02
Timeline * PHQ-9	1	1.51	.23	0.03	2.26
Timeline * Education	1	0.86	.23	0.02	0.60
Personal control	1	2.07	.16	0.04	180.97
Personal control * PHQ-9	1	0.03	.87	< 0.001	0.7
Personal control * Education	1	0.09	.77	0.00	0.49
Illness coherence	1	0.05	.83	< 0.001	4.15
Illness coherence * PHQ-9	1	0.77	.39	0.02	2.75
Illness coherence * Education	1	0.01	.91	< 0.001	0.64

Note. There is anecdotal evidence to include PHQ-9 as a predictor within the timeline subscale.

Table D8

Frequentist and Bayesian T-test Results for Duration > 30 Minutes (N = 50)

	Frequentist						Bayesian
	T-test				Wilcoxon		
Subscale	t	df	p	d	V	p	BF_{-0}
Timeline	2.24	49	.02*	0.32			2.96
Personal control	4.06	49	< .001***	0.58	726.50	< .001***	275.39
Illness coherence	3.06	49	.00**	0.43	434.50	.00**	18.30

Note. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. *There is a significant effect for all subscales.*

Table D9

Frequentist and Bayesian Repeated Measures ANOVA Results for N = 50

	Frequentist				Bayesian
Factor	df	F	p	η_p^2	BF_{incl}
Timeline	1	0.38	.54	0.01	1.71
Timeline * PHQ-9	1	0.57	.45	0.01	88.38
Timeline * Education	1	0.24	.62	0.01	0.38
Personal control	1	2.50	.12	0.05	126.89
Personal control * PHQ-9	1	0.55	.46	0.01	3.44
Personal control * Education	1	1.20	.28	0.03	0.46
Illness coherence	1	1.12	.30	0.02	9.57
Illness coherence * PHQ-9	1	0.10	.75	0.00	0.96
Illness coherence * Education	1	0.27	0.60	0.01	0.59

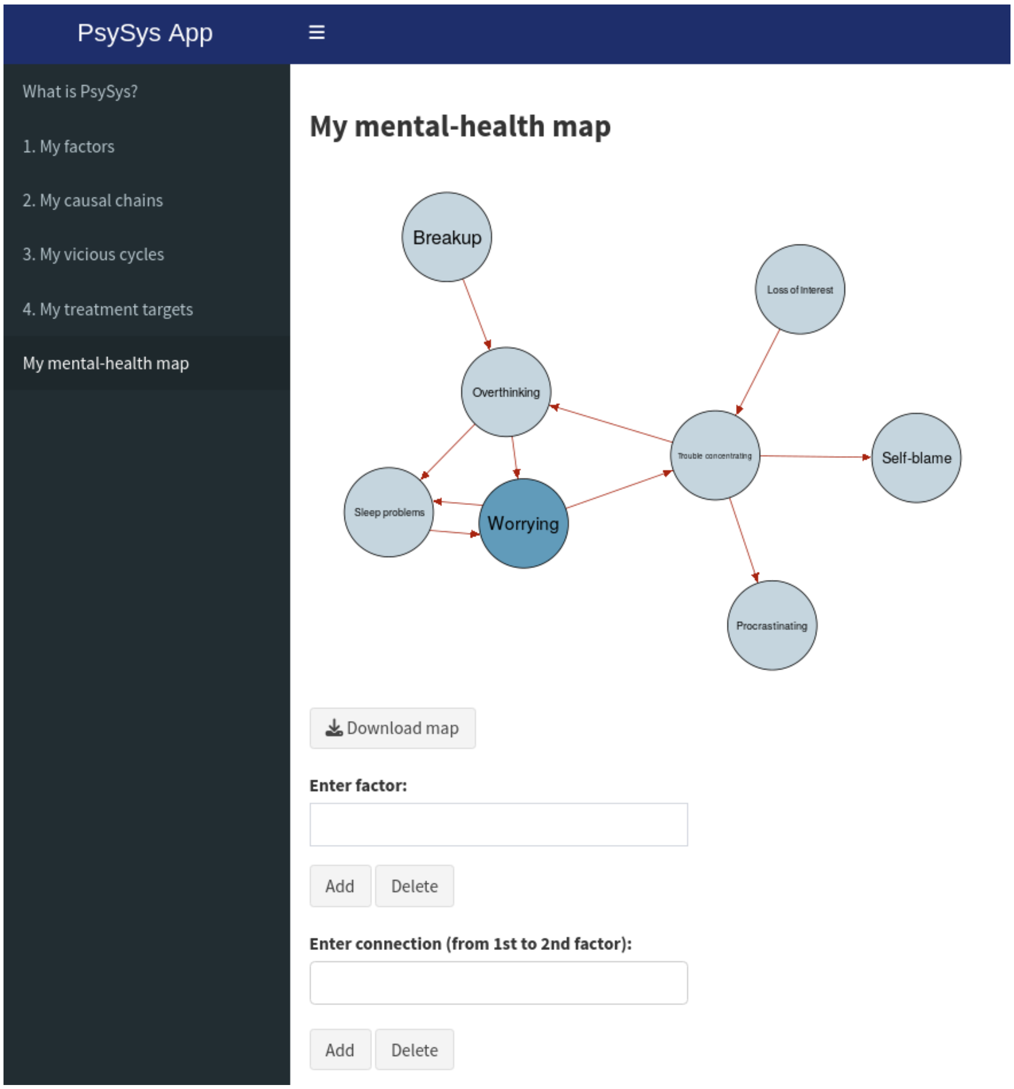
Note. There is decisive evidence to include PHQ-9 as a predictor within the timeline, and moderate evidence to include it as a predictor within the personal control subscale.

Appendix E

PsySys App

Figure E1

"My Mental-health Map" Tab in the PsySys R Shiny App



Note. *The user is able to switch between the tabs to track the progress within their map, as well as change their input. After exercise three, the user can add and delete nodes and edges to fine-tune their map. Within exercise four, the user should pick one factors they think would be the most promising treatment target. This factor is then colored in a darker shade of blue (in this case Worrying).*