Investigating Associations Between Engagement Quality and Symptom Improvement in Trauma-Focused Digital Therapies

by

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Abstract

Posttraumatic Stress Disorder (PTSD) remains undertreated despite the efficacy of evidence-based therapies like Prolonged Exposure (PE) and Written Exposure Therapy (WET), largely due to access barriers and high attrition rates. This study introduces a novel engagement quality rating scale and presents preliminary data from a digital trauma-focused intervention (RainFrog) delivered to 47 college students with elevated PTSD symptoms. A piecewise multilevel model revealed greater symptom reductions in participants who engaged in imaginal exposure (IE) modules compared to participants who dropped out early. Exploratory analyses suggested a positive correlation between engagement quality, as assessed via the novel scale, and symptom improvement. Findings highlight the importance of measuring engagement quality to optimize outcomes in digital PTSD treatments.

Introduction

Posttraumatic Stress Disorder (PTSD) is a highly disabling mental disorder that can develop after exposure to one or more Category A traumatic events (e.g., actual or threatened death, serious injury, or sexual violence) (American Psychiatric Association, 2013; Pai et al., 2017). PTSD is a leading cause of disability worldwide (U.S. Department of Health and Human Services, n.d.) and, left untreated, can result in persistent symptoms linked to chronic disease, accelerated aging, and premature mortality (Koenen et al., 2017). Cognitive and behavioral theories have identified core psychological processes that maintain PTSD, informing evidence-based psychological treatments (Schrader & Ross, 2021). Below, we present a brief overview of these major theories.

The Cognitive Model of PTSD (Ehlers & Clark, 2000) suggests that PTSD is maintained by a sense of current threat, which arises from negative appraisals of the trauma and its aftermath, as well as fragmented and poorly integrated trauma memories. This ongoing threat perception is further sustained by cognitive and behavioral strategies, such as avoidance, safety behaviors, and rumination, that inhibit the processing and contextualization of trauma-related information. Recommended treatments include Trauma-Focused Cognitive-Behavioral Therapy (CBT), cognitive restructuring, imagery rescripting, and narrative elaboration of the trauma memory.

The Dual Representation Theory (Brewin et al., 1996) asserts that PTSD results from the imbalance between two types of memory representations: Situationally Accessible Memories (SAMs), which are sensory-based and involuntarily triggered, and Verbally Accessible Memories (VAMs), which are consciously retrievable and contextually integrated. The persistence of PTSD symptoms is attributed to the dominance of SAMs in memory retrieval, leading to intrusive re-experiencing in the absence of contextual and narrative coherence. Suggested interventions include therapies that include deliberate recall, verbal processing, and contextualization of the traumatic memory.

Information Processing Theory (Bomyea et al., 2016) posits that PTSD arises when trauma is poorly encoded and stored in memory, leading to fragmented, disorganized recollections that are easily triggered by reminders. This dysfunction in memory processing, coupled with hypervigilance and attentional biases, perpetuates intrusive symptoms and prevents effective adaptation to trauma-related cues. Proposed therapies include Trauma-Focused CBT, Eye Movement Desensitization and Reprocessing (EMDR), psychophysiological interventions, imagery rescripting, and attention training.

Emotional Processing Theory, initially developed by Foa & Kozak (Foa & Kozak, 1986) states that PTSD is maintained by maladaptive fear structures, which involve trauma-related stimuli, responses, and meanings stored in memory, and that avoidance behaviors prevent the processing and modification of these structures. As a result, trauma memories remain unintegrated, continually reactivated by reminders, and lead to persistent distress and symptoms. Consistent with this framework, exposure-based therapies are strongly recommended as a means for facilitating the activation and restructuring of fear networks.

Prolonged Exposure (PE) therapy grew out of Emotional Processing Theory and has since amassed a substantial evidence base. Currently, PE is recommended as a first-line treatment for PTSD in every clinical practice guideline due to its effectiveness across diverse patient presentations (McSweeny et al., 2019). PE is a manualized, evidence-based cognitive-behavioral treatment that aims to reduce PTSD symptoms by helping individuals confront and emotionally process trauma-related memories and avoided cues, which are believed to maintain pathological fear structures. The treatment protocol includes psychoeducation, breathing retraining, in vivo exposure to avoided situations, and imaginal exposure (IE) to trauma memories. IE, a central component of PE, involves the repeated, detailed verbal recounting of the traumatic experience in the present tense during therapy sessions. This technique is designed to activate the trauma memory and allow the client to process it within a safe therapeutic context, thereby reducing distress and facilitating habituation to trauma-related emotions. Following each IE, the therapist guides the client through a structured processing discussion, helping them identify new insights, challenge maladaptive beliefs, and integrate corrective information that disconfirms existing fears. Over time, repeated IEs are theorized to promote a reconsolidation of the trauma memory in a less distressing and more adaptive form, diminishing avoidance behaviors and intrusive symptoms.

Despite its effectiveness, dropout rates in PE are high, with estimates approaching 40%

(Kehle-Forbes et al., 2016). PE is also underutilized in part due to access barriers such as financial constraints, stigma, and a lack of trained providers (Najavits 2015). Traditionally, PE is delivered in-person by a clinical psychologist over the course of 8-15 weekly 90-minute sessions. This longer session format can be constraining or perceived as burdensome by patients (Foa et al., 2019), and may be related to high attrition rates (Foa & Kozak, 1986). Additionally, engagement is a critical factor in the success of trauma-focused treatments, yet up to 36% of patients in PE discontinue treatment early (Gutner et al., 2016). Written Exposure Therapy (WET) is a shorter, evidence-based alternative to PE. In WET, patients emotionally process traumatic memories by engaging in written-imaginal exposures (e.g., writing their trauma narrative in detail; McLean et al., 2024) over 5 condensed (50 minute) sessions. Compared to PE, fewer patients drop-out of WET (Sloan et al., 2023), and preliminary studies comparing their effectiveness have found no meaningful differences in outcomes (Sloan et al., 2018; Sloan et al., 2022). Still, more research is needed comparing WET with PE, especially in digital contexts.

Digital therapies offer opportunities to address access barriers to evidence-based, trauma-focused psychological treatments, and better measure engagement. WET, in particular, is well suited for digital adaptation due to its brief, structured format and reliance on written narrative rather than in-session therapist guidance (McLean et al., 2024). It is a low/no cost treatment, reduces stigma due to its asynchronous delivery, and is self-guided or peer supported, suggesting that WET can be effectively disseminated in settings with limited access to trained providers, while still maintaining clinical effectiveness.

Other elements of PE are also well-suited to digital adaptation. The downward arrow technique has the patient identify an automatic thought and then work towards what they are most worried about, known as a core belief. Once identified, these core beliefs can be evaluated and challenged. This is straightforward to implement in digital therapy, as the patient can be prompted to think deeper about what would happen next. Safety behaviors are actions or mental strategies individuals use to try to prevent feared outcomes or reduce anxiety in the moment. While they may provide short-term relief, identifying safety behaviors and removing them allows cognitive restructuring to occur, which is associated with greater symptom reduction. This is also feasible for digital therapies, which can include prompts to aid users in the process of addressing these maladaptive behaviors. IE, which is the verbal portion of PE, is also well suited to digital adaptation as participants can upload voice recordings on their own. Lastly, discussion of what the patient learned post-treatment is vital, and this can be achieved digitally through clinically-based prompts. However, despite the potential for digital adaptations of PE and WET for addressing access barriers, engagement and attrition remain a major concern.

Engagement in therapy is a critical factor in determining treatment outcomes, yet many individuals discontinue treatment prematurely due to perceived ineffectiveness, logistical challenges, or stigma (Hoge et al., 2014). These barriers highlight the need for interventions that not only promote initial uptake but also sustain participation over time. Digital therapy may improve accessibility and reduce stigma, but its effectiveness similarly relies on maintaining engagement through personalized, credible, and user-centered design. Clearly, measuring and promoting engagement in these therapies is critical for treatment efficacy. Until recently, however, researchers and clinicians have had little guidance on how best to assess engagement quality. To address this gap, Cohen et al. (2023) proposed a framework for measuring the “Active Elements” of cognitive-behavioral interventions to identify key drivers of therapeutic change. They argue that measures like attendance or homework don’t fully capture treatment effectiveness. Instead, evaluating how clients receive and apply evidence-based techniques (engagement quality) is crucial for improved outcomes (Cohen et al., 2023). The advantages of digital therapy can be leveraged to measure the active elements, and learn more about engagement.

To our knowledge, there are no established guidelines for quantifying engagement quality for IE in digital therapies. Accordingly, we introduce the development and preliminary validation of a new rating scale to quantify engagement quality in IE modules within a trauma-focused digital therapy. We also present preliminary results using the engagement scale and other objective metrics (e.g., treatment adherence) to illustrate how measuring engagement can improve our understanding of who is most likely to respond in digital therapy for PTSD.

Methods

Participants

Participants were *N*=47 students at East Los Angeles College, a community college that serves predominantly low-income and non-white, Hispanic/Latinx students. Participants had elevated PTSD symptoms and were undergoing personalized digital therapy as part of an ongoing clinical trial (Wen et al., 2023).

RainFrog Digital Therapy Ecosystem

RainFrog (RF) is a digital therapy platform that was originally developed at the University of California, Los Angeles (UCLA) by Dr. Michelle Craske, Dr. Zachary Cohen, and colleagues as part of the Depression Grand Challenge's Screening and Treatment of Anxiety and Depression (STAND) program. RF is composed of distinct modules that make up treatment packages (Figure 1). Each package contains 6 to 8 modules which are designed as standalone lessons, each spanning approximately 30 to 45 minutes. Each module is designed to be completed weekly on a computer rather than a smartphone, encouraging participants to complete each lesson in one sitting, which more closely resembles traditional face-to-face or telehealth (e.g., live-video) psychotherapy.

Each module consists of psychoeducation, high-quality and culturally adaptable videos demonstrating the clinical techniques, and quantitative and qualitative opportunities for participants to engage with the digital therapy. Additionally, participants are prompted to complete homework and practices each week, simulating traditional face-to-face CBT. There are self-guided and peer coach-supported formats, as well as a toolbox where participants can complete their homework and track progress.

Participants are assigned a personalized package based on their baseline scores for common mental health disorders (e.g., PTSD and depression). The trauma-focused packages each contain two core IE modules: Dealing Directly with Trauma Memories (DDTM) A and B.

Figure 1. *RainFrog Digital Therapy Ecosystem*

Dealing Directly with Trauma Memories Modules

The Dealing Directly with Trauma Memories (DDTM) A and B modules are digitally-adapted versions of PE where users learn the rationale for addressing trauma memories and receive psychoeducation on avoidance and PTSD (trauma) symptoms. They identify the trauma memory they would like to work on, identify their greatest worry (of what might happen if they engage with the memory), and identify safety behaviors that they might use to avoid some of the distress associated with reliving the traumatic memory. Users then confront their avoided trauma memory through prolonged exposure—recounting it aloud or in writing. In DDTM B, the user reviews and repeats past imaginal exposures, addressing avoidance issues, and reviews progress.

Measures

PTSD symptoms were assessed at baseline, as well as every two weeks over the course of the 40-week treatment. The PCL-5 8-item adaptation was used (Price et al., 2016), which is a brief, validated screening tool derived from the full 20-item PTSD Checklist for DSM-5, designed to efficiently assess core PTSD symptoms across all four DSM-5 symptom clusters (Blevins et al., 2015). It maintains strong psychometric properties and is well-suited for use in digital interventions or high-throughput clinical settings where minimizing assessment burden is essential.

Engagement was measured using objective metrics (who started the DDTM modules) as well as the Engagement Quality Rating Scale. This scale was developed using a hybrid inductive/deductive approach. For the inductive portion, we reviewed the anonymized written responses in the DDTM modules. The deductive portion consisted of an extensive literature review on trauma and PTSD, digital therapies, engagement (quality, in-person vs digital, etc.), and on how to develop codebooks. The scale consists of 38 variables divided into three categories of engagement: alignment with intended technique, emotional engagement, and detail. Rating criteria were developed for each variable based on the existing literature and were quantified using either a yes/no (0-1) binary or low/medium/high (0-2) Likert scale. Each variable was then weighted based on the author's knowledge of the most critical aspects of IE, before being converted into a final engagement quality score for each participant.

Three raters independently scored participant responses according to the Engagement Quality Rating Scale. The author scored responses for all participants who engaged with DDTM modules (N=24), and raters 2 and 3 each scored a separate subset of N=7 responses. Inter-rater reliability was assessed for item-level, total score, and total weighted scores via intraclass correlation coefficients (ICCs).

Analytic Plan

We assessed associations between engagement in trauma-focused RF digital therapy packages and PTSD symptom trajectories through a combination of multilevel models and exploratory graph analyses. Specifically, we constructed two separate multilevel piecewise linear models with two slopes (one for the active treatment phase, and one for the follow-up phase). Engagement scores were coded using the Engagement Quality Rating Scale (see Appendix). We assigned relative importance values to each item based on theoretical and practical considerations, then normalized these values to create proportional weights (summing to 1), which were applied to participant responses to calculate a weighted composite engagement score.

Model 1 is a basic growth model with time (coded as week) as the independent variable and PCL-5 scores as the dependent variable. It provides a fixed effect for each slope (treatment and follow-up). The treatment slope represents the average trajectory of PCL-5 scores during weeks 0-16. The post-treatment slope represents the average trajectory of PCL-5 scores during weeks 16-40. Model 1 also provides a random effect for each slope (treatment and follow-up) to account for individual differences in symptom trajectories during both periods.

In Model 2, we added a cross-level interaction of group, splitting participants according to whether they reached the first DDTM module, to assess whether symptom trajectories were significantly different between these groups.

The third analysis examined the association between engagement quality and PTSD symptom trajectories. Participants were categorized into low, medium, and high engagement groups based on scores derived from the novel rating scale. Mean symptom trajectories were subsequently plotted for each group to explore differences in symptom trajectories by engagement group.

Results

Demographics and Descriptive Statistics

Table 1 presents demographics and descriptive statistics. Participants were split into two groups based on treatment adherence: those who started a trauma-focused digital therapy package and dropped out before reaching the DDTM modules, and those who began at least one DDTM module. Participants in both groups were predominantly female and Hispanic/Latinx with a high number of comorbidities.

Table 1. *Demographics and Descriptive Statistics*

Variable	Started DDTM Module ($N = 24$)	Early Dropout ($N = 23$)
Age, $M(SD)$	27.97(6.71)	25.58(5.05)
Female, n(%)	16(66.67)	18(78.26)
White, n(%)	10(41.67)	11(47.83)
Asian, n(%)	1(4.17)	3(13.04)

Multiple races, *n*(%)	4(16.67)	2(8.70)
Hispanic/Latinx, *n*(%)	18(75.00)	19(82.61)
Comorbidities, *M*(*SD*)	4.46(1.67)	5.13(1.32)
Modules completed, *M*(*SD*)	6.42(1.69)	1.78(2.00)
Coach sessions, M(SD)	6.92(2.00)	2.39(2.15)
Baseline PCL-5, M(SD)	47.56(12.08)	46.91(10.06)
PCL Observations, M(SD)	8.96(6.89)	3.91(4.35)

Engagement Rating Scale: Preliminary Validation

Below, we present preliminary psychometric analyses from the development of the Engagement Rating Scale. Table 2 provides a summary of inter-rater reliability statistics. Agreement for the total weighted engagement score was moderate-to-good for both raters. For rater 2, the item-level score was *ICC* = .715, 95% CI [.651, .769], $p < .001$. For rater 3, the item-level score was *ICC* = .696, 95% CI [.627, .753], $p < .001$. For rater 2, the raw engagement ICC was 0.784, and the weighted engagement ICC was 0.776. For rater 3, the raw engagement ICC was 0.898, and the weighted engagement ICC was 0.900.

Table 2. *Inter-rater Reliability Psychometrics*

Variable	Rater 2	Rater 3
ICC	0.715	0.696
Lower Confidence Interval	0.651	0.627
Upper Confidence Interval	0.769	0.753
Degrees of Freedom 1	265	265
Degrees of Freedom 2	265.429	248.601
p-value	< .001	< .001
Number of Items	266	266
Raw Engagement ICC	0.784	0.898
Weighted Engagement ICC	0.776	0.900

Table 3. *Engagement Ratings Summary*

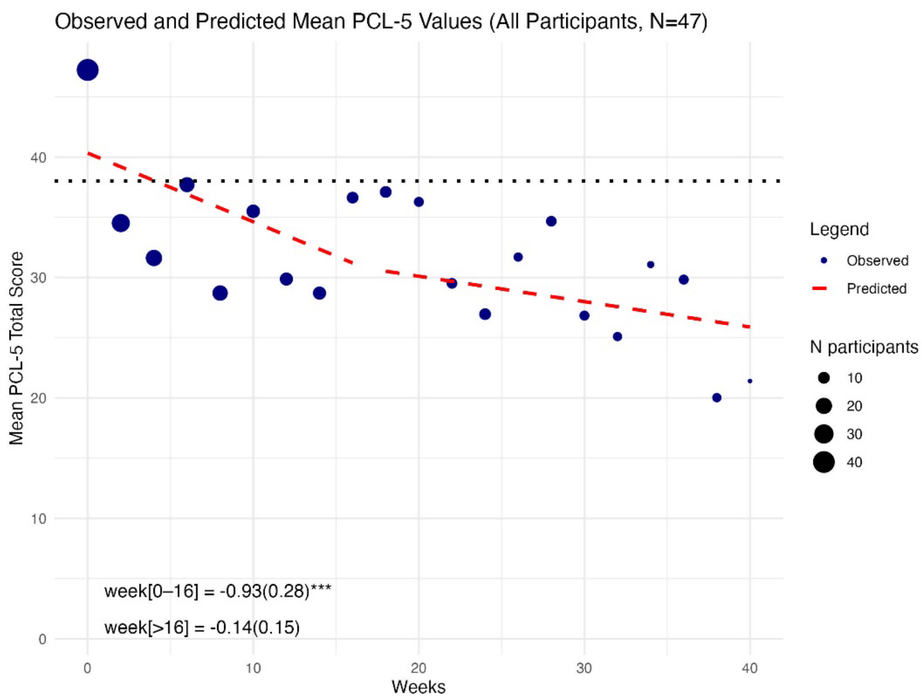
Variable	Mean	Std Dev	Min	Max
Memory Selection	2.54	0.83	1	3
Greatest Worry	3.29	2.07	0	6
Safety Behavior	1.33	0.87	0	3
No Avoid Alignment	1.67	0.56	0	2
No Avoid Detail	2.46	1.22	0	4
WET Alignment	3	2.95	0	11
WET Emotion	3.92	3.16	0	11
WET Detail	4.38	3.73	0	12
Learn Alignment	1.96	0.86	0	3
Learn Detail	2.67	1.69	0	6
Practice Alignment	0.92	0.5	0	2
Raw Engagement Total	28.12	12.39	3	51
Weighted Engagement Total	2.7	1.29	0.26	5.24

PTSD Symptom Trajectories

Piecewise Multilevel Model Results

Results for the basic piecewise growth model and cross-level interaction model are provided in Table 4 (models 1 and 2, respectively). Figures 2 and 3 present visual depictions of the model results. In Model 1, there was a significant decrease in PCL-5 scores during the acute treatment phase (weeks 1-16). For every two weeks of treatment, PCL-5 scores decreased by 0.93 points (b = -0.93, SE = 0.28, 95% CI [-1.47, -0.39], p < .001). During the follow-up phase, (weeks 18-40), PCL-5 scores decreased by 0.14 points for every two weeks; however, this effect was not statistically significant (b = -0.14, SE = 0.15, 95% CI [-0.43, 0.15], p =.354). Random effects indicated substantial between-person variability in baseline PCL-5 scores (SD = 10.3) and symptom trajectories during the acute treatment phase (SD = 1.07).

Figure 2. *Observed and Predicted Mean PCL-5 Value*



In Model 2, there were no statistically significant differences in estimated baseline PCL-5 scores between participants who started the DDTM modules (*N*=24) and participants who dropped out of treatment early (*N*=23; b = 1.91, *SE* = 4.28, 95% CI [-6.62, 10.44], *p* = .66). There was a significant decrease in PCL-5 scores during the acute treatment phase among participants who started the DDTM modules. For every two weeks, PCL-5 scores decreased by 1.28 points (*b* = -1.28, *SE* = 0.28, 95% CI [-1.83, -0.72], *p* < .001). On average, participants who dropped out of treatment prior to initiating the DDTM modules showed significantly less symptom improvement during treatment (*b* = 1.88, *SE* = 0.53, 95% CI [0.85, 2.90], *p* < .001). During follow-up, however, PCL-5 scores did not significantly change among participants who started the DDTM modules (*b* = 0.05, *SE* = 0.16, 95% CI [-0.26, 0.35], *p* = .77), and early dropouts showed a greater reduction in symptoms, comparatively (*b* = -1.34, *SE* = 0.43, 95% CI [-2.17, -0.51], *p* = .002). Random effects indicated moderate individual variability in symptom trajectories during the treatment phase (*SD* = 0.83). There was a weak negative correlation between baseline PCL-5 scores and symptom trajectories (r = -0.23), such that participants with higher baseline scores tended to exhibit greater decreases in symptoms over time. A likelihood ratio test indicated that model 2 fit the data significantly better than model 1 ($\chi^2(3) = 16.84$, $p <$ .001).

Figure 3. *Observed and Predicted PCL-5 by Group with Piecewise Fit*

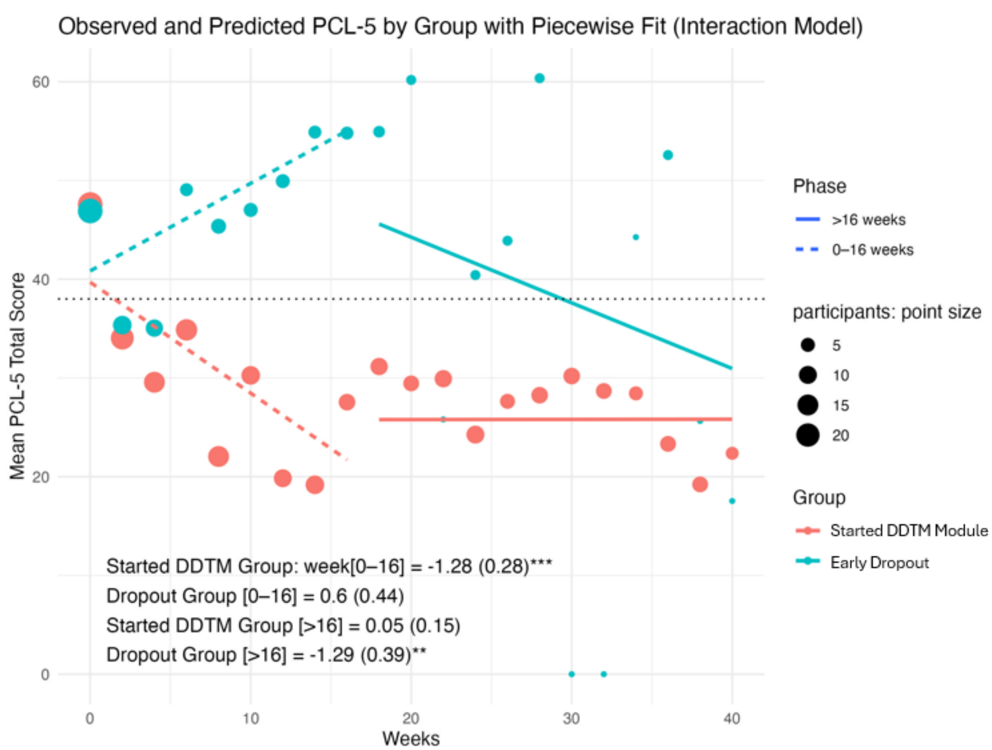


Table 4. *Piecewise Multilevel Model Summary*

Table 4.1. *Fixed Effects*

Model	Predictor	Estimate	SE	CI	p
Model 1	(Intercept)	41.87	2.05	[37.86, 45.89]	< 0.001
Model 1	b1	-0.93	0.28	[-1.47, -0.39]	< 0.001
Model 1	b2	-0.14	0.15	[-0.43, 0.15]	0.354
Model 2	(Intercept)	40.68	2.91	[35, 46.35]	< 0.001

Model 2	b1	-1.28	0.28	[-1.83, -0.72]	< 0.001
Model 2	groupEarly Dropout	1.91	4.28	[-6.62, 10.44]	0.658
Model 2	b2	0.05	0.15	[-0.26, 0.35]	0.765
Model 2	b1xgroupEarly Dropout	1.88	0.53	[0.85, 2.9]	< 0.001
Model 2	groupEarly Dropoutxp2	-1.34	0.43	[-2.17, -0.51]	0.002

Table 4.2. *Random Effects*

Model	Effect	Std Dev	Variance
Model 1	(Intercept)	10.27	105.49
Model 1	p1	1.07	1.14
Model 1	Residual	12.17	148.13
Model 2	(Intercept)	11.07	122.46
Model 2	p1	0.83	0.69
Model 2	(Residual)	11.96	143.10

Table 4.3. *Model Fit Indices*

Model	AIC	BIC	logLik
Model 1	2,505.13	2,531.17	-1,245.56
Model 2	2,494.28	2,531.49	-1,237.14

Table 4.4. *R^2 and ICC*

Model	Marginal R^2	Conditional R^2	ICC
Model 1	0.095	0.669	0.635
Model 2	0.252	0.660	0.545

Table 4.5. *Model Comparison (ANOVA: m1 vs m2)*

Model Label	df	AIC	BIC	logLik	Test	L.Ratio	p
m1	7	2,505.13	2,531.17	-1,245.56			NA
m2	10	2,494.28	2,531.49	-1,237.14	1 vs 2	16.84	< 0.001

Exploratory Engagement Findings

Preliminary findings depicted in Figure 4 indicated that higher engagement quality assessed via the novel Engagement Quality Rating Scale was associated with greater symptom improvement among participants who started the DDTM modules during the 40-week study period. Figure 5 illustrates the distribution of scaled engagement quality ratings, which informed the construction of three categories: low-, medium-, and high-engagement.

Figure 4.

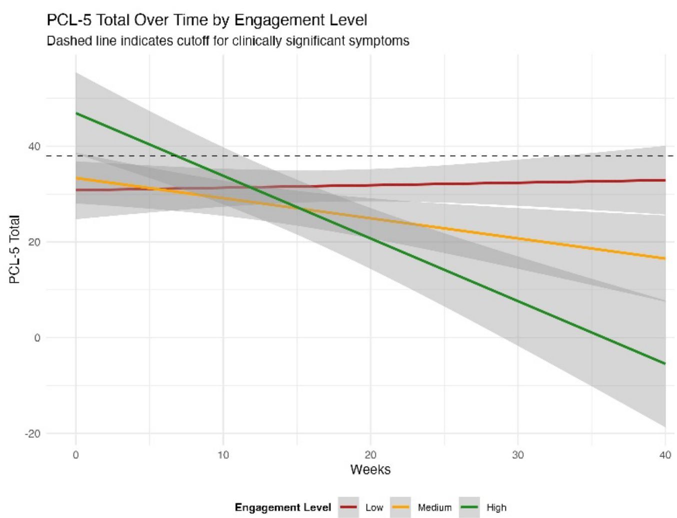
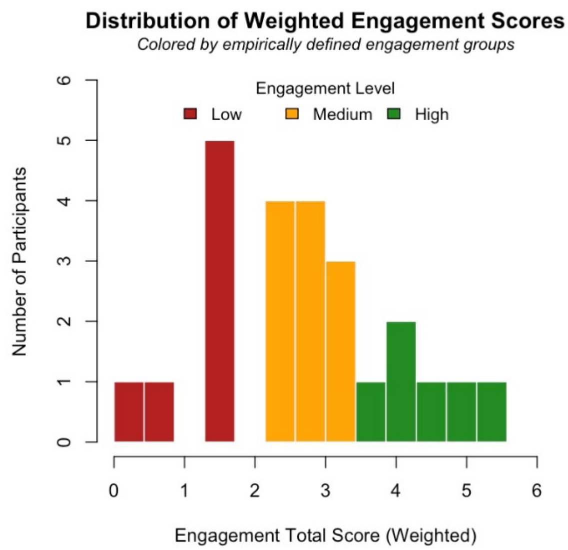


Figure 5.



Discussion

Preliminary evidence suggests that higher digital mental health engagement may be associated with greater reductions in PTSD symptoms among college students receiving a trauma-focused intervention package intervention through RF. Participants who initiated the Dealing Directly with Trauma Memories (DDTM) modules during the 16-week acute treatment phase experienced meaningful reductions in PTSD symptoms over the course of treatment. In contrast, participants who disengaged early did not experience these symptom improvements, highlighting the importance of sustained engagement for therapeutic benefit. Exploratory analyses further stratified participants into low-, medium-, and high-engagement groups based on module completion and interaction metrics. Those in the high-engagement group showed the steepest and most sustained decline in PTSD symptoms throughout the study period.

Limitations

While encouraging, our findings are not without limitations. Importantly, the statistical models were fit on relatively small sample sizes, which may have confounded the results. For example, the statistically significant decrease in symptoms during follow-up in the early dropout group (see Figure 3) should be interpreted with caution, due to high variability and a low number of PCL-5 observations during these timepoints. The small sample also precluded us from investigating additional variables that may be related to treatment response (e.g., attending peer-coaching sessions). Another limitation is that we did not collect data on potential external treatments (e.g., face-to-face therapy or initiating psychotropic medication) during the follow-up phase. Additionally, our Engagement Quality Rating Scale has only undergone preliminary steps for validation. Thus, the observed differences in symptom trajectory by engagement quality (Figure 4) should be interpreted with caution.

Conclusions

Digital therapies offer a promising means of addressing barriers to trauma-focused psychological care, particularly when patient engagement is optimized. Enhancing engagement quality during digital imaginal exposure may be essential for achieving lasting therapeutic outcomes. Future research efforts will focus on establishing greater inter-rater reliability for the psychometric properties of our engagement rating scale to confirm its validity, and extending its application to additional RF exposure-based modules (e.g., in vivo exposure, which is delivered in RF Packages targeting PTSD and panic disorder). Further developments include training a large language model (e.g., Natural Language Processing) to automate engagement coding and embedding just-in-time adaptive prompts to deliver tailored reinforcement and corrective feedback—simulating the clinical guidance typically provided in face-to-face treatment. Piloting a randomized trial of standard versus engagement-enhanced delivery could begin to test whether automated, real-time feedback can replicate the benefits of live coaching. Finally, qualitative interviews with early dropouts may uncover motivational or contextual barriers that quantitative metrics alone cannot capture, informing more targeted strategies to sustain user engagement.

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