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Abstract

Global depression prevalence continues to rise despite the clinical literature offering ubiquitous evidence-based treatments, necessitating the identification of interventions' key mechanisms that instigate meaningful clinical change. The present study addresses this gap in the field by investigating acceptance of unpleasant experiences as a change mechanism in participants' depression severity during CBT on both within- and between-participant levels. We hypothesised, first, that individual participants' session-wise increases in acceptance of unpleasant experiences predict lower depression severity. Second, we hypothesised that across participants, higher average levels of acceptance of unpleasant experiences across treatment predict lower depression severity. In a sample of 139 participants with major depressive disorder undertaking 22 sessions of CBT, we utilised multilevel modelling to disaggregate the within- and between-participant effects of session-wise fluctuations in acceptance on depression severity. The results supported both our hypotheses, demonstrating that fluctuations in individuals' session-wise levels of acceptance predicted fluctuations in their depression severity and that the more acceptance people experienced over the course of the intervention, the lower their depression severity across treatment. Taken together, the results supported acceptance of unpleasant experiences as a notable mechanism of change in depression treatment on both the individual- and group-levels. Consequently, these findings contribute to improving clinical interventions by elucidating *how* therapeutic change occurs in individuals undergoing treatment. Future research is encouraged to optimise treatments by increasing patients' acceptance of unpleasant experiences. The clinical implications of this may improve psychotherapeutic outcomes in CBT for depression, enhancing treatment effectiveness to reduce the global burden of mental health care.

Keywords: acceptance, mechanisms of change, depression, CBT, ACT, hybrid random effects model

Layman's Abstract

Despite having many available treatments, the number of people who experience depression continues to rise and they often have re-occurring depression after finishing treatment. Therefore, it's crucial to not only have treatments that provide immediate results, but to understand to *how* the treatments work and what specific components make a difference in people's lives. Focusing on these pathways of change will pinpoint which elements are most important to focus on during psychotherapy. To this end, we investigated whether people's acceptance of unpleasant experiences was related to their depression severity. We assumed that acceptance would be one such key mechanism that explains positive change in psychotherapy. A such, we researched 139 people with depression who participated in 22 sessions of cognitive behavioural therapy. Most scientific studies' results provide insights on the whole group of participants *on average*. A unique strength of our study was that we additionally analysed the results of *individual people*, enabling us to come to conclusions about how individuals' changes in acceptance from session-to-session influenced their depression severity each week. Our results showed that indeed, on average, people who have generally higher levels of acceptance tend to have lower levels of depression. Moreover, we found that when individual people's acceptance increased from session-to-session, their depression severity decreased accordingly. We identified acceptance of unpleasant experiences as an important aspect of treatment that explains how people get better. The real-life application of this suggests that focusing on increasing people's acceptance during psychotherapy could enhance treatment effectiveness and increase people's well-being.

Introduction

Global depression prevalence is steadily rising on an annual basis, imposing a substantial burden on individuals and healthcare providers alike (Proudman et al., 2021). This necessitates an urgent effort to evaluate the effectiveness of current treatments and to investigate means of enhancing their clinical significance. Indeed, state of the art scientific literature is abound with efficacious evidence-based treatments while the working mechanisms of *how* these treatments work remains understudied (Johannsen et al., 2022). Such an understanding is imperative for improving treatments by targeting the key mechanisms that instigate meaningful clinical change.

Depressive disorders are amongst the leading causes of disability worldwide (World Health Organization, 2017) with a lifetime prevalence of 12% (Johannsen et al., 2022). Depression encompasses a wide range of symptoms characterised by low mood, loss of interest or pleasure, and changes in cognition (American Psychiatric Association, 2000), and is commonly understood using Beck's cognitive theory of depression (Beck, 1967, as cited in Sudak, 2012). This model states that cognitive, biological, social, and behavioural aspects interact to produce a negative mood state which contributes to negatively biased information processing, thus shaping how the individual thinks and interacts with the world (Sudak, 2012). As such, negative thoughts about the self, others, and the world produce an ongoing and relentless cycle of hopelessness. Accordingly, treatment interventions have been developed to target this triad with the goal of modifying negative information processing.

Cognitive behavioural therapy (CBT)—a direct application of Beck's cognitive theory of depression—is an established efficacious psychological intervention for major depressive disorder and is considered a first-line treatment in clinical practice (National Institute for Health and Care Excellence, 2022). Cognitive behavioural therapy for depression employs intervention techniques using cognitive restructuring and behavioural experiments to challenge and restructure the individual's negative biases and beliefs. These tools are designed to develop the capacity for more accurate information processing, by which increasing objective and functional thinking (Sudak, 2012). Indeed, CBT has consistently been found to reduce the acute symptoms of depression (Driessen & Hollon, 2010).

Despite strong empirical support for CBT, relapse and recurrence rates for depression remain high, with 33.4% of CBT patients who responded to treatment experiencing relapse

within 36 months (Wojnarowski et al., 2019). It thus follows that despite short-term effectiveness, CBT may not sufficiently address underlying key change mechanisms necessary for long term improvement in depressive symptoms. Similarly, despite ubiquitous available evidence-based treatments, there has not been a reduction in the population prevalence of depression (Ormel et al., 2022), accentuating the need for more effective interventions. Consequently, it is imperative to identify potential change mechanisms responsible for improvement in depression outcomes. Indeed, while efficacy studies are most prevalent in clinical research, many experts advocate an equal priority of understanding *how* these treatments work (Johannsen et al., 2022). Elucidating the working mechanisms of psychological treatments will in turn allow for optimisation of existing interventions by targeting the components necessary for change.

A foundational framework for studying change in psychotherapy is Doss's (2004) multiphase model that emphasises the importance of distinguishing between change processes and change mechanisms. First, therapy change processes entail the specific therapist interventions (i.e., the "active ingredients") that subsequently influence client change processes, which are in-session changes in client variables as a response to the therapeutic intervention or direct results of assigned homework. These interacting change processes subsequently lead to changes in client characteristics or skills (change mechanisms) outside of the direct influence of the therapist's facilitating presence. As such, change mechanisms are defined as client changes that extend to their life beyond the therapy setting and are expected to improve therapeutic outcomes (Doss, 2004). This provides a foundation for investigating how specific treatment interventions lead to psychotherapeutic change.

A potential, yet underexplored, mechanism of change in depression is the client's acceptance of unpleasant experiences. Psychological acceptance refers to a willingness to choose valued actions when faced with uncomfortable experiences and actively embracing one's internal experience (Forman et al., 2015). Depression may be influenced by an expectation of mood repair and is associated with a lack of experiential acceptance, leading to a habitual response of emotional and experiential avoidance—defined as the opposite of acceptance (Jimenez et al., 2010). In contrast, acceptance of experiences may contribute to mood regulation as a form of exposure, by facilitating nonevaluative appraisal of experiences without efforts to avoid, suppress, or modify them (Jimenez et al., 2010). Yet, research on acceptance as a mechanism of change in CBT remains lacking.

Conversely, acceptance is a key component of acceptance and commitment therapy (ACT), a “third wave” cognitive behavioural therapy promoting acceptance of unwanted and distressing psychological or emotional experiences and living in congruence with personal values (S. C. Hayes et al., 2012). The ACT theory posits psychological flexibility as the main change mechanism of the treatment, comprising defusion, self-as-context, committed action, values clarity, contact with the present moment, and psychological acceptance (Hayes et al., 2012). In the same vein, psychological inflexibility is considered the core process of the development and maintenance of psychopathology, including maladaptive responses to internal experiences such as experiential avoidance (Levin et al., 2024). Moreover, experiential avoidance has been suggested as a transdiagnostic risk factor for psychopathology and for depression in particular (Johannsen et al., 2022). It thus follows that acceptance of unpleasant experiences may play a key role in alleviating depression symptoms. Additionally, despite different theoretical underpinnings of ACT and CBT (S. C. Hayes et al., 2012), some authors suggest that they are not distinct treatments (Hofmann & Cook, 2008, as cited in Forman et al., 2015). Taken together, this warrants investigation of potentially shared mechanisms of change, namely acceptance, within the context of CBT.

Notwithstanding the above change theories for acceptance in depression, few empirical studies have been conducted to test this in CBT specifically. Nevertheless, a recent meta-analysis of 441 studies found experiential avoidance to have a moderately strong correlation ($r = 0.56$) with depression (Akbari et al., 2022). However, the authors cautioned that non-clinical undergraduate students were overrepresented in the reviewed studies (Akbari et al., 2022) and the scope of the review was not limited to CBT or to depressive disorders. More specifically, a flagship randomised controlled trial (RCT) by Forman et al. (2007) compared the effects of ACT and cognitive therapy (CT) on participants with anxiety and depression. They demonstrated that both experiential avoidance and acceptance mediated treatment outcomes in the ACT group, but not the CT group (Forman et al., 2007). Importantly however, this study and most others in the literature investigated only the between-patient differences in acceptance (or experiential avoidance) as a predictor of therapy outcomes.

As the most common method of analysing the effects of predictors on outcome variables, between-patient analyses can answer the question of whether generally high levels of acceptance across participants predict treatment outcomes. Yet, the primary limitation of

between-patient analyses is the inability to determine whether the change mechanism under investigation improves treatment outcomes for individual participants (Falkenström et al., 2017). Conversely, within-patient analyses can elucidate how change mechanisms may predict therapeutic outcomes over the course of treatment, with repeated measures nested within individual participants providing the best possible approximation of causality (Falkenström et al., 2017). As such, it is crucial to also analyse within-patient effects of acceptance on therapeutic outcomes, especially in the context of depression.

Yet, within-patient research on acceptance as a mechanism of change remains scarce and mostly within the context of anxiety disorders. Indeed, Niles et al. (2014) conducted an RCT comparing ACT and CBT in a sample of participants with social anxiety disorder. Their results showed significant nonlinear decreases in experiential avoidance in both treatment groups, whereby the nonlinear effects of experiential avoidance during treatment significantly mediated posttreatment social anxiety and depressive symptoms in ACT, but not in CBT (Niles et al., 2014). Similarly, by analysing within-patient effects, Forman et al. (2012) found that utilisation of acceptance strategies mediated symptom severity for mixed participants with depression and anxiety disorders receiving ACT, but not for those receiving CT. Additionally however, willingness to engage in behavioural activity despite unpleasant thoughts or emotions (a core defining component of acceptance) mediated outcomes in both treatment groups (Forman et al., 2012). Lastly, Eustis et al. (2020) utilised longitudinal data to investigate experiential avoidance as a change mechanism of anxiety disorders in CBT. Their results demonstrated both significant reductions in experiential avoidance across patients over the course of treatment, and that change in experiential avoidance was significantly associated with changes in anxiety. Moreover, change in experiential avoidance preceded and predicted subsequent changes in anxiety, but not vice versa, further supporting reductions in experiential avoidance as a mechanism of change (Eustis et al., 2020). Given that the above studies mostly investigated acceptance in the context of anxiety disorders in ACT, the verdict is still out on acceptance as a within-patient change mechanism for depressive disorders in CBT.

Building upon the current state of the art, the present study investigates acceptance as a mechanism of change in CBT for depression. Specifically, we question whether inter-session variations in acceptance of unpleasant experiences across CBT treatment are related to therapeutic outcomes in the treatment of depression. This addresses an important gap in the

literature by investigating not only between-patient, but also within-patient effects. By doing so, we aim to strengthen evidence for acceptance as a mechanism of change and provide a stronger basis for inferring potential causal mechanisms of change in depression treatment.

Accordingly, to address both within- and between-patient effects, two hypotheses are formulated. First, we hypothesise that individual participants' session-wise increases in acceptance of unpleasant experiences predict lower depression severity (hypothesis 1; within-patients). Second, we hypothesise that across participants, higher average levels of acceptance of unpleasant experiences across treatment predict lower depression severity (hypothesis 2; between-patients).

The rationale of the present study is to improve the understanding of *how* change in depression occurs during CBT, by examining acceptance of unpleasant experiences as a potential mechanism. Indeed, to increase the effectiveness of CBT, future researchers and clinicians may aim to address the underlying key change mechanisms responsible for improved psychotherapeutic outcomes. Thus, the clinical implications of the present research lie in informing more targeted treatments, potentially by encouraging clinicians to incorporate a focus and awareness of acceptance in CBT protocols. Ultimately, this may enhance CBT interventions to produce more sustained change and recovery in depression.

Methods

Design

The present study was a secondary analysis that drew on the data from a randomised controlled trial comparing the effects of CBT and exposure-based cognitive therapy (EBCT) in participants with depression (grosse Holtforth et al., 2019). Both treatments were highly effective in reducing depression severity during acute treatment and outcomes remained stable at 12-month follow-up. Moreover, there were no significant differences between CBT and EBCT at either measurement (grosse Holtforth et al., 2019). Seeing as the treatments yielded similar results, the present study considered them comparable variations of CBT and analysed the data from the whole sample of participants.

Participants

Patients

The present study comprised 139 eligible participants (as a secondary analysis of the parent study's 149-participant pool on an intent-to-treat basis). To be included in the parent study (grosse Holtforth et al., 2019), individuals needed to provide informed consent, be between 18–65 years old, and meet diagnostic criteria for a major depressive disorder. Diagnoses were assessed using the Structured Clinical Interview for *Diagnostic and Statistical Manual of Mental Disorders* (4th ed., text rev.; *DSM-IV-TR*; American Psychiatric Association, 2000). Exclusion criteria were: meeting current or lifetime *DSM-IV-TR* criteria for psychotic disorders, bipolar disorder, borderline, schizotypal, or antisocial personality disorder; current substance dependence; acute suicidality; mood disorders due to medical conditions; receiving concurrent psychological treatment for depression; or having health conditions requiring medications that could potentially exacerbate depression (e.g., steroids). Individuals taking antidepressant medication were included if the dose had been stable for at least one month prior to screening. Participation in the psychotherapeutic research intervention was free of charge and participants were not compensated financially. Those who did not meet the inclusion criteria were informed of alternative therapeutic treatments available in the community. Sociodemographic and descriptive data of the current sample are presented in the Results.

Therapists

Twenty-five masters-level psychologists from a certified postgraduate CBT training institute were recruited to deliver the treatments for the parent study (for further details on therapist characteristics, see grosse Holtforth et al., 2019). To mitigate potential confounding of treatment effects with therapist effects, all therapists administered interventions in both treatment groups to an equal number of participants in each group. For assessments of therapist allegiance and treatment adherence, see grosse Holtforth et al. (2019).

Treatment

Participants received up to 22 weekly sessions of either CBT or EBCT, as the acute treatment. In addition, they were offered a booster session of their designated treatment type after each follow-up assessment at 3, 6, and 12 months.

Cognitive Behavioural Therapy

The CBT treatment followed the German manual for depression (Hautzinger, 2003), which is based on Beck's cognitive therapy (Beck et al., 1979) and comprised three phases. The first phase consisted of psychoeducation, socialisation to treatment, and behavioural activation techniques. In the second phase, therapists employed cognitive restructuring techniques aimed at identifying and challenging maladaptive cognitions and assumptions. Lastly, the third phase focused on consolidating treatment gains and strategies to prevent relapse. In attempt to differentiate between the two original treatment groups, therapists were explicitly instructed to refrain from using emotion-focused or exposure-based techniques.

Exposure-Based Cognitive Therapy

The EBCT treatment consisted of an adaptation of A. M. Hayes' (2015) original intervention emphasising emotion-focused techniques aimed at increasing emotional processing. The first phase focused on teaching skills to engage with emotions while reducing avoidance and rumination, including psychoeducation and behavioural activation. The second phase consisted of imaginal exposure to negative emotional events while employing emotion-focused interventions. Lastly, the third phase focused on consolidating the new learning and positive emotions from the previous phases.

Measures

Acceptance of Unpleasant Experiences

To assess acceptance as a mechanism of change, we utilised a pre-session report based on the Bern Post-Session Report (Flückiger et al., 2010) which was administered before each session to measure changes in the participant during the week prior to each session. The self-report questionnaire included 33 items, each assessing a different mechanism of change (e.g., acceptance, self-efficacy, insight, etc.). The item measuring acceptance read "[since the last therapy session] I was able to accept unpleasant experiences". Items were rated on a 5-point Likert scale, ranging from 1 ("not at all true") to 5 ("completely true").

Of special note was the use of a single-item predictor as a valid reflection of acceptance as a mechanism of change. Despite criticism of single-item measures potentially having uncertain reliability and restricted range of measures, arguments in favour of single-item measures have come to the forefront of methodological discourse in recent years (Allen

et al., 2022). Notably, single-item measures are most parsimonious in terms of administration time and reduce participant fatigue and frustration resulting from repetitive questions that can negatively affect responses. Importantly, single-item measures are acceptable when the construct is unidimensional, clearly defined, and narrow in scope (Fuchs & Diamantopoulos, 2009 as cited in Allen et al., 2022). As such, the validity of single-item measures can be determined using the same standards as multiple-items, namely face, criterion, and test-retest reliability (Allen et al., 2022).

Depression Severity

In the present study, we utilised the German version of the World Health Organization Well-Being Index (WHO-5; World Health Organization, 1998) as a measure of depression severity. The WHO-5 measures (lack of) positive mood, vitality, and general interest and engagement and has demonstrated robust psychometric properties and validity in assessing depression severity (Krieger et al., 2014). The self-report questionnaire comprised five items measuring distress (e.g., “I have felt cheerful and in good spirits”) rated on a 6-point Likert scale ranging of 0 (“at no time”) to 5 (“all of the time”). As a proxy for depression, a lower WHO-5 sum-score represented greater depression severity. In the current sample, the questionnaire’s within- and between-participant standardised alpha was 0.94 and 0.90, respectively.

Although the parent study (grosse Holtforth et al., 2019) included additional measures of depression severity, such as the German Beck Depression Inventory-II (BDI-II; Hautzinger et al., 2006), the WHO-5 was the only instrument administered at each session. As such, it was the most appropriate measure for conducting within-participant analyses necessary for the current study. In our sample, the WHO-5 had a moderate to large correlation with the BDI-II (r = -0.63) across the four time points that both questionnaires were administered.

Procedure

The parent study was conducted at the outpatient clinic of the University of Zurich’s Department of Psychology and was approved by the local ethics committee (grosse Holtforth et al., 2019). Individuals enrolled in the study between January 2010 and February 2012, recruited via local psychiatrists, general practitioners, public advertisements, local media, and the internet. Potential participants underwent a structured telephone screening to determine eligibility for depressive symptoms, using the BDI-II and the WHO-5. Those scoring at least

14 points on the BDI-II and no more than 13 points on the WHO-5 were invited for a face-to-face diagnostic interview using the Structured Clinical Interview for *DSM-IV-TR* conducted by trained graduate students and research assistants (participants gave their written consent prior to the intake interview). Next, an unaffiliated senior researcher from a different university randomised the participants into either the CBT or EBCT treatment groups, using block randomisation such that each subsequent participant was assigned to the next therapist on a time capacity list. This further ensured that the number of participants in each treatment group was balanced within therapists. Before the first therapy session, participants completed the pre-session report and WHO-5 to establish baseline levels of acceptance and depression severity, respectively, in addition to other measures from the parent study (grosse Holtforth et al., 2019). In both treatment groups, therapy sessions took place once a week for up to 22 sessions per participant whereby the pre-session report and WHO-5 were administered at the beginning of each session to establish weekly within-participant ratings. The therapists did not receive any feedback regarding participants' ratings on either measure. After the acute treatment period, participants were offered a subsequent therapy booster session (of their assigned treatment intervention) at 3-, 6-, and 12-months follow-up at which they completed both measures prior to the session.

Statistical Analyses

Power Analysis and Sample Size

The authors of the parent study (grosse Holtforth et al., 2019) conducted a power analysis using G*Power (Faul et al., 2007) to determine the sample size needed to detect a medium between-group effect of $d = 0.50$ with 80% power and $\alpha = 0.05$. They based the analysis on a two-tailed independent samples *t* test for comparing continuous primary outcome measures at 12-month follow-up. The analysis revealed a minimum necessary sample size of $N = 128$ participants to detect the above effect. They also employed multilevel modelling (MLM) to estimate the between-group effects because MLM can capture all the available data points during the follow-up period (for details on this analysis, see grosse Holtforth et al., 2019). The MLM analysis revealed that their sample of $N = 149$ participants would yield a power of 85% to detect a between-group effect of $d = 0.50$.

Data Clean Up

As previously described, the parent study found no significant differences in average WHO-5 scores between treatment groups at any measurement (grosse Holtforth et al., 2019). As such, the present study analysed the original sample ($N = 149$) as a single pool of participants. Data were included on an intent-to-treat basis such that participants were included in the present analysis given they had at least one measurement point on both the acceptance item of the pre-session report and on the WHO-5, resulting in a final sample of $N = 139$ participants.

Descriptives

Sociodemographic characteristics of the current sample were calculated. Additionally, we computed baseline mean scores and respective standard deviations of our sample for both the acceptance item of the pre-session report and the WHO-5.

Data Analyses

We analysed our data in R software (R Core Team, 2021) using multilevel modelling (Falkenström et al., 2017). The present study utilised session-wise measurements of the WHO-5 as an outcome variable, such that these scores were nested within participants. Multilevel modelling accounted for dependency in the data resulting from repeated measures and also allowed for a robust strategy for handling missing data within participants (Falkenström et al., 2017).

Preliminary Analyses. Before testing our hypotheses, we followed the recommendations of Falkenström et al. (2017) and first estimated a fully unconditional model that included no predictor variables, with the purpose of disaggregating the variance in WHO-5 scores into within- and between-participant components (Equation 1).

$$\text{Level 1: } Y_{i,t} = \beta_{0i} + e_{i,t}$$

$$\text{Level 2: } \beta_{0i} = \gamma_{00} + u_{0i} \tag{1}$$

Where $Y_{i,t}$ is the WHO-5 score for participant *i* at time *t*, β_{0i} is the participant-specific mean WHO-5 score, $e_{i,t}$ is the random variation of participant *i* at time *t*, γ_{00} is the grand mean of WHO-5 scores across all participants and all time points, and u_{0i} is the participant-

specific deviation from that grand mean. This unconditional model enabled the calculation of the intraclass correlation coefficient (ICC), which provided the proportion of the variance in WHO-5 scores attributable to individual differences (i.e., between-participant variance in mean WHO-5 scores). Intraclass correlation coefficient scores above 0.01 provided evidence in favour of including between-participant variation in the analyses (i.e., justification for including random intercepts u_{0i}).

Next, we modelled an unconditional time-as-only-predictor model which captured changes in WHO-5 scores over time without including any additional predictor variables (Equation 2). In addition to the components of Equation 1, $Session_{i,t}$ denotes session number, β_{1i} is the participant-specific rate of change in session-wise WHO-5 scores, γ_{10} is the sample-wise average change in session-wise WHO-5 scores, and u_{1i} is the participant-specific deviation from that average rate of change (random slopes). To determine the best-fitting model, we conducted a model comparison test (ANOVA) comparing the fixed effects model (assuming all participants had the same rate of change in WHO-5 scores over time) and random effects model (allowing each participant their own rate of change in WHO-5 scores over time).

$$\text{Level 1: } Y_{i,t} = \beta_{0i} + \beta_{1i}(Session_{i,t}) + e_{i,t}$$

$$\text{Level 2: } \beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i} \quad (2)$$

Main Analyses. Lastly, to test our hypotheses, we utilised the full MLM, consistent with a hybrid random effects model (HREM) which allowed for the disaggregation of within- and between-participant effects of acceptance on WHO-5 scores. Thus, our analyses were conducted using a two-level HREM (Equation 3), including both within-participant (Level 1) and between-participant (Level 2) components.

$$\text{Level 1 model: } Y_{i,t} = \beta_{0i} + \beta_{1i}(X_{i,t} - \bar{X}_i) + e_{i,t}$$

$$\text{Level 2 model: } \beta_{0i} = \gamma_{00} + \gamma_{01}\bar{X}_i + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

(3)

Accordingly, to test our first hypothesis—that session-wise increases in acceptance of unpleasant experiences would predict lower depression severity—we examined the within-participant component of the HREM (level 1). This level of the model assessed how session-wise deviations in acceptance from each participant's mean acceptance score ($X_{i,t} - \bar{X}_i$) predicted fluctuations in their WHO-5 scores. The individual slopes for this effect (β_{1i}) were modelled at Level 2, where the fixed effect γ_{10} captured the sample-wise average rate of change in WHO-5 scores when a participant's session-wise acceptance score deviated from their mean acceptance score. To determine the best-fitting model, we conducted a model comparison test (ANOVA) comparing the fixed effects model, which assumed that all participants had the same rate of change in WHO-5 scores as their individual session-wise acceptance scores fluctuated, to the random effects model. Adding random effects u_{1i} allowed each participant their own rate of change in WHO-5 scores as their individual session-wise acceptance scores fluctuated.

Next, to test our second hypothesis—that participants with higher average levels of acceptance across treatment would report lower average depression severity—we examined the between-participant component of the HREM (level 2). This level assessed how each participant's mean acceptance score ($\bar{X}_i$) predicted their mean WHO-5 score across all sessions (β_{0i}). The between-participant fixed effect, captured by γ_{01}, described individual participants' change in mean WHO-5 scores as their mean acceptance scores changed.

Results

Descriptive Statistics

Sociodemographic characteristics of the whole sample (N = 139) are presented in Table 1. The baseline sample-wise mean acceptance and mean WHO-5 scores were M = 2.76, SD = 0.79 and M = 1.35, SD = 0.75, respectively. At baseline, the correlation between acceptance scores and WHO-5 scores was $r(123) = .25$, $p = .200$.

Table 1

Sociodemographic Sample Characteristics

	M	*SD*
Sessions completed	20.00	4.42[a]
Age	40.72	11.50
	n	*%*
Sex		
Female	77	55.40
Male	62	44.60
Marital status		
Single	56	40.29
Married/ relationship	54	38.85
Separated/ divorced/ widowed	21	15.11
Education		
Less than nine years	3	2.16
Professional training	53	38.13
High school	24	17.27
University or higher	54	38.85

[a] The skewness of the completed sessions was -1.59, indicating that this distribution was left-skewed.

Preliminary Analyses

Unconditional Model

The fully unconditional model revealed a grand mean of WHO-5 scores during treatment across all participants of γ_{00} = 2.03, *SE* = 0.07, 95% CI [1.91, 2.16], $t(138) = 31.80$, $p < .001$. Additionally, the ICC was 0.50, 95% CI [0.42, 0.57], showing that the proportion of the variance in WHO-5 scores that was attributable to between-participant variance was 50%. This justified the use of random intercepts in all subsequent models, allowing each participant to have an individual mean WHO-5 score across sessions.

Time-as-Predictor Model

Including random effects of time (session number) significantly improved the model fit compared to the fully unconditional model, $\chi^2(3) = 743.52$, $p < .001$. Further, including the individual slopes (random effects) significantly improved the model fit compared to the fixed effects time-as-predictor model, $\chi^2(2) = 305.23$, $p < .001$.

The random effects time-as-predictor model showed a significant positive effect of time on WHO-5 scores, $\gamma_{10} = 0.05$, $SE = 0.005$, 95% CI [0.04, 0.06], $t(122) = 10.28$, $p < .001$. On average, participants increased 0.05 units in their WHO-5 scores from session to session. The estimated WHO-5 score across all participants at $Session_0$ was $\gamma_{00} = 1.47$, $SE = 0.07$, 95% CI [1.33, 1.62], $t(138) = 21.23$, $p < .001$.

Hybrid Random Effects Model

Fixed Effects

Compared to the fully unconditional model, the fixed slopes HREM that included both within- and between-participant components of acceptance as predictors of WHO-5 scores demonstrated a significant improvement in model fit, $\chi^2(2) = 317.93$, $p < .001$. Moreover, the fixed slopes HREM outperformed the random effects time-as-predictor model in fitting the data, $\chi^2(1) = 425.60$, $p < .001$. As such, both participant-specific average acceptance scores and individuals' session-wise fluctuations in acceptance improved the prediction of their WHO-5 scores.

Random Effects

Including individual (random) slopes of the within-participant component significantly improved the model fit compared to the fixed slopes model, $\chi^2(2) = 91.16$, $p < .001$. There was a significant improvement in the model fit when including participant-specific changes in WHO-5 scores as their acceptance scores fluctuated (individual/random slopes), compared to using a sample-wise (fixed) slope.

Within-Participant Component (Hypothesis 1). Level 1 of the random slopes HREM revealed a significant within-participant effect of acceptance scores on WHO-5 scores, $\gamma_{10} = 0.37$, $SE = 0.03$, 95% CI [0.30, 0.44], $t(135) = 11.16$, $p < .001$. There was a sample-wise average of a 0.37-unit fluctuation in participant-specific session-wise WHO-5 scores as their

participant-specific session-wise acceptance scores fluctuated by one unit relative to their own mean acceptance score. On average across the sample, individuals' session-wise fluctuations in acceptance scores relative to their own mean acceptance score (i.e., within-participant component) predicted fluctuations in their individual session-wise WHO-5 scores.

Between-Participant Component (Hypothesis 2). Level 2 of the random slopes HREM showed a significant between-participant effect of acceptance scores on WHO-5 scores, γ_{01} = 0.60, *SE* = 0.09, 95% CI [0.42, 0.76], $t(137) = 6.49$, $p < .001$. Accordingly, there was a 0.60-unit increase in participant-specific mean WHO-5 scores as participant-specific mean acceptance scores increased by one unit. More generally, higher individual average acceptance scores (i.e., between-participant component) predicted higher individual average WHO-5 scores.

Discussion

The present study aimed to determine whether within- and between-participant variations in acceptance of unpleasant experiences across CBT treatment predicted depression severity. In support of our first hypothesis, the results demonstrated that individual participants' session-wise increases in acceptance predicted lower depression severity. Additionally, in support of our second hypothesis, the results revealed that across participants, higher average levels of acceptance across treatment predicted lower depression severity. As such, the findings strengthened the evidence for acceptance of unpleasant experiences as a key component for instigating meaningful change in depression treatment on both the individual and group levels.

Expounding the multi-layered results of the hybrid random effects model, the between-participant component showed that the higher people's average levels of acceptance of unpleasant experiences, the lower their depressive symptoms. This implies that on the group level, the more acceptance people experienced during the course of psychotherapy (CBT), the more they tended to benefit from treatment. Moreover, nature of the HREM provided insight into acceptance as a potential vehicle for change not only on the group level, but also within the personal processes of individual participants.

On the individual level, our results demonstrated that acceptance of unpleasant experiences played a significant role in predicting therapeutic outcomes over the course of treatment. Specifically, the within-participant component of the HREM revealed that fluctuations in individuals' levels of acceptance predicted fluctuations in their depression severity. Given the data was nested within participants, this conclusion is the best approximation for causality when testing mechanism effects in a non-experimental study design (Falkenström et al., 2017). Further, the results expanded Doss's (2004) framework of change in psychotherapy by showing that changes in acceptance within an individual extended beyond the therapy setting to influence their therapeutic outcomes. Taken together, our results supported acceptance of unpleasant experiences as a relevant mechanism of change in depression treatment.

Although these results aligned with our expectations, they were not completely consistent with the findings of the existing literature. With the exception of Eustis et al. (2020), previous studies (Forman et al., 2007, 2012; Niles et al., 2014) have not found support for acceptance of unpleasant experiences as a mechanism of change in CBT, only in ACT. A potential explanation for this discrepancy lies in the operationalisation of acceptance in these studies. Forman et al. (2007) and Niles et al. (2014) both utilised the Acceptance and Action Questionnaire (AAQ; Hayes et al., 2004) which was developed specifically to measure psychological flexibility, which is the proposed mechanism of change in ACT (Bond et al., 2011). However in doing so, they overextended the content validity of their studies by measuring constructs contained within psychological flexibility in addition to acceptance (e.g., committed action and cognitive defusion). By measuring the broader concept of psychological flexibility, they may have failed to find support for the specific role of acceptance as a change mechanism in CBT. In contrast, the present study utilised a straightforward item measuring acceptance, which wasn't conflated with the proposed theory underlying a singular therapeutic framework.

A similar measurement issue presented in Forman et al.'s (2012) study regarding the item they used to operationalise acceptance. The item, taken from the Philadelphia Mindfulness Scale (Cardaciotto et al., 2008), was specifically worded to evaluate the use of acceptance *strategies*. By evaluating a strategy (i.e., implementation of a behaviour) rather than the internal manner in which participants related to their experience (i.e., acceptance or avoidance), they may have constricted the relevance of the item to only ACT. Indeed, such

acceptance strategies are an explicit component of ACT interventions, but not in CBT. This is further supported by the fact that their item demonstrated weak criterion validity ($r = 0.28$) when correlated with an undisclosed questionnaire measuring acceptance (Forman et al., 2012). As a result, it is likely that their predictor item was not applicable for use in CBT interventions, explaining why they didn't find support for acceptance (the construct) as a change mechanism in CBT compared to ACT. On the other hand, the present study utilised an item assessing acceptance that didn't confine participants' responses to the use of an ACT-specific strategy, enabling us to detect the significance of acceptance as a change mechanism in CBT.

A second explanation for the present study's divergence from previous results is the use of different study populations and subsequent outcome measures. Previous studies on the topic investigated either mixed samples of people diagnosed with either depression or an anxiety disorder (Forman et al., 2007, 2012) or with solely an anxiety disorder (Eustis et al., 2020; Niles et al., 2014). It is thus plausible that acceptance plays a more central role as a change mechanism in therapeutic outcomes for depression specifically. Indeed, acceptance of unpleasant experiences may contribute to mood regulation in depression (Jimenez et al., 2010) and experiential avoidance—a lack of acceptance—has been suggested as a risk factor for depression (Johannsen et al., 2022). As such, the present study filled a gap in the literature by demonstrating the role of acceptance in symptom improvement for people with depression.

The implications of our results on the theory of psychotherapeutic mechanisms of change are thus two-fold. First, the present study extended the evidence for the role of acceptance of unpleasant experience as a change mechanism from being specific to ACT theory, to predicting therapeutic outcomes in CBT as well. Second, we identified acceptance as an important component in the reduction of depressive symptoms. Moreover, by utilising multilevel modelling, these effects were found both at the group level (between-participant) and at the individual level (within-participant), accentuating the support for acceptance as a change mechanism with practical relevance for individual participants. Taken together, these findings expand the theoretical framework of psychotherapeutic change mechanisms by identifying acceptance as a transdiagnostic mechanism for enhancing treatment outcomes.

Consequently, the clinical implications of these findings lie in their potential to optimise clinical interventions. We investigated acceptance as a working mechanism within

CBT, shedding light on *how* therapeutic change occurs in individuals undergoing treatment. Indeed, participants with higher levels of acceptance across treatment responded better to the intervention and individuals' changes in acceptance from session-to-session predicted their well-being. The clinical significance of these results implies that optimising treatments to target improvements in patients' acceptance of unpleasant experiences may enhance psychotherapeutic outcomes in CBT for depression, increasing treatment effectiveness.

The present study had several limitations that should be addressed in future research. First, we did not perform a sensitivity analysis to test whether the relationship detected between acceptance and depression severity remains after detrending (controlling for the effects of time in the hybrid random effects model; Falkenström et al., 2017). We recommend future research to explore whether such an effect remains robust after detrending by using time as a covariate, to potentially strengthen the causal probability of the results given the non-experimental design (Falkenström et al., 2017). Additionally, as a result of the present study being a secondary analysis, the power analysis from the parent study (grosse Holtforth et al., 2019) may not be representative of the current data (Dziak et al., 2020). The power analysis from the grosse Holtforth et al. (2019) study was calculated with the aim of detecting between-group effects, while the present study utilised MLM to detect within- and between-participant effects. The implication of this may be that the present analysis was either underpowered or overpowered, depending on the true effects (Dziak et al., 2020).

Lastly, due to constraints of the parent study, the present study assessed depression severity using the WHO-5 questionnaire, which was originally designed as a measure of general well-being (World Health Organization, 1998). Despite the WHO-5 demonstrating robust psychometric properties and validity as a proxy for broad depression severity, it fails to capture individual differences in severe depression severity (Krieger et al., 2014). As a result, some of the symptoms specific to severe depression may not have been captured in our results. Thus, we recommend future research to also employ measures specific to depressive diagnostics (e.g., the BDI-II), with the aim of strengthening the evidence and robustness of our results.

Notwithstanding, the strengths of the present study lie in the robust statistical methods used to differentiate between individual- and group-level effects in a generalisable sample. While most empirical studies' results allow for statements on the group level, the multilevel

modelling utilised in the present study enabled conclusions relevant to changes in individual participants (Falkenström et al., 2017). Moreover, incorporating random slopes in the model further allowed the results to capture the unique relationship between session-wise variations in individuals' acceptance and their depression severity. As such, within-patient effects are most relevant to applying scientific conclusions to clinical practice.

Additionally, our large sample of participants reflected the clinical reality of typical outpatient settings in which comorbid diagnoses are the rule rather than the exception (Cramer et al., 2010). The participants in the present study met the diagnostic criteria for a major depressive disorder, yet weren't disqualified for having other common conditions, as is the case in most clinical studies (Perlman et al., 2019). Indeed, Perlman et al. (2019) conclude that such comorbidities with depression often predict treatment outcomes and therefore recommend that studies deliberately include participants with common comorbidities with the aim of enhancing the generalisability of research results to clinical settings. Taken together, the design of the present study deliberately lends its results to real-life applicability with substantial clinical relevance.

Altogether, our results provided compelling support for the role of acceptance of unpleasant experiences as a mechanism of change in improving depressive outcomes for individual patients undergoing CBT. By identifying acceptance as a specific treatment component that explains *how* interventions work, the present study contributes to the future optimisation of efficacious interventions, such as CBT, to enhance their effectiveness. In targeting said key mechanisms, researchers and clinicians can improve interventions to instigate meaningful clinical change in people with depression. Our findings suggest that improving treatment outcomes relies not only on targeting symptom reduction, but that interventions could be further enhanced by fostering patients' acceptance of unpleasant experiences, in turn reducing depression severity and increasing well-being. More broadly, identifying acceptance as a transdiagnostic mechanism of change may inform preventative strategies and optimised interventions to reduce the global burden of mental health care.

References

Akbari, M., Seydavi, M., Hosseini, Z. S., Krafft, J., & Levin, M. E. (2022). Experiential avoidance in depression, anxiety, obsessive-compulsive related, and posttraumatic stress disorders: A comprehensive systematic review and meta-analysis. In *Journal of Contextual Behavioral Science* (Vol. 24, pp. 65–78). Elsevier Inc. https://doi.org/10.1016/j.jcbs.2022.03.007

Allen, M. S., Iliescu, D., & Greiff, S. (2022). Single item measures in psychological science: A call to action. In *European Journal of Psychological Assessment* (Vol. 38, pp. 1–5). Hogrefe Publishing GmbH. https://doi.org/10.1027/1015-5759/a000699

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders* (4th ed., text rev.).

Beck, A. T., Rush, A. J., Shaw, B. F., & Emery, G. (1979). *Cognitive therapy of depression.* Guilford Press.

Bond, F. W., Hayes, S. C., Baer, R. A., Carpenter, K. M., Guenole, N., Orcutt, H. K., Waltz, T., Zettle, R. D., Curtiss, L., Fox, E. J., Kulesza, M., Orsillo, S. M., Roemer, L., & Wilson, K. G. (2011). *Preliminary psychometric properties of the Acceptance and Action Questionnaire-II: A revised measure of psychological inflexibility and experiential avoidance*. www.sciencedirect.comwww.elsevier.com/locate/bt

Cardaciotto, L., Herbert, J. D., Forman, E. M., Moitra, E., & Farrow, V. (2008). The assessment of present-moment awareness and acceptance: The Philadelphia mindfulness scale. *Assessment*, *15*, 204–223. https://doi.org/10.1177/1073191107311467

Cramer, A. O. J., Waldorp, L. J., Van Der Maas, H. L. J., & Borsboom, D. (2010). Comorbidity: A network perspective. In *Behavioral and Brain Sciences* (Vol. 33, pp. 137–150). Cambridge University Press. https://doi.org/10.1017/S0140525X09991567

Doss, B. D. (2004). Changing the way we study change in psychotherapy. In *Clinical Psychology: Science and Practice* (Vol. 11, Issue 4, pp. 368–386). https://doi.org/10.1093/clipsy/bph094

Driessen, E., & Hollon, S. D. (2010). Cognitive behavioral therapy for mood disorders: Efficacy, moderators and mediators. In *Psychiatric Clinics of North America* (Vol. 33, pp. 537–555). W.B. Saunders. https://doi.org/10.1016/j.psc.2010.04.005

Dziak, J. J., Dierker, L. C., & Abar, B. (2020). The interpretation of statistical power after the data have been gathered. *Current Psychology*, *39*(3), 870–877. https://doi.org/10.1007/s12144-018-0018-1

Eustis, E. H., Cardona, N., Nauphal, M., Sauer-Zavala, S., Rosellini, A. J., Farchione, T. J., & Barlow, D. H. (2020). Experiential avoidance as a mechanism of change across cognitive-behavioral therapy in a sample of participants with heterogeneous anxiety disorders. *Cognitive Therapy and Research*, *44*(2), 275–286. https://doi.org/10.1007/s10608-019-10063-6

Falkenström, F., Finkel, S., Sandell, R., Rubel, J., & Holmqvist, R. (2017). Dynamic models of individual change in psychotherapy process research. *Journal of Consulting and Clinical Psychology*. https://doi.org/10.1037/ccp0000203.supp

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175–191. https://doi.org/10.3758/BF03193146

Flückiger, C., Regli, D., Zwahlen, D., Hostettler, S., & Caspar, F. (2010). Der Berner Patienten - und therapeutenstundenbogen 2000: Ein instrument zur erfassung von therapieprozessen. *Zeitschrift Fur Klinische Psychologie Und Psychotherapie*, *39*, 71–79. https://doi.org/10.1026/1616-3443/a000015

Forman, E. M., Chapman, J. E., Herbert, J. D., Goetter, E. M., Yuen, E. K., & Moitra, E. (2012). Using session-by-session measurement to compare mechanisms of action for acceptance and commitment therapy and cognitive therapy. *Behavior Therapy*, *43*, 341–354. https://doi.org/10.1016/j.beth.2011.07.004

Forman, E. M., Herbert, J. D., Moitra, E., Yeomans, P. D., & Geller, P. A. (2007). A randomized controlled effectiveness trial of acceptance and commitment therapy and cognitive therapy for anxiety and depression. *Behavior Modification*, *31*(6), 772–799. https://doi.org/10.1177/0145445507302202

Forman, E. M., Juarascio, A. S., & Herbert, J. D. (2015). *Acceptance and Commitment Therapy*. https://www.researchgate.net/publication/282817204

grosse Holtforth, M., Krieger, T., Zimmermann, J., Altenstein-Yamanaka, D., Dörig, N., Meisch, L., & Hayes, A. M. (2019). A randomized-controlled trial of cognitive–behavioral therapy for depression with integrated techniques from emotion-focused and exposure therapies. *Psychotherapy Research*, *29*(1), 30–44. https://doi.org/10.1080/10503307.2017.1397796

Hautzinger, M. (2003). *Kognitive verhaltenstherapie bei depressionen: Behandlungsanleitungen und materialien* (6th ed.). Beltz.

Hautzinger, M., Keller, F., & Kühner, C. (2006). *Das Beck Depressionsinventar II. Deutsche Bearbeitung und Handbuch zum BDI II*. Harcourt Test Services.

Hayes, A. M. (2015). Facilitating emotional processing in depression: The application of exposure principles. In *Current Opinion in Psychology* (Vol. 4, pp. 61–66). Elsevier. https://doi.org/10.1016/j.copsyc.2015.03.032

Hayes, S. C., Pistorello, J., & Levin, M. E. (2012). Acceptance and commitment therapy as a unified model of behavior change. *The Counseling Psychologist*, *40*(7), 976–1002. https://doi.org/10.1177/0011000012460836

Hayes, S. C., Strosahl, K., Wilson, K. G., Bissen·, R. T., Pistorello, J., Toarmino, D., Polusny, M. A., Dykstra, E. A., Batten, S. V, Bergan, J., Stewart, S. H., Zvolensky, M. J., Eifert, G. H., Bond, F. W., Forsyth, J. P., Karekla, M., & Mccurry, S. M. (2004). Measuring experiential avoidance: A preliminary test of a working model. In *The Psychological Record* (Vol. 54).

Jimenez, S. S., Niles, B. L., & Park, C. L. (2010). A mindfulness model of affect regulation and depressive symptoms: Positive emotions, mood regulation expectancies, and self-acceptance as regulatory mechanisms. *Personality and Individual Differences*, *49*(6), 645–650. https://doi.org/10.1016/j.paid.2010.05.041

Johannsen, M., Nissen, E. R., Lundorff, M., & O'Toole, M. S. (2022). Mediators of acceptance and mindfulness-based therapies for anxiety and depression: A systematic

review and meta-analysis. In *Clinical Psychology Review* (Vol. 94). Elsevier Inc. https://doi.org/10.1016/j.cpr.2022.102156

Krieger, T., Zimmermann, J., Huffziger, S., Ubl, B., Diener, C., Kuehner, C., & Grosse Holtforth, M. (2014). Measuring depression with a well-being index: Further evidence for the validity of the WHO Well-Being Index (WHO-5) as a measure of the severity of depression. *Journal of Affective Disorders*, *156*, 240–244. https://doi.org/10.1016/j.jad.2013.12.015

Levin, M. E., Krafft, J., & Twohig, M. P. (2024). An overview of research on acceptance and commitment therapy. In *Psychiatric Clinics of North America* (Vol. 47, Issue 2, pp. 419–431). W.B. Saunders. https://doi.org/10.1016/j.psc.2024.02.007

National Institute for Health and Care Excellence. (2022). *Depression in adults: Treatment and management NICE guideline*. www.nice.org.uk/guidance/ng222

Niles, A. N., Burklund, L. J., Arch, J. J., Lieberman, M. D., Saxbe, D., & Craske, M. G. (2014). Cognitive mediators of treatment for social anxiety disorder: Comparing acceptance and commitment therapy and cognitive-behavioral therapy. *Behavior Therapy*, *45*, 664–677. https://doi.org/10.1016/j.beth.2014.04.006

Ormel, J., Hollon, S. D., Kessler, R. C., Cuijpers, P., & Monroe, S. M. (2022). More treatment but no less depression: The treatment-prevalence paradox. In *Clinical Psychology Review* (Vol. 91). Elsevier Inc. https://doi.org/10.1016/j.cpr.2021.102111

Perlman, K., Benrimoh, D., Israel, S., Rollins, C., Brown, E., Tunteng, J. F., You, R., You, E., Tanguay-Sela, M., Snook, E., Miresco, M., & Berlim, M. T. (2019). A systematic meta-review of predictors of antidepressant treatment outcome in major depressive disorder. In *Journal of Affective Disorders* (Vol. 243, pp. 503–515). Elsevier B.V. https://doi.org/10.1016/j.jad.2018.09.067

Proudman, D., Greenberg, P., & Nellesen, D. (2021). The growing burden of major depressive disorders (MDD): Implications for researchers and policy makers. In *PharmacoEconomics* (Vol. 39, pp. 619–625). Adis. https://doi.org/10.1007/s40273-021-01040-7

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Sudak, D. M. (2012). Cognitive behavioral therapy for depression. In *Psychiatric Clinics of North America* (Vol. 35, pp. 99–110). https://doi.org/10.1016/j.psc.2011.10.001

Wojnarowski, C., Firth, N., Finegan, M., & Delgadillo, J. (2019). Predictors of depression relapse and recurrence after cognitive behavioural therapy: A systematic review and meta-analysis. *Behavioural and Cognitive Psychotherapy*, *47*(5), 514–529. https://doi.org/10.1017/S1352465819000080

World Health Organization. (1998). *Wellbeing measure in primary health care/The Depcare Project.* WHO Regional Office for Europe.

World Health Organization. (2017). Global health estimates: Depression and other common mental disorders. In *https://policycommons.net/artifacts/546082/depression-and-other-common-mental-disorders/1523689/*. https://doi.org/COI: 20.500.12592/thw4fb.