**Does It Matter How Meditation Feels?**

**An Experience Sampling Study**

Simon B. Goldberg[1,2*], Daniel M. Bolt[3], Cortland J. Dahl[2,4], Richard J. Davidson[2,4], Matthew J. Hirshberg[2]

[1]Department of Counseling Psychology, University of Wisconsin–Madison, Madison, WI, USA

[2]Center for Healthy Minds, University of Wisconsin–Madison, Madison, WI, USA

[3]Department of Educational Psychology, University of Wisconsin – Madison, Madison, WI, USA

[4]Healthy Minds Innovations Inc., Madison, WI, USA

**Author Note**

Simon B. Goldberg https://orcid.org/0000-0002-6888-0126

Daniel M. Bolt https://orcid.org/0000-0001-7593-4439

Cortland J. Dahl https://orcid.org/0000-0002-2994-115X

Richard J. Davidson https://orcid.org/0000-0002-8506-4964

Matthew J. Hirshberg https://orcid.org/0000-0001-9070-1270

Cortland J. Dahl is the primary content developer of the Healthy Minds Program and a scientist at Healthy Minds Innovations, Inc. Richard J. Davidson is the founder, president, and serves on the board of directors for the non-profit organization, Healthy Minds Innovations, Inc. Matthew J. Hirshberg has been a paid consultant at Healthy Minds Innovations, Inc. for work unrelated to this research.

This study was supported by an award from the Chan Zuckerberg Initiative (DAF 2020-218037 [5022]; RJD & SBG), a National Academy of Education / Spencer Foundation

Postdoctoral Research Fellowship (MJH), National Center for Complementary and Integrative Health Grants K23AT010879 (SBG) and U24AT011289-01 (RJD), Hope for Depression Research Foundation Defeating Depression Award (SBG), the Wisconsin Center for Education Research and the University of Wisconsin Madison Graduate School through support from the Wisconsin Alumni Research Foundation (SBG), REDCap software licensing through the University of Wisconsin–Madison's Institute for Clinical and Translational Research (UL1TR002373), and by generous individual donations to the Center for Healthy Minds and the University of Wisconsin-Madison's School of Education. No donors, either anonymous or identified, have participated in the design, conduct, or reporting of research results in this manuscript. The data and conclusions presented in this manuscript have not been presented previously orally, on poster, or in print. Data and analysis output are available online (https://osf.io/t8qxm/).

*Correspondence should be addressed to: Simon B. Goldberg, Department of Counseling Psychology, University of Wisconsin-Madison, 335 Education Building, 1000 Bascom Mall, Madison, Wisconsin, 53706, United States, phone: 608-265-8986, fax: 608-265-4174, email: sbgoldberg@wisc.edu

## Abstract

**Objective:** Meditation apps are the most widely used mental health apps. The precise mechanisms underlying their effects remain unclear. In particular, the degree to which affect experienced during meditation is associated with outcomes has not been established. **Method:** We used the meditation app arm of a recently completed randomized controlled trial comparing a self-guided meditation app (Healthy Minds Program) to a waitlist control. Predominantly distressed public school employees (*n*=243, 80.9% with clinically elevated depression and/or anxiety) reported positive and negative affect during meditation practice. Data were analyzed using two-level multivariate latent growth curve models (observations nested within participants) that simultaneously attended to both positive and negative affect. We examined whether positive and negative affect during meditation changed over time and whether these changes were associated with changes in psychological distress (parent trial's preregistered primary outcome) at post-test or 3-month follow-up. **Results**: On average, participants reported decreased negative affect but no change in positive affect during meditation over time. Increased positive affect and decreased negative affect during meditation were associated with improvements in distress at post-test and follow-up. Change in positive affect was a stronger predictor of distress at follow-up than change in negative affect. **Conclusions**: Despite notions embedded within mainstream mindfulness meditation training that deemphasize the importance of the affective experience of practice (i.e., nonjudgmental awareness of present moment experience, regardless of valence), results indicate that these experiences contain signal associated with outcomes. Monitoring affect during meditation may be worthwhile to guide intervention delivery (i.e., measurement-based care, precision medicine).

**Keywords:** meditation apps; mobile health; mindfulness; mechanisms; measurement-based care

## Public Significance Statement

This study suggests that affect experienced during meditation is associated with both short- and long-term changes in psychological distress that occur in the context of smartphone app-delivered meditation training. While both increases in positive affect and decreases in negative affect were associated with improvements in distress, increases in positive affect were the stronger predictor of long-term improvements in distress.

Mindfulness- and other meditation-based interventions (MBIs) have become mainstream in the past several decades (Creswell, 2017). This popularity is based, at least in part, on empirical evidence from hundreds of randomized controlled trials (RCTs) suggesting that, on average, MBIs produce effects on various mental health outcomes that are superior to waitlist controls and on par with other evidence-based treatments (Galante et al., 2021; Goldberg et al., 2022; Kuyken et al., 2016). Although traditionally delivered via in-person group formats, MBIs are increasingly prominent within mobile health (mHealth) apps. Mindfulness meditation specifically has emerged as by far the most popular content within mental health apps, with the two most widely used meditation apps (Headspace and Calm) alone accounting for 90% of monthly active users of mental health apps (Wasil et al., 2020). Data available from RCTs testing meditation apps suggests that these MBIs produce beneficial effects on mental health outcomes (Gál et al., 2021).

Meditation apps hold considerable promise as a means for expanding access to evidence-based strategies to promote mental health. At once, these interventions are limited in important ways. Meditation apps, like other mental health apps, demonstrate high and rapid rates of user disengagement (Baumel et al., 2019). There is also evidence that exposure to meditation initially through a meditation app may be associated with higher rates of adverse reactions to meditation practice (Goldberg et al., 2021). As these interventions are often self-guided, users may be ill-equipped to work with challenging experiences that are known to arise for some during meditation practice (Aizik-Reebs et al., 2021; Britton et al., 2022). In addition, effect sizes from meta-analyses of RCTs testing meditation app have been smaller than those observed for in-person MBIs (Gál et al., 2021; Linardon, 2020; Goldberg et al., 2022), suggesting a potential tradeoff between scalability and efficacy.

A clearer understanding of the mechanisms at play within mHealth MBIs may help treatment developers increase the efficacy of these interventions. A variety of psychological mechanisms have been proposed for in-person MBIs including the cultivation of mindful awareness (i.e., attending to the present moment, on purpose, and without judgment; Kabat-Zinn, 1994), the capacity to regulate attention and emotion (Tang et al., 2015), acceptance (Lindsay & Creswell, 2017), connection with others (Dahl et al., 2020), and cognitive reappraisal (Garland et al., 2015). A smaller body of work has examined aspects of the meditation practice itself such as the amount of formal meditation practice (e.g., minutes spent engaging in sitting meditation; Hirshberg et al., 2020; Parsons et al., 2017). A relatively small number of studies have examined the subjective experience of meditation.

Understanding the role of the subjective experience of meditation practice may be particularly valuable in the context of mHealth MBIs. The digital delivery format makes collecting participants' ratings of their experience highly feasible and the routine monitoring of relevant mechanisms could, in theory, be used to address known limitations of mHealth MBIs. Similar to routine outcome monitoring within psychotherapy (de Jong et al., 2021), feedback derived from monitoring subjective experiences during meditation that are known to predict long-term effects may help increase the acceptability, safety, and efficacy of mHealth MBIs.

Some aspects of the subjective experience of meditation have been examined for in-person MBIs. For example, state mindfulness and decentering (i.e., curiosity and awareness of experience with healthy psychological distance; Lau et al., 2006) during meditation have been shown to increase over the course of training (Shoham et al., 2017), with improvements in state mindfulness during meditation linked to decreases in distress within the context of Mindfulness-Based Stress Reduction (MBSR; Kiken et al., 2015). Practice quality, defined as the degree to which one is bringing balanced perseverance in one's application of mindful attention during formal meditation practice (Del Re et al., 2013) has been associated with improvements in distress and trait mindfulness and shown to mediate the association between formal practice and outcomes within MBSR (Del Re et al., 2013; Goldberg et al., 2014; Goldberg, Knoeppel, et al., 2020).

To our knowledge, only one study has investigated the subjective experience of meditation within the context of an mHealth MBI. In a sample of 86 undergraduates, Walsh et al. (2019) demonstrated that a mindfulness app produced larger improvements in mood post-meditation practice relative to a cognitive training active control condition. Although Walsh et al. used a measure of mood that assessed both positive and negative affect, their analyses focused on a mood composite and did not examine positive and negative mood separately.

Affect during meditation may be an important part of the subjective experience that is worth examining further within mHealth MBIs. How meditation "feels" may signal users' responsiveness to the practices they are doing and provide actionable feedback that can be used to customize interventions. Traditional early Buddhist sources such as the "mindfulness sutta" (*Satipatthana Sutta*) that have served as a major part of the basis for secular forms of mindfulness meditation (Harrington & Dunne, 2015) highlight the value of attending to the affective valence of present moment experience (Analayo, 2018). On the one hand, these sources emphasize simply recognizing when an experience is present or not, e.g., "If restlessness-and-worry is present in [one], [one] knows 'there is restlessness-and-worry in me'" (Analayo, 2006, p. 9). This aligns with the kind of non-judgmental awareness emphasized in MBSR and other MBIs (Kabat-Zinn, 1994). On the other hand, these same sources provide clear descriptions of the process of meditative development that includes the waning of certain affective experiences such as aversion and restlessness-and-worry, two of the “five hindrances” which hinder the development of meditative concentration (Analayo, 2018). These sources also describe the increase in other affective experiences such as joy and calm, two of the “seven factors of awakening” that are viewed as mental factors that mature over the course of training (Analayo, 2018). In addition, non-mindfulness styles of meditation practice including practices drawn from later Buddhist traditions (e.g., Tibetan Buddhism) often emphasize the cultivation of particular mental qualities and affective experiences (Dahl et al., 2015). For example, loving-kindness and compassion practices involve the intentional cultivation of feelings of warmth and kindness towards oneself and others, which have an affective valence (Dahl et al., 2020). To date, it is unclear the degree to which affective experience during meditation changes over the course of training and whether such changes are associated with short- and long-term treatment outcomes. In addition, the prior study investigating mood post-meditation practice in the context of an mHealth MBI (Walsh et al., 2019) combined positive and negative mood into a single dimension. However, there is evidence that positive and negative affect can and often do co-occur in the context of daily life (Barford et al., 2020; Dejonckheere et al., 2018). That is, individuals can experience high (or low) levels of both positive and negative affect simultaneously. It would therefore be valuable to clarify the degree to which outcomes within mHealth MBIs are linked to the waning of negative affect (e.g., as characterized by the five hindrances) and/or the increase of positive affect (e.g., as characterized by the seven factors of awakening; Analayo, 2018).

## Current Study

The current study sought to clarify the degree to which positive and negative affect during meditation change over the course of training and whether such changes are linked to short- and long-term outcomes in the context of an mHealth MBI. To do so, we used data drawn from the intervention arm of a recently completed RCT testing a meditation app in a sample of predominantly distressed (i.e., reported clinically elevated depression and/or anxiety) public school employees during the early months of the COVID-19 pandemic (Hirshberg et al., 2022). Participants provided experience samples of their positive and negative affect immediately following meditation. We examined whether ratings of positive and negative affect changed over the course of training, whether changes were associated with changes in psychological distress (preregistered primary outcome in the RCT) at post-treatment and 3-month follow-up, and whether patterns differed across positive and negative affect dimensions. The RCT from which these data were drawn was preregistered (Hirshberg et al., 2022; NCT04426318 ) although the analyses reported here were exploratory and not preregistered. Data and analysis output are available online (https://osf.io/t8qxm/). Study procedures were approved by the University of Wisconsin – Madison Institutional Review Board.

## Method

### Participants and Procedure

The RCT from which these data were drawn included 662 public school employees recruited during the early months of the COVID-19 pandemic (enrolled between June and August 2020). Participants were randomly assigned to use the Healthy Minds Program [HMP] app ($n$ = 344) or to a waitlist control condition ($n$ = 318). Efficacy results have been reported elsewhere (Hirshberg et al., 2022). The preregistered target sample size for the RCT was 400 which was estimated to provide 80% power to detect between-group differences of Cohen's $d \geq$ 0.38, assuming 43.4% attrition (Linardon & Fuller-Tyszkiewicz, 2020) with $\alpha$ = .050. This between-group difference is similar to that observed in meta-analyses of mHealth MBIs (e.g., Gál et al., 2021). It was noted in the preregistration that a larger sample may be recruited if additional funding was secured.

Public school employees were eligible to participate if they had no or minimal prior meditation experience and did not report severe depressive symptoms (Patient-Reported Outcomes Monitoring Information System [PROMIS] Depression T-score ≤ 70; Pilkonis et al., 2011). The preregistered primary outcome for the RCT was psychological distress which was computed as a composite of depression, anxiety, and stress measures. The current study used psychological distress assessments from baseline, post-treatment, and 3-month follow-up. Affective experience during meditation was assessed immediately following practices delivered via the HMP app.

The current study included participants randomized to the HMP condition who completed one or more ratings of affect during meditation practice ($n = 243$). Participants completing one or more ratings did not differ from those who did not complete ratings on demographic or clinical variables at baseline ($p$s > .100). The subsample completing one or more ratings was on average 42.24 years old ($SD = 10.59$); 88.9% were female, 10.7% male, and 0.4% of unknown gender; 88.5% were non-Hispanic White, 2.1% Black, 0.4% Latinx, 1.6% Asian/Pacific Islander, 4.5% multiracial, and 2.9% of unknown race/ethnicity; 89.3% had completed college; 16.5% had an annual income of ≤ $50,000. Most (80.9%) reported PROMIS Depression and/or PROMIS Anxiety scores in the clinically elevated range (T-score ≥ 55).

**Intervention**

The HMP app includes training in four pillars of well-being: Awareness, Connection, Insight, and Purpose (ACIP; Dahl et al., 2020). The Awareness module emphasizes training the regulation of attention (e.g., focused attention; meta-awareness of thoughts, sensations, and emotions). The Connection module emphasizes the cultivation of capacities that support positive relations with oneself and others such as gratitude and compassion. The Insight module includes practices designed to clarify the nature of self-identity and experience (e.g., seeing thoughts as only thoughts). The Purpose module involves clarifying one's values and expressing values in daily activities. Thus, HMP includes both traditional mindfulness (e.g., Awareness module) as well as non-mindfulness (e.g., Connection module) practices. HMP includes a combination of didactic "podcast-style" lessons discussing the science of well-being along with guided meditation practices aimed at cultivating ACIP skills. For further details about HMP, see Goldberg, Imhoff-Smith, et al. (2020) and Hirshberg et al. (2022).

## Measures

### ***Psychological Distress***

Psychological distress was operationalized as the composite of the computer adaptive PROMIS Depression and PROMIS Anxiety scales (v1.0; Pilkonis et al., 2011) and the 10-item Perceived Stress Scale (PSS; Cohen & Williamson, 1988). The computer adaptive PROMIS Depression and PROMIS Anxiety measures have shown strong convergent validity with legacy measures assessing these constructs (Choi et al., 2014; Schalet et al., 2014). Items assess symptoms of depression (e.g., "I felt worthless") and anxiety (e.g., "I felt fearful) in the past 7 days on a 5-point Likert-type scale ranging from 1 (*never*) to 5 (*always*). The computer adaptive versions yield T-scores (i.e., mean = 50, *SD* = 10), with a T-score ≥ 55 indicating clinical elevations. Although internal consistency cannot be computed for the computer adaptive versions, the fixed form versions of the PROMIS Depression and PROMIS Anxiety scales have shown adequate internal consistency reliability (αs ≥ .90; Pilkonis et al., 2011).

The PSS is a widely used measure assessing perceived stress in the past month (e.g., "How often have you felt that you were unable to control the important things in your life?"). Items are rated on a 5-point Likert-type scale ranging from 1 (*never*) to 5 *(very often*). The 10-item PSS has shown strong convergent and discriminant validity (Roberti et al., 2006). A total score was computed by taking the mean of all items, with higher scores reflecting higher perceived stress. Internal consistency was adequate ($\alpha$ = .85).

A psychological distress composite was computed based on prior work showing high correlations between these measures (Goldberg, Imhoff-Smith, et al., 2020). To compute this composite, scores on the measures of depression, anxiety, and stress were z-transformed and then averaged.

***Post-Practice Affect***

Participants completed items assessing positive and negative affect immediately following meditation practice delivered via the HMP app. Items were drawn from prior experience sampling work investigating the subjective experience of meditation practice (Shoham et al., 2017). Participants were asked "During the meditation practice, to what extent did you feel each of the following emotions" and provided ratings on a 5-point visual analog scale ranging from 1 (*not at all*) to 5 (*very much*). The two positive affect items were "happy" and "calm" and the two negative affect items were "sad" and "nervous." We calculated inter-item correlations and correlations across affect dimensions at the overall level (i.e., not disaggregated into within- and between-participant components), as well as disaggregated into within-participant (i.e., subtracting participant-level means from each rating) and between-participant (i.e., participant-level mean rating) components. Inter-item correlations for the two positive affect items were $r$ = .57 (overall), $r$ = .44 (within participant), and $r$ = .66 (between participant) and for the two negative affect items were $r = .49$ (overall), $r = .38$ (within participant), $r = .51$ (between participant), all *p*s < .001, indicating acceptable internal consistency reliability (Clark & Watson, 1995). Positive and negative affect subscale scores were computed by averaging across the two items in each dimension. Correlations between affect dimensions were $r = -.34$ (overall), $r = -.42$ (within participant), and $r = -.27$ (between participant), all *p*s < .001. Ratings were z-scored for use in analyses.

**Data Analysis**

Data were analyzed using two-level multivariate latent growth curve models (MacCallum et al., 1997; Plewis, 2005) implemented in HLM (Raudenbush & Congdon, 2021). Our approach mimics a multivariate extension of HLM employed by Raudenbush et al. (1995). HLM output is included in Supplemental Materials Table 1 to 3. Data are available through OSF (https://osf.io/t8qxm/). As can be seen in the data file (and in Raudenbush et al.'s [1995] Table 2 on p. 166), data were converted into long format with a row for each affect rating. Two separate indicator variables were included (coded as 0 or 1, *PosAff* and *NegAff* in the models below) to reflect whether a rating was associated with positive or negative affect. When a positive affect rating was made, the positive affect indicator variable was coded as 1 and the negative affect indicator variable was coded as 0. Similarly, two separate time variables were included (*PosTime and NegTime* in the models below), coded as time (i.e., day, but scaled to range from 0 to 1 as described below) when a particular affect rating was drawn from that dimension and coded as 0 when a particular affect rating was drawn from the opposite dimension. The two-level models included assessment timepoint (Level 1) nested within participant (Level 2). Models also allowed different Level 1 error variances for the positive versus negative affect measures. This permitted our simultaneous modeling of both measures. In analyses, negative affect was reverse scored, such that higher scores reflected lower levels of negative affect. This was used to allow a hypothesis test (described below) comparing trajectories of change for positive and negative affect with one another. However, for ease of interpretation, negative affect was not reverse scored in figures.

We conducted three separate models. An initial model (Model 1) assessed change in affect during meditation over time:

$$Aff_{ti} = \beta_{10} * (PosAff_{ti}) + \beta_{20} * (NegAff_{ti}) + \beta_{30} * (PosTime_{ti}) + \beta_{40} * (NegTime_{ti}) + [r_{1i} * (PosAff_{ti}) + r_{2i} * (NegAff_{ti}) + r_{3i} * (PosTime_{ti}) + r_{4i} * (NegTime_{ti}) + e_{ti}],$$

(Equation 1)

where affect (*Aff*) at timepoint *t* for participant *i* is predicted by fixed intercepts (i.e., grand mean) for positive ($PosAff_{ti}$) and negative ($NegAff_{ti}$) affect ($\beta_{10}$ and $\beta_{20}$), coded as 0 or 1 depending on dimension of affect ratings, fixed slopes for time ($PosTime_{ti}$, $NegTime_{ti}$; $\beta_{30}$ *and* $\beta_{40}$) scaled from 0 to 1 with time coded as 0 when affect ratings are drawn from the opposite dimension (i.e., *PosTime* = 0 when *Aff* corresponds to negative affect), along with participant-level (i.e., Level 2) random components for both intercepts and slopes (in brackets) along with residual error ($e_{ti}$). A hypothesis test was conducted to compare trajectories of change in positive versus negative affect (i.e., fixed effects *PosTime* vs. *NegTime*, $\beta_{30}$ vs. $\beta_{40}$) using the "linear hypothesis testing" feature in the HLM software. We used the HLM software to conduct a Wald $\chi^2$ test to evaluate the equivalence of the fixed effect trajectory parameters (see Supplemental Materials Tables 1 to 3).

A second model (Model 2) evaluated whether pre-post change in psychological distress was associated with trajectories of change in affect during meditation practice. To characterize change in psychological distress over time, residualized change scores were calculated reflecting change from baseline to post-test or from baseline to 3-month follow-up (i.e., scores at post-test or 3-month follow-up regressed onto baseline). These change scores were then entered into Model 2 and Model 3. The equation for Model 2 was:

$$Aff_{ti} = \beta_{10} * (PosAff_{ti}) + \beta_{11} * (PosAff_{ti} * Residual\ change_i) + \beta_{20} * (NegAff_{ti}) + \beta_{21} * (NegAff_{ti} * Residual\ change_i) + \beta_{30} * (PosTime_{ti}) + \beta_{31} * (PosTime_{ti} * Residual\ change_i) + \beta_{40} * (NegTime_{ti}) + \beta_{41} * (NegTime_{ti} * Residual\ change_i) + [r_{1i} * (PosAff_{ti}) + r_{2i} * (NegAff_{ti}) + r_{3i} * (PosTime_{ti}) + r_{4i} * (NegTime_{ti}) + e_{ti}],$$

(Equation 2)

where affect (*Aff*) at timepoint *t* for participant *i* is predicted by fixed intercepts and fixed slopes as in Equation 1 (i.e., $\beta_{10}$, $\beta_{20}$, $\beta_{30}$, $\beta_{40}$) along with the interaction between these intercepts and slopes with pre-post residualized change in psychological distress ($Residual\ change_i$, a participant-level variable; $\beta_{11}$, $\beta_{21}$, $\beta_{31}$, $\beta_{41}$), and participant-level (i.e., Level 2) random components for both intercepts and slopes along with residual error ($e_{ti}$). As in Model 1, a hypothesis test was used to assess whether the interaction between pre-post change in psychological distress and trajectories of change in affect differed across positive and negative affect dimensions (i.e., $\beta_{31}$ vs. $\beta_{41}$).

A final model (Model 3) was identical to Model 2 but instead examined associations with pre- to follow-up change in psychological distress rather than pre-post change. Thus, the participant-level variable *Residual change*$_i$ in Equation 2 was modified to reflect pre- to follow-up residualized change.

To quantify the magnitude of the association between changes in psychological distress (i.e., residualized change from baseline to post-test or baseline to follow-up) with trajectories of change in positive and negative affect, we calculated $R^2$ values (i.e., variance explained). Specifically, we calculated the change in residual variances for positive and negative affect slopes when adding the predictive effects of change in psychological distress to the models. The reduction in residual variances for positive and negative affect slopes when adding change in psychological distress to the models quantifies the degree to which change in distress is associated with change in affect.

Maximum likelihood estimation was used for all models which is robust to data missing at random (Graham, 2009). Given the large number of Level 2 units, we interpreted results using robust standard errors as these are less sensitive to violations of multilevel model assumptions (Snijders & Bosker, 2012).

## Results

Participants ($n$ = 243) provided an average of 7.82 (standard deviation [$SD$] = 3.76) post-meditation practice ratings, resulting in a total of 1,893 ratings of positive affect and 1,896 ratings of negative affect. Average positive affect was 3.66 ($SD$ = 0.80, range = 1.00 to 5.00) and average negative affect was 1.42 ($SD$ = 0.64, range = 1 to 4.55). Of participants providing one or more post-meditation practice ratings, residualized change in psychological distress was available for 219 (90.1%) at post-test and 218 (89.7%) at 3-month follow-up. Average residualized change in psychological distress was -0.23 ($SD$ = 0.70) at post-test and -0.13 ($SD$ = 0.62) at follow-up. These negative values are consistent with the significantly larger improvements in psychological distress for the HMP group versus the waitlist control at both time points previously reported (Hirshberg et al., 2022). Participants' first post-meditation practice ratings showed moderate magnitude associations with baseline distress (*r*s = -.25 and .35, *p*s < .001, for positive and negative affect, respectively).

An initial model (Model 1) examined change in affect during meditation over the course of the 4-week intervention. Negative affect decreased significantly over time ($B$ = 0.18, $p$ = .017; recall negative affect was reverse scored in analyses) while positive affect did not change over time ($B$ = -0.080, $p$ = .295). The difference between these slope parameters was significant ($\chi^2$ [1] = 8.24, $p$ = .004). There was significant between-participant variation in changes in both positive and negative affect over time (i.e., random effects). The *SD* for positive affect slopes was 0.64 and for negative affect slopes was 0.52 (both *p*s < .001). Average and participant-level trajectories of change in positive and negative affect are displayed in Figure 1.

We then examined whether trajectories of change in affect during meditation was associated with changes in our primary outcome. Pre- to post-test change in psychological distress was associated with trajectories of change in both positive affect ($B$ = -0.42, $p$ < .001) and negative affect ($B$ = -0.34, $p$ = .003). The difference between these coefficients was not significant ($\chi^2$ [1] = 0.43, $p$ = .512). As shown in Figure 2, larger pre- to post-test improvements in psychological distress were associated with steeper increases in positive affect and steeper decreases in negative affect during meditation practice over time.

To characterize the magnitude of associations between pre- to post-test change in psychological distress and trajectories of change in positive and negative affect, we calculated $R^2$ values. Prior to adding pre- to post-test change in psychological distress to the model (i.e., in Model 1), there was 0.41 variance in positive affect slopes and 0.27 variance in negative affect slopes. With the addition of pre- to post-test change in psychological distress to the model (i.e., Model 2), these variances were reduced to 0.33 and 0.22, for positive and negative affect slopes, respectively. Thus, the addition of pre- to post-test psychological distress was associated with an $R^2$ of 0.20 for positive affect slope (i.e., [0.41 – 0.33] / 0.41) and an $R^2$ of 0.19 for negative affect slope (i.e., [0.27 – 0.22] / 0.27).

A final model examined associations with pre- to follow-up change in psychological distress. Pre- to follow-up change in psychological distress was again associated with trajectories of change in both positive affect ($B$ = -0.56, $p$ < .001) and negative affect ($B$ = -0.20, $p$ = .033). The difference between these coefficients was significant ($\chi^2$ [1] = 7.24, $p$ = .007), indicating that pre- to follow-up change in psychological distress was more strongly associated with changes in positive affect during meditation practice over time than with changes in negative affect (Figure 3).

To characterize the magnitude of these associations, we again calculated $R^2$ values. With the addition of pre- to follow-up change in psychological distress to the model (i.e., Model 3), these variances were reduced to 0.30 and 0.25, for positive and negative affect slopes, respectively. Thus, the addition of pre- to follow-up psychological distress was associated with an $R^2$ of 0.27 for positive affect slope (i.e., [0.41 – 0.30] / 0.41) and an $R^2$ of 0.07 for negative affect slope (i.e., [0.27 – 0.25] / 0.27).

## Discussion

mHealth MBIs including meditation apps have emerged as a promising means for dissemination of evidence-based strategies to support mental health (Wasil et al., 2020). At once, effect sizes associated with these interventions remain modest (Gál et al., 2021), naturalistic use of these tools shows rapid disengagement (Baumel et al., 2019), and the mechanisms underlying potential beneficial effects remain unclear (Goldberg, 2022). The subjective affective experience of meditation practice may be a relevant indicator of response to mHealth MBIs that could be used to guide the delivery of these interventions.

The current study demonstrated that negative affect decreases on average over the course of training and that changes over time in both positive and negative affect during meditation are associated with changes in psychological distress at post-treatment and 3-month follow-up. This supports the notion that affect during meditation is a relevant proximal indicator of treatment response that contains signal associated with short- and long-term effects. However, our results also indicate that associations between changes in affect during meditation and long-term outcomes were not uniform across affect dimensions. Although it was negative affect (and not positive affect) that changed (decreased) on average over time, increases in positive affect more strongly predicted outcomes at 3-month follow-up than decreases in negative affect. From a traditional early Buddhist perspective, these findings suggest an average waning of negative affective states during meditation practice that aligns with a weakening of the five hindrances (Analayo, 2018). Results also highlight the increase of positive affective states during meditation as being most important for long-term benefits, in keeping with the seven factors of awakening (Analayo, 2018) as well as the emphasis in non-mindfulness meditative practices designed to cultivate affective states (e.g., loving-kindness and compassion practices; Dahl et al., 2015).

These results support the notion that affect during meditation may be a highly relevant target for routine monitoring with mHealth MBIs. Changes in affect during meditation practice in particular may be an important state-like construct (as opposed to a trait-like construct; Zilcha-Mano, 2021; Zilcha-Mano & Fisher, 2022) that can guide intervention customization. The digital delivery format may lower the bar for gathering such assessments relative to in person delivery where logistical barriers may limit implementation of routine monitoring systems (Duncan & Murray, 2012). Moreover, digital interventions could in theory be readily customized based on participants' responses, in keeping with notions of precision medicine in which interventions are targeted to a given patient at a given time (Collins & Varmus, 2015). Such customization could include the delivery of specific intervention content (e.g., components that may boost positive affect, for example if a participant is not showing increases over time) or the provision of additional human support (e.g., text message support from a meditation instructor, for example if negative affect is not reducing over time). Of course, the development of customized mHealth MBIs that achieve the promise of precision medicine will require surmounting both scientific challenges (e.g., identification of proximal indicators of long-term treatment response) as well as technical and design challenges (i.e., implementing feedback-informed modifications within the interventions in ways that are acceptable to users).

Modern clinical trial designs may play an important role in the development and testing of more responsive mHealth MBIs. Micro-randomized trials (Klasnja et al., 2015) could be used to clarify which practices are most likely to produce specific affective responses, with participants randomly assigned to receive specific practices at different times. With many randomizations per participant, such designs can be highly efficient and do not necessarily require the large sample sizes typically needed for adequately powered traditional RCTs (Liao et al., 2016). Sequential multiple assignment randomized trials (SMART; Collins et al., 2007) could implement information gleaned from micro-randomized trials to investigate whether the provision of specific content based on participants' feedback in fact improves outcomes. For example, a study could model changes in affect during meditation practice over the first week of an mHealth MBI and then randomly assign participants to receive feedback-informed modifications (e.g., positive affect inducing practices if demonstrating decreases in positive affect over time) or to continue receiving the mHealth MBI as usual. These groups could then be compared at follow-up to assess the impact of customization. Of course, it will be vital for studies investigating customization to attend to individual differences and the possibility that different participants will respond differently to the same practices. The gathering of passive data and the use of machine learning may aid in the development of highly customized, idiographic models that are capable of accounting for these individual differences (Mohr et al., 2017).

These results may also have clinical implications for the delivery of MBIs more generally. Although it will be important to replicate these analyses within an in-person MBI, should these patterns replicate they support routine monitoring of affect during meditation practice in contexts like MBSR. Ideally such assessment can be done regularly and quantitatively, to allow examination of the trajectories of change in affect that predicted outcomes in the current study. A future study could explore whether these changes can be evaluated qualitatively as well, for example through conversations between meditation teachers and students. Precisely how routine monitoring particularly of the subjective experience of meditation (or other outcomes, for that matter) should be incorporated into instructor-led MBIs is a topic worthy of further investigation. Discussing routinely monitored outcomes in MBIs may require some delicacy. Participants are being both encouraged to engage with their moment-to-moment experience with non-judgmental awareness (Kabat-Zinn, 1994) while at once receiving feedback that their particular pattern of moment-to-moment experience suggests they may not be on track to maximally benefit from the MBI, therefore requiring intervention. This barrier may be surmountable, as this tension is present to varying degrees in all third-wave behavioral therapies that integrate a combination of acceptance- and change-based strategies (Lau &

McMain, 2005) as well as in efforts to integrate routine outcome monitoring into clinical practice generally (Duncan & Murray, 2012).

**Limitations**

The current study has several important limitations. First, our assessment of the subjective experience of meditation focused on affect. There are almost certainly other aspects of the meditative experience that are linked to outcomes, perhaps more strongly than affect. Future studies will ideally assess a wider range of subjective experiences such as state mindfulness (Kiken et al., 2015), self-compassion (Neff, 2003), motivation for practice (Jiwani et al., 2022), and connection with others (Riordan et al., 2023). Future studies could also examine whether associations between meditative experiences and outcomes differ based on affect items' location in the affective circumplex (i.e., valence [unpleasant to pleasant] crossed with arousal [activation to deactivation]; Posner et al., 2005). Second, and relatedly, affect was assessed using a small number of items which captured only a limited range of potential affective experiences that may occur during meditation. Moreover, the small number of items may have reduced reliability of affect ratings (although this presumably would have made it more difficult to detect associations with changes in distress). Third, we did not assess affect prior to each meditation practice session nor outside of the context of meditation practice. Lacking these assessments, it is impossible to say whether the meditation practice itself led to changes in affective state or whether affect during meditation was simply an indicator of participants' general affective state. The moderate magnitude association between baseline psychological distress and affect during participants' first meditation practice (*r*s = -.25 and .35, for positive and negative affect, respectively) suggest that these are at least partially overlapping. Thus, it is entirely possible that the changes in affect during meditation mirror changes being generally experienced by the participants and that it is this general change in affect, rather than a meditation-specific or meditation-induced change in affect, that is associated with outcomes. Including pre-practice and daily life experience sampling, as has been done in previous studies (e.g., Shoham et al., 2017; Walsh et al., 2019) will help clarify these issues. Having parallel daily life affect ratings from control condition participants who are not receiving meditation training may be a powerful way to clarify any causal role that affect during meditation may play on changes in psychological distress. It may also be worthwhile examining whether affect during meditation shows different associations across outcome types (e.g., linkages with depression vs. anxiety vs. well-being). Fourth, we did not manipulate affect and thus associations between changes in affect and changes in outcomes are ultimately correlational. A future randomized design could intentionally manipulate changes in affect over time, for example by delivering practices known to increase positive affect such as loving-kindness meditation (Fredrickson et al., 2008). Changes in affect during meditation could then be formally examined as a mediator of intervention effects on outcomes which would provide far stronger causal evidence. Fifth, we used a two-step approach for modeling change from pre- to post-test and pre- to follow-up (i.e., extracting residualized change scores from regression models). This approach is vulnerable to attenuation-related regressor bias, as change scores were estimated with error that was ignored when the change scores were subsequentially entered into multilevel models. Future work could employ a one-step approach within a structural equation modeling (SEM) framework where pre- to post-test and pre- to follow-up changes in outcomes are modeled alongside changes in post-practice items. Lastly, our sample was predominantly non-Hispanic White and female, which limits generalizability to other gender and racial/ethnic groups. In addition, the sample was predominantly distressed participants drawn from a non-clinical setting (public schools) and results may or may not generalize to treatment seeking populations.

**Conclusion**

To our knowledge, this is the first study to establish links between affect experienced during meditation with long-term outcomes and one of the few studies investigating the subjective experience of meditation within an mHealth MBI. Results suggest that how meditation feels may have implications for the benefits participants ultimately receive from their practice. Changes in positive affect may be particularly important for long-term effects of mHealth MBIs. Results support future efforts understanding micro-processes within meditation training. The mHealth MBI context may be a fruitful place to explore these dynamics, given proximal indicators of long-term effects can be readily assessed and theoretically responded to within digital interventions. Ultimately, these efforts may result in highly responsive mHealth MBIs that are more engaging and more effective than current programs. Such precision medicine mHealth MBIs may more fully realize the public health potential of this intervention approach.

## Data Transparency Statement

Manuscripts using data drawn from the same randomized trial have been published elsewhere. However, no prior manuscripts have included the post-practice affect ratings reported here. The primary outcomes paper (Hirshberg et al., 2022) includes evaluation of the study's primary and secondary outcomes. A study validating the measure of working alliance included in the trial has been published (Goldberg, Baldwin, et al., 2022). A study investigating baseline characteristics that predict treatment response has been published (Webb et al., 2022). A study using baseline data evaluating distress among school employees has been published (Hirshberg et al., 2023).

# References


Aizik-Reebs, A., Shoham, A., & Bernstein, A. (2021). First, do no harm: An intensive experience sampling study of adverse effects to mindfulness training. *Behaviour Research and Therapy 145*, 103941.

Analayo (2006). *Satipatthana: The direct path to realization.* Selangor, Malaysia: Buddhist Wisdom Centre.

Analayo. (2018). *Satipatthana meditation: A practice guide*. Cambridge, UK: Windhorse Publications.

Hirshberg, M. J., Goldberg, S. B., & Davidson, R. J. (n. d.). *COVID and the Healthy Minds Program for educators.* Open Science Framework. https://osf.io/t8qxm/

Barford, K. A., Koval, P., Kuppens, P., & Smillie, L. D. (2020). When good feelings turn mixed: Affective dynamics and big five trait predictors of mixed emotions in daily life. *European Journal of Personality, 34*(3), 393-411.

Baumel, A., Muench, F., Edan, S., & Kane, J. M. (2019). Objective user engagement with mental health apps: Systematic search and panel-based usage analysis. *Journal of Medical Internet Research, 21*(9), e14567.

Britton, W. B., Lindahl, J. R., Cooper, D. J., Canby, N. K., & Palitsky, R. (2021). Defining and measuring meditation-related adverse effects in mindfulness-based programs. *Clinical Psychological Science, 9*(6), 1185-1204.

Choi, S. W., Schalet, B., Cook, K. F., & Cella, D. (2014). Establishing a common metric for depressive symptoms: Linking the BDI-II, CES-D, and PHQ-9 to PROMIS depression. *Psychological Assessment, 26*(2), 513-527.

Clark, L.A., Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment, 7*(3), 309-319.

Cohen, S., & Williamson, G. (1988). Perceived stress in a probability sample of the United States. In S. Spacapan & S. Oskamp (Eds.), *The social psychology of health: Claremont Symposium on Applied Social Psychology* (pp. 31–67). Newbury Park, CA: Sage.

Collins, L. M., Murphy, S. A., & Strecher, V. (2007). The multiphase optimization strategy (MOST) and the sequential multiple assignment randomized trial (SMART): New methods for more potent eHealth interventions. *American Journal of Preventive Medicine, 32*(5), S112-S118.

Collins, F. S., & Varmus, H. (2015). A new initiative on precision medicine. *New England Journal of Medicine, 372*(9), 793-795.

Creswell, J.D. (2017). Mindfulness interventions. *Annual Review of Psychology, 68*, 491-516. doi: 10.1146/annurev-psych-042716-051139

Dahl, C.J., Lutz, A., & Davidson, R.J .(2015). Reconstructing and deconstructing the self: Cognitive mechanisms in meditation practice. *Trends in Cognitive Sciences, 19*(9), 515-523. doi:10.1016/j.tics.2015.07.001

Dahl, C. J., Wilson-Mendenhall, C. D., & Davidson, R. J. (2020). The plasticity of well-being: A training-based framework for the cultivation of human flourishing. *Proceedings of the National Academy of Sciences, 117*(51), 32197-32206.

de Jong, K., Conijn, J. M., Gallagher, R. A., Reshetnikova, A. S., Heij, M., & Lutz, M. C. (2021). Using progress feedback to improve outcomes and reduce drop-out, treatment duration, and deterioration: A multilevel meta-analysis. *Clinical Psychology Review, 85*, 102002.

Dejonckheere, E., Mestdagh, M., Houben, M., Erbas, Y., Pe, M., Koval, P., ... & Kuppens, P.

(2018). The bipolarity of affect and depressive symptoms. *Journal of Personality and Social Psychology, 114*(2), 323.

Del Re, A.C., Flűckiger, C., Goldberg, S.B., & Hoyt, W.T. (2013). Monitoring mindfulness practice quality: An important consideration in mindfulness practice. *Psychotherapy Research, 23*(1), 54-66. doi:10.1080/10503307.2012.729275

Duncan, E.A.S., & Murray, J. (2012). The barriers and facilitators to routine outcome measurement by allied health professionals in practice: A systematic review. *BMC Health Services Research, 12*(96), 1-9.

Fredrickson, B.L., Cohn, M.A., Coffey, K.A., Pek. J., & Finkel, S.M. (2008). Open hearts build lives: Positive emotions, induced through loving-kindness meditation, build consequential personal resources. *Journal of Personality and Social Psychology, 95*(5), 1045-1062. doi: 10.1037/a0013262

Gál, É., Ștefan, S., & Cristea, I. A. (2021). The efficacy of mindfulness meditation apps in enhancing users' well-being and mental health related outcomes: a meta-analysis of randomized controlled trials. *Journal of Affective Disorders, 279*, 131-142.

Galante, J., Friedrich, C., Dawson, A. F., Modrego-Alarcón, M., Gebbing, P., Delgado-Suárez, I., ... & Jones, P. B. (2021). Mindfulness-based programmes for mental health promotion in adults in nonclinical settings: A systematic review and meta-analysis of randomised controlled trials. *PLoS Medicine, 18*(1), e1003481.

Garland, E. L., Farb, N. A., R. Goldin, P., & Fredrickson, B. L. (2015). Mindfulness broadens awareness and builds eudaimonic meaning: A process model of mindful positive emotion regulation. *Psychological Inquiry, 26*(4), 293-314. doi: 10.1080/1047840X.2015.1064294

Goldberg, S. B. (2022). A common factors perspective on mindfulness-based interventions.

*Nature Reviews Psychology, 1*, 605-619.

Goldberg, S. B., Baldwin, S. A., Riordan, K. M., Torous, J., Dahl, C. J., Davidson, R. J., & Hirshberg, M. J. (2022). Alliance with an unguided smartphone app: Validation of the Digital Working Alliance Inventory. *Assessment, 29*(6), 1331-1345. doi:10.1177/10731911211015310

Goldberg, S.B., Del Re, A.C., Hoyt, W.T., & Davis, J.M. (2014). The secret ingredient in mindfulness interventions? A case for practice quality over quantity. *Journal of Counseling Psychology, 61*(3), 491-497. doi: 10.1037/cou0000032

Goldberg, S. B., Imhoff-Smith, T., Bolt, D. M., Wilson-Mendenhall, C. D., Dahl, C. J., Davidson, R. J., & Rosenkranz, M. A. (2020). Testing a multi-component, self-guided, smartphone-based meditation app: three-armed randomized controlled trial. *JMIR Mental Health, 7*(11), e23825. doi: 10.2196/23825

Goldberg, S. B., Knoeppel, C., Davidson, R. J., & Flook. L. (2020). Does practice quality mediate the relationship between practice time and outcome in mindfulness-based stress reduction? *Journal of Counseling Psychology, 67*(1), 115-122. doi: 10.1037/cou0000369

Goldberg, S. B., Lam, S., Britton, W. B., & Davidson, R. J. (2022). Prevalence of meditation-related adverse effects in a population-based sample in the United States. *Psychotherapy Research, 32*(3), 291-305. doi: 10.1080/10503307.2021.1933646

Goldberg, S. B., Riordan, K., Sun, S., & Davidson, R. J. (2022). The empirical status of mindfulness-based interventions: A systematic review of 44 meta-analyses of randomized controlled trials. *Perspectives on Psychological Science, 17*(1), 108-130. doi: 10.1177/1745691620968771

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review* *of Psychology, 60*, 549-576.

Harrington, A., & Dunne, J. D. (2015). When mindfulness is therapy: Ethical qualms, historical perspectives. *American Psychologist, 70*(7), 621-631. doi:10.1037/a0039460

Hirshberg, M. J., Davidson, R. J., & Goldberg, S. B. (2023). Educators are not alright: Mental health during COVID-19. *Educational Researcher, 52*(1), 48-52. doi: 10.3102/0013189X221142595

Hirshberg, M. J., Flook, L., Enright, R. D., & Davidson, R. J. (2020). Integrating mindfulness and connection practices into preservice teacher education improves classroom practices. *Learning and Instruction, 66*, 101298.

Hirshberg, M. J., Frye, C., Dahl, C. J., Riordan, K. M., Vack, N. J., Sachs, J., Goldman, R., Davidson, R. J., & Goldberg, S. B. (2022). A randomized controlled trial of a smartphone-based well-being training in public school system employees during the COVID-19 pandemic. *Journal of Educational Psychology, 114*(8), 1895–1911. doi: 10.1037/edu0000739

Jiwani, Z., Lam, S., Davidson, R. J., & Goldberg, S. B. (2022). Motivation for meditation and its association with meditation practice in a national sample of Internet users. *Mindfulness*.

Kabat-Zinn, J. (1994). *Wherever you go, there you are: Mindfulness meditation in everyday life.* New York: Hyperion.

Kiken, L. G., Garland, E. L., Bluth, K., Palsson, O. S., & Gaylord, S. A. (2015). From a state to a trait: Trajectories of state mindfulness in meditation during intervention predict changes in trait mindfulness. *Personality and Individual Differences, 81*, 41-46. doi:10.1016/j.paid.2014.12.044

Klasnja, P., Hekler, E. B., Shiffman, S., Boruvka, A., Almirall, D., Tewari, A., & Murphy, S. A. (2015). Microrandomized trials: An experimental design for developing just-in-time adaptive interventions. *Health Psychology, 34*(S), 1220-1228. doi:10.1037/hea0000305

Kuyken, W., Warren, F.C., Taylor, R.S., Whalley, B., Crane, C., Bondolfi, G.,...& Dalgeish, T. (2016). Efficacy of mindfulness-based cognitive therapy in prevention of depressive relapse: An individual patient data meta-analysis from randomized trials. *JAMA Psychiatry, 73*(6), 565-574. doi:10.1001/jamapsychiatry.2016.0076

Lau, M.A., Bishop, S.R., Segal, Z.V., Buis, T., Anderson, N.D., Carlson, L.,...Devins, G. (2006). The Toronto Mindfulness Scale: Development and validation. *Journal of Clinical Psychology, 62*(12), 1445-1467. doi: 10.1002/jclp.20326

Lau, M. A., & McMain, S. F. (2005). Integrating mindfulness meditation with cognitive and behavioural therapies: The challenge of combining acceptance-and change-based strategies. *The Canadian Journal of Psychiatry, 50*(13), 863-869.

Liao, P., Klasnja, P., Tewari, A., & Murphy, S. A. (2016). Sample size calculations for micro-randomized trials in mHealth. *Statistics in Medicine, 35*(12), 1944-1971.

Linardon, J. (2020). Can acceptance, mindfulness, and self-compassion be learned by smartphone apps? A systematic and meta-analytic review of randomized controlled trials. *Behavior Therapy, 51*, 646-658. doi: 10.1016/j.beth.2019.10.002

Lindsay, E. K., & Creswell, J. D. (2017). Mechanisms of mindfulness training: Monitor and Acceptance Theory (MAT). *Clinical Psychology Review, 51*, 48-59.

MacCallum, R. C., Kim, C., Malarkey, W. B., & Kiecolt-Glaser, J. K. (1997). Studying multivariate change using multilevel models and latent curve models. *Multivariate Behavioral Research, 32*(3), 215-253.

Mohr, D. C., Zhang, M., & Schueller, S. M. (2017). Personal sensing: Understanding mental health using ubiquitous sensors and machine learning. *Annual Review of Clinical Psychology, 13*, 23-47.

Neff, K. (2003). The development and validation of a scale to measure self-compassion. *Self and Identity, 2*, 223-250.

Parsons, C. E., Crane, C., Parsons, L. J., Fjorback, L. O., & Kuyken, W. (2017). Home practice in Mindfulness-Based Cognitive Therapy and Mindfulness-Based Stress Reduction: A systematic review and meta-analysis of participants' mindfulness practice and its association with outcomes. *Behaviour Research and Therapy, 95*, 29-41. doi: 10.1016/j.brat.2017.05.004

Pilkonis, P. A., Choi, S. W., Reise, S. P., Stover, A. M., Riley, W. T., Cella, D., & PROMIS Cooperative Group. (2011). Item banks for measuring emotional distress from the Patient-Reported Outcomes Measurement Information System (PROMIS): Depression, anxiety, and anger. *Assessment, 18*(3), 263-283.

Plewis, I. (2005). Modelling Behaviour with Multivariate Multilevel Growth Curves. *Methodology, 1*(2), 71-80.

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology, 17*(3), 715-734.

Raudenbush, S. W., Brennan, R. T., & Barnett, R. C. (1995). A multivariate hierarchical model for studying psychological change within married couples. *Journal of Family Psychology, 9*(2), 161-174.

Riordan, K. M., Simonsson, O., Frye, C., Vack, N. J., Sachs, J., Fitch, D., Goldman, R. I., Chiang, E. S., Dahl, C. J., Davidson, R. J., & Goldberg, S. B.s (2023). *How often should I meditate? A randomized trial examining the role of meditation frequency when total amount of meditation is held constant.* PsyArXiv. https://psyarxiv.com/rj4vu

Roberti, J. W., Harrington, L. N., & Storch, E. A. (2006). Further psychometric support for the 10-item version of the Perceived Stress Scale. Journal of College Counseling, 9(2), 135-147.

Schalet, B. D., Pilkonis, P. A., Yu, L., Dodds, N., Johnston, K. L., Yount, S., ... & Cella, D. (2016). Clinical validity of PROMIS depression, anxiety, and anger across diverse clinical samples. *Journal of Clinical Epidemiology, 73*, 119-127.

Shoham, A., Goldstein, P., Oren, R., Spivak, D., & Bernstein, A. (2017). Decentering in the process of cultivating mindfulness: An experience-sampling study in time and context. *Journal of Consulting and Clinical Psychology, 85*(2), 123-134.

Snijders, T.A. & Bosker, R.J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling (2nd ed.).* London: Sage.

Tang, Y. Y., Hölzel, B. K., & Posner, M. I. (2015). The neuroscience of mindfulness meditation. *Nature Reviews Neuroscience, 16*(4), 213-225.

Walsh, K. M., Saab, B. J., & Farb, N. A. (2019). Effects of a mindfulness meditation app on subjective well-being: Active randomized controlled trial and experience sampling study. *JMIR Mental Health, 6*(1), e10844. doi:10.2196/10844

Wasil, A. R., Gillespie, S., Patel, R., Petre, A., Venturo-Conerly, K. E., Shingleton, R. M., ... & DeRubeis, R. J. (2020). Reassessing evidence-based content in popular smartphone apps for depression and anxiety: Developing and applying user-adjusted analyses. *Journal of Consulting and Clinical Psychology, 88*(11), 983-993.

https://doi.org/10.1037/ccp0000604

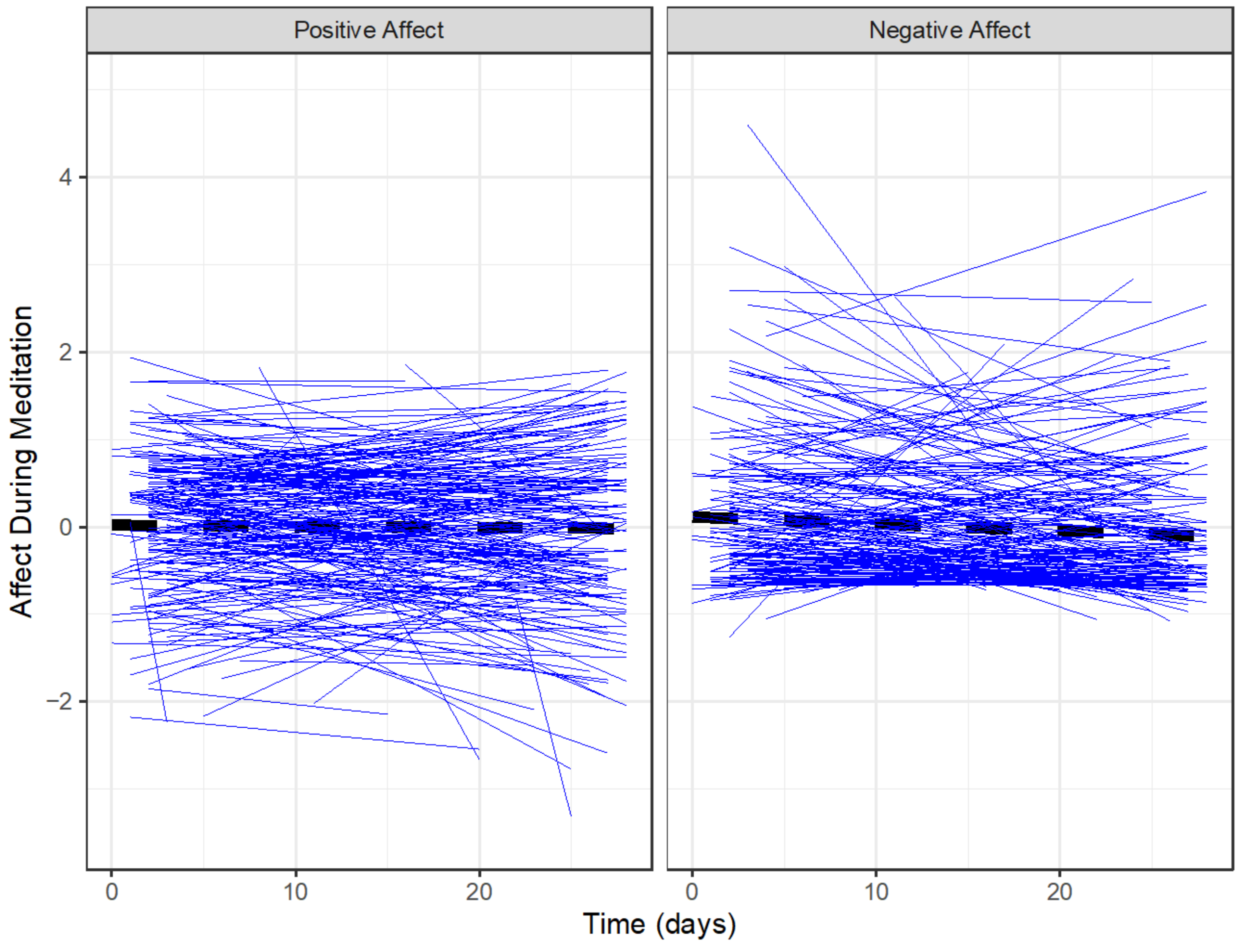
Webb, C. A., Hirshberg, M. J., Davidson, R. J., & Goldberg, S. B. (2022). Personalized prediction of response to smartphone-delivered meditation training: A machine learning approach. *Journal of Medical Internet Research, 24*(11), e41566.

Zilcha-Mano, S. (2021). Toward personalized psychotherapy: The importance of the trait-like/state-like distinction for understanding therapeutic change. *American Psychologist, 76*(3), 516-528.

Zilcha-Mano, S., & Fisher, H. (2022). Distinct roles of state-like and trait-like patient–therapist alliance in psychotherapy. *Nature Reviews Psychology, 1*(4), 194-210.

**Figure 1**

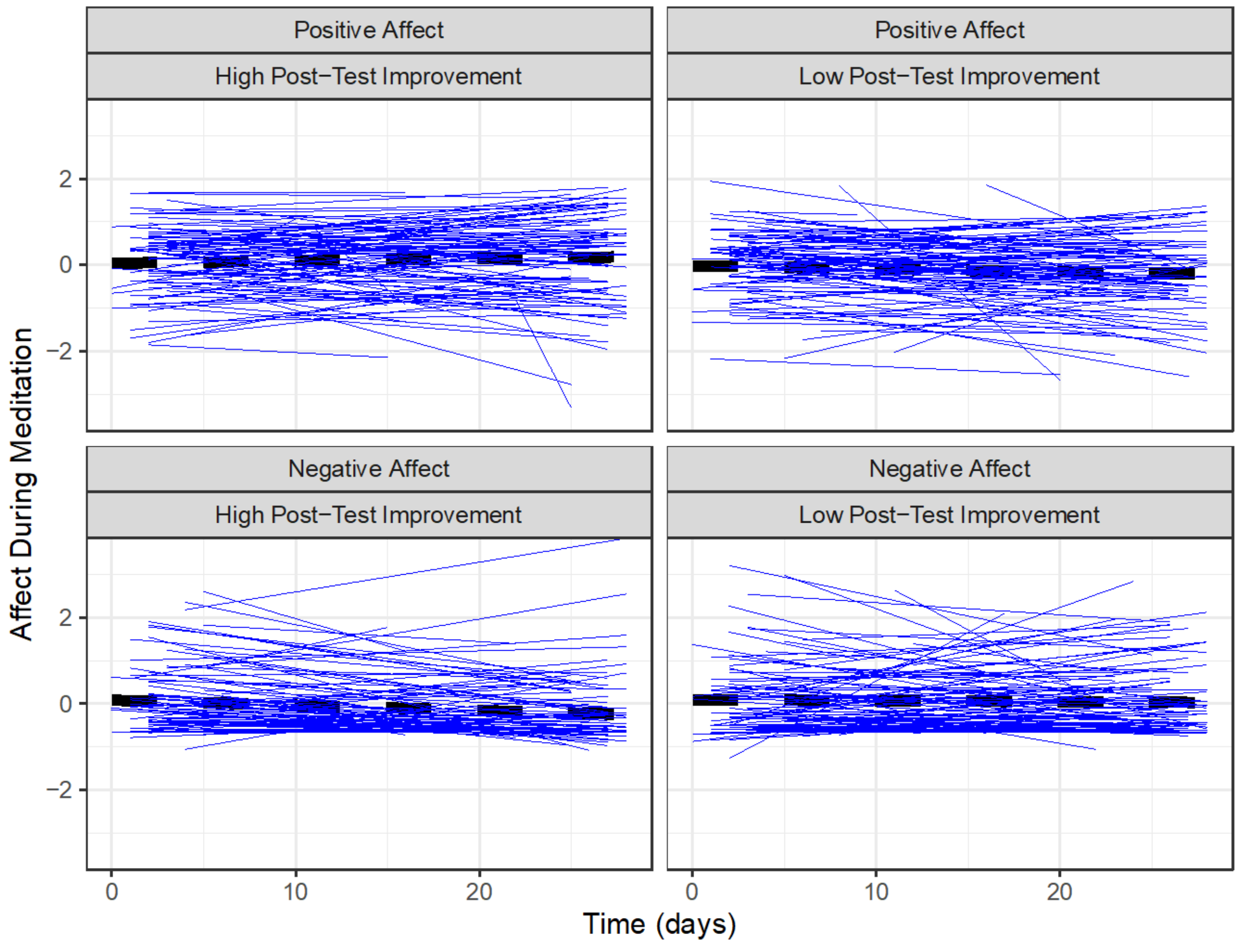
*Changes in Positive and Negative Affect During Meditation*




*Note.* Figures display overall (dashed black lines) and participant-level (solid blue lines) trajectories of change in positive (left panel) and negative (right panel) affect during meditation practice over the course of mobile health meditation training. On average, positive affect did not change ($p$ = .295) while negative affect decreased significantly over time ($p$ = .017).

**Figure 2**

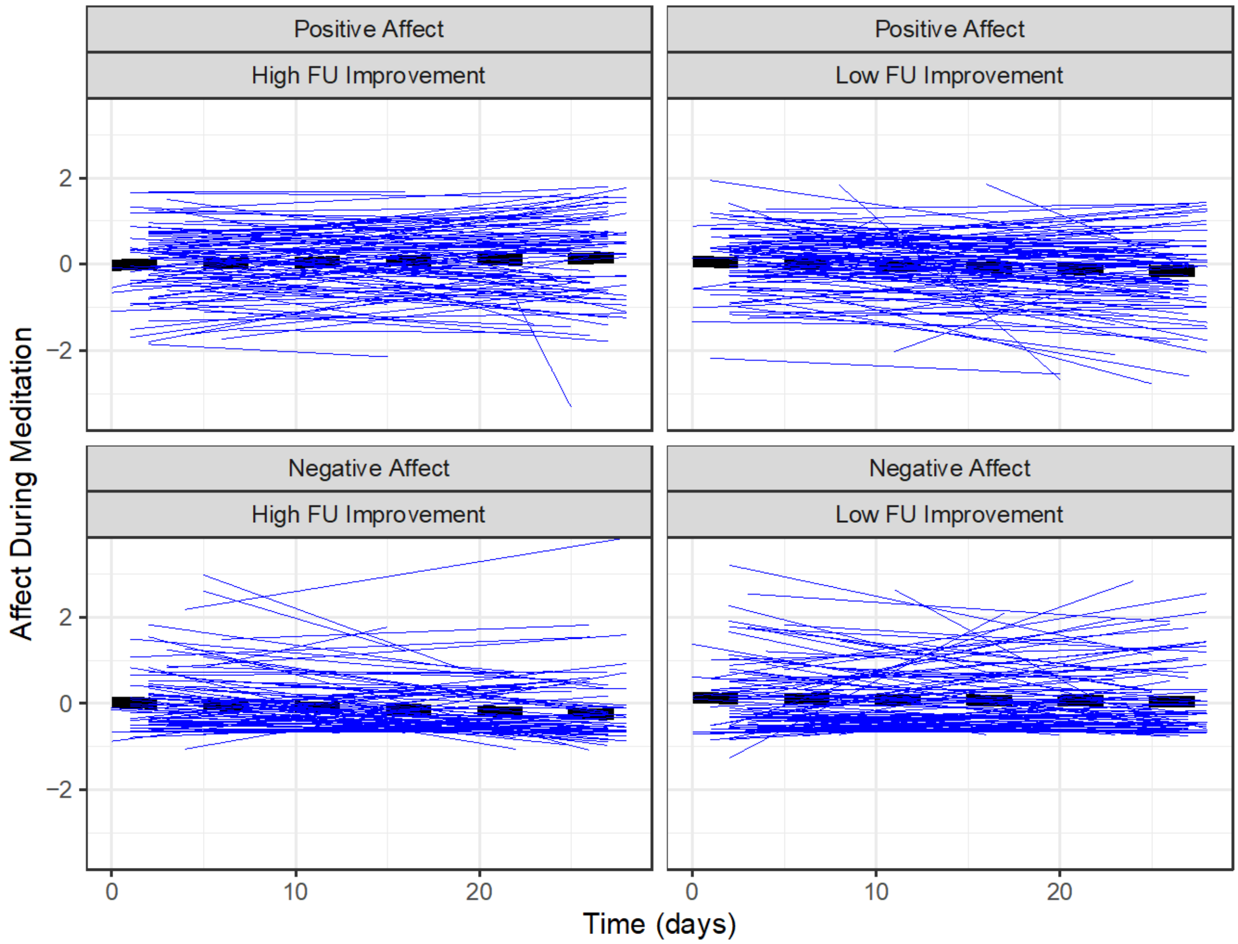
*Changes in Positive and Negative Affect During Meditation Separated by Outcomes at Post-test*




*Note.* Larger pre- to post-test improvement in psychological distress (dichotomized into high improvement [left panels] and low improvement [right panels] for display purposes only) is associated with increased positive affect ($p < .001$, top panels) and decreased negative affect ($p =$ .003, bottom panels) during meditation practice. This association did not differ across affect dimensions ($p = .512$). Dashed black lines represent overall trajectories and solid blue lines represent participant-level trajectories.

**Figure 3**

*Changes in Positive and Negative Affect During Meditation Separated by Outcomes at Follow-up*




*Note.* Larger pre- to follow-up improvement in psychological distress (dichotomized into high improvement [left panels] and low improvement [right panels] for display purposes only) is associated with increased positive affect ($p < .001$, top panels) and decreased negative affect ($p = .033$, bottom panels) during meditation practice. Association with positive affect was significantly stronger than association with negative affect ($p = .007$). Dashed black lines represent overall trajectories and solid blue lines represent participant-level trajectories.

## Supplemental Materials Table 1

*HLM software output for Model 1*



| | |
|---|---|
| Program: | HLM 8 Hierarchical Linear and Nonlinear Modeling |
| Authors: | Stephen Raudenbush & Richard Congdon |
| Copyright: | Copyright © 1996-2022 Scientific Software International, Inc |
| Technical Support: | hlm@ssicentral.com |
| Website: | www.ssicentral.com |

| | |
|---|---|
| Module: | HLM2.EXE (8.2.3.14) |
| Date: | 1 May 2023, Monday |
| Time: | 13:53:34 |
| License: | HLM Basic |
| Master Key: | 90d0fb50-****-****-****-5929e967b80d |
| Installation Key: | 9da83844-****-****-****-befd4d1774f6 |
| Expiration: | 10/29/2023 10:15:19 AM |

### Specifications for this HLM2 run

Problem Title: no title

The data source for this run = hlm_new_jccp
[redacted]
The maximum number of level-1 units = 3802
The maximum number of level-2 units = 243
The maximum number of micro iterations = 100
Method of estimation: full maximum likelihood

Maximum number of macro iterations = 100
Heterogeneous sigma_squared specified

The outcome variable is AFF

#### Summary of the model specified

**Step 2 model**

**Level-1 Model**

$$AFF_{ti} = \pi_{1i}*(POSA_{ti}) - \pi_{2i}*(NEGA_{ti}) + \pi_{3i}*(POSTIME_{ti}) + \pi_{4i}*(NEGTIME_{ti}) + e_{ti}$$

**Level-2 Model**

$$\pi_{1i} = \beta_{10} - r_{1i}$$
$$\pi_{2i} = \beta_{20} \quad r_{2i}$$

$\pi_{3i} = \beta_{30} + r_{3i}$
$\pi_{4i} = \beta_{40} + r_{4i}$

**Mixed Model**

$AFF_{ti} = \beta_{10}*POSA_{ti}$
$+ \beta_{20}*NEGA_{ti}$
$+ \beta_{30}*POSTIME_{ti}$
$+ \beta_{40}*NEGTIME_{ti}$
$+ r_{1i}*POSA_{ti} + r_{2i}*NEGA_{ti} + r_{3i}*POSTIME_{ti} + r_{4i}*NEGTIME_{ti} + e_{ti}$

Run-time deletion has reduced the number of level-1 records to 3789

# Results for Homogeneous $\sigma^2$

Var(R) = $\sigma^2$

$\sigma^2$ = 0.53142

Standard error of $\sigma^2$ = 0.01383

$\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.40281 | 0.22311 | -0.04524 | -0.18006 |
| NEGA,$\pi_2$ | 0.22311 | 0.58045 | -0.10615 | -0.22567 |
| POSTIME,$\pi_3$ | -0.04524 | -0.10615 | 0.38846 | 0.25689 |
| NEGTIME,$\pi_4$ | -0.18006 | -0.22567 | 0.25689 | 0.34841 |

Standard errors of $\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.06559 | 0.05406 | 0.07082 | 0.06320 |
| NEGA,$\pi_2$ | 0.05406 | 0.08255 | 0.07177 | 0.08269 |
| POSTIME,$\pi_3$ | 0.07082 | 0.07177 | 0.11898 | 0.08394 |
| NEGTIME,$\pi_4$ | 0.06320 | 0.08269 | 0.08394 | 0.11447 |

$\tau$ (as correlations)

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 1.000 | 0.461 | -0.114 | -0.481 |
| NEGA,$\pi_2$ | 0.461 | 1.000 | -0.224 | -0.502 |
| POSTIME,$\pi_3$ | -0.114 | -0.224 | 1.000 | 0.698 |
| NEGTIME,$\pi_4$ | -0.481 | -0.502 | 0.698 | 1.000 |

Confidence intervals of $\tau$ correlations

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | ( 1.000, 1.000) | (-0.148, 0.817) | (-0.192,-0.036) | (-0.608,-0.329) |
| NEGA,$\pi_2$ | (-0.148, 0.817) | ( 1.000, 1.000) | (-0.309,-0.135) | (-0.601,-0.387) |
| POSTIME,$\pi_3$ | (-0.192,-0.036) | (-0.309,-0.135) | ( 1.000, 1.000) | (-1.000, 1.000) |
| NEGTIME,$\pi_4$ | (-0.608,-0.329) | (-0.601,-0.387) | (-1.000, 1.000) | ( 1.000, 1.000) |

| Random level-1 coefficient | Reliability estimate |
|---|---|

| | |
|---|---|
| POSA, $\pi_1$ | 0.528 |
| NEGA, $\pi_2$ | 0.608 |
| POSTIME, $\pi_3$ | 0.279 |
| NEGTIME, $\pi_4$ | 0.259 |

Note: The reliability estimates reported above are based on only 225 of 243 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Final estimation of fixed effects:**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.033298 | 0.055415 | 0.601 | 242 | 0.548 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.126053 | 0.061930 | -2.035 | 242 | 0.043 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.077780 | 0.077462 | -1.004 | 242 | 0.316 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.182098 | 0.075752 | 2.404 | 242 | 0.017 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.033298 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.126053 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.077780 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.182098 | -1.0000 |
| Estimate | | -0.2599 |
| Standard error of estimate | | 0.0947 |

$\chi^2$ statistic = 7.532209
Degrees of freedom = 1
*p*-value = 0.006202

**Final estimation of fixed effects**
**(with robust standard errors)**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.033298 | 0.054914 | 0.606 | 242 | 0.545 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.126053 | 0.061546 | -2.048 | 242 | 0.042 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.077780 | 0.076171 | -1.021 | 242 | 0.308 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.182098 | 0.074439 | 2.446 | 242 | 0.015 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.033298 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.126053 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.077780 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.182098 | -1.0000 |
| Estimate | | -0.2599 |
| Standard error of estimate | | 0.0904 |

$\chi^2$ statistic = 8.259556
Degrees of freedom = 1
$p$-value = 0.004360

**Final estimation of variance components**

| Random Effect | Standard Deviation | Variance Component | $d.f.$ | $\chi^2$ | $p$-value |
|---|---|---|---|---|---|
| POSA slope, $r_1$ | 0.63467 | 0.40281 | 224 | 533.55493 | <0.001 |
| NEGA slope, $r_2$ | 0.76187 | 0.58045 | 224 | 620.59325 | <0.001 |
| POSTIME slope, $r_3$ | 0.62326 | 0.38846 | 224 | 309.67122 | <0.001 |
| NEGTIME slope, $r_4$ | 0.59026 | 0.34841 | 224 | 299.14803 | <0.001 |
| level-1, $e$ | 0.72898 | 0.53142 | | | |

Note: The chi-square statistics reported above are based on only 225 of 243 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Statistics for the current model**

Deviance = 9391.621436
Number of estimated parameters = 15

## Results for Heterogeneous $\sigma^2$
### (macro iteration 12)

Var(R) = $\sigma^2$ and log($\sigma^2$) = $\alpha_0 + \alpha_1$(NEGA)

**Model for level-1 variance**

| Parameter | Coefficient | Standard Error | *Z*-ratio | *p*-value |
|---|---|---|---|---|
| INTRCPT1 ,$\alpha_0$ | -0.70759 | 0.036853 | -19.200 | 0.000 |
| NEGA ,$\alpha_1$ | 0.15154 | 0.052058 | 2.911 | 0.004 |

**Summary of Model Fit**

| Model | Number of Parameters | Deviance |
|---|---|---|
| 1. Homogeneous $\sigma^2$ | 15 | 9391.62144 |
| 2. Heterogeneous $\sigma^2$ | 16 | 9382.22103 |

| Model Comparison | $\chi^2$ | d.f. | *p*-value |
|---|---|---|---|
| Model 1 vs Model 2 | 9.40041 | 1 | 0.003 |

$\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.41267 | 0.22909 | -0.05597 | -0.19187 |
| NEGA,$\pi_2$ | 0.22909 | 0.55412 | -0.11815 | -0.18608 |
| POSTIME,$\pi_3$ | -0.05597 | -0.11815 | 0.41202 | 0.27675 |
| NEGTIME,$\pi_4$ | -0.19187 | -0.18608 | 0.27675 | 0.27019 |

Standard errors of $\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.06498 | 0.05363 | 0.06982 | 0.06230 |
| NEGA,$\pi_2$ | 0.05363 | 0.08224 | 0.07061 | 0.08187 |
| POSTIME,$\pi_3$ | 0.06982 | 0.07061 | 0.11740 | 0.08233 |
| NEGTIME,$\pi_4$ | 0.06230 | 0.08187 | 0.08233 | 0.11326 |

Approximate confidence intervals of tau variances
POSA : (0.303,0.563)
NEGA : (0.414,0.742)
POSTIME : (0.235,0.722)
NEGTIME : NS

$\tau$ (as correlations)

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 1.000 | 0.479 | -0.136 | -0.575 |

| | | | | |
|---|---|---|---|---|
| NEGA,$\pi_2$ | 0.479 | 1.000 | -0.247 | -0.481 |
| POSTIME,$\pi_3$ | -0.136 | -0.247 | 1.000 | 0.829 |
| NEGTIME,$\pi_4$ | -0.575 | -0.481 | 0.829 | 1.000 |

Confidence intervals of τ correlations

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | ( 1.000, 1.000) | (-0.200, 0.847) | (-0.213,-0.057) | (-0.712,-0.395) |
| NEGA,$\pi_2$ | (-0.200, 0.847) | ( 1.000, 1.000) | (-0.334,-0.157) | (-0.616,-0.319) |
| POSTIME,$\pi_3$ | (-0.213,-0.057) | (-0.334,-0.157) | ( 1.000, 1.000) | (-1.000, 1.000) |
| NEGTIME,$\pi_4$ | (-0.712,-0.395) | (-0.616,-0.319) | (-1.000, 1.000) | ( 1.000, 1.000) |

| Random level-1 coefficient | Reliability estimate |
|---|---|
| POSA,$\pi_1$ | 0.550 |
| NEGA,$\pi_2$ | 0.582 |
| POSTIME,$\pi_3$ | 0.304 |
| NEGTIME,$\pi_4$ | 0.205 |

Note: The reliability estimates reported above are based on only 225 of 243 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.
The value of the log-likelihood function at iteration 2 = -4.691111E+03

**Final estimation of fixed effects:**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.034201 | 0.054964 | 0.622 | 242 | 0.534 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.123907 | 0.061716 | -2.008 | 242 | 0.046 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.079809 | 0.076401 | -1.045 | 242 | 0.297 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.179032 | 0.074941 | 2.389 | 242 | 0.018 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.034201 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.123907 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.079809 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.179032 | -1.0000 |
| Estimate | | -0.2588 |
| Standard error of estimate | | 0.0920 |

$\chi^2$ statistic = 7.923112
Degrees of freedom = 1
*p*-value = 0.005123

**Final estimation of fixed effects (with robust standard errors)**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.034201 | 0.054819 | 0.624 | 242 | 0.533 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.123907 | 0.061501 | -2.015 | 242 | 0.045 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.079809 | 0.076025 | -1.050 | 242 | 0.295 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.179032 | 0.074215 | 2.412 | 242 | 0.017 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.034201 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.123907 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.079809 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.179032 | -1.0000 |
| Estimate | | -0.2588 |
| Standard error of estimate | | 0.0902 |

$\chi^2$ statistic = 8.237568
Degrees of freedom = 1
*p*-value = 0.004405

**Final estimation of variance components**

| Random Effect | Standard Deviation | Variance Component | *d.f.* | $\chi^2$ | *p*-value |
|---|---|---|---|---|---|
| POSA slope, $r_1$ | 0.64239 | 0.41267 | 224 | 575.31453 | <0.001 |
| NEGA slope, $r_2$ | 0.74439 | 0.55412 | 224 | 574.99442 | <0.001 |
| POSTIME slope, $r_3$ | 0.64189 | 0.41202 | 224 | 333.94281 | <0.001 |

| | | | | | |
|---|---|---|---|---|---|
| NEGTIME slope, $r_4$ | 0.51980 | 0.27019 | 224 | 277.21016 | 0.009 |

Note: The chi-square statistics reported above are based on only 225 of 243 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Statistics for the current model**

Deviance = 9382.221026
Number of estimated parameters = 16

## Supplemental Materials Table 2

*HLM software output for Model 2*



| | |
|---|---|
| Program: | HLM 8 Hierarchical Linear and Nonlinear Modeling |
| Authors: | Stephen Raudenbush & Richard Congdon |
| Copyright: | Copyright © 1996-2022 Scientific Software International, Inc |
| Technical Support: | hlm@ssicentral.com |
| Website: | www.ssicentral.com |

| | |
|---|---|
| Module: | HLM2.EXE (8.2.3.14) |
| Date: | 1 May 2023, Monday |
| Time: | 13:57:52 |
| License: | HLM Basic |
| Master Key: | 90d0fb50-****-****-****-5929e967b80d |
| Installation Key: | 9da83844-****-****-****-befd4d1774f6 |
| Expiration: | 10/29/2023 10:15:19 AM |

### Specifications for this HLM2 run

Problem Title: no title

The data source for this run hlm_new_jeep
[redacted]
The maximum number of level-1 units = 3802
The maximum number of level-2 units = 243
The maximum number of micro iterations = 100
Method of estimation: full maximum likelihood

Maximum number of macro iterations = 100
Heterogeneous sigma_squared specified

The outcome variable is AFF

#### Summary of the model specified

**Step 2 model**

**Level-1 Model**

$$AFF_{ti} = \pi_{1i}*(POSA_{ti}) + \pi_{2i}*(NEGA_{ti}) + \pi_{3i}*(POSTIME_{ti}) + \pi_{4i}*(NEGTIME_{ti}) + e_{ti}$$

**Level-2 Model**

$$\pi_{1i} = \beta_{10} + \beta_{11}*(T5\_DISTR_i) + r_{1i}$$
$$\pi_{2i} = \beta_{20} + \beta_{21}*(T5\_DISTR_i) + r_{2i}$$

$\pi_{3i} = \beta_{30} + \beta_{31}*(T5\_DISTR_i) + r_{3i}$
$\pi_{4i} = \beta_{40} + \beta_{41}*(T5\_DISTR_i) + r_{4i}$

**Mixed Model**

$$AFF_{ti} = \beta_{10}*POSA_{ti} + \beta_{11}*T5\_DISTR_i*POSA_{ti}$$
$$+ \beta_{20}*NEGA_{ti} + \beta_{21}*T5\_DISTR_i*NEGA_{ti}$$
$$+ \beta_{30}*POSTIME_{ti} + \beta_{31}*T5\_DISTR_i*POSTIME_{ti}$$
$$+ \beta_{40}*NEGTIME_{ti} + \beta_{41}*T5\_DISTR_i*NEGTIME_{ti}$$
$$+ r_{1i}*POSA_{ti} + r_{2i}*NEGA_{ti} + r_{3i}*POSTIME_{ti} + r_{4i}*NEGTIME_{ti} + e_{ti}$$

Run-time deletion has reduced the number of level-1 records to 3617
Run-time deletion has reduced the number of level-2 groups to 219

## Results for Homogeneous $\sigma^2$

$\mathrm{Var}(R) = \sigma^2$

$\sigma^2 = 0.53520$

Standard error of $\sigma^2 = 0.01419$

$\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.40998 | 0.21308 | -0.02230 | -0.17204 |
| NEGA,$\pi_2$ | 0.21308 | 0.52651 | -0.08765 | -0.20110 |
| POSTIME,$\pi_3$ | -0.02230 | -0.08765 | 0.30932 | 0.19435 |
| NEGTIME,$\pi_4$ | -0.17204 | -0.20110 | 0.19435 | 0.28986 |

Standard errors of $\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.06830 | 0.05423 | 0.06974 | 0.06304 |
| NEGA,$\pi_2$ | 0.05423 | 0.07996 | 0.06824 | 0.08002 |
| POSTIME,$\pi_3$ | 0.06974 | 0.06824 | 0.11242 | 0.07911 |
| NEGTIME,$\pi_4$ | 0.06304 | 0.08002 | 0.07911 | 0.11003 |

$\tau$ (as correlations)

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 1.000 | 0.459 | -0.063 | -0.499 |
| NEGA,$\pi_2$ | 0.459 | 1.000 | -0.217 | -0.515 |
| POSTIME,$\pi_3$ | -0.063 | -0.217 | 1.000 | 0.649 |
| NEGTIME,$\pi_4$ | -0.499 | -0.515 | 0.649 | 1.000 |

Confidence intervals of $\tau$ correlations

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | ( 1.000, 1.000) | (-0.200, 0.832) | (-0.121,-0.004) | (-0.645,-0.318) |
| NEGA,$\pi_2$ | (-0.200, 0.832) | ( 1.000, 1.000) | (-0.328,-0.101) | (-0.641,-0.362) |
| POSTIME,$\pi_3$ | (-0.121,-0.004) | (-0.328,-0.101) | ( 1.000, 1.000) | (-1.000, 1.000) |
| NEGTIME,$\pi_4$ | (-0.645,-0.318) | (-0.641,-0.362) | (-1.000, 1.000) | ( 1.000, 1.000) |

| Random level-1 coefficient | Reliability estimate |
|---|---|
| POSA, $\pi_1$ | 0.539 |
| NEGA, $\pi_2$ | 0.595 |
| POSTIME, $\pi_3$ | 0.244 |
| NEGTIME, $\pi_4$ | 0.234 |

Note: The reliability estimates reported above are based on only 211 of 219 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Final estimation of fixed effects:**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.056414 | 0.061369 | 0.919 | 217 | 0.359 |
| T5_DISTR, $\beta_{11}$ | 0.086309 | 0.083516 | 1.033 | 217 | 0.303 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.111004 | 0.066162 | -1.678 | 217 | 0.095 |
| T5_DISTR, $\beta_{21}$ | -0.048864 | 0.090255 | -0.541 | 217 | 0.589 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.167994 | 0.081796 | -2.054 | 217 | 0.041 |
| T5_DISTR, $\beta_{31}$ | -0.417943 | 0.109855 | -3.804 | 217 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.076727 | 0.080621 | 0.952 | 217 | 0.342 |
| T5_DISTR, $\beta_{41}$ | -0.343174 | 0.108664 | -3.158 | 217 | 0.002 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.056414 | 0.0000 |
| T5_DISTR, $\beta_{11}$ | 0.086309 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.111004 | 0.0000 |
| T5_DISTR, $\beta_{21}$ | -0.048864 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.167994 | 0.0000 |
| T5_DISTR, $\beta_{31}$ | -0.417943 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.076727 | 0.0000 |
| T5_DISTR, $\beta_{41}$ | -0.343174 | -1.0000 |
| Estimate | | -0.0748 |
| Standard error of estimate | | 0.1379 |

$\chi^2$ statistic = 0.294119

Degrees of freedom = 1
$p$-value = >.500

**Final estimation of fixed effects (with robust standard errors)**

| Fixed Effect | Coefficient | Standard error | $t$-ratio | Approx. $d.f.$ | $p$-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.056414 | 0.058130 | 0.970 | 217 | 0.333 |
| T5_DISTR, $\beta_{11}$ | 0.086309 | 0.111300 | 0.775 | 217 | 0.439 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.111004 | 0.069055 | -1.607 | 217 | 0.109 |
| T5_DISTR, $\beta_{21}$ | -0.048864 | 0.088972 | -0.549 | 217 | 0.583 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.167994 | 0.076316 | -2.201 | 217 | 0.029 |
| T5_DISTR, $\beta_{31}$ | -0.417943 | 0.120179 | -3.478 | 217 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.076727 | 0.084720 | 0.906 | 217 | 0.366 |
| T5_DISTR, $\beta_{41}$ | -0.343174 | 0.111100 | -3.089 | 217 | 0.002 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.056414 | 0.0000 |
| T5_DISTR, $\beta_{11}$ | 0.086309 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.111004 | 0.0000 |
| T5_DISTR, $\beta_{21}$ | -0.048864 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.167994 | 0.0000 |
| T5_DISTR, $\beta_{31}$ | -0.417943 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.076727 | 0.0000 |
| T5_DISTR, $\beta_{41}$ | -0.343174 | -1.0000 |
| Estimate | | -0.0748 |
| Standard error of estimate | | 0.1237 |

$\chi^2$ statistic = 0.365567
Degrees of freedom = 1
$p$-value = >.500

**Final estimation of variance components**

| Random Effect | Standard Deviation | Variance Component | $d.f.$ | $\chi^2$ | $p$-value |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| POSA slope, $r_1$ | 0.64030 | 0.40998 | 209 | 501.59276 | <0.001 |
| NEGA slope, $r_2$ | 0.72561 | 0.52651 | 209 | 543.89123 | <0.001 |
| POSTIME slope, $r_3$ | 0.55617 | 0.30932 | 209 | 265.67998 | 0.005 |
| NEGTIME slope, $r_4$ | 0.53839 | 0.28986 | 209 | 259.69565 | 0.010 |
| level-1, $e$ | 0.73157 | 0.53520 | | | |

Note: The chi-square statistics reported above are based on only 211 of 219 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Statistics for the current model**

Deviance = 8941.145123
Number of estimated parameters = 19

## Results for Heterogeneous $\sigma^2$ (macro iteration 13)

$\mathrm{Var}(R) = \sigma^2$ and $\log(\sigma^2) = \alpha_0 + \alpha_1(\mathrm{NEGA})$

**Model for level-1 variance**

| Parameter | Coefficient | Standard Error | *Z*-ratio | *p*-value |
|---|---|---|---|---|
| INTRCPT1 ,$\alpha_0$ | -0.70110 | 0.037552 | -18.670 | 0.000 |
| NEGA ,$\alpha_1$ | 0.15180 | 0.053043 | 2.862 | 0.005 |

**Summary of Model Fit**

| Model | Number of Parameters | Deviance |
|---|---|---|
| 1. Homogeneous $\sigma^2$ | 19 | 8941.14512 |
| 2. Heterogeneous $\sigma^2$ | 20 | 8931.97192 |

| Model Comparison | $\chi^2$ | d.f. | *p*-value |
|---|---|---|---|
| Model 1 vs Model 2 | 9.17320 | 1 | 0.003 |

$\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.41878 | 0.21895 | -0.03110 | -0.18402 |
| NEGA,$\pi_2$ | 0.21895 | 0.50355 | -0.09831 | -0.16702 |
| POSTIME,$\pi_3$ | -0.03110 | -0.09831 | 0.32983 | 0.21320 |
| NEGTIME,$\pi_4$ | -0.18402 | -0.16702 | 0.21320 | 0.22180 |

Standard errors of τ

| | | | | |
|---|---|---|---|---|
| POSA, $\pi_1$ | 0.06754 | 0.05385 | 0.06850 | 0.06234 |
| NEGA, $\pi_2$ | 0.05385 | 0.07993 | 0.06708 | 0.07979 |
| POSTIME, $\pi_3$ | 0.06850 | 0.06708 | 0.11052 | 0.07762 |
| NEGTIME, $\pi_4$ | 0.06234 | 0.07979 | 0.07762 | 0.10992 |

Approximate confidence intervals of tau variances
POSA : (0.305,0.575)
NEGA : (0.368,0.689)
POSTIME : (0.170,0.638)
NEGTIME : NS

τ (as correlations)

| | | | | |
|---|---|---|---|---|
| POSA, $\pi_1$ | 1.000 | 0.477 | -0.084 | -0.604 |
| NEGA, $\pi_2$ | 0.477 | 1.000 | -0.241 | -0.500 |
| POSTIME, $\pi_3$ | -0.084 | -0.241 | 1.000 | 0.788 |
| NEGTIME, $\pi_4$ | -0.604 | -0.500 | 0.788 | 1.000 |

Confidence intervals of τ correlations

| | | | | |
|---|---|---|---|---|
| POSA, $\pi_1$ | ( 1.000, 1.000) | (-0.259, 0.862) | (-0.150,-0.017) | (-0.757,-0.388) |
| NEGA, $\pi_2$ | (-0.259, 0.862) | ( 1.000, 1.000) | (-0.353,-0.123) | (-0.669,-0.281) |
| POSTIME, $\pi_3$ | (-0.150,-0.017) | (-0.353,-0.123) | ( 1.000, 1.000) | (-1.000, 1.000) |
| NEGTIME, $\pi_4$ | (-0.757,-0.388) | (-0.669,-0.281) | (-1.000, 1.000) | ( 1.000, 1.000) |

| Random level-1 coefficient | Reliability estimate |
|---|---|
| POSA, $\pi_1$ | 0.560 |
| NEGA, $\pi_2$ | 0.569 |
| POSTIME, $\pi_3$ | 0.269 |
| NEGTIME, $\pi_4$ | 0.181 |

Note: The reliability estimates reported above are based on only 211 of 219 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.
The value of the log-likelihood function at iteration 2 = -4.465986E+03

**Final estimation of fixed effects:**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.057595 | 0.060821 | 0.947 | 217 | 0.345 |
| T5_DISTR, $\beta_{11}$ | 0.087751 | 0.082808 | 1.060 | 217 | 0.290 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.109657 | 0.066049 | -1.660 | 217 | 0.098 |
| T5_DISTR, $\beta_{21}$ | -0.049958 | 0.090020 | -0.555 | 217 | 0.579 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.169777 | 0.080455 | -2.110 | 217 | 0.036 |

| | | | | | |
|---|---|---|---|---|---|
| T5_DISTR, $\beta_{31}$ | -0.419180 | 0.108175 | -3.875 | 217 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.075930 | 0.080096 | 0.948 | 217 | 0.344 |
| T5_DISTR, $\beta_{41}$ | -0.338393 | 0.107724 | -3.141 | 217 | 0.002 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.057595 | 0.0000 |
| T5_DISTR, $\beta_{11}$ | 0.087751 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.109657 | 0.0000 |
| T5_DISTR, $\beta_{21}$ | -0.049958 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.169777 | 0.0000 |
| T5_DISTR, $\beta_{31}$ | -0.419180 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.075930 | 0.0000 |
| T5_DISTR, $\beta_{41}$ | -0.338393 | -1.0000 |
| Estimate | | -0.0808 |
| Standard error of estimate | | 0.1340 |

$\chi^2$ statistic = 0.363530
Degrees of freedom = 1
*p*-value = >.500

**Final estimation of fixed effects (with robust standard errors)**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.057595 | 0.058066 | 0.992 | 217 | 0.322 |
| T5_DISTR, $\beta_{11}$ | 0.087751 | 0.111008 | 0.790 | 217 | 0.430 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.109657 | 0.069179 | -1.585 | 217 | 0.114 |
| T5_DISTR, $\beta_{21}$ | -0.049958 | 0.089013 | -0.561 | 217 | 0.575 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.169777 | 0.076198 | -2.228 | 217 | 0.027 |
| T5_DISTR, $\beta_{31}$ | -0.419180 | 0.119831 | -3.498 | 217 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.075930 | 0.084775 | 0.896 | 217 | 0.371 |
| T5_DISTR, $\beta_{41}$ | -0.338393 | 0.110786 | -3.054 | 217 | 0.003 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.057595 | 0.0000 |
| T5_DISTR, $\beta_{11}$ | 0.087751 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.109657 | 0.0000 |
| T5_DISTR, $\beta_{21}$ | -0.049958 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.169777 | 0.0000 |
| T5_DISTR, $\beta_{31}$ | -0.419180 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.075930 | 0.0000 |
| T5_DISTR, $\beta_{41}$ | -0.338393 | -1.0000 |
| Estimate | | -0.0808 |
| Standard error of estimate | | 0.1231 |

$\chi^2$ statistic = 0.430590
Degrees of freedom = 1
*p*-value = >.500

**Final estimation of variance components**

| Random Effect | Standard Deviation | Variance Component | *d.f.* | $\chi^2$ | *p*-value |
|---|---|---|---|---|---|
| POSA slope, $r_1$ | 0.64713 | 0.41878 | 209 | 541.25994 | <0.001 |
| NEGA slope, $r_2$ | 0.70961 | 0.50355 | 209 | 504.11656 | <0.001 |
| POSTIME slope, $r_3$ | 0.57430 | 0.32983 | 209 | 286.65800 | <0.001 |
| NEGTIME slope, $r_4$ | 0.47096 | 0.22180 | 209 | 240.71990 | 0.065 |

Note: The chi-square statistics reported above are based on only 211 of 219 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Statistics for the current model**

Deviance = 8931.971924
Number of estimated parameters = 20

**Supplemental Materials Table 3**

*HLM software output for Model 3*



| | |
|---|---|
| Program: | HLM 8 Hierarchical Linear and Nonlinear Modeling |
| Authors: | Stephen Raudenbush & Richard Congdon |
| Copyright: | Copyright © 1996-2022 Scientific Software International, Inc |
| Technical Support: | hlm@ssicentral.com |
| Website: | www.ssicentral.com |

| | |
|---|---|
| Module: | HLM2.EXE (8.2.3.14) |
| Date: | 1 May 2023, Monday |
| Time: | 14: 0:42 |
| License: | HLM Basic |
| Master Key: | 90d0fb50-****-****-****-5929e967b80d |
| Installation Key: | 9da83844-****-****-****-befd4d1774f6 |
| Expiration: | 10/29/2023 10:15:19 AM |

## Specifications for this HLM2 run

Problem Title: no title

The data source for this run = hlm_new_jeep
[redacted]
The maximum number of level-1 units = 3802
The maximum number of level-2 units = 243
The maximum number of micro iterations = 100
Method of estimation: full maximum likelihood

Maximum number of macro iterations = 100
Heterogeneous sigma_squared specified

The outcome variable is AFF

### Summary of the model specified

**Step 2 model**

**Level-1 Model**

$$AFF_{ti} = \pi_{1i}*(POSA_{ti}) + \pi_{2i}*(NEGA_{ti}) + \pi_{3i}*(POSTIME_{ti}) + \pi_{4i}*(NEGTIME_{ti}) + e_{ti}$$

**Level-2 Model**

$$\pi_{1i} = \beta_{10} + \beta_{11}*(T6\_DISTR_i) + r_{1i}$$
$$\pi_{2i} = \beta_{20} + \beta_{21}*(T6\_DISTR_i) + r_{2i}$$

$\pi_{3i} = \beta_{30} + \beta_{31}*(T6\_DISTR_i) + r_{3i}$
$\pi_{4i} = \beta_{40} + \beta_{41}*(T6\_DISTR_i) + r_{4i}$

**Mixed Model**

$$AFF_{ti} = \beta_{10}*POSA_{ti} + \beta_{11}*T6\_DISTR_i*POSA_{ti}$$
$$+ \beta_{20}*NEGA_{ti} + \beta_{21}*T6\_DISTR_i*NEGA_{ti}$$
$$+ \beta_{30}*POSTIME_{ti} + \beta_{31}*T6\_DISTR_i*POSTIME_{ti}$$
$$+ \beta_{40}*NEGTIME_{ti} + \beta_{41}*T6\_DISTR_i*NEGTIME_{ti}$$
$$+ r_{1i}*POSA_{ti} + r_{2i}*NEGA_{ti} + r_{3i}*POSTIME_{ti} + r_{4i}*NEGTIME_{ti} + e_{ti}$$

Run-time deletion has reduced the number of level-1 records to 3581
Run-time deletion has reduced the number of level-2 groups to 218

## Results for Homogeneous $\sigma^2$

$Var(R) = \sigma^2$

$\sigma^2 = 0.53169$

Standard error of $\sigma^2 = 0.01418$

τ

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.39356 | 0.19154 | -0.00550 | -0.14782 |
| NEGA,$\pi_2$ | 0.19154 | 0.48807 | -0.07792 | -0.17108 |
| POSTIME,$\pi_3$ | -0.00550 | -0.07792 | 0.28057 | 0.20606 |
| NEGTIME,$\pi_4$ | -0.14782 | -0.17108 | 0.20606 | 0.31715 |

Standard errors of τ

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.06668 | 0.05210 | 0.06779 | 0.06304 |
| NEGA,$\pi_2$ | 0.05210 | 0.07637 | 0.06577 | 0.07859 |
| POSTIME,$\pi_3$ | 0.06779 | 0.06577 | 0.10946 | 0.07954 |
| NEGTIME,$\pi_4$ | 0.06304 | 0.07859 | 0.07954 | 0.11367 |

τ (as correlations)

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 1.000 | 0.437 | -0.017 | -0.418 |
| NEGA,$\pi_2$ | 0.437 | 1.000 | -0.211 | -0.435 |
| POSTIME,$\pi_3$ | -0.017 | -0.211 | 1.000 | 0.691 |
| NEGTIME,$\pi_4$ | -0.418 | -0.435 | 0.691 | 1.000 |

Confidence intervals of τ correlations

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | ( 1.000, 1.000) | (-0.204, 0.816) | (-0.036, 0.003) | (-0.568,-0.243) |
| NEGA,$\pi_2$ | (-0.204, 0.816) | ( 1.000, 1.000) | (-0.335,-0.079) | (-0.569,-0.279) |
| POSTIME,$\pi_3$ | (-0.036, 0.003) | (-0.335,-0.079) | ( 1.000, 1.000) | (-1.000, 1.000) |
| NEGTIME,$\pi_4$ | (-0.568,-0.243) | (-0.569,-0.279) | (-1.000, 1.000) | ( 1.000, 1.000) |

| Random level-1 coefficient | Reliability estimate |
|---|---|
| POSA,$\pi_1$ | 0.529 |
| NEGA,$\pi_2$ | 0.578 |
| POSTIME,$\pi_3$ | 0.227 |
| NEGTIME,$\pi_4$ | 0.248 |

Note: The reliability estimates reported above are based on only 210 of 218 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Final estimation of fixed effects:**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.075342 | 0.058673 | 1.284 | 216 | 0.200 |
| T6_DISTR, $\beta_{11}$ | 0.170970 | 0.091333 | 1.872 | 216 | 0.063 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.094712 | 0.062668 | -1.511 | 216 | 0.132 |
| T6_DISTR, $\beta_{21}$ | -0.050989 | 0.097816 | -0.521 | 216 | 0.603 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.170751 | 0.078189 | -2.184 | 216 | 0.030 |
| T6_DISTR, $\beta_{31}$ | -0.560429 | 0.119419 | -4.693 | 216 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.116505 | 0.079301 | 1.469 | 216 | 0.143 |
| T6_DISTR, $\beta_{41}$ | -0.204560 | 0.121751 | -1.680 | 216 | 0.094 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.075342 | 0.0000 |
| T6_DISTR, $\beta_{11}$ | 0.170970 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.094712 | 0.0000 |
| T6_DISTR, $\beta_{21}$ | -0.050989 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.170751 | 0.0000 |
| T6_DISTR, $\beta_{31}$ | -0.560429 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.116505 | 0.0000 |
| T6_DISTR, $\beta_{41}$ | -0.204560 | -1.0000 |
| Estimate | | -0.3559 |
| Standard error of estimate | | 0.1513 |

$\chi^2$ statistic = 5.529960
Degrees of freedom = 1

$p$-value = 0.017683

**Final estimation of fixed effects (with robust standard errors)**

| Fixed Effect | Coefficient | Standard error | $t$-ratio | Approx. $d.f.$ | $p$-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.075342 | 0.056728 | 1.328 | 216 | 0.186 |
| T6_DISTR, $\beta_{11}$ | 0.170970 | 0.089164 | 1.917 | 216 | 0.056 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.094712 | 0.063644 | -1.488 | 216 | 0.138 |
| T6_DISTR, $\beta_{21}$ | -0.050989 | 0.082383 | -0.619 | 216 | 0.537 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.170751 | 0.078347 | -2.179 | 216 | 0.030 |
| T6_DISTR, $\beta_{31}$ | -0.560429 | 0.131105 | -4.275 | 216 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.116505 | 0.080730 | 1.443 | 216 | 0.150 |
| T6_DISTR, $\beta_{41}$ | -0.204560 | 0.095809 | -2.135 | 216 | 0.034 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.075342 | 0.0000 |
| T6_DISTR, $\beta_{11}$ | 0.170970 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.094712 | 0.0000 |
| T6_DISTR, $\beta_{21}$ | -0.050989 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.170751 | 0.0000 |
| T6_DISTR, $\beta_{31}$ | -0.560429 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.116505 | 0.0000 |
| T6_DISTR, $\beta_{41}$ | -0.204560 | -1.0000 |
| Estimate | | -0.3559 |
| Standard error of estimate | | 0.1348 |

$\chi^2$ statistic = 6.964913
Degrees of freedom = 1
$p$-value = 0.008248

**Final estimation of variance components**

| Random Effect | Standard Deviation | Variance Component | *d.f.* | $\chi^2$ | *p*-value |
|---|---|---|---|---|---|
| POSA slope, $r_1$ | 0.62735 | 0.39356 | 208 | 491.10524 | <0.001 |
| NEGA slope, $r_2$ | 0.69862 | 0.48807 | 208 | 519.45983 | <0.001 |
| POSTIME slope, $r_3$ | 0.52969 | 0.28057 | 208 | 253.67354 | 0.017 |
| NEGTIME slope, $r_4$ | 0.56316 | 0.31715 | 208 | 268.02446 | 0.003 |
| level-1, *e* | 0.72917 | 0.53169 | | | |

Note: The chi-square statistics reported above are based on only 210 of 218 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Statistics for the current model**

Deviance = 8829.982776
Number of estimated parameters = 19

# Results for Heterogeneous $\sigma^2$
## (macro iteration 13)

Var(R) = $\sigma^2$ and $\log(\sigma^2) = \alpha_0 + \alpha_1$(NEGA)

**Model for level-1 variance**

| Parameter | Coefficient | Standard Error | *Z*-ratio | *p*-value |
|---|---|---|---|---|
| INTRCPT1 ,$\alpha_0$ | -0.71156 | 0.037738 | -18.855 | 0.000 |
| NEGA ,$\alpha_1$ | 0.15997 | 0.053326 | 3.000 | 0.003 |

**Summary of Model Fit**

| Model | Number of Parameters | Deviance |
|---|---|---|
| 1. Homogeneous $\sigma^2$ | 19 | 8829.98278 |
| 2. Heterogeneous $\sigma^2$ | 20 | 8819.88823 |

| Model Comparison | $\chi^2$ | d.f. | *p*-value |
|---|---|---|---|
| Model 1 vs Model 2 | 10.09455 | 1 | 0.002 |

$\tau$

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.40095 | 0.19705 | -0.01155 | -0.15967 |
| NEGA,$\pi_2$ | 0.19705 | 0.46485 | -0.08818 | -0.13696 |
| POSTIME,$\pi_3$ | -0.01155 | -0.08818 | 0.29606 | 0.22483 |

| | | | | |
|---|---|---|---|---|
| NEGTIME,$\pi_4$ | -0.15967 | -0.13696 | 0.22483 | 0.24705 |

Standard errors of τ

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 0.06568 | 0.05165 | 0.06612 | 0.06225 |
| NEGA,$\pi_2$ | 0.05165 | 0.07644 | 0.06439 | 0.07851 |
| POSTIME,$\pi_3$ | 0.06612 | 0.06439 | 0.10675 | 0.07780 |
| NEGTIME,$\pi_4$ | 0.06225 | 0.07851 | 0.07780 | 0.11368 |

Approximate confidence intervals of tau variances
POSA : (0.290,0.554)
NEGA : (0.336,0.643)
POSTIME : (0.145,0.603)
NEGTIME : NS

τ (as correlations)

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | 1.000 | 0.456 | -0.034 | -0.507 |
| NEGA,$\pi_2$ | 0.456 | 1.000 | -0.238 | -0.404 |
| POSTIME,$\pi_3$ | -0.034 | -0.238 | 1.000 | 0.831 |
| NEGTIME,$\pi_4$ | -0.507 | -0.404 | 0.831 | 1.000 |

Confidence intervals of τ correlations

| | | | | |
|---|---|---|---|---|
| POSA,$\pi_1$ | ( 1.000, 1.000) | (-0.268, 0.851) | (-0.067,-0.000) | (-0.676,-0.288) |
| NEGA,$\pi_2$ | (-0.268, 0.851) | ( 1.000, 1.000) | (-0.365,-0.101) | (-0.583,-0.188) |
| POSTIME,$\pi_3$ | (-0.067,-0.000) | (-0.365,-0.101) | ( 1.000, 1.000) | (-1.000, 1.000) |
| NEGTIME,$\pi_4$ | (-0.676,-0.288) | (-0.583,-0.188) | (-1.000, 1.000) | ( 1.000, 1.000) |

| Random level-1 coefficient | Reliability estimate |
|---|---|
| POSA,$\pi_1$ | 0.551 |
| NEGA,$\pi_2$ | 0.549 |
| POSTIME,$\pi_3$ | 0.250 |
| NEGTIME,$\pi_4$ | 0.195 |

Note: The reliability estimates reported above are based on only 210 of 218 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.
The value of the log-likelihood function at iteration 2 = -4.409944E+03

**Final estimation of fixed effects:**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.076491 | 0.058031 | 1.318 | 216 | 0.189 |
| T6_DISTR, $\beta_{11}$ | 0.172704 | 0.090398 | 1.910 | 216 | 0.057 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.092914 | 0.062592 | -1.484 | 216 | 0.139 |
| T6_DISTR, $\beta_{21}$ | -0.051383 | 0.097634 | -0.526 | 216 | 0.599 |
| For POSTIME slope, $\pi_3$ | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| INTRCPT2, $\beta_{30}$ | -0.172886 | 0.076595 | -2.257 | 216 | 0.025 |
| T6_DISTR, $\beta_{31}$ | -0.562776 | 0.117087 | -4.806 | 216 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.114283 | 0.078836 | 1.450 | 216 | 0.149 |
| T6_DISTR, $\beta_{41}$ | -0.203403 | 0.120857 | -1.683 | 216 | 0.094 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.076491 | 0.0000 |
| T6_DISTR, $\beta_{11}$ | 0.172704 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.092914 | 0.0000 |
| T6_DISTR, $\beta_{21}$ | -0.051383 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.172886 | 0.0000 |
| T6_DISTR, $\beta_{31}$ | -0.562776 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.114283 | 0.0000 |
| T6_DISTR, $\beta_{41}$ | -0.203403 | -1.0000 |
| Estimate | | -0.3594 |
| Standard error of estimate | | 0.1468 |

$\chi^2$ statistic = 5.994524
Degrees of freedom = 1
*p*-value = 0.013722

**Final estimation of fixed effects**
**(with robust standard errors)**

| Fixed Effect | Coefficient | Standard error | *t*-ratio | Approx. *d.f.* | *p*-value |
|---|---|---|---|---|---|
| For POSA slope, $\pi_1$ | | | | | |
| INTRCPT2, $\beta_{10}$ | 0.076491 | 0.056609 | 1.351 | 216 | 0.178 |
| T6_DISTR, $\beta_{11}$ | 0.172704 | 0.089058 | 1.939 | 216 | 0.054 |
| For NEGA slope, $\pi_2$ | | | | | |
| INTRCPT2, $\beta_{20}$ | -0.092914 | 0.063729 | -1.458 | 216 | 0.146 |
| T6_DISTR, $\beta_{21}$ | -0.051383 | 0.082067 | -0.626 | 216 | 0.532 |
| For POSTIME slope, $\pi_3$ | | | | | |
| INTRCPT2, $\beta_{30}$ | -0.172886 | 0.078175 | -2.212 | 216 | 0.028 |
| T6_DISTR, $\beta_{31}$ | -0.562776 | 0.131024 | -4.295 | 216 | <0.001 |
| For NEGTIME slope, $\pi_4$ | | | | | |
| INTRCPT2, $\beta_{40}$ | 0.114283 | 0.080729 | 1.416 | 216 | 0.158 |
| T6_DISTR, $\beta_{41}$ | -0.203403 | 0.094960 | -2.142 | 216 | 0.033 |

**Results of General Linear Hypothesis Testing - Test 1**

| | Coefficients | Contrast |
|---|---|---|
| For POSA slope, $\pi_1$ | | |
| INTRCPT2, $\beta_{10}$ | 0.076491 | 0.0000 |
| T6_DISTR, $\beta_{11}$ | 0.172704 | 0.0000 |
| For NEGA slope, $\pi_2$ | | |
| INTRCPT2, $\beta_{20}$ | -0.092914 | 0.0000 |
| T6_DISTR, $\beta_{21}$ | -0.051383 | 0.0000 |
| For POSTIME slope, $\pi_3$ | | |
| INTRCPT2, $\beta_{30}$ | -0.172886 | 0.0000 |
| T6_DISTR, $\beta_{31}$ | -0.562776 | 1.0000 |
| For NEGTIME slope, $\pi_4$ | | |
| INTRCPT2, $\beta_{40}$ | 0.114283 | 0.0000 |
| T6_DISTR, $\beta_{41}$ | -0.203403 | -1.0000 |
| Estimate | | -0.3594 |
| Standard error of estimate | | 0.1336 |

$\chi^2$ statistic = 7.240792
Degrees of freedom = 1
$p$-value = 0.007172

**Final estimation of variance components**

| Random Effect | Standard Deviation | Variance Component | *d.f.* | $\chi^2$ | $p$-value |
|---|---|---|---|---|---|
| POSA slope, $r_1$ | 0.63321 | 0.40095 | 208 | 531.99444 | <0.001 |
| NEGA slope, $r_2$ | 0.68180 | 0.46485 | 208 | 479.40734 | <0.001 |
| POSTIME slope, $r_3$ | 0.54412 | 0.29606 | 208 | 274.78971 | 0.002 |
| NEGTIME slope, $r_4$ | 0.49704 | 0.24705 | 208 | 247.39110 | 0.032 |

Note: The chi-square statistics reported above are based on only 210 of 218 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Statistics for the current model**

Deviance = 8819.888228
Number of estimated parameters = 20