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- A Meta-Analysis of Expressive Writing on Positive Psychology Variables and Traumatic
- 2 Stress
- Jeffrey M. Pavlacic¹, Erin M. Buchanan², Nicholas P. Maxwell², Tabetha G. Hopke², &
- Stefan E. Schulenberg¹
 - ¹ University of Mississippi
- ² Missouri State University

Author Note

- ₈ Jeffrey M. Pavlacic is a doctoral candidate at the University of Mississippi and a
- 9 member of the University of Mississippi Clinical-Disaster Research Center (UM-CDRC). Erin
- 10 M. Buchanan is an Associate Professor of Psychology at Missouri State University. Nicholas
- P. Maxwell and Tabetha G. Hopke are master's degree candidates at Missouri State
- University. Stefan E. Schulenberg is a Professor of Psychology at the University of
- 13 Mississippi and director of the UM-CDRC.
- 14 Correspondence concerning this article should be addressed to Jeffrey M. Pavlacic, 205
- Peabody Hall, University, MS 38655. E-mail: jpavlaci@go.olemiss.edu

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16 Abstract

Emotional expression has been shown to be beneficial for promoting both positive 17 psychological and physical health outcomes. Unfortunately, inhibiting emotions can lead to 18 impairments in physical and psychological health. James Pennebaker showed that expressive 19 writing is an effective form of emotional expression, and he and others have used expressive 20 writing as an experimental manipulation to gauge its effectiveness in treating a wide variety 21 of health-related and psychological outcomes. While many studies have been conducted that 22 examine the effectiveness of expressive writing across such outcomes, a considerable amount 23 of these studies tend to neglect necessary considerations such as power and meaningfulness of 24 respective effect sizes. Six previous meta-analyses have been conducted that examine 25 expressive writing's effect on psychological outcomes. However, these studies focus on the experimental versus control group effect size. Thus, our meta-analysis sought to examine the 27 effectiveness of an expressive writing intervention on only the experimental conditions in studies measuring posttraumatic growth, posttraumatic stress, and quality of life using random effects models. Results indicated a small overall effect size for posttraumatic stress and negligible to small effect sizes for posttraumatic growth and quality of life. Implications 31 for future research design and interpretation of published research are discussed. 32

Keywords: meta-analysis, positive psychology, expressive writing

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A Meta-Analysis of Expressive Writing on Positive Psychology Variables and Traumatic

Stress

Emotional expression, especially focusing on negative emotions or trauma, has been

shown to increase both mental and physical health (Esterling, Antoni, Kumar, & 37 Schneiderman, 1990; Fawzy et al., 1993; Lieberman & Goldstein, 2006; Rachman, 1980; 38 Scheff, 1979). In contrast, inhibiting repressive thoughts or emotions can be detrimental to both physical and psychological health (H. S. Goldstein, Edelberg, Meier, & Davis, 1988; Gross & Levenson, 1997; Larson & Chastain, 1990). Additionally, repressing or avoiding 41 certain emotions may prevent an individual from living in accordance with his or her values (Wilson & DuFrene, 2009). Value-congruent behavior allows individuals to foster a sense of 43 meaning (Frankl, 1959; Schulenberg, Hutzell, Nassif, & Rogina, 2008). Individuals experiencing traumatic events are more likely to repress thoughts and feelings about a given traumatic experience compared to individuals who have not experienced such events (Bodor, 2002). Generally, preventing the disclosure of harmful thoughts and feelings can be detrimental to individuals, while disclosing these events can reduce stress and lead to various positive health outcomes, such as with diabetes (Bodor, 2002), breast cancer related illnesses (Stanton et al., 2002), and other physical health conditions. 50 However, the disclosure or acceptance of harmful thoughts or emotions may lead to 51 negative outcomes. As such, caution should be used when interpreting results from 52 interventions based on emotional expression (Wilson & DuFrene, 2009). For example, Brounéus (2010) found that truth telling, a form of emotional expression, caused harm to individuals. However, in general, tendencies to repress emotional experiences may lead to social concerns, overall psychological dysfunction, and inhibit people from living in accordance with their values (Frankl, 1959; Pennebaker, 1989; Pennebaker & Beall, 1986; Schulenberg et al., 2008; Wilson & DuFrene, 2009). This resulting psychological dysfunction may lead to detrimental effects on health, including unhealthy everyday life habits, which 59 could lead to biological problems, especially immune system and neurotransmitter

deficiencies (Pennebaker & Beall, 1986). By preventing an individual from living in accordance with his or her values, emotional inhibition may prohibit individuals from gaining access to values that are intrinsically reinforcing. Additionally, living in accordance with personal values allows the individual to foster a sense of meaning despite debilitating life circumstances (Frankl, 1959; Schulenberg et al., 2008). Therefore, it is important to identify and foster ways in which individuals can effectively express emotions, thereby improving both physical and psychological health.

Pennebaker and Beall (1986) first showed that emotional expression can be both 68 experimentally manipulated and have positive benefits to participants. In their seminal study, they randomly assigned participants to several writing groups including writing about 70 an experienced trauma or a neutral event. The group that disclosed both regarding their 71 trauma and the emotions surrounding said trauma later showed a reduction in health visits. Pennebaker has replicated the use of expressive writing (i.e., a paradigm in which one writes about emotions) across a number of studies ranging from improved health (Pennebaker, Colder, & Sharp, 1990; Pennebaker, Kiecolt-Glaser, & Glaser, 1988) to improvements in school (Pennebaker & Francis, 1996) and work (Francis & Pennebaker, 1992). Others have expanded this work to show positive effects on mood (Schoutrop, Lange, Hanewald, Davidovich, & Salomon, 2002) and asthma (Smyth, Stone, Hurewitz, & Kaell, 1999); however, several controlled studies have shown to not replicate (Harris, Thoresen, Humphreys, & Faul, 2005) or null effects (Gidron, Peri, Connolly, & Shaley, 1996; Walker, Nail, & Croyle, 1999). 81

The idea that a brief, controlled writing intervention can have numerous positive
health and psychological benefits can certainly be controversial, given the existing literature.
For example, Henry, Schlegel, Talley, Molix, and Bettencourt (2010) found that expressive
writing only benefited a rural population for those individuals surviving breast cancer, while
Lancaster, Klein, and Heifner (2015) found no significant evidence that expressive writing
can be considered an effective approach. Additionally, Brounéus (2010) found that "truth

telling" caused harm to individuals in a forensic setting. Regardless, the concept remains interesting due to the nature and inexpensive implementation of expressive writing. Many 89 individuals who have experienced traumatic events do not wish to disclose their feelings regarding the events with others. Additionally, those who do not meet diagnostic criteria are 91 sometimes neglected despite probable suffering (Wilson & DuFrene, 2009). However, by 92 utilizing expressive writing as a personal method of treatment, individuals are able to 93 effectively express their emotions while avoiding talking to another individual or clinician about the traumatic event (Smyth, 1998). Pennebaker (1993) found that experimental conditions assigned to participate in an expressive writing task generally report more positive changes than those in control conditions. Some controversy has been observed over 97 whether or not writing about a formerly disclosed event is more effective than writing about an undisclosed event. M. A. Greenberg and Stone (1992) conducted an experiment where they separated participants into three groups: writing about a formerly disclosed trauma, writing about an undisclosed trauma, and a control group. They found no difference between 101 groups in effectiveness. However, they did find that those who disclosed more severe traumas 102 reportedly experienced fewer physical symptoms at follow up, which suggests that the type 103 of trauma revealed can play a significant impact on symptom reduction and physical health. 104 From a meta-analytic perspective, Mogk, Otte, Reinhold-Hurley, and Kröner-Herwig (2006) 105 found a non-meaningful effect size when examining the effect of expressive writing on 106 somatic health symptoms, psychological health, and miscellaneous outcomes, such as grades 107 and self-efficacy. These results were in contrast to the meta-analysis conducted by Smyth 108 (1998), which found a medium overall effect size (d = 0.47). A more recent analysis 100 examined the efficacy of expressive writing interventions on depressive symptoms using 110 randomized clinical trials (Reinhold, Bürkner, & Holling, 2018). 111

In order to understand why expressive writing is considered to be an effective, intervention-based approach, one must examine the cognitive and social processes by which it allows an individual to process information. Pennebaker et al. (1990) discovered that

individuals who had benefited from expressive writing attributed their success to ways in 115 which the intervention allowed them to understand what had happened to them. 116 Furthermore, in an additional study, Pennebaker (1993) conducted a textual analysis on 117 expressive writing content and found that those who were more successful during the 118 intervention used words that can be categorized as causation words. Pennebaker attributed 119 these results as individuals effectively processing the event in their own minds. Aside from 120 cognitive-processing and inhibition theories, there are a number of other theories that 121 researchers have used to explain emotional disclosure. The first theory that warrants 122 explanation is the social integration model (Pennebaker & Graybeal, 2001). This model 123 discusses how emotional disclosure can have a positive impact on how people interact in their 124 environment. This increased environmental interaction has been shown to have positive 125 benefits on health (Frattaroli, 2006). Finally, expressive writing parallels exposure therapy for a variety of phobias and post-traumatic stress disorder, which suggests that repeatedly 127 exposing oneself to the seemingly anxious thought or trauma can reduce the anxiety, fear, or 128 stress associated with that event (Meshberg-Cohen, Svikis, & McMahon, 2014). Given that 129 exposure therapy has been shown to be effective for reducing symptoms of post-traumatic 130 stress (PTS; Sloan, Marx, & Epstein, 2005), one would expect individuals in these studies to 131 experience a reduction in PTS symptoms after taking part in an expressive writing 132 intervention. Additionally, Wilson and DuFrene (2009) discussed how the nonjudgmental 133 acceptance of emotions leads to positive health benefits by promoting value-congruent 134 behavior, one of the main facets of Acceptance and Commitment Therapy. Engaging in 135 value-congruent behavior in the presence of inevitable human suffering is also the foundation 136 of Logotherapy. Further, these value-based approaches can be integrated with orientations 137 dedicated to symptom reduction (Frankl, 1959; Schulenberg et al., 2008). Enhancing life 138 circumstances through valued action is important, as it has built the foundation for modern 130 psychotherapy. Sometimes, however, emotional inhibition prevents an individual from 140 engaging in such action. 141

42 Meta-Analytic Techniques

Meta-analyses allow researchers the opportunity to collectively examine the 143 effectiveness of different psychological interventions on outcome variables (Borenstein, 144 Hedges, & Rothstein, 2007; Glass, 1976; Hedges, 1982). Although many studies produced 145 positive outcomes associated with expressive writing, some of these studies tend to neglect 146 important questions, the most important of which is whether or not the effect sizes are 147 meaningful (Smyth, 1998). Meta-analyses are a technique that allows researchers to pool 148 studies to examine an overall, weighted, population effect (Borenstein et al., 2007). Several 149 meta-analyses of expressive writing and emotional expression have been explored: Smyth 150 (1998), Frisina, Borod, and Lepore (2004), Frattaroli (2006), Reinhold et al. (2018), Van 151 Emmerik, Reijntjes, and Kamphuis (2013) and Mogk et al. (2006). These meta-analyses 152 have laid a foundation for exploring the effects of writing on psychological outcomes. For our 153 purposes, we used Cohen's (1988) standards for nomenclature for small (0.20), medium 154 (0.50), and large (0.80) d values, although it is important to note that Cohen himself 155 suggested that these values should be based on the area of study. Generally, however, these 156 effect size criteria are used within the social sciences. 157 The meta-analysis conducted by Smyth (1998) found an overall medium effect size, d 158 = 0.47, for the experimental group compared to the control group. This particular analysis 159 examined the effectiveness of expressive writing on psychological well-being, general health, 160 and physical functioning. Frisina et al. (2004) expanded these analyses and found that 161 expressive writing had a small to no effect on health outcomes, weighted d = 0.07 to d =162 0.21. The meta-analyses conducted by Mogk et al. (2006) corroborated findings from Frisina et al. (2004). Specifically, Mogk et al. (2006) examined the effectiveness of expressive writing on somatic health symptoms, psychological outcomes, grades, and self-efficacy. The 165 meta-analyses conducted by Smyth (1998) and Frisina et al. (2004) were relatively small in 166 nature, using only 12-14 studies. The meta-analysis conducted by Mogk et al. (2006) 167 included 30 studies. Newer methods of meta-analysis, including p-curve (Simonsohn, Nelson, 168

& Simmons, 2014; Simonsohn, Simmons, & Nelson, 2015), p-uniform (Aert, Wicherts, & Van Assen, 2016), PET-PEESE (Stanley & Doucouliagos, 2014), selection models (Vevea & Hedges, 1995), and trim and fill methods (Carter & McCullough, 2014) allow for better estimation of meta-analytic effect sizes. These analyses would be best performed by examining each potential effect separately, rather than averaging effects of each publication into one study effect size.

Additionally, Frattaroli (2006) conducted a meta-analysis to examine the effects of 175 emotional disclosure on a variety of variables such as psychological health, physiological 176 functioning, reported health, health behaviors, subjective impact of intervention, and general 177 functioning/life outcomes. This meta-analysis is different from the meta conducted by Smyth 178 (1998) in that it utilizes random effects modeling in order to calculate effect sizes. The 179 current meta-analysis includes both random and fixed effects models for comparison. Fixed 180 effects models assume that all studies assess the same "true" population effect size, which 181 may be an untenable assumption across different assessments and populations (Borenstein et 182 al., 2007). Random effects models estimate the mean of a proposed distribution of 183 population effect sizes, which may vary by subject type or research design. Overall, 184 Frattaroli (2006) found a weighted r effect size of .08 for all outcomes combined, which 185 would be considered small. This meta-analysis included a very large range of studies, N =186 146, but individual studies were again collapsed into one publication effect size, although 187 these effects were also examined separately by health outcome. Another meta-analysis 188 examining the effects of writing therapies found expressive writing to be effective for 189 reducing posttraumatic stress symptoms (Van Emmerik et al., 2013). Although, this meta-analysis included only 6 eligible studies and compared treatment groups to control 191 groups. Finally, a recently published meta analysis conducted by Reinhold et al. (2018) 192 examined the effects of expressive writing on depression using randomized controlled trials. 193 While this study did not support utilizing expressive writing as an intervention, utilizing a 194 wider range of studies may enhance applicability to such interventions. 195

The previous meta-analyses often focused on experimental versus control group effect 196 sizes or p-values, rather than emphasizing change for an intervention group. This focus is 197 likely because of the analyses provided in these publications, especially when using 198 randomized controlled trial research designs. While this design is the gold standard for 199 medicine, we sought to examine the magnitude of change for participants who experienced an 200 expressive writing intervention. For example, a comparison group may increase their quality 201 of life scores by two points in a controlled study, while the experimental group increases their 202 quality of life scores by four points; thus, creating a significant difference in change between 203 the two groups. This information is valuable, but it does not tell us the magnitude of the 204 change for the intervention group, wherein four points might only be a small effect when 205 examined within the group who received the intervention. This study will focus on changes 206 across time for groups who received the expressive writing task to determine what size of effects one might expect given a specific measurement schedule (i.e., one to three months, 208 three months to six months, etc.). Additionally, we will examine the change in effects across measurement time to determine whether or not effects decrease over time. 210

Expressive writing tasks fit well within the framework of different psychological 211 interventions and can be adapted for treatment, which is why the literature includes a 212 multitude of different studies looking at a wide variety of outcomes. However, it is important 213 to focus on individual variables in order to determine the effectiveness of expressive writing 214 for specific diagnoses and psychopathology. As previously mentioned, some studies have 215 found long-term benefits of expressive writing on psychological well-being (Park & Blumberg, 216 2002). However, other studies, such as the research completed by Lancaster et al. (2015), found no evidence supporting the utilization of expressive writing as an effective therapeutic 218 approach. Thus, it is necessary to evaluate the effectiveness of expressive writing on specific 219 outcome variables, and we chose to focus specifically on post-traumatic stress (PTS), 220 post-traumatic growth (PTG), and quality of life (QOL), in line with the current positive 221 psychology trends. By focusing on specific outcome variables, rather than specific patient or study characteristics (which are covered extensively in Frattaroli, 2006), we can examine how effective writing can be for changing stress and positive psychology phenomena as described below. With this knowledge, we can decide whether or not to incorporate this type of intervention into protocols for certain diagnoses.

Post-traumatic Stress Disorder (PTSD) is a disorder involving re-experiencing thoughts

227 Posttraumatic Stress

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or experiences after a traumatic event or experience. This generates a context where 220 individuals are prone to affect-related deficiencies and maladaptive behaviors (American 230 Psychiatric Association, 2013). The diagnosis is based on 20 symptoms structured into four 231 different subsets. These subsets are as follows: re-experiencing, avoidance, negative 232 alterations in cognition and mood, and arousal (Crespo & Gomez, 2016). PTSD affects a 233 wide variety of groups, a few of which are sexual assault survivors (Klump, 2008), Iraq and 234 Afghanistan war veterans (Gentes et al., 2014), and those exposed to natural disasters 235 (Wang et al., 2000). Research conducted on the effectiveness of expressive writing on PTSD 236 symptoms has been less successful and shows outcomes that are not as effective as other studies. While PTSD symptoms decreased after a written emotional disclosure intervention, 238 this decrease was not significantly different than a control group change (Sloan, Marx, & 230 Greenberg, 2011). Additionally, the emotional disclosure group showed greater emotional and heart rate responding, leading the researchers to conclude that writing may not be 241 effective for treating PTSD. 242 Di Blasio et al. (2015) suggested that those meeting the criteria for moderate PTSD benefit more from expressive writing interventions in comparison to those with greater PTSD symptoms. They recruited women who had just given birth and assessed them a few days after experiencing childbirth along with a three-month follow-up. Results showed that women who had participated in the expressive writing task had lower depression and 247 post-traumatic stress symptoms than the group assigned to a neutral writing condition.

Additionally, regression models showed that expressive writing was significantly linked to a reduction of PTSD symptoms across different dimensional levels of symptom severity. 250 Contradicting the work conducted by Sloan et al. (2011), these results suggest that 251 expressive writing may be an effective tool for women managing postpartum distress. 252 However, it is important to note that only 20 of the 113 women recruited for this study 253 qualified for a diagnosis of PTSD. This limitation suggests that those with moderate distress 254 could perhaps benefit more from an expressive writing intervention than those diagnosed 255 with or meeting the qualifications for PTSD. It may also explain the differences in results 256 between the two studies, as Sloan et al. (2011) found that those with a clinical diagnosis of 257 PTSD did not respond to an emotional disclosure writing task. Di Blasio et al. (2015) found 258 that those who reported mild symptomology better responded to the intervention than those 259 meeting the criteria for a diagnosis of PTSD. As previously mentioned, expressive writing mirrors exposure therapy in that it encourages individuals to express avoided emotions related to the aversive event. Thus, given this observation, one would expect PTS scores to decrease in those taking part in an expressive writing intervention. 263

264 Posttraumatic Growth

While the literature mostly discusses potentially harmful outcomes to traumatic events 265 such as emotional distress, traumatic events also provide opportunities for personal growth 266 (Aslam & Kamal, 2013). Traumatic events, either natural or human-inflicted, can lead to 267 positive outcomes by allowing the individual to take a different perspective (Cobb, Tedeschi, 268 Calhoun, & Cann, 2006; Taku, Calhoun, Cann, & Tedeschi, 2008). The relationship between positive growth after a traumatic event and symptom reduction is unclear, as it is a complex 270 process. Thus, it is necessary to examine how expressive writing might influence each 271 variable separately, which is one of the key goals of this meta-analysis (Slavin-Spenny, Cohen, 272 Oberleitner, & Lumley, 2011). Models receiving empirical support within the last decade 273 suggest that traumatic events offer opportunities for both negative and positive experiences 274

(Tedeschi & Calhoun, 1995; Weiss, 2002). Post-traumatic Growth (PTG) is a positive experience after a traumatic event (Aslam & Kamal, 2013; Yilmaz & Zara, 2016). 276 Specifically, PTG is classified as broad cognitive benefits that are seen after a traumatic 277 experience. These benefits can be categorized into building closer relationships, examining 278 new possibilities, appreciating life, recognizing personal strengths, and undergoing spiritual 270 changes. (Dursun, Steger, Bentele, & Schulenberg, 2016; Tedeschi & Calhoun, 2004). 280 PTG is associated with a variety of desired outcomes (Dursun et al., 2016). PTG has 281 been studied in those experiencing natural disasters, war, and other harms such as sexual 282 assault. Finally, PTG has been studied in those experiencing medical diagnoses such as 283 different types of cancer and diseases. Although the relationship between PTG and symptom 284 reduction is not yet fully understood, perhaps expressive writing allows the individual to 285 fully comprehend the event. Expressive writing has been shown to be an effective method for 286 reducing psychological distress among those suffering from trauma (Sloan, Marx, Epstein, & 287 Lexington, 2007). Thus, it only makes sense to examine positive growth in response to a 288 traumatic event after exposing participants to an expressive writing intervention. 280 Pennebaker and Graybeal (2001) speculated that expressive writing allows an individual to 290 feel more connected with his or her surroundings. Although this speculation does not 29 directly explain positive outcomes after an expressive writing intervention, perhaps 292 individuals gain a better appreciation for life after gaining a better sense of connectedness 293 with that individual's surroundings.

295 Quality of Life

QOL is another positive outcome variable that is worth examining with expressive writing interventions. QOL is described as a concept comprised of multiple domains, both subjective and objective. QOL is a measure of the extent to which an individual's needs are met. Subjectively, QOL measures an individual's attitude towards their given situation (Costanza et al., 2007). Pennebaker and Graybeal (2001) suggested that expressive writing

allows one to feel more connected with their surroundings. Furthermore, they explain that
expressive writing allows people to see things in a different way and better understand
themselves. By understanding a traumatic event, one is able to see things differently and
perhaps look at the situation with a more positive mindset. The changes that occur after
expressive writing may also allow one to find meaning in the traumatic event, thereby
increasing the QOL of that individual (Frankl, 1959). Higher QOL may be considered a type
of PTG, which is why we thought to examine the effectiveness of studies utilizing expressive
writing to improve QOL and PTG in the same study.

309 Current Meta-Analysis

The purpose of this meta-analysis was to examine studies utilizing expressive writing 310 on positive outcome variables (PTG and QOL) and PTS. Due to inconsistent results in 311 current studies published and outdated meta-analyses, it is important to clarify the 312 effectiveness of expressive writing on promoting positive change after a traumatic event, 313 improving overall quality of life, and reducing post-traumatic stress. This meta-analysis will 314 provide researchers with a collective look at the use of expressive writing to promote 315 increased PTG, increased QOL, and decreased PTS. This particular meta-analysis examines 316 studies of patients with different types of psychopathology and medical diagnoses on PTG, 317 QOL, and PTS. The main focus of this study is to examine PTG, QOL, and PTS by 318 estimating effect sizes of experimental groups assigned to participate in the expressive writing intervention using newer techniques that have not been implemented in previous research. In addition to an estimate of overall effect sizes, we estimate power for effects on 321 intervention groups, as research has shown a consistent under-powering of psychological 322 studies, combined with a misunderstanding of the sample size needed for adequately 323 powering one's work (Bakker, Hartgerink, Wicherts, & Maas, 2016).

325 Method

Data Collection

Studies were collected through online databases, such as PsycINFO and Google Scholar, 327 using the following search terms and their combinations: Posttraumatic Growth, PTG, 328 Quality of Life, QOL, Posttraumatic Stress, PTS, Expressive Writing, Emotional Disclosure. 329 Within these articles, the change in outcome variables (PTS, PTG, QOL) from pre- to 330 post-test was the dependent variable of interest. Generally, groups were separated into an 331 experimental and control group and then examined at different time points. For purposes of 332 this meta-analysis, only participants assigned to the experimental condition were examined 333 due to having received the expressive writing intervention. If a study included multiple 334 assessment time points, then these measurements were examined sequentially (i.e., time 1 to 335 time 2, time 2 to time 3) to determine change across time for the dependent variable. 336 220 citations focusing on PTS, PTG, and QOL were identified through the literature 337 search and previous meta-analyses. After screening these studies, forty-five articles were 338 retained for containing the appropriate information for this meta-analysis. A complete list of 339 excluded articles can be found at https://osf.io/4mjqt, along with reasons why they were excluded. After coding articles, 202 effect sizes were calculated from the forty-five studies. On average, each study represented M = 4.49 (SD = 3.50) effects, ranging from 1 to 16 342 effects. 144 effects were calculated for PTS, 21 for PTG, and 37 for QOL.

Calculations for Effect Size, Variance, and Confidence Intervals

Each study implemented a pre-test to post-test style repeated measures design, usually with paired t-tests, ANOVA, or regression analyses. The means, standard deviations, and N values were collected from each study. In general, Cohen's d values were calculated using the following formula for paired t using means and standard deviations:

$$d_{av} = \frac{M_1 - M_2}{\frac{SD_1 + SD_2}{2}}$$

This equation is described in detail in Cumming (2012) as an alternative to the traditional calculation of d for paired samples t, wherein the denominator is the standard deviation of the difference scores:

$$d_z = \frac{M_1 - M_2}{SD_{diff}}$$

This equation for d_{av} not only allows for calculations from published articles that do 352 not include SD_{diff} (i.e., most articles included), but also has been shown to be less upwardly 353 biased than d_z . Alternative formulas include controlling for r between paired levels, as 354 described in Lakens (2013); however, these values were not available in the selected articles, 355 and Lakens also recommends d_{av} as an effect size for paired designs. When only mean 356 differences and standard deviation of the difference scores were available, the second 357 equation for d_z was used. 358 We planned to use traditional and newer methods of meta-analysis, following guidelines 359 from Cooper, Hedges, and Valentine (2009) and Borenstein et al. (2007), as well as Aert et al. (2016). Sampling variance of the effect sizes were estimated using the escale() function

$$v = \frac{1}{n} \left(\frac{n-1}{n-3}\right) \left(1 + n * d^2\right) - \frac{d^2}{[c(n-1)]^2}$$

from the metafor package in R (Viechtbauer, 2010). The variance formula was originally

published in S. B. Morris and DeShon (2002) and is shown below:

In this formula, n is the number of paired observations, d is the calculated effect size, and c is a correction factor, wherein df are n-1 (Hedges, 1982):

$$c = 1 - \frac{3}{4 * df - 1}$$

We used the metagen() function in the metafor package to calculate both fixed and random effects models, which uses standard error of the effect to calculate overall estimates

of an effect and their confidence intervals. Thus, we took the square root of the variance 368 estimate for standard error. Given these calculations, the goal of this analysis was to 369 calculate a combined effect size, along with a confidence interval for study planning and an 370 assessment of the literature. A fixed effects model requires the assumption that there is a 371 true population effect size across all studies. By including multiple measures of psychological 372 outcomes, this assumption may be tenuous, and therefore, a random effects model was also 373 calculated. In random effects models, the true effect is assumed to vary across studies 374 (Borenstein et al., 2007). For a fixed effects model, the effect sizes are weighted by their 375 inverse variance (v; Sánchez-Meca & Marín-Martínez, 2008), which is calculated 376 automatically in *metafor* by:

$$w_i^{FE} = \frac{1}{v}$$

The advantage to this procedure is that analyses are weighted by their precision, that is, that studies with more information (often, larger samples), are given larger weights in the overall estimated effect size (Borenstein et al., 2007). Random effects models are also weighted by inverse variance, with an additional correction for variance between studies, τ_{DL}^2 , as described by DerSimonian and Laird (1986):

$$w_i^{RE} = \frac{1}{v + \tau_{DL}^2}$$

Confidence intervals were calculated in two ways for this study. Cumming (2012),
Kelley (2007), and Smithson (2001) have shown that the distribution of d values are
non-normal, and thus, CIs should be estimated using the non-centrality parameter and a
non-normal distribution. These values were calculated using the functions in the MOTElibrary which iteratively estimates the appropriate non-centrality parameter and converts
back to d values (i.e., non-centrality parameter divided by the square root of n; Buchanan,
Valentine, & Scofield, 2017; Smithson, 2001, 2003). However, the metafor package in R uses
central distributions to estimate CIs for each study and overall effect sizes. Therefore, we

present both sets of values for the interested reader, as meta-analytic procedures have not implemented non-central distributions of effect sizes.

Additional Meta-Analytic Techniques

p-Curve and p-Uniform. We used p-curve.com to conduct a p-curve analysis 394 (Simonsohn et al., 2014). The purpose of this type of analysis is to detect true effects. Specifically, p-curve is used to reveal possible p-hacking in published literature in order to decipher whether or not a true effect exists. Broadly, p-hacking occurs when researchers use 397 questionable research practices to create significant results by manipulating dependent 398 variables or covariates. Additionally, authors may add participants if the initial findings are 399 not significant (Bruns & Ioannidis, 2016). Researchers may also decide to exclude 400 participants for final analyses if that exclusion leads to a significant difference (L. K. John, 401 Loewenstein, & Prelec, 2012). Thus, it is necessary to distinguish between true and false 402 effects in order to effectively interpret effect sizes corresponding to those p-values. p-curve 403 accomplishes this task by examining the distributions of the published p-values. If an effect 404 exists, or rather the results should be interpreted as presented, the distribution of p-values 405 will be positively skewed (Simonsohn et al., 2014). If, however, no effect exists, then the 406 distribution of p-values will be flat. p-curve analyses ultimately provide evidence of 407 p-hacking in groups of studies and has become an important tool for interpreting 408 meta-analyses. In order to accurately estimate effect sizes because of scrutiny associated 400 with effect size estimation of p-curve, we also conducted p-uniform. p-uniform analyses, too, 410 are interpreted by examining the distribution of p-values in a set of studies (Aert et al., 2016). However, it is assumed that the population effect size equals the effect size from the 412 dataset. Because of this assumption, the population effect size is referred to as uniform. This analysis also examines for publication bias and presents the researcher with a corrected effect 414 size. Publication bias occurs when only select studies are published, usually only significant 415 studies, although many factors can bias a study's publication (McShane, Böckenholt, & 416

Hansen, 2016). p-uniform was calculated from code provided by Van Aert (2017) on GitHub.

PET-PEESE. Originally, meta-analyses relied on the calculation of Egger's 418 regression test which examined the relationship of the standard error (predictor) to the effect 419 size estimates (criterion). In this regression, the intercept values were used to determine if 420 effect size measures were different than zero, by providing a meta-analytic estimate (Egger, 421 Davey Smith, Schneider, & Minder, 1997; Stanley, 2005). PET-PEESE analyses examine for 422 publication bias by adapting parts from Egger's traditional regression tests: PET (Precision 423 Effect Test) and PEESE (Precision Effect Estimate with Standard Error, Carter & 424 McCullough, 2014). PET is a more reliable test of publication bias with effect size estimates 425 of zero, $b_0 = 0$, while PEESE is more accurate with non-zero effect size estimates, $b_0 \neq 0$ 426 (Stanley & Doucouliagos, 2014). PET-PEESE was calculated using Hilgard's (2016) code 427 provided on GitHub. 428

Selection Models. Selection model analyses provide the researcher with a test of publication bias and effect size estimates using maximum likelihood estimation (Vevea & Hedges, 1995; Vevea & Woods, 2005). Using selection models, researchers are able to discover effect size estimates as well as evidence of publication bias (McShane et al., 2016) by using a mixed general linear model to estimate these values. Selection models were calculated with the weightr package in R (Coburn & Vevea, 2017).

Trim and Fill. Trim and Fill analyses, in contrast to PET-PEESE, regress standard error (criterion) and effect size estimates (predictor). Specifically, the purpose of Trim and Fill techniques is to examine whether or not publication bias may influence the regression equation (Carter & McCullough, 2014). Effect sizes and standard error terms are graphically displayed on x and y-axes, respectively, in a funnel plot. If this graphical representation indicates asymmetry, considered a gap of missing data points in the lower center area of the plot, the study set can be assumed to have studies that are both non-significant and small in sample size (Van Assen, Van Aert, & Wicherts, 2015). This funnel is then trimmed until symmetry is achieved. Missing studies from the symmetrical graph are imputed (filled) while

maintaining the given symmetry (Duval & Tweedie, 2000). The meta-analytic effect size is then estimated from the trimmed and filled funnel plot. Trim and fill analyses, as well as funnel plots included below, were calculated with the *metafor* package.

Overall Effect Size. As described above, both fixed effects and random effects

models with centralized confidence intervals are presented in Table 1. Studies were examined

Results

448 **PTS**

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for potential outliers using the metafor package in R. This package calculates traditional 451 regression influence values, such as Cook's and hat values (J. Cohen, 1988). These values indicate change in overall meta-analytic model with and without the effect; thus, 453 determining their impact on the pooled effect size (Viechtbauer, 2010). Because published studies likely represent the range of the sampling distribution of effect sizes, we included the 455 analyses with and without outliers to present evidence for both paths a researcher might 456 take when examining an overall effect. 457 Three outliers were detected with this procedure, all showing very large effect sizes, 458 average d = 1.63. The fixed and random effects estimates without these points are also 450 included in Table 1. Figures 1, 2, 3, and 4 portray the effect sizes for PTS studies, separated 460 by intrusions, avoidance, hyperarousal, and total scores for easier viewing (i.e., over 100+ 461 effect sizes did not fit easily on one combined graph). Although these categories are not 462 reflective of updated DSM-5 criteria, researchers have not yet conducted enough studies using 463 expressive writing on PTS with updated PTSD criteria to warrant a meta-analysis. Name acronym coding can be found in the data online. This forest plot includes the non-centralized confidence interval calculated from the MOTE library (Buchanan et al., 2017). Shape size indicates study weight, and these values were taken from the overall random effects 467 meta-analysis and normalized by dividing by the mean weight. The dashed lines indicate the 468 average non-weighted lower and upper confidence interval limit for the non-centralized 469

estimates. Overall, PTS studies include a small effect size that appears to be significantly greater than zero across all estimate types (fixed, random, with or without outliers).

Homogeneity. A prerequisite for newer meta-analytic techniques includes the 472 assessment of homogeneity of the effects (Aert et al., 2016). Using the metafor package in R, 473 we calculated the Q-statistic and the I^2 index (Cochran, 1954; Huedo-Medina, 474 Sánchez-Meca, Marín-Martínez, & Botella, 2006). Significant values imply inconsistencies 475 across the variable or variables of interest and are represented by Q. In contrast, I^2 indicates 476 the percentage of heterogeneity along with a 95% CI. Both can, however, be biased with a 477 small number of experiments included for analyses (Higgins, Thompson, Deeks, & Altman, 478 2003; Huedo-Medina et al., 2006). Thus, we sought to calculate an overall level of 470 heterogeneity after examining each variable separately before and after excluding outliers. 480 For PTS studies including outliers, we found significant heterogeneity, Q(143) = 639.98, p <481 .001 and $I^2 = 77.7$, 95% CI[73.9 - 80.9]. These values were reduced slightly with the 482 exclusion of outliers, Q(140) = 519.75, p < .001 and $I^2 = 73.1$, 95% CI[68.2 - 77.2]. 483

Power was calculated in two different ways using the pwr package in R 484 (Champely, 2016). Post hoc power was first calculated using sample size and effect size 485 statistics from each individual study. Additionally, we calculated power using the study 486 sample size and estimated overall effect size from the random effects model with and without 487 outliers, as explained by G. Francis (2012) and G. Francis (2014). The first estimate 488 indicates the likelihood of finding an effect from our sample statistics, while the second 480 indicates the likelihood of finding the true population effect size. If each study had been 490 conducted on only the change in the experimental group, 45.1% of studies would have been considered significant at $\alpha < .05$. The average power of these studies based on their original study characteristics was .46 (SD = .36). Power for the random-effects meta-analytic effect 493 size with outliers was .47 (SD = .24) and without outliers was .42 (SD = .23). Therefore, power consistently was around 40-50% for studies examining PTS, regardless of outlier 495 effects. In these studies, only 26.4% achieved recommended 80% power for their found effect 496

size, a smaller 16.7% for the random-effect outlier effect size, and even smaller 6.9% for power calculations on the random-effect size without the outliers.

Other Meta-Analytic Estimates. As noted in Aert et al. (2016), p-curve and 490 p-uniform analyses are upwardly biased when heterogeneity is high. Therefore, we use 500 caution when interpreting these analyses on PTS outcomes. As seen in Table 1, the 501 estimates for p-uniform were higher than other techniques, likely because of the focus on 502 significant p-values and the great degree of heterogeneity described earlier. P-curve pictures 503 can be found at https://osf.io/4mjqt/online, and this analysis indicated evidentiary value at 504 p < .001. Additionally, the p-uniform analysis indicated that there was likely no publication 505 bias present, Z = -5.02, p = 1.000. When examining the PET analysis, we found that the intercept was significant, which indicated that PEESE was likely a better estimator of the meta-analytic effect size. PEESE estimates were lower than the original meta-analytic 508 estimate, but confidence intervals indicated that the effect is small to medium, and still 509 larger than zero. Selection models indicated a larger effect size, especially with the 510 random-effects models, and these effects were influenced by the outliers found in the 511 published studies. Trim and fill models are shown in Table 1, and figures are included online. 512 Nineteen missing studies were imputed for both models with and without outliers. Across all 513 these effect size estimates, we found that expressive writing was likely to decrease PTS 514 symptoms in a small to moderate way. The correlation of effect size with time between 515 measurement times was r = -.16, 95% CI [-.32, .00], t(142) = -1.99, p = .049, and516 r = -.15, 95% CI [-.30, .02], t(139) = -1.75, p = .082 without outliers. This result 517 indicated that the effect of expressive writing slightly decreased across time. 518

19 PTG

Overall Effect Size. Both fixed and random effects models with centralized confidence intervals for PTG are presented in Table 2. When examining expressive writing on PTG, no outliers were detected. Fixed and random effects estimates are included in Table

2, while Figure 5 shows effect sizes for PTG studies where shape size indicates the normalized weight of the study. Dashed lines indicate non-weighted lower and upper confidence intervals for non-centralized estimates. Overall, PTG studies indicated a negligible to small effect size across both random and fixed effects models, and the non-centralized confidence intervals indicated an effect that crossed zero.

Homogeneity. Using the *metafor* package in R, we calculated both a Q statistic and I^2 index. Since PTG studied did not contain any outliers, we did not calculate two separate analyses to examine heterogeneity both with and without outliers. We did not find significant heterogeneity across PTG studies, Q(20) = 14.18, p = .82 and $I^2 = 0.0$, 95% CI[0.0 - 25.3].

Power. First, we calculated *post hoc* power using both sample and effect size statistics from individual studies. Individual studies examining change in experimental groups showed that 9.5% of studies would have been considered significant at $\alpha < .05$. Average power of PTG studies was .15 (SD = .16). 0.0% achieved recommended 80% power for their found effect size. Additionally, we calculated power using study sample size and estimated effect size from our random effects model. Power for the true effect size was .08 (SD = .02). Again, 0.0% achieved recommended 80% power.

Other Meta-Analytic Estimates. Due to no heterogeneity across PTG studies,
we can use both p-curve and p-uniform analyses with more confidence. A pictorial
representation of p-curve can be found at https://osf.io/4mjqt/. This analysis did not
indicate evidentiary value, p = .75, as only two of the results would be considered significant
at $\alpha < .05$. p-uniform estimates are presented in Table 2. Specifically, these analyses
indicated that there was no publication bias present, Z = 0.70, p = .243. The p-uniform
estimates of the effect size for PTG were negative, in contrast to the fixed and random
effects overall model. The confidence interval for this analysis indicates a wide range of
possible effects. In examining PET-PEESE analyses, we did not find a significant intercept,
indicating that PET is most likely a better effect size estimator. PET analyses indicated

that the effect size is negligible to small, with our confidence interval crossing zero. These results corroborated our original effect size calculations. Selection models indicated negligible to small effect sizes, again wherein the confidence interval includes zero effect. Trim and fill models are shown in Table 2, and figures are included online. Zero studies were imputed for our model, and thus, the effect size estimate is the same as the overall model. Across techniques, we found that expressive writing has little to no effect on PTG. The correlation of effect size across measurement times in PTG studies at subsequent time points was r = .09, 95% CI [-.36, .50], t(19) = 0.38, p = .707, and no change over time was found.

558 **QOL**

Overall Effect Size. Finally, for QOL, both fixed and random effects models with 559 centralized confidence intervals are presented in Table 3. Two outliers were detected with 560 this procedure, average d = -0.07. While the average effect of these outliers indicates a small 561 number, it is important to note that these two outliers were the largest positive and negative 562 effects found from the Possemato, Ouimette, and Geller (2010) study. Fixed and random 563 effects estimates without these points are also included in Table 3, while Figure 6 shows 564 effect sizes for QOL studies. Overall, QOL studies indicated a negligible to small effect that 565 showed a non-significant decrease in quality of life as a result of expressive writing. 566

Homogeneity. For QOL studies including outliers, we found significant heterogeneity from our random effects model, Q(36) = 200.09, p < .001 and $I^2 = 82.0$, 95% CI[75.9 - 86.5]. After excluding outliers, our random effects model still indicated heterogeneity, Q(34) = 93.18, p < .001 and $I^2 = 63.5$, 95% CI[47.6 - 74.6].

Power. In conducting post hoc power using sample and effect size statistics from individual studies, we found that 21.6% of studies would have been considered significant at $\alpha < .05$. Average power based on actual study characteristics was .33 (SD = .32). Power for the random effects meta-analytic effect size with outliers was .05 (SD = .00) and without outliers was .05 (SD = .00). Unfortunately, power was around 5% for both random effects

models with and without outliers. In these studies, 18.9% achieved adequate power of 80% on their found effect size, while 0.0% achieved 80% power for our random effects model with outliers. Finally, without outliers, 0.0% achieved 80% power.

Other Meta-Analytic Estimates. We exert caution in interpreting p-curve and 579 p-uniform analyses on QOL outcomes with and without outliers due to heterogeneity. As 580 seen in Table 1, p-uniform estimates were stronger and positive than other techniques 581 because of the high degree of heterogeneity recently described. p-curve pictures can be found 582 at the following OSF Link: https://osf.io/4mjqt. Eight studies were significant at $\alpha < .05$, 583 and the studies indicated evidentiary value, p = .004. p-uniform analyses did not indicate 584 publication bias, Z = -2.75, p = .997. In PET-PEESE analyses, we found that the intercept 585 was not significant, and therefore, PET was a better estimator of the meta-analytic effect. Table 1 indicates that both of these analyses estimate the effect size around zero, with a confidence interval that includes zero. Selection models correspondingly show small effects 588 crossing zero, except for random effects models with outliers, that appear to be heavily 589 influenced by the outliers. Trim and fill models are shown in Table 3, and figures are 590 included online. No studies were imputed for these analyses, and therefore, the effect size 591 estimates match the original meta-analysis. Overall, these results appear to point to no 592 effects, ranging across zero with several negative estimates. Interestingly, the correlation of 593 effect sizes across measurement times with outliers was r = -.37, 95% CI [-.62, -.05],594 t(35) = -2.33, p = .026 and r = -.64, 95% CI [-.80, -.39], t(33) = -4.75, p < .001 without 595 outliers. The effect of expressive writing appears to be positive at short time intervals and 596 decreases into negative effects at longer time intervals. 597

Discussion

In examining pre- to post-test comparisons across each variable separately, we found that PTS studies indicated a small effect size across all meta-analytic estimates. Both QOL and PTG studies indicated a negligible to small effect size using random effects models.

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Although the PTG effect in our overall meta-analysis estimate was significant, other methods indicate this small effect is likely not different from zero. QOL was not different from zero, which suggests no effect of expressive writing on quality of life. Interestingly, these results are in contrast to Sloan et al. (2011), which suggested that only certain groups may respond to these interventions. Potentially, the high heterogeneity may be due to the mixed levels of PTSD in these studies, as Di Blasio et al. (2015) indicates that only certain levels of PTSD are responsive to an expressive writing condition.

Expressive writing does not appear to play an important role in influencing positive 609 growth or improved quality of life post intervention. Ineffective emotional expression may be 610 a contributing factor. In line with this observation, the authors note several limitations. If 611 participants/clients are not deeply engaged with the material, an expressive writing 612 intervention may not be effective, as Pennebaker and Graybeal (2001) imply that 613 connectedness is an important factor for the intervention. However, it may be difficult to 614 implement a check for engagement in these types of research designs. Doing so may also set 615 a context that will inhibit emotional processing and general responses. Research on 616 expressive writing has found a wide range of outcomes for different variables (Frattaroli, 617 2006), and these various results may explain the large heterogeneity found in this study. Encouragingly, we did not find much evidence of publication bias, and therefore, these 619 estimates may represent a true population effect size. Regardless, methodology of expressive 620 writing studies is variable, as it is applied in different forms across different contexts. Ideally, 621 it would be possible to control for these varied instructions and protocols. However, this is 622 simply not feasible, as most studies do not use measures that examine how engaged an 623 individual is with the material. As such, this current meta-analysis sought to provide readers 624 with a global effect of expressive writing on the aforementioned outcome variables. More 625 studies are needed to examine potential moderating effects of participant engagement. 626

We also examined the relationship of time between measurements of the dependent variables and the corresponding effect size to determine if effects change over time. For both

PTS and PTG, there was no relationship between effect size and time; yet, PTS indicated a small negative correlation. This correlation was not, however, significant. For QOL studies, a medium to large negative correlation was found. A negative relationship between time and effect size implies that interventions were more effective in the initial time points, and effects decreased over longer time spans.

The psychological scientific community has shifted focus to reproducibility and 634 research design in the last several years (Nelson, Simmons, & Simonsohn, 2018), and much of 635 this discussion has focused on adequately powering studies for publication (Bakker et al., 636 2016; S. E. Maxwell, Lau, & Howard, 2015). S. E. Maxwell et al. (2015) and Open Science 637 Collaboration (2015) have shown that the "replication crisis" may be attributed to low power 638 in published studies. The power found in the current meta-analysis was very poor, with very 639 few studies reaching the suggested 80% criterion to adequately power their study. This result 640 was the same when considering individual study characteristics or the estimate true population effect size. Research by Bakker et al. (2016) indicates that researchers' intuitions 642 about power are particularly poor, and many studies could benefit from more informed 643 power analyses. Anderson, Kelley, and Maxwell (2017) recently published a primer on power, with an online application to help with sample size planning for many types of research designs. Additionally, we encourage researchers to report power analyses of studies in order to better understand methodology for replication and reproducibility.

Meta-analyses, while useful tools to pool for population effect sizes, contain various limitations to their usefulness (Van Elk et al., 2015). As mentioned previously, these analyses can be affected by high heterogeneity, which was found in this study (Aert et al., 2016). Selection models have been criticized when using a smaller number of studies (Van Assen et al., 2015), and trim and fill analyses may not always estimate accurate confidence intervals and funnel plots may be biased with heterogeneity (Terrin, Schmid, Lau, & Olkin, 2003). When focusing on improving the psychological sciences, Van Elk et al. (2015) suggest that the reliability and size of effects may be best elucidated by conducting large

preregistered studies. This suggestion will also improve the outlook for power in published studies, and projects such as Many Labs can aide in subsidizing large samples (R. A. Klein et al., 2014). Even with limitations, meta-analyses allow researchers to examine the state of a research area, and we find potential with expressive writing on reducing PTS symptoms, and an overall need for better sample size and power planning for studies.

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 $\begin{tabular}{ll} Table 1 \\ Effect Size Estimates for PTS Results \end{tabular}$

Model	Fixed Effects	Random Effects	Fixed No Outliers	Random No Outliers
Overall Effects	0.34 [0.31, 0.37]	0.39 [0.32, 0.46]	$0.32 \ [0.29, \ 0.35]$	0.36 [0.29, 0.42]
Z Values	21.75, p < .001	11.06, p < .001	20.00, p < .001	11.03, p < .001
<i>p</i> -Uniform	0.60 [0.50, 0.71]	-	$0.57 \ [0.47, 0.67]$	-
PET	0.12 [0.03, 0.21]	-	$0.11 \ [0.02, \ 0.20]$	-
PEESE	0.25 [0.20, 0.30]	-	$0.23 \ [0.18, \ 0.28]$	-
Selection Models	0.33 [0.28, 0.37]	$0.45 \ [0.33, \ 0.57]$	$0.29\ [0.24,\ 0.33]$	$0.39 \ [0.27, \ 0.50]$
Trim and Fill	0.26 [0.23, 0.29]	0.26 [0.18, 0.34]	$0.25 \ [0.22, \ 0.28]$	0.25 [0.18, 0.32]

 $\it Note.$ [] indicates the 95 percent confidence interval for each effect size estimate.

 $\begin{tabular}{ll} Table 2 \\ Effect Size Estimates for PTG Results \end{tabular}$

Model	Fixed Effects	Random Effects	
Overall Effects	0.10 [0.02, 0.17]	0.10 [0.02, 0.17]	
Z Values	2.45, p = .014	2.45, p = .014	
<i>p</i> -Uniform	-0.11 [-1.43, 0.42]	-	
PET	0.06 [-0.20, 0.32]	-	
PEESE	0.08 [-0.04, 0.20]	-	
Selection Models	0.09 [-0.01, 0.18]	0.09 [-0.03, 0.20]	
Trim and Fill	$0.10 \ [0.02, \ 0.17]$	$0.10 \ [0.02, \ 0.17]$	

Note. [] indicates the 95 percent confidence interval for each effect size estimate.

Table 3 ${\it Effect Size Estimates for QOL Results}$

Model	Fixed Effects	Random Effects	Fixed No Outliers	Random No Outliers
Overall Effects	-0.01 [-0.07, 0.05]	-0.01 [-0.16, 0.13]	-0.01 [-0.07, 0.05]	-0.01 [-0.11, 0.09]
Z Values	-0.33, p = .745	-0.18, p = .860	-0.25, p = .805	-0.20, p = .838
<i>p</i> -Uniform	0.79 [0.33, 1.61]	-	$0.62 \ [0.10, \ 0.96]$	-
PET	0.05 [-0.26, 0.36]	-	0.05 [-0.29, 0.38]	-
PEESE	0.00 [-0.17, 0.17]	-	0.00 [-0.19, 0.19]	-
Selection Models	-0.06 [-0.12, 0.01]	0.51 [-0.09, 1.12]	-0.04 [-0.11, 0.03]	$0.05 \ [-0.15, \ 0.24]$
Trim and Fill	-0.01 [-0.07, 0.05]	-0.01 [-0.16, 0.13]	-0.01 [-0.07, 0.05]	-0.01 [-0.11, 0.09]

Note. [] indicates the 95 percent confidence interval for each effect size estimate.

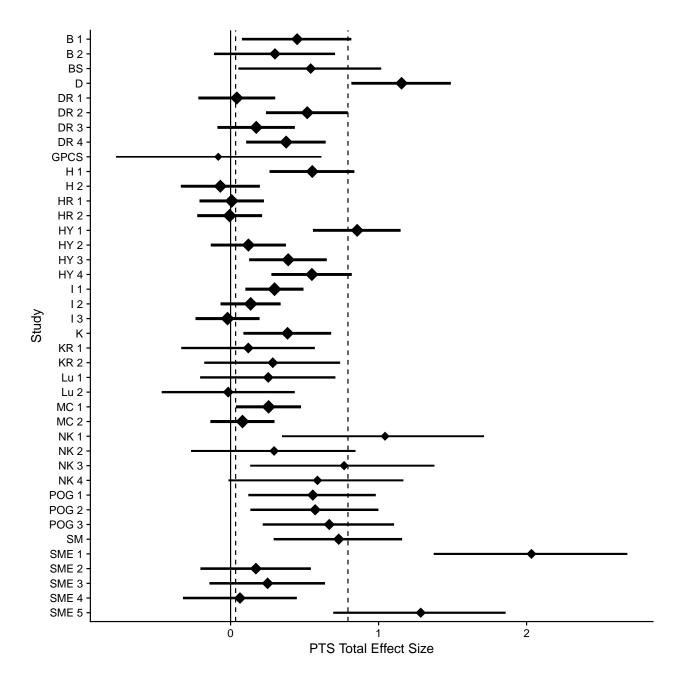


Figure 1. Effect sizes and their non-centralized confidence interval for PTS total scores. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model.

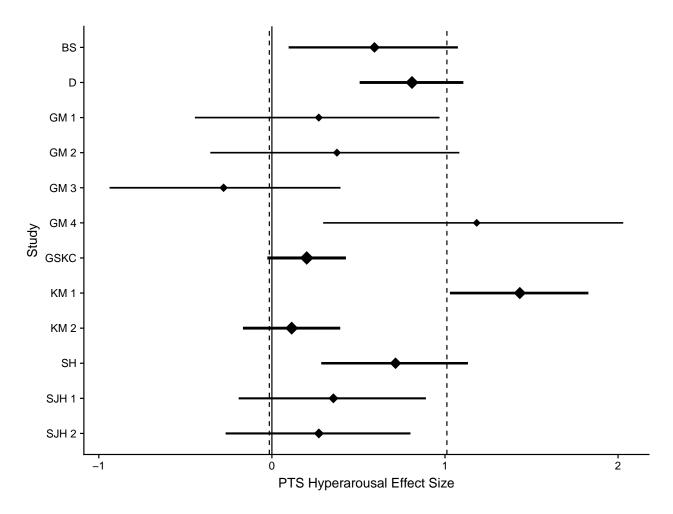


Figure 2. Effect sizes and their non-centralized confidence interval for PTS Hyperarousal. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model.

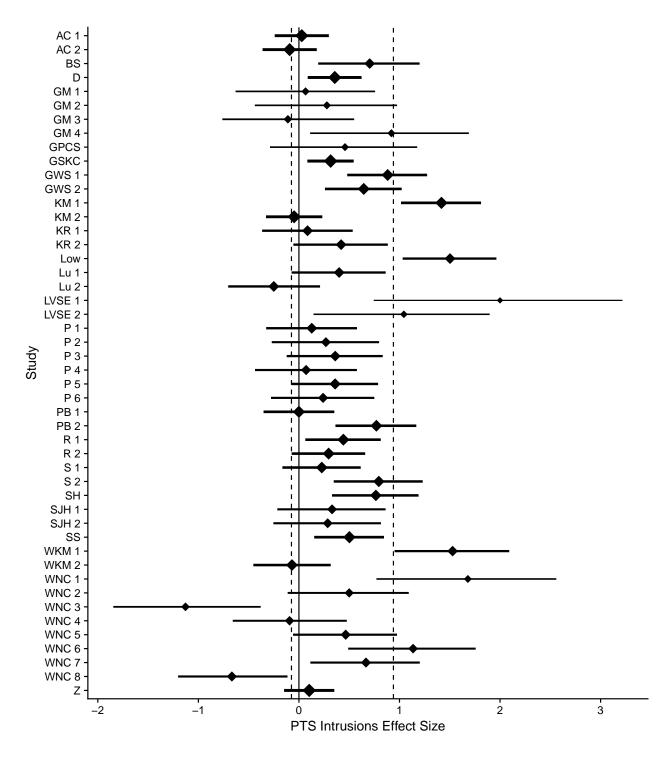


Figure 3. Effect sizes and their non-centralized confidence interval for PTS Intrusion scores. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model.

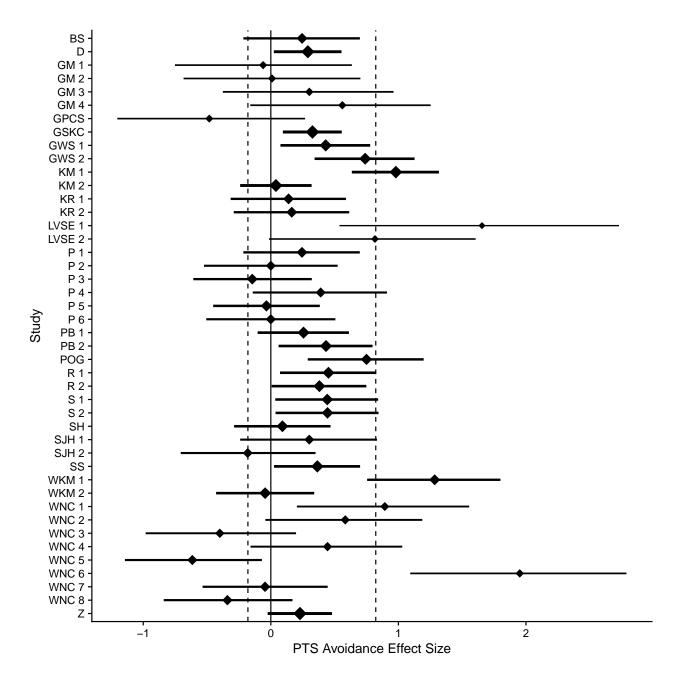


Figure 4. Effect sizes and their non-centralized confidence interval for PTS Avoidance Scores. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model.

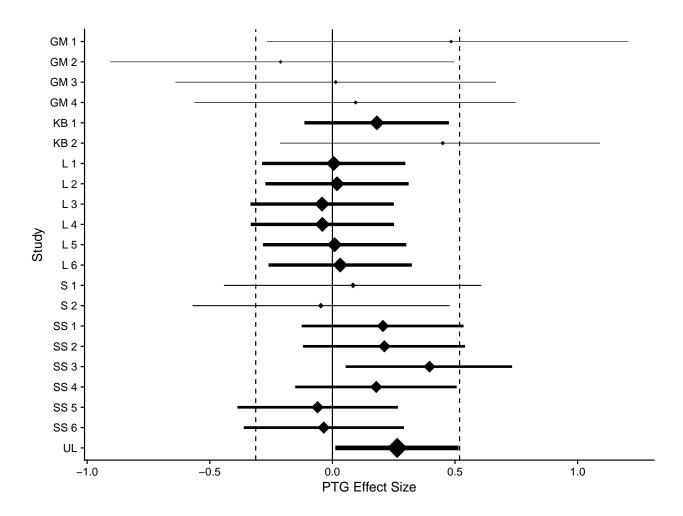


Figure 5. Effect sizes and their non-centralized confidence interval for PTG outcome variables. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model.

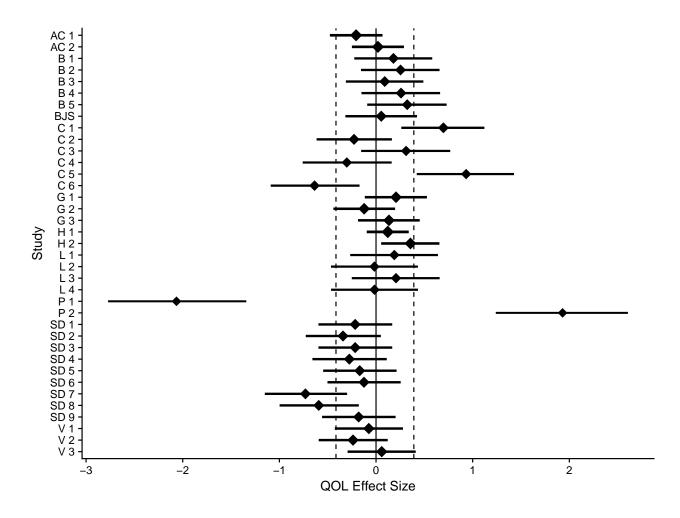


Figure 6. Effect sizes and their non-centralized confidence interval for QOL outcome variables. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model.