**Stage 1 Registered Report: Stress regulation via being in nature and social support in adults, a meta-analysis**

Alessandro Sparacio

Université Grenoble Alpes & Swansea University

Ivan Ropovik

Charles University in Prague & Presov University

Gabriela M. Jiga-Boy

Swansea University

Hans IJzerman

Université Grenoble Alpes & Institut Universitaire de France

**Author Note:** The preparation of this work was partly funded by a French National Research Agency ”Investissements d’avenir” program grant (ANR-15-IDEX-02) awarded to Hans IJzerman and also PRIMUS/20/HUM/009 and APVV-17-0418 grants awarded to Ivan Ropovik**.** Note that we wrote this registered report in the past tense to avoid errors upon finishing the manuscript. Our OSF page can be found at https://osf.io/6wpav/. The funding sources had no role in the study design, collection, analysis or interpretation of the data, writing the manuscript, or the decision to submit the paper for publication.

**Abstract**

This meta-analysis explored whether being in nature and emotional social support are effective in reducing levels of stress through a Registered Report. We retrieved all the relevant articles that investigated a connection between one of these two strategies and various components of stress (physiological, affective and cognitive) as well as affective consequences of stress. We followed a stringent analysis workflow (including permutation-based selection models and multilevel regression-based models) to provide publication bias-corrected estimates. We carried out several subgroup analyses to investigate the heterogeneity caused by variations in population characteristics or conceptual aspects of utilized study designs and we found [no evidence for x subgroup analyses and/or evidence for x subgroup analyses].We found [no evidence for the efficacy of either strategy/evidence for one of the two strategies/evidence for both strategies] with an estimated mean effect size of [xx/xx] and we recommend [recommendation will be provided if necessary].

**Keywords:** Stress regulation, being in nature, social support, meta-analysis, Registered Report, corelab

**Stage 1 Registered Report: Stress regulation via being in nature and social support in adults, a meta-analysis**

How can we live in a fast-paced world where every unexpected challenge is just around the corner? Sometimes the obstacles are low or easy to get around; others may seem insurmountable. Life’s obstacles can trigger a stress response that can be understood as, “a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources and endangering his or her well-being” (Lazarus & Folkman, 1984, p. 19). Stress experienced on a daily basis has an impact on health and on well-being of individuals (Bolger, Kessler, & Schilling 1989).

Thus, stifling the build-up of excessive stress is of paramount importance. In a previous meta-analysis, we synthesized empirical research on two stress regulation strategies (self-administered mindfulness and heart rate variability biofeedback; Sparacio et al., 2022). As we aim to build a comprehensive database in which different stress regulation strategies are evaluated based on their efficacy, here we add the synthesis of two other strategies: Being in nature and emotional social support. The reason why we chose these two strategies is similar to what guided the choice in our previous work: The decision was partly based on the fact that we were interested in analyzing scalable, non-invasive and cheap strategies that could be used by an extended number of individuals and partly arbitrary as to where we start with our approach. To check whether the named strategies have an effective role in reducing stress levels we conducted a meta-analysis with the following objectives: 1) To assess the evidential value of identified studies in both literatures, 2) for both being in nature and emotional social support, to calculate mean effect sizes for the stress response and also for the affective consequences of stress , 3) to apply publication bias correction techniques to have more realistic estimates of the efficacy of either regulation strategy 4) and to determine whether personality traits were used as moderators in stress regulation studies.

We intend to shed light on whether being in nature and emotional social support has stress reducing effects or not through our meta-analysis and how big the effect - if any - is. Our combination of publication bias-correction techniques can provide a less biased estimate of the effects of interest (Cf., IJzerman et al., 2022; Sparacio et al., 2022).

**Stress Regulation**

Stress is usually defined as a state of strain and tension that occurs when we are overwhelmed by external demands with the impossibility of dealing with them for lack of resources (Lazarus & Folkman, 1984). In our previous meta-analysis we classified the stress response based on three components: Affective, physiological, and cognitive (see Du, Huang, An, & Xu, 2018; Schneiderman, Ironson, & Siegel, 2005; Sparacio et al., 2022; Watson & Clark, 1988). As we noted there, these different components are not truly conceptually separate (Pessoa, 2006; Phelps, 2008), but we apply them as useful categories for application. Because stress can have long-term consequences if not kept under control, we also included an assessment of the affective consequences of stress (such as depression and chronic anxiety). We decided to pick depression and chronic anxiety as relatively arbitrary starting points for constraints of time and resource and because those are traditionally the most investigated outcomes for these interventions.

The first strategy we focused on here, being in nature, we restricted to interventions like walking in a natural environment and/or watching it (Antonelli, Barbieri, & Donelli, 2019). According to the “stress recovery theory” ([Ulrich, 1983)](https://www.zotero.org/google-docs/?WHqLNe), nature provides a restorative influence helping individuals recover from stress. Ulrich’s (1983) theory relies on a psycho-evolutionary theorizing: Humans evolved in the course of centuries in natural places adapting both psychologically and physiologically to these types of environments. The argument is that when a stressor is encountered, an unthreatening natural environment might evoke feelings of pleasantness, decrease stressful thoughts, and promote physiological restoration (see also Ulrich et al., 1979).

In the empirical literature, being in nature has been found to have a positive influence on the different components of stress. For the affective component, one study found that participants that walked in a natural setting (as compared to when they walked in a built environment) had a greater reduction of levels of self-reported stress (Beil & Hanes, 2013). For what concerns the physiological component, in one study coronary artery disease participants, who were randomly allocated to a seven days walking-in-a-park (vs. a seven days walking-in-an-urban-environment) condition had lower cortisol levels and lower heart rates (Grazuleviciene et al., 2015). As it pertains to the cognitive component, a brief walk in a natural setting (vs. 90 minutes walk in an urban setting) reduced self-reported levels of rumination (Bratman, Hamilton, Hahn, Daily, & Gross 2015). Finally, for what concerns the affective consequences of stress, one study found that a walk in a green area (as compared to a group of non-walkers) reduced symptoms of depression (Marselle et al, 2014).

The other strategy, emotional social support,has probably garnered the most empirical support out of the two (e.g., Cohen, 2004; Lakey & Cronin, 2008). Cohen and Wills (1985) suggested that social support can act as a shield protecting the individual from negative consequences of stress. There are two main models that explain the relationship between stress and close relationships. The first, the stress-buffering hypothesis, states that social support is connected to wellbeing by reducing stress appraisals or weakening the association between stress and negative health outcomes. The second, the main effect hypothesis, posits that social support has a beneficial effect, decreasing the level of distress, regardless of whether people are under stress (Cohen & Wills, 1985). The buffering effect has been thought to be associated with a dampened hypothalamic–pituitary–adrenal (HPA) axis activity and a decrease in the response of the autonomic nervous system (ANS; Carter, 1998).

One particular theory, “social baseline theory” (e.g., Beckes & Coan, 2011) offers an account that can provide a mechanism for the stress-buffering hypothesis, as it suggests that social support and proximity to others reduces the perceived threat of a stressor and people can thus exert less effort in regulating stress (Coan & Sbarra, 2015; Ein-Dor et al., 2015). Stress reduction, according to the theory, is reduced because individuals can distribute the efforts needed to achieve particular goals with other people (e.g., partner, friends, family members, or even strangers), a phenomenon known as “load sharing”. In one particular study illustrating this phenomenon, people held hands with a partner or a stranger and were confronted with the threat of a (mild) electric shock. When people held hands with someone, areas related to stress were less activated when confronted with the electric shock and the reduction of stress was greater the more familiar the partner (Coan, Schaefer, & Davidson, 2006; Coan et al., 2017).

For the current Registered Report meta-analysis we take a more narrow view on social support, as we restrict ourselves to emotional social support that is defined at a global level as the act of talking, listening, and being empathetic with a distressed individual (Zellars & Perrewé, 2001). Emotional social support can be achieved through verbal expressions (talking to or listening to the partner) or via physical contact (e.g., holding a partner’s hand or talking with the partner; Coan, Schaefer, & Davidson, 2006; Ditzen et al. 2007). For now, we leave out other forms of social support (informational, instrumental, and appraisal) as emotional social support is thought to be associated with well-being and consequently lower mortality and lower levels of stress (Reblin & Uchino, 2008).

For what concerns the affective component of stress, in one study participants’ state anxiety decreased when emotional support was provided by a friend (compared to participants that did not receive any kind of support; Bowers & Gesten, 1986). In a study focused on the physiological component, participants that were assigned to a physical contact condition (as compared to the no social support condition) exhibited lower heart rate activation and cortisol response (Ditzen et al., 2007). For what concerns the cognitive component, one study found that participants with high levels of emotional social support responded to daily stressors with less ruminative behaviors (as compared to participants with low levels of emotional social support; Puterman, DeLongis, & Pomaki, 2010). Finally, as regards to the affective consequences of stress, studies have found that low levels of social support predict depression both in a non-clinical and clinical populations (Revenson et al. 1991; Brugha et al. 1987).

**Bias in estimating the efficacy of stress regulation**

How can we assess whether there is solid evidence on the efficacy of these strategies? Many fields of science, including psychology, have been confronted with a replication crisis (the fact that replication studies have failed to find the same results as original studies; Klein et al. 2018; Maxwell, Lau, & Howard, 2015; Open Science Collaboration, 2015). Publication bias (the likelihood that positive results have a higher probability of getting published; Rosenthal, 1979; Sutton, Duval, Tweedie, Abrams, & Jones, 2000) and questionable research practices (which is generally used as a term to encompass various scientific misconducts such as excluding data on the basis of post-hoc criteria; John et al., 2012) are often seen as two of the main culprits for low replicability rates.

The psychological literature therefore contains an unknown proportion of unreliable and false positive findings that also characterize the field of stress regulation. For instance, in our previous meta-analysis, we analyzed whether self-administered mindfulness and biofeedback were effective strategies to decrease stress. We detected an effect for both strategies. However, when we applied the same publication bias techniques as we intend to apply here, we found no more evidence that self-administered mindfulness and biofeedback were successful in reducing stress. The originally detected effect was thus largely due to publication bias (Sparacio et al., 2022). Thus, a thorough systematic assessment of the empirical evidence contained in the literature is needed (IJzerman et al., 2020).

At present, we have no way of knowing whether the two strategies are reliably effective interventions againsts stress. Some meta-analyses do exist on the topic, but they need necessary improvements. For example, some meta-analyses were conducted on emotional social support, but these have not been updated for many years and do not account for publication bias at all (e.g., Schwarzer, & Leppin, 1989). Others do not account for publication bias or use publication bias techniques that demonstrated an excessive false-positive rate under most realistic conditions (e.g., trim-and-fill and fail-safe N; Harandi, Taghinasab, & Nayeri, 2017).

For being in nature, only one meta-analysis exists (Antonelli et al., 2019), which did not account for publication bias at all. We tried to improve upon these prior approaches by updating the state-of-the-art through the newest available studies, as well as by applying the most up-to-date bias correction techniques. In so doing, we followed a workflow similar to our previous meta-analysis on stress regulation (Sparacio et al., 2022).

**Method**

For the sake of methodological rigor and transparency, we have made our materials public on the Open Science Framework (https://osf.io/6wpav/). As our goal is to build a database of data on different stress regulation strategies, we added the data to PsychOpenCAMA, an existing public repository in which data from other meta-analyses are stored (Burgard, 2021). We already submitted data of our first pre-registered meta-analysis (Sparacio et al., 2022) to this platform on 24/09/2021, which is currently under review.

If other researchers contribute to the same platform the possibility of creating cumulative knowledge on stress regulation can become reality (Tsuji, Bergmann, & Cristia, 2014). Our meta-analysis was pre-registered on the OSF (https://osf.io/6wpav/). Any changes to the pre-registration were fully disclosed on our OSF page using the template provided by Moreau and Gamble (2020; Appendix A).

**Inclusion criteria and search strategy**

To frame the eligibility criteria in a structured way, we followed the Participants, Intervention, Comparator, Outcome, and Study design (PICOS) Framework (Schardt et al., 2007). We chose to only include studies on participants that are adults (people aged 18 years or older). For the current meta-analysis, we selected two interventions (being in nature and emotional social support). In case of designs comparing groups, for being in nature, we included effects based on a comparison to a control group in which participants performed the same activities (e.g., walking or viewing the surroundings) in an urban environment, or to a passive control condition (participants are in an untreated comparison group; e.g., waitlist control). For emotional social support, we included effects based on a comparison to an active control condition (in that participants were involved in tasks that were not related to stress regulation) and/or to a passive control condition. In case there were more sources of emotional social support for each study, we included the effect based on the closest connection with the participant (e.g., partners over friends, friends over strangers).

If there was more than one comparator in the same study (i.e., presence of both an active and a passive control group), we chose the contrast with the active control group. We measured the affective, the cognitive, and the physiological component of stress taken at post-test of both the experimental group and the control group. For the affective and cognitive components as well as the affective consequences, we relied on self-report measures. For the physiological component, we relied on physiological biomarkers of the stress response (e.g., heart rate, cortisol levels).

To ensure a search strategy that was reproducible, we documented 1) the exact search strategy 2) the dates on which the research was conducted 3) the exact search string. Our search strategy followed the recommendations provided by Maggio et al. (2011). The following databases were searched: ProQuest, (an online platform which covers research indexed in APA PsycArticles, APA Psycinfo, ProQuest Dissertations & Theses Global‎), PubMED, and Scopus. We searched the titles and abstracts of the articles.

The first author (AS) performed the literature search and excluded articles that did not match the inclusion criteria. Screening by title and abstract was carried out using Rayyan QCRI (Ouzzani, Hammady, Fedorowicz, & Elmagarmid, 2016), a web and mobile app for systematic reviews and meta-analyses. The first author then manually searched reference lists of the included studies for relevant citations and unpublished reports. Finally, we used social networks (Facebook groups and Twitter) and mailing lists (Society for Personality and Social Psychology; SPSP, European Association of Social Psychology; EASP, European Society for Cognitive and Affective Neuroscience; ESCAN) to request unpublished data. To ensure that we did not miss relevant articles, we also searched references of past meta-analyses related to the named regulation strategies. We included studies of existing meta-analyses that satisfied our inclusion criteria. Finally, we contacted authors that published studies on the topic to inquire whether they had any unpublished research, in-progress manuscripts, or in-press manuscripts (see our templates in Appendices B and C).

Following the inclusion criteria of our meta-analytical approach: 1) We included published articles, preprint articles, working papers, dissertations, and books (we excluded studies that were not published in English), 2) we included any type of study (randomized control trials and observational studies) that estimated the effect of (or exposure to) being in nature or emotional social support, 3) we included studies that measured at least one of the three components of the stress response or at least that measured the affective consequences of stress, and 4) the participants of the study had to be humans. A study was excluded if 1) it was a review (either narrative or systematic) 2) The sampling frame of the study explicitly involved participants below 18 years of age,, 3) the data necessary to compute our analyses were missing (and not obtainable after having requested them to the authors of the paper) or 4) other active treatments (e.g., mindfulness) were combined with the stress regulation strategies of interest (being in nature or emotional social support). We then added sub-exclusion criteria related to the two stress-regulation strategies. Namely, for being in nature, we excluded studies in which participants engaged in physical activities besides walking (e.g., running or exercising). For social support, we excluded studies with types of support that were not emotional (e.g., informational, instrumental and appraisal social support). A PRISMA flow chart of the overall literature search and inclusion procedure is shown in Appendices D and E.

**Coding and Data Preparation**

Two coders independently coded the data. The coding process was cross-checked for systematic coding errors twice – after the first 10% and 20% of the data on each strategy separately. In case of systematic coding discrepancies, the coding scheme for the relevant variables was made more specific, the coding decisions were revisited, and the discrepancies resolved. Cohen’s Kappa was used as a measure of inter-rater agreement and following the guidelines of Landis and Koch (1977), we considered an agreement of κ > 0.60 for metric or multinomial variables acceptable. For binary variables, we assessed the coding agreement using the percentage agreement. In case of diverging coding decisions, consensus between two coders was reached through discussion or by consulting another author.

We extracted data for the following variables: Publication year, the number of citations of the paper by Google Scholar at date of extraction , journal name, reported overall N, gender ratio, publication status, reported effect sizes, total *N*, cell means, standard deviations and *N*s, test statistic, degrees of freedom, the type of effect (e.g., bivariate effects, covariate-adjusted effects), whether the effect was considered focal (reported in the abstract), the design of the study, the type of population, the category of stress-regulation strategy (being in nature, emotional social support), the type of control group (no control group, active, passive, being in an urban environment, different source of emotional social support), whether it was on one of the components of stress (affective, cognitive, or physiological) or on the affective consequences of stress, and the instrument employed to assess stress levels. We converted all the relevant effect sizes (ES) to Hedges’ *g*, the standardized mean difference corrected for small samples (Hedges & Olkin, 1985). For that purpose, we used primarily the group posttest means, standard deviations (or *SE*s), and *N*s. If these data were not available, we tried to convert from the reported test statistics or other types of reported effect sizes. The computation and conversion of all effect sizes were carried out in code, using formulas laid out in Borenstein et al. (2009).

To mitigate the effect of undisclosed participant exclusions, we checked whether the sum of group *N*s approximately matched the total sample size (*N* +/-2). We used the respective group *N*s if it did. If not, we computed group Ns based on the reported degrees of freedom, assuming a balanced design. If only the total sample size was reported, we also assumed a balanced design. We applied by default a correlation of .50 for within-participants designs.

**Analyses**

**Analysis Strategy**

Prior to the synthesis, we screened for influential outliers using the Baujat plot and influence diagnostics indices. Outliers with an excessive influence on the meta-analytic model (standardized residual > 2.58) were then excluded in a sensitivity analysis. Our analysis strategy closely mirrors the workflow of IJzerman et al. (2022) and Sparacio et al. (2022). By default, we used a multilevel random-effects model using the restricted maximum-likelihood estimation with Satterthwaite’s small-sample adjustment.[[1]](#footnote-3) We included all the relevant outcomes from each included study. The dependencies among the effects were handled by using robust variance estimation, assuming correlated and hierarchical effects (CHE working model; Pustejovsky & Tipton, 2020). This allowed us to simultaneously account for both types of dependencies among the effects, namely due to nesting of effects within studies and estimation of the effects based on the same participants. Because the data on sampling correlations among the effects tend to be unavailable, we assumed a constant sampling correlation of .5. A robust HTZ-type Wald test was used to test the equality of effect sizes across the levels of the studied moderators.

To estimate the range of effect sizes that can be expected in similar future studies, we calculated the 95% prediction intervals. For each analysis we conducted, when the included effects (*k*) were less than 10, we did not interpret the estimates. Similarly as we did for our previous meta-analyses (See Sparacio et al., 2022; IJzerman et al., 2022), we have chosen this threshold arbitrarily, because of the large expected sampling variability of such estimates, leading to imprecise results in smaller sets of effects.

To investigate the heterogeneity caused by variations in population characteristics or conceptual aspects of utilized study designs, we pre-registered a set of subgroup analyses for both categories: proportion of females (versus males) in the sample, type of comparison group, and type of population (student non-clinical, non-student non-clinical, clinical). For being in nature, we tested the type of exposure as a possible source of heterogeneity (nature walking, nature viewing, mixed). For emotional social support, we conducted two additional subgroup analyses: The type of social support (0=not specified, 1=physical, 2=verbal, 3=mixed, 4=other) and the source of social support (0=not specified, 1= stranger, 2=known person; see for more details our coding sheet; https://osf.io/4cjux/). Although we believe that this coding is exhaustive, if we realized when we started the data collection that our coding sheet is inadequate, we changed our coding scheme, which we documented in Appendix A: Protocols and deviations sheet.

Finally, we ran two moderation analyses to assess whether studies with high risk of bias and mathematically inconsistent means or standard deviations showed inflated effect sizes. In case of additional subgroup analyses, we disclosed it on our OSF page using the template provided by Moreau and Gamble (2020; Appendix A).

The R code also allows the reader to easily change numerous arbitrary values (e.g., the assumed constant sampling correlation, the within-subjects correlation, etc.) to explore the impact on the results. All models were fitted using restricted maximum-likelihood estimation using R packages metafor, version 2.5 (Viechtbauer, 2010) and clubSandwich, version 0.4.2. (Pustejovsky, 2020). The data analysis was carried out in R also using the following packages: esc (Lüdecke, 2017), tidyverse (Wickham et al., 2019), lme4 (Bates, Maechler, Bolker, Walker, 2015), dmetar (Harrer et al., 2021), and psych (Revelle, 2018).

**Correction for publication bias**

If null or negative results are less likely to be written up and consequently published, the literature is a biased sample of the conducted science. This tends to lead to an inflation of the observed mean effect sizes and the Type I error rate (Carter et al., 2019; Hong & Reed, 2020; Ioannidis, 2008). In an effort to adjust the meta-analytic estimates for publication bias, we primarily used the selection modeling approach.

We employed a 3- or 4-parameter selection model (4PSM; McShane, Böckenholt, & Hansen, 2016) and used it as the primary inferential and estimation bias-adjustment method. Selection models are a statistically principled family of models that directly model the publication selection process. The 4PSM implementation has two components: A data model of two parameters that describes how data are generated in absence of publication bias (effect size and heterogeneity parameters) and a selection model mimicking the publication process, represented by a weight parameter– likelihood that a study with non-significant results is published compared to a study with significant findings and a parameter reflecting the likelihood of the result being in the opposite direction (McShane et al., 2016). If a given set of results yielded less than four focal *p*-values per interval, the model dropped the fourth parameter to provide for a more stable estimation. To deal with dependencies in the data and avoid arbitrariness in the selection of effects within studies, we applied a permutation-based procedure, iteratively selecting only a single focal effect size from each independent study, estimating the model in 5000 iterations, and averaging over the iterations by picking a model having the median ES estimate (where both, the interpretation and inference was based on that median model).[[2]](#footnote-4)

To further explore the results of publication bias-adjustment, we did the following. First, we tried to assess the variability in adjusted estimates under different assumptions of the publication selection process using Vevea and Woods’ (2005) step function models with a priori defined selection weights (instead assessing them via estimates of maximum likelihood). These step function models allowed us to explore the results by varying the assumed severity of bias, modeling moderate, severe, and extreme selection.

Second, we employed a multi-level RVE-based implementation of the PET-PEESE model (see IJzerman et al., 2022; Sparacio et al., 2022), having the same hierarchical structure as the random-effects models. PET-PEESE regresses the effect size on a measure of precision. Because larger studies are less likely to stay unpublished, model slope is assumed to indicate the presence of small-study effects (this includes publication bias). On the other hand, model intercept can then be interpreted as an average ES for a hypothetical, infinitely precise study (Stanley & Doucouliagos, 2014). To use a measure of precision that is uncorrelated with the effect size, we used √(2/*N*) and a 2/*N* terms instead of standard error and variance for PET and PEESE, respectively.[[3]](#footnote-5)

Third, we used a robust Bayesian model-averaging approach to integrate the selection modeling and regression-based approaches and let the data determine the contribution of each model by its relative predictive accuracy to fit the observed data (Bartoš et al., 2021). This approach effectively dodges the need of choosing among competing approaches – and commits us to only a single set of assumptions about the nature of the true biasing selection process.

Substantive interpretations were guided by the estimates and inferential results of the 4PSM solely. The other exploratory bias-adjustment methods served a descriptive purpose, to provide the reader with a more comprehensive view on bias adjustment under quantitatively and qualitatively different assumptions (Vevea & Woods models and PET-PEESE, respectively) and using a more general model-averaging approach (RoBMA)[[4]](#footnote-6).

The detailed specification of the employed models can be found in code in the supplementary materials. There, we also report the results for the following bias-adjustment methods: *P*-uniform\* (Van Aert & Van Assen, 2021) and the Weighted Average of the Adequately Powered studies (WAAP-WLS; Stanley et al., 2016). A summary of the workflow employed to account for publication bias can be found in Appendix F.

**The quality of evidence assessment**

As one of the main objectives of every meta-analysis should be to appraise the quality and integrity of the underlying reported evidence, we assessed the risk of bias at the study level, assessed the evidential value by looking for indications of *p*-hacking, looked for numerical inconsistencies in the reported data, and estimated the average power in the literature to detect various magnitudes of effects.

First, we evaluated the study quality using the Revised Cochrane risk of bias tool for randomized trials (RoB 2; Sterne et al., 2019). This tool assessed the risk of bias in five predetermined domains related to the experimental design and methodology of the study in question (e.g., randomization process, measurement of the outcome). Based on the judgment for each individual domain, an overall algorithmic-based judgment on the risk of bias was drawn up (i.e., “high risk-of-bias”, “some concern”, or “low risk-of-bias”). The rater had the right to override the suggested risk of bias judgments when justified only by downgrading the judgment.

Second, we assessed the evidential value in a set of significant findings, using the *p*-curve method (Simonsohn, Nelson, & Simmons, 2014). A right-skewed distribution of significant *p*-values indicates evidential value, i.e., that selective reporting is not the sole explanation of the observed findings. Conversely, a left-skewed *p*-curve points to a substantial prevalence of selective reporting or other forms of questionable research practices. To handle the dependencies among the *p*-values derived from the same sample, a permutation-based procedure was employed. We recomputed all focal *p-*values from the reported descriptive or test statistics, randomly extracted only a single effect size for each set of interdependent effects, estimated the *p*-curve in 200 iterations, and averaged over the set by interpreting the model having the median *z*-score for the right-skew of full *p*-distribution.

Third, we checked for numerical inconsistencies in the reported means and *SD*s using the GRIM (Brown & Heathers, 2016) and GRIMMER (Anaya, 2016) tests, respectively, and *p*-values. In case of discrete variables (e.g., Likert scales), decimals in means and *SD*s follow a granular pattern for each combination of *N* and the number of items, which makes it possible to identify instances where a given mean or *SD* is mathematically impossible given the reported *N* (Anaya, 2016; Brown & Heathers, 2016). We also screened the entire included papers for inconsistencies in the reported *p*-values using the statcheck package (Epskamp & Nuijten, 2018). The method works as follows: (1) article pdf files are converted to plain text, (2) they are scanned for statistical results reported in APA style, (3) test statistics and degrees of freedom are extracted to recompute the *p*-value, (4) which then gets compared to the reported *p*-value. We examined in which proportion of primary studies were the *p*-values inconsistent with the reported test statistics and how many of those inconsistencies led to an inferential decision error.

Fourth, we computed mean statistical power in the literature to detect various hypothetical effect sizes (.20, .50, and .70). In the supplementary materials, we also report median power to detect the bias-corrected estimates based on the 4PSM and PET-PEESE models.

**Data availability**

**Underlying data**

Data from this article will be shared via the OSF page.

**Extended data**

To ensure methodological rigor and transparency, we have made our data and the script available on the Open Science Framework (https://osf.io/6wpav/)

Data are available under the terms of the [Creative Commons Attribution 4.0 International license](https://creativecommons.org/licenses/by/4.0/legalcode) (CC-BY 4.0). At least some of the data/evidence that will be used to answer the research question already exists AND is accessible in principle to the authors (e.g., residing in a public dataset or with a colleague). The authors used the data to create a coding scheme BUT the authors certify that they have not yet accessed any part of summary statistics.

**Contributors**

Conceptualization: Alessandro Sparacio, Ivan Ropovik, Gabriela Jiga-Boy, and Hans IJzerman.

Data curation: Alessandro Sparacio and Ivan Ropovik.

Formal analysis: Alessandro Sparacio, Ivan Ropovik, and Hans IJzerman.

Funding acquisition: Hans IJzerman and Gabriela Jiga-Boy.

Investigation: Alessandro Sparacio.

Methodology: Alessandro Sparacio, Ivan Ropovik, and Hans IJzerman.

Project administration: Alessandro Sparacio, Ivan Ropovik, Gabriela Jiga-Boy, and Hans IJzerman.

Resources: Alessandro Sparacio, Ivan Ropovik, Gabriela Jiga-Boy, and Hans IJzerman.

Software: Alessandro Sparacio and Ivan Ropovik.

Supervision: Ivan Ropovik, Gabriela Jiga-Boy, and Hans IJzerman.

Validation: Ivan Ropovik, Gabriela Jiga-Boy, and Hans IJzerman.

Visualization: Alessandro Sparacio and Ivan Ropovik.

Writing - original draft: Alessandro Sparacio.

Writing - review & editing: Alessandro Sparacio, Ivan Ropovik, Gabriela Jiga-Boy, and Hans IJzerman

**References**

**Allen, L., Scott, J., Brand, A., Hlava, M., & Altman, M. (2014). Credit where credit is**

**due. *Nature*, 508, 312–313. https://doi.org/10.1038/508312a.**

Antonelli, M., Barbieri, G., & Donelli, D. (2019). Effects of forest bathing (shinrin-yoku) on

levels of cortisol as a stress biomarker: A systematic review and meta-analysis.

*International Journal of Biometeorology*, *63*(8), 1117–1134.

Bartoš, F., Maier, M., Wagenmakers, E., Doucouliagos, H., & Stanley, T. D. (2021).

No need to choose: Robust bayesian meta-analysis with competing publication bias adjustment methods. *PsyArxiv,* <https://doi.org/10.31234/osf.io/kvsp7>.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models

Using lme4. *Journal of Statistical Software, 67*(1), 1 - 48.

Beckes, L., & Coan, J. A. (2011). Social baseline theory: The role of social proximity in

emotion and economy of action. *Social and Personality Psychology Compass, 5*(12), 976–988.

Beil, K., & Hanes, D. (2013). The influence of urban natural and built environments on

physiological and psychological measures of stress: A pilot study. *International Journal of Environmental Research and Public Health*, *10*(4), 1250–1267.

Bolger, N., DeLongis, A., Kessler, R. C., & Schilling, E. A. (1989). Effects of daily stress

on negative mood. *Journal of Personality and Social Psychology*, *57*(5), 808–818.

Bowers, C. A., & Gesten, E. L. (1986). Social support as a buffer of anxiety: An

experimental analogue. *American Journal of Community Psychology, 14*(4), 447–451.

Bratman, G. N., Hamilton, J. P., Hahn, K. S., Daily, G. C., & Gross, J. J. (2015). Nature

experience reduces rumination and subgenual prefrontal cortex activation*.*

*Proceedings of the National Academy of Sciences, 112*(28), 8567–8572.

Brugha, T., Bebbington, P., MacCarthy, B., Potter, J., Sturt, E. & Wykes, T., (1987) Social

networks, social support and the type of depressive illness. *Acta Psychiatrica Scandinavica, 76*(6), 664–673.

Burgard, T., Bosnjak, M., & Studtrucker, R. (2021). Towards cumulative evidence and

reproducible meta-analyses. Introduction and demonstration of PsychOpen CAMA. ZPID (Leibniz Institute for Psychology). *Available via PsychArchives:* https://doi.org/10.23668/PSYCHARCHIVES.4809

Carter, E. C., Schönbrodt, F. D., Gervais, W. M., & Hilgard, J. (2019). Correcting for bias in

psychology: A comparison of meta-analytic methods. *Advances in Methods and Practices in Psychological Science, 2*(2), 115–144.

Coan, J. A., Schaefer, H. S., & Davidson, R. J. (2006). Lending a hand: Social regulation of

the neural response to threat. *Psychological Science*, *17*(12), 1032–1039.

Coan, J. A., & Sbarra, D. A. (2015). Social Baseline Theory: The social regulation of

risk and effort. *Current Opinion in Psychology*, *1*, 87–91.

Coan, J. A., Beckes, L., Gonzalez, M. Z., Maresh, E. L., Brown, C. L., & Hasselmo, K.

(2017). Relationship status and perceived support in the social regulation of neural responses to threat. Social Cognitive and Affective Neuroscience, 12(10), 1574–1583.

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress.

*Journal of Health and Social Behavior*, *24*(4), 385–396.

Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis.

*Psychological Bulletin*, *98*, 310-357.

Cohen, S. (2004). Social Relationships and Health. *American Psychologist, 59*(8), 676–684.

Ditzen, B., Neumann, I. D., Bodenmann, G., von Dawans, B., Turner, R. A., Ehlert, U., &

Heinrichs, M. (2007). Effects of different kinds of couple interaction on

cortisol and heart rate responses to stress in women. *Psychoneuroendocrinology*, *32*(5), 565–574.

Du, J., Huang, J., An, Y., & Xu, W. (2018). The relationship between stress and negative

emotion: The mediating role of rumination. *Clinical Research and Trials*, *4*(1), 1–5.

Ein-Dor, T., Coan, J. A., Reizer, A., Gross, E. B., Dahan, D., Wegener, M. A., Carel, R.,

Cloninger, C. R., & Zohar, A. H. (2015). Sugarcoated isolation: Evidence that social

avoidance is linked to higher basal glucose levels and higher consumption of glucose.

Frontiers in Psychology, 6, 492.

Grazuleviciene, R., Vencloviene, J., Kubilius, R., Grizas, V., Dedele, A., Grazulevicius, T.,

Ceponiene, I., Tamuleviciute-Prasciene, E., Nieuwenhuijsen, M. J., Jones, M., &

Gidlow, C. (2015). The effect of park and urban environments on coronary artery

disease patients: A randomized trial. *BioMed Research International*, *2015*, 403012.

Harandi, T. F., Taghinasab, M. M., & Nayeri, T. D. (2017). The correlation of social

support with mental health: A meta-analysis. *Electronic Physician*, *9*(9), 5212–5222.

Harrer, M., Cuijpers, P., Furukawa, T.A., & Ebert, D.D. (2021). Doing

meta-analysis with R: A Hands-on guide. Boca Raton, FL and London:

Chapman & Hall/CRC Press. ISBN 978-0-367-61007-4.

Hedges, L. V., Tipton, E., & Johnson, M. C. (2010). Robust variance estimation in

meta-regression with dependent effect size estimates. *Research Synthesis Methods*, *1*(1)*,* 39–65.

Hedges, L.V. & Olkin, I. (1985). *Statistical methods for meta-analysis.* Academic

Press.

IJzerman, H., Hadi, R., Coles, N. A., Paris, B., Sarda, E., Fritz, W., … Ropovik, I. (2022,

February 26). Social Thermoregulation: A Meta-Analysis.

*Available via PsyArxiv,* https://doi.org/10.31234/osf.io/fc6yq.

Ioannidis, J. P. A. (2008). Why most discovered true associations are inflated.

*Epidemiology*, *19*(5), 640–648.

Klein, R. A., Vianello, M., Hasselman, F., Adams, B. G., Adams, R. B., Alper, S., Aveyard,

M., Axt, J. R., Babalola, M. T., Bahník, Š., Batra, R., Berkics, M., Bernstein, M. J.,

Berry, D. R., Bialobrzeska, O., Binan, E. D., Bocian, K., Brandt, M. J., Busching, R.,

... Nosek, B. A. (2018). Many labs 2: Investigating variation in replicability across

samples and settings. *Advances in Methods and Practices in Psychological Science*,

*1*(4), 443–490.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for

categorical data. *Biometrics*, *33*(1), 159–174.

Lazarus, R. S., & Folkman, S. (1984). Stress, appraisal, and coping. Springer.

Lüdecke D (2019). esc: Effect Size Computation for Meta Analysis (Version 0.5.1).

https://CRAN.R-project.org/package=esc.

John, L. K., Loewenstein, G., & Prelec, D. (2012). Measuring the prevalence of questionable

research practices with incentives for truth telling. *Psychological Science*, *23*(5), 524–532.

Maggio, L. A., Tannery, N. H., & Kanter, S. L. (2011). Reproducibility of literature search

reporting in medical education reviews. *Academic Medicine*, *86*(8), 1049–1054.

Maxwell, S. E., Lau, M. Y., & Howard, G. S. (2015). Is psychology suffering from a

replication crisis? What does “failure to replicate” really mean? *American Psychologist*, *70*(6), 487–498.

Marselle, M., Irvine, K., & Warber, S., (2014). Examining group walks in nature and multiple

aspects of well-being: A large-scale study. *Ecopsychology*, 134–147.

McShane, B. B., Böckenholt, U., & Hansen, K. T. (2016). Adjusting for publication bias in

meta-analysis. *Perspectives on Psychological Science*, *11*(5), 730–749.

Moreau, D., & Gamble, B. (2020). Conducting a meta-analysis in the age of open science:

Tools, tips, and practical recommendations. *Psychological Methods.* Advance online publication. [https://doi.org/10.1037/met0000351](https://psycnet.apa.org/doi/10.1037/met0000351)

Open Science Collaboration. (2015). Estimating the reproducibility of psychological

science. *Science*, *349*(6251), 943–952.

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—a web and

mobile app for systematic reviews. *Systematic Reviews*, *5*(1), 210–220.

Pessoa, L. (2008). On the relationship between emotion and cognition. *Nature Reviews*

*Neuroscience*, *9*(2), 148–158.

Phelps, E. A. (2006). Emotion and cognition: Insights from studies of the human amygdala.

*Annual Review of Psychology*, *57*(1), 27–53.

Pustejovsky, J. (2017). You wanna PEESE of d's? Blogpost.

https://www.jepusto.com/pet-peese-performance/

Puterman, E., DeLongis, A., & Pomaki, G. (2010). Protecting us from ourselves: Social

support as a buffer of trait and state rumination*. Journal of Social and Clinical Psychology, 29*(7), 797–820.

Reblin, M., & Uchino, B. N. (2008). Social and emotional support and its implication for

health. *Current Opinion in Psychiatry*, *21*(2), 201–205.

Revelle, W. and Condon, D. M. (2018). Reliability. In Irwing, P., Booth, T., and Hughes, D.,

editors. *Wiley-Blackwell Handbook of Psychometric Testing*. Wiley-Blackwell.

Revenson, T. A., Schiaffino, K. M., Majerovitz, S. D., & Gibofsky, A. (1991). Social

support as a double-edged sword: The relation of positive and problematic

support to depression among rheumatoid arthritis patients. *Social Science &*

*Medicine*, 33*(7),* 807–813.

Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological*

*Bulletin*, *86*(3), 638–641.

Schardt, C., Adams, M. B., Owens, T., Keitz, S., & Fontelo, P. (2007). Utilization of the

PICO framework to improve searching PubMed for clinical questions. *BMC Medical Informatics and Decision Making*, *7*, 16.

Schneiderman, N., Ironson, G., & Siegel, S. D. (2005). Stress and health: Psychological,

behavioral, and biological determinants. *Annual Review of Clinical Psychology*, *1*,

607–628.

Schwarzer, R., & Leppin, A. (1989). Social support and health: A meta-analysis. *Psychology*

*& Health, 3*(1), 1–15.

Simmons, J., Nelson, L., & Simonsohn, U. (2011). False-positive psychology: Undisclosed

flexibility in data collection and analysis allows presenting anything as

significant. *Psychological Science*, *22*(11), 1359–1366.

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2014). *P*-curve: A key to the file-drawer.

*Journal of Experimental Psychology: General*, *143*(2), 534–547.

Sparacio, A., Ropovik, I., Jiga-Boy, G. M., Forscher, P. S., Paris, B., & IJzerman, H. (2022).

Stress regulation via self-administered mindfulness and biofeedback interventions in

adults: A pre-registered meta-analysis. *Available via PsyArXiv*,

https://psyarxiv.com/zpw28/

Stanley T.D. & Doucouliagos C.H. (2014). Meta-regression approximations to reduce

publication selection bias. *Research Synthesis Methods*, *5*(1), 60–78.

Sterne, J., Savović, J., Page, M. J., Elbers, R. G., Blencowe, N. S., Boutron, I., Cates, C. J.,

Cheng, H. Y., Corbett, M. S., Eldridge, S. M., Emberson, J. R., Hernán, M. A.,

Hopewell, S., Hróbjartsson, A., Junqueira, D. R., Jüni, P., Kirkham, J. J., Lasserson,

T., Li, T., McAleenan, A., … Higgins, J. (2019). RoB 2: A revised tool for assessing

risk of bias in randomised trials. *The BMJ*, *366*, l4898.

[Sutton, A. J., Duval, S. J., Tweedie, R. L., Abrams, K. R., & Jones, D. R. (2000). Empirical](https://www.zotero.org/google-docs/?i1zMLq)

[assessment of effect of publication bias on meta-analyses. *The BMJ*, *320*(7249),](https://www.zotero.org/google-docs/?i1zMLq)

[1574–1577.](https://www.zotero.org/google-docs/?i1zMLq)

Tsuji, S., Bergmann, C., & Cristia, A. (2014). Community-augmented meta-analyses.

*Perspectives on Psychological Science*, *9*(6), 661–665.

Ulrich, R.S. (1979). Visual landscapes and psychological well‐being. *Landscape Research,*

*4*, 17-23.

Ulrich, R. S. (1983). Aesthetic and affective response to natural environment. In I. Altman &

J. F. Wohlwill (Eds.), *Behavior and the Natural Environment* (pp. 85–125). New York: Springer.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of*

*Statistical Software*, *36*(3), 1–48.

Watson, D., Clark, L. A., & Carey, G. (1988). Positive and negative affectivity and their

relation to anxiety and depressive disorders. *Journal of Abnormal Psychology*, *97*(3), 346–353.

Wickham, H., Averick, M., Bryan, J., [Chang](https://joss.theoj.org/papers/by/Winston%20Chang), W., McGowan, L., D., François, R., … Yutani, H. (2019). Welcome to the Tidyverse. J*ournal of Open Source Software*, *4*(43),

1686.

Yeung, S., K., Fillon, A., Protzko, J.,[Elsherif](https://osf.io/e7bs8/), M., [Moreau](https://osf.io/us7wz/)[D.,](https://osf.io/us7wz/) & Feldman G. (2021).

Experimental meta-analysis Registered Report template. https://osf.io/ytgrp/.

Zellars, K. L., & Perrewé, P. L. (2001). Affective personality and the content of emotional

social support: Coping in organizations. *Journal of Applied Psychology, 86*(3), 459–467.

**Appendix A: Protocols and deviations**

Any changes with respect to the choices established in this pre-registration will be fully disclosed on our OSF page, and will be incorporated into this form: https://osf.io/6wpav/.

**Appendix B: Call for unpublished data**

**Subject:** Call for unpublished data for a meta-analysis: “**Stress regulation via being in nature and emotional social support for adults: A pre-registered meta-analysis”**

Dear Prof/Dr/Ms/Mr XXXX,

I am Alessandro Sparacio, PhD student in social psychology, at the University of Grenoble-Alpes and I’m conducting a meta-analysis on stress regulation, along with my co-authors Hans IJzerman, Ivan Ropovik, Gabriela Jiga-Boy & Patrick Forscher.

The pre-registered protocol for this meta-analysis is publicly available on the Open Science Framework (OSF) at [https://osf.io/6wpav/]

Our meta-analysis aims to address whether being in nature and emotional social support have any demonstrated efficacy in reducing stress levels.

As you have published studies relevant to this topic, we are getting in touch to see if you have any unpublished/file-drawer data, or papers in-press, which we may have missed through database searching, and which you would like to have included in the meta-analysis.

Feel free to email either the raw data (from which we will calculate summary scores) or the summary scores themselves. While any raw data emailed to us will of course remain confidential, please know that summary scores included in the meta-analysis will be made publicly available in a dataset on the OSF.

We are hoping to include as many relevant studies as possible, so any additional data is greatly appreciated.

Sincerely (also on behalf of my co-authors),

Alessandro Sparacio

*This template was provided by Moreau and Gamble (2020)*

**Appendix C: Requesting for specific data**

**Subject:** Requesting data for a meta-analysis, from your paper: ‘XXXX’

Dear Prof/Dr/Ms/Mr XXXX,

I am Alessandro Sparacio, PhD student in social psychology, at the University of Grenoble-Alpes and I’m conducting a meta-analysis on stress regulation, along with my co-authors Hans IJzerman, Ivan Ropovik, Gabriela Jiga-Boy & Patrick Forscher.

The pre-registered protocol for this meta-analysis is publicly available on the Open Science Framework (OSF) at [https://osf.io/6wpav/].

We think your study ‘XXXX’ meets inclusion criteria for our meta-analysis. However, the effect size we’re interested in (i.e., the correlation/difference between XXX and XXX) does not seem to be reported in the published paper.

We would be grateful if you could send either the summary scores or the raw data themselves (from which we can calculate the effect size). While any raw data emailed to us will of course remain confidential, please know that summary scores included in the meta-analysis will be made publicly available in a dataset on the OSF.

The latest we will be able to accept your data for inclusion is XXth of XXX, XXXX.

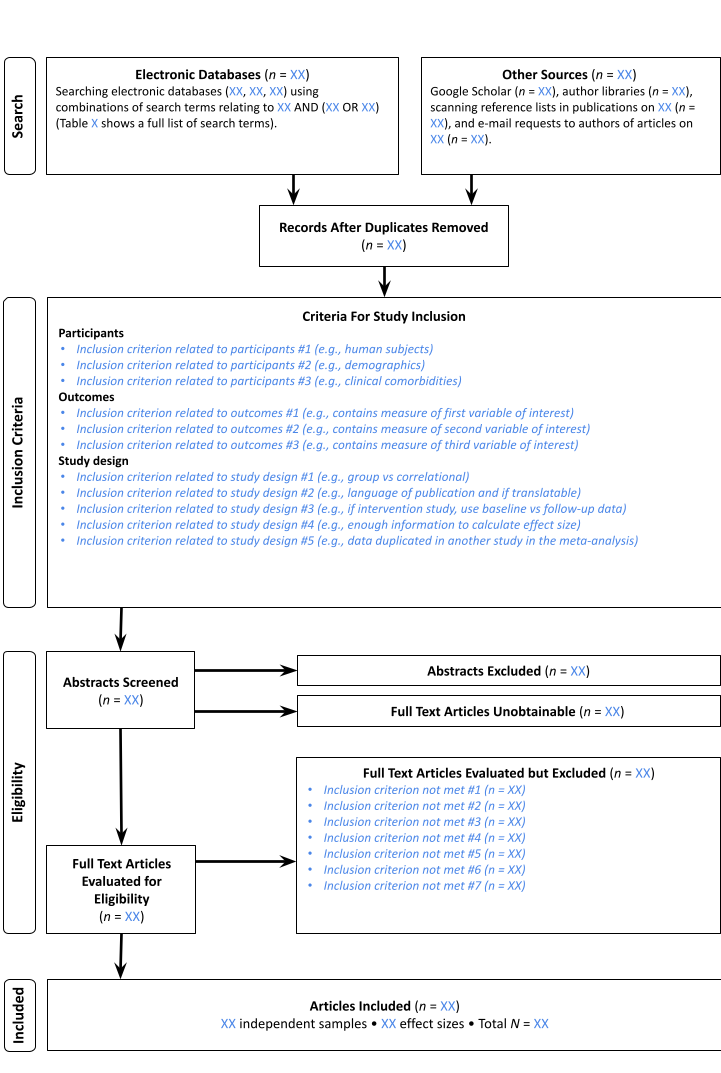
We are hoping to include as many relevant studies as possible, so any additional data is greatly appreciated.

Sincerely (also on behalf of my co-authors),

Alessandro Sparacio

*This template was provided by Moreau and Gamble (2020)*

**Appendix D: Search criteria**

****

*This template was provided by Moreau and Gamble (2020)*

**Appendix E: Search strategy**

**BEING IN NATURE**

**PUBMED**

(“natural space” OR “natural environment\*” OR “natural landscape” OR “urban nature” OR “nearby nature” OR “nature view\*” OR “outdoor nature” OR "natural space” OR “green area” OR “green environment” OR “nature contact” OR “contact with natur\*” OR park OR “urban forest” OR “forest walking” OR “forest” OR “forest environment\*” OR "shinrin" OR “forest bathing”) AND (walk\* OR sitt\* OR watch\* OR view\* OR stay\* OR contact\*) AND stress AND (“negative affect” OR “positive affect” OR emotion\* OR cogniti\* OR ruminati\* OR physiological\* OR biomarker\* OR depression OR anxiety)

Search date: XX

Results: XX

Notes:

**PROQUEST (APA PsycArticles, APA Psycinfo, ProQuest Dissertations & Theses Global‎)**

(“natural space” OR “natural environment\*” OR “natural landscape” OR “urban nature” OR “nearby nature” OR “nature view\*” OR “outdoor nature” OR "natural space” OR

“nature contact” OR “contact with natur\*” OR park OR “urban forest” OR “forest walking” OR “forest environment\*” OR "shinrin"

OR “forest bathing”) AND (walk\* OR sitt\* OR watch\* OR view\* OR stay\*) AND stress AND (“negative affect” OR “positive affect” OR emotion\* OR cogniti\* OR ruminati\* OR physiological\* OR biomarker\* OR depression OR anxiety)

Search date: XX

Results: XX

Notes:

**SCOPUS**

TITLE-ABS ((“greenspace\*” OR “green space” OR “green landscape\*” OR “natural space” OR “natural environment\*” OR “natural landscape” OR “urban nature” OR “nearby nature” OR “nature view\*” OR “nature viewing” OR “viewing nature” OR “outdoor nature” OR "natural space” OR “nature contact” OR “contact with natur\*” OR park OR “urban forest” OR “forest walking” OR “forest environment\*” OR “nature therapy” OR “nature experience” OR “forest therapy” OR "shinrin" OR “forest bathing”) AND (walk\* OR sitt\* OR watch\* OR view\* OR stay\*) AND stress AND (“negative affect” OR “positive affect” OR emotion\* OR cogniti\* OR ruminati\* OR physiological\* OR biomarker\* OR depression OR anxiety)

Search date: XX

Results: XX

Notes:

**EMOTIONAL SOCIAL SUPPORT**

**PUBMED**

## ( "emotional support" OR "emotional social support") AND ( encourage\* OR help OR assist\* OR love OR trust\* OR contact or touch) AND stress AND ( "negative affect" OR "positive affect" OR emotion\* OR cogniti\* OR ruminati\* OR physiological\* OR biomarker\* OR depression OR anxiety)

Search date: XX

Results: XX

Notes:

**PROQUEST (APA PsycArticles, APA Psycinfo, ProQuest Dissertations & Theses Global‎)**

## ( "emotional support" OR "emotional social support") AND ( encourage\* OR help OR assist\* OR love OR trust\* OR contact or touch) AND stress AND ( "negative affect" OR "positive affect" OR emotion\* OR cogniti\* OR ruminati\* OR physiological\* OR biomarker\* OR depression OR anxiety )

Search date: XX

Results: XX

Notes:

**SCOPUS**

## TITLE-ABS ( ( "emotional support" OR "emotional social support" ) AND ( encourage\* OR help OR assist\* OR love OR trust\* OR contact OR touch ) AND stress AND ( "negative affect" OR "positive affect" OR emotion\* OR cogniti\* OR ruminati\* OR physiological\* OR biomarker\* OR depression OR anxiety ) )

Search date: XX

Results: XX

Notes:

**Appendix F: Correction for publication bias**

1. *Primary confirmatory analysis: 4-parameter selection model (Carter et al., 2019; McShane, Böckenholt, & Hansen, 2016).*

If there were less than four focal *p*-values per interval, the procedure fell back to the 3-parameter selection model. The selection models were implemented using a permutation-based procedure, iteratively selecting only a single focal effect size from each independent study, estimating the model in 5000 iterations, and averaging over the iterations by picking the model with the median ES estimate.

1. *Exploratory analyses*

*2.1.* Vevea and Woods (2005) step function models with a priori defined selection weights, varying the assumed severity of bias, modeling moderate, severe, and extreme selection.

2.2. Multi-level RVE-based implementation of the PET-PEESE model (Stanley & Doucouliagos, 2014), employing √(2/*N*) and a 2/*N* terms instead of standard error and variance for PET and PEESE, respectively, as a measure of precision (see Pustejovsky, 2017). Additionally, the R code also allows the interested reader to use the 4PSM as a conditional estimator for PET-PEESE instead of traditional PET and explore the effect of such decision on the resulting inference (for more details, see IJzerman et al., 2022).

2.3. Robust Bayesian model-averaging approach integrating the selection modeling and regression-based approaches (Bartoš et al., 2021), letting the data determine the contribution of each model by its relative predictive accuracy to fit the observed data.

**Inferential criteria**: If the results of the 4-parameter selection model disagreed with the more general Bayesian model-averaging approach, we chose to remain in doubt with respect to the evidence for the given effect.

1. We switched to ordinary two-level random-effects model if (1) the multilevel model failed to converge in the overall model or in any of the subgroups; or (2) if the variance components of the model were not well identifiable (specifically, if the log-likelihood did not peak at the variance estimates for both variance components). [↑](#footnote-ref-3)
2. That is, we picked the median estimate from the parameter distribution and, with it, the corresponding model that the estimate was originating from. The goal of this procedure was to preserve the mutual consistency between the estimate, z-value, CIs, and p-value. [↑](#footnote-ref-4)
3. As the 4PSM tends to have more favorable error rates under many conditions than PET, the reader can also define the 4PSM as a conditional estimator for PET-PEESE instead of the traditional PET in the R code, to explore the effect of such decision on the resulting inference. [↑](#footnote-ref-5)
4. Apart from reporting the results of these bias adjustments, we examined whether the primary 4/3-PSM estimate fell within the 95% credible interval of the RoBMA estimate (being based on a more general model). [↑](#footnote-ref-6)