Suicidal Thoughts, Behaviors, and Event-Related Potentials: A Meta-Analysis

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Abstract

Suicidal thoughts and behaviors (STBs) are thought to be the result, at least in part, of abnormalities in various neural systems. Event-related potentials (ERPs) are a useful method for studying neural activity, and can be leveraged to study neural deficits related to STBs, but it is unknown how effective ERPs are at differentiating various STB groups. The present meta-analysis examined how well ERPs can differentiate those with and without suicidal ideation (SI), suicide attempts (SA), and those determined to be at different levels of suicide risk, or suicidality. Our meta-analysis included 192 effect sizes from 24 studies. We used a random effects meta-analysis and found a small-to-moderate relationship between ERPs and STBs. However, we also found evidence that the literature may be suffering from small sample publication bias. Our results suggest that ERPs may compliment other approaches, such as fMRI, in the study of the neurobiology of individuals with STBs. However, the clinical utility of ERPs to predict STBs remains to be tested, and larger samples are needed to confirm the results of the present meta-analysis.

Keywords: suicide, event-related potentials, meta-analysis, suicidal ideation, suicide attempt

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Suicide is a concern around the world. Estimates indicate that well over 800,000 people die by suicide around the world annually (World Health Organization, 2014). In the United States (U.S.) alone, over 47,000 people die by suicide each year, making suicide the 10th leading cause of death (Centers for Disease Control [CDC], 2017). In contrast to trends in other western countries, suicide rates in the U.S. have been increasing over the last two decades (Hedegaard et al., 2018). This increase in the suicide rate has contributed to the decreasing trend in U.S. life expectancy every year since 2014 (Woolf & Schoomaker, 2019).

Many scientists have suggested that suicidal thoughts and behaviors (STBs) are partially the result of differences or abnormalities in neurobiological systems (Joiner et al., 2005; Mann, 2003; Van Heeringen & Mann, 2014). This suggestion has led to many studies investigating the brain regions that may be implicated in STBs, with most studies using magnetic resonance imaging (MRI) to examine structural and functional brain differences between those with and without a history of STBs.

A recent qualitative systematic review of the neuroimaging literature of STBs concluded that there is tentative but converging evidence for two brain networks implicated in STBs (Schmaal et al., 2019). First, the authors proposed that the ventral prefrontal cortex and many of its connections are involved in increasing negative and decreasing positive internal states, which may lead to suicidal ideation (SI). Second, they identified other regions, including the dorsomedial prefrontal cortex, the dorsolateral prefrontal cortex, and the inferior frontal gyrus, as a separate network that may be important for suicide attempts (SAs) due to these regions' roles in planning and cognitive control. The authors concluded that further studies investigating brain regions could aid in the development of novel treatments for STBs.

In contrast, a quantitative meta-analysis of neuroimaging studies using whole-brain analyses did not find significant associations between SA and any brain region; the study concluded that there were not enough studies to analyze the relationship between SI and neural structure and function (Huang, Rootes-Murdy, et al., 2020). Though these two reviews reached different conclusions about the state of the STB brain imaging literature, both highlight the need for larger sample sizes in future studies examining the relationship between the brain and STBs.

An alternative approach to examining the neurobiology of STBs is to use event-related potentials (ERPs). ERPs are derived from electroencephalographic (EEG) data and reflect neural responses to specific, repeated events (Luck, 2014). ERP waveforms are calculated by averaging the electrocortical responses to a specific task event (e.g., stimulus presentation, error commission) across multiple trials. Although ERPs generally lack the excellent spatial resolution of MRI (i.e., the ability to accurately localize neural functions to regions in the brain), this methodology has several strengths. First, ERPs are direct measures of brain activity with excellent temporal resolution (i.e., over 1000 samples per second), which allows researchers to examine distinct neural activity that might typically overlap with that assessed in MRI (e.g., ERPs can separately index multiple distinct processes that occur within hundreds of milliseconds of one another). Many ERPs have been shown to have excellent internal consistency with sufficient trial numbers (e.g., Meyer et al., 2013; Moran et al., 2013). Electrocortical data are also less expensive to collect relative to other forms of neuroimaging, thereby making larger samples sizes more feasible. Importantly, the extant literature has demonstrated that many ERPs reflect different neural functions, such as emotion regulation, response inhibition, reward processing, reward anticipation, and error monitoring (Luck & Kappenman, 2011), that might be relevant for understanding STBs.

Because of their potential clinical utility (Hajcak et al., 2019), researchers have begun to employ ERPs in the study of STBs. For example, Gibb and Tsypes (2019) suggested that the inclusion of ERPs in machine learning algorithms may improve the prediction of STBs. Though there have been studies examining differences in ERPs between those with SI or a history of SA and those without SI or SAs (e.g., Albanese et al., 2019), the literature on the relationship between ERPs and STBs is quite mixed. For example, one study found that a reduced late positive potential (LPP; a slow wave ERP that indexes emotional salience of stimuli) to pleasant pictures was related to increased SI (Weinberg et al., 2016). However, a follow-up study did not find a relationship between the late positive potential to rewarding stimuli and SI (Weinberg et al., 2017), and another study found a relationship only when individuals were asked to volitionally increase their reward responses (Albanese, Macatee, Stanley, et al., 2019). Though there are many reasons for these mixed findings, a possibility involves the definitions of STBs used across studies. According to ideation-to-action theories of suicide (e.g., interpersonal theory of suicide, 3-step theory; Joiner, 2005; Klonsky & May, 2015), factors that predict SI do not necessarily predict SAs or death by suicide (Klonsky et al., 2018). This is supported by a meta-analysis showing that most risk factors for suicide (e.g., depression) have stronger associations with SI than SAs (May & Klonsky, 2016). Given these findings, ERPs may have different associations with various STBs.

In addition to these uncertainties, recent meta-analyses have called into question the clinical significance of most risk factors for STBs when examined in isolation (Chang et al., 2016; Franklin et al., 2017; Ribeiro et al., 2018). Given these mixed findings and previous meta-analyses, the current meta-analysis aims to: (1) examine whether ERPs, in general, differentiate between individuals who have and have not engaged in STBs; (2) examine which ERP, if any, is

the most effective at differentiating those who have and have not engaged in STBs; and (3) investigate whether other factors moderate the relationship between ERPs and STBs. We examined each of these aims in three separate STBs: between those with and without SI, between those with and without a SA history, and among those with varying degrees of suicide risk.

Method

Inclusion and Exclusion Criteria

All of our data, analysis scripts, coding spreadsheets, figures, and supplementary material are available on the Open Science Framework (https://osf.io/k4cpe/). Our meta-analysis was conducted in adherence with the PRISMA Statement (Moher et al., 2009). The following criteria were established to select relevant effect sizes.

Language

Only articles written in English were included.

Event-related potential

Only articles that had an effect size that included an event-related potential (ERP) were included. ERPs were defined as measures using EEG responses to specific, time-locked events of mental processes. Given these criteria, studies that used cortical recordings or that stimulated the brain to produce neural activity were excluded.

Suicide-related outcomes

Effect sizes were required to include a measure of suicidal thoughts, behaviors, or suicide risk/suicidality. Suicidal thoughts were defined as any measure of severity or history of suicidal ideation. We did not distinguish between death/suicidal ideation, or passive/active suicidal ideation. Suicidal behaviors were defined as a history of engaging in a self-harm behavior with nonzero intent to die. Importantly, we did not distinguish among aborted, interrupted, and actual

SAs. Moreover, effect sizes that included SA frequency were not included. Last, suicide risk/suicidality was used when a measure/group with STBs that did not fit in the SI or SA categories was obtained. For example, studies that used the Suicidal Behavior Questionnaire—Revised (Osman et al., 2001) were categorized as "suicide risk." Given these definitions, studies that examined nonsuicidal self-injury or a history of nonsuicidal self-injury were excluded.

Published in print or online by October 2019

Our search results were limited to articles published in print or online by October 25, 2019.

Literature Search

We conducted literature searches across PubMed, PsycInfo, Web of Science, and ProQuest Dissertations & Theses to find relevant literature. Full search terms for each database are available on an online repository stored on the Open Science Framework (https://osf.io/k4cpe/). To summarize, search terms included different permutations related to ERPs and suicidal thoughts and behaviors, including: "event-related potential," "event-related potentials," "electroencephalography," "EEG," "evoked potential," "evoked potentials," "late positive potential," "reward positivity," "P3a," "P3b," "error-related negativity," "suicide," "suicidal," "suicidal ideation," "self-harm," "self-injury," "parasuicide," "suicide ideation," "suicide attempt," "suicide plan," "suicidality," "suicide risk," "attempter," "attempters," and "ideators." We also checked the reference list of every article included in the final meta-analysis for additional studies. In addition to these efforts, we made several attempts to gather unpublished literature. These efforts included: (1) social media announcements on Twitter and (2) contacting researchers who were either a first or last author on at least two papers included in the meta-analysis. Of the nine researchers we emailed asking for unpublished or yet-to-be

published studies, six responded, with three providing data and three indicating that they did not have any other unpublished data. The remaining three did not respond.

Data Extraction and Coding

For each effect size, the following were also coded: mean age of the sample, suicide measure, EEG reference, scoring ERP procedure, specific ERP, type of suicidal group, and the type of comparison group. All studies were initially coded by the first author (AJG) in an Excel spreadsheet. We also had one doctoral student (SPD) recode data included in our meta-analysis. We conducted reliability analyses for our codes, using agreement rate and Cohen's kappa for categorical variables and using intercoder correlation and two-way random effects intraclass correlation (ICC) for continuous variables. For categorical variables, agreement rate ranged from 85.1% to 99.4%, and Cohen's kappa ranged from fair to excellent (κ = .59 - .99). For continuous variables, intercoder correlations ranged from .99 to 1.0, and ICCs also ranged from .99 to 1.0. Disagreements for categorical variables were resolved through discussion.

Using our search terms across all our included databases produced 270 papers. Figure 1 displays an overview of our search process and number of articles within each search process. After accounting for duplicates, we examined the abstracts of 200 papers and excluded studies that did not meet inclusion criteria. After examining abstracts, 51 studies entered full-text review. In the end, 24 studies had at least one effect size that met inclusion criteria, resulting in 192 total effect sizes. The 27 studies that were not included after full-text review were excluded for the following reasons: (1) no measure that met definition of ERP (n = 3), (2) no measure that met one of our definitions of STBs (n = 6), (3) no, or not enough, information to calculate effect sizes, including when access to the full text was inaccessible due to the article's being a poster or dissertation (n = 17), and (4) paper was a review article (n = 1). For articles for which the full

text was available but for which we did not have enough information to calculate effect sizes, we sought to email the corresponding or last author. We emailed four researchers for more information to calculate effect sizes from their papers. One responded and indicated that they no longer had access to the data. No other researchers responded, and we were unable to locate contact information for authors for two studies.

Effect Size

Information was extracted from each study to calculate Hedges' *g*. For most effect sizes, means, standard deviations, and sample size were used to calculate effect sizes. However, in some cases, existing effect sizes had to be converted to Hedges' *g*. Specifically, several studies reported Pearson's *r* or an *F* value. For one effect size, Pearson's *r* was estimated by using the computer program WebPlotDigitizer (Version 4.2; Rohatgi, 2019). All effect sizes were calculated using the "compute.es" package (Version 0.2-4; Del Re, 2013). Because the aim of this meta-analysis was to examine how well ERPs can differentiate those with and without STBs, we converted all Hedges' *g* effect sizes to $|g|$. This conversion was done because ERPs may have differing relationships with STBs, with some studies reporting blunted ERPs in those with STBs and other studies reporting increased ERPs in those with STBs. Moreover, we made this change because a blunted or larger ERP could be conceptualized as a risk factor, depending on the neural processes the ERP represents.

Combining Effect Sizes

All of our analyses were conducted in R (Version 3.5.2; R Core Team, 2018), using the "metafor" package (Version 2.1; Viechtbauer, 2010). We opted to use a random-effects model that estimated heterogeneity using restricted maximum-likelihood. We chose this model for two reasons: First, our literature search produced studies with many effect sizes. This dependence

between effect sizes violates the assumptions of fixed-effect models, which would lead to an incorrectly estimated pooled effect size and would increase the probability of a Type I error (Hedges et al., 2010). Second, given that we combined many different ERPs that measure different neural functions, it is likely that our meta-analysis would result in significant heterogeneity in effect sizes. We also used robust variance estimation to account for the small number of clusters (i.e., studies) in our analyses (Hedges et al., 2010). To address outliers, we first conducted our meta-analysis using all effect sizes. Then, any effect sizes whose confidence interval did not overlap with the pooled effect size was removed. We then reran our analyses with outliers removed.

To examine whether publication bias was present, we used two approaches: (1) we visually inspected the funnel plot for each outcome and (2) we conducted moderation analyses using study sample size as the moderating variable. We also ran moderation analyses examining whether specific ERPs, ERP scoring method, and sample age moderated the pooled effect size. In line with our second aim, we examined which specific ERP best differentiated those with and without each of our three STBs. We planned to examine suicide measurement, location of the reference electrode(s), and method of quantifying ERPs (e.g., mean, area-around-the-peak) as moderators, but, for each of these variables, either there were not enough studies reporting these measures, or there was not enough variation in the methods used. We also conducted unplanned sensitivity analyses by comparing our results to the results if (a) outlier effect sizes were included and if (b) only published studies' effect sizes were included.

Results

Suicidal Ideation

Overall SI Results and Publication Bias

After excluding one outlier effect size, our SI meta-analysis consisted of eight studies and 104 effect sizes (M = 13.00 effect sizes per study). The difference in ERPs between those with SI and those without SI was significant, with an average weighted Hedges' g = 0.27 (95% CI [0.14, 0.39]). We did not find evidence of significant heterogeneity (Q[103] = 79.84, p = 0.956, I^2 = 19.75%). Regarding publication bias, visually inspecting the funnel plot (see Figure 2) revealed small-sample publication bias, with smaller samples more frequently having larger effect sizes. As a test of this observation, we examined study sample size as a moderator of the relation between ERPs and SI. The model was significant (F[1, 6] = 25.63, p = .002), with sample size revealing a negative relationship with the pooled effect size estimate (b = -0.001, p = .002). This result suggests that studies with smaller sample sizes tended to find significantly larger effects than studies with larger sample sizes. Though this unstandardized effect appears small, it results in our smallest sample having an estimated effect size of Hedges' g = 0.35; in comparison, our largest sample had an estimated effect size of Hedges' g = 0.10 (see Figure 3).

Moderation of SI by Specific ERP

We tested specific ERPs as a moderator of the relation between ERPs and SI. All ERPs that had 10 or more effect sizes were given their own code; ERPs that did not meet this cutoff were grouped together. Thus, ERPs were coded as follows: loudness dependence of auditory evoked potential (LDAEP) = 0; late positive potential (LPP) = 1; reward positivity (RewP) = 2; positive 300 (P3) = 3; positive slow wave (PSW) = 4; and negative 100 (N1), contingent

negative variation (CNV), negative 200 (N2), positive 200 (P2), post-imperative negative variation (PINV), and stimulus-preceding negativity (SPN) were all coded collectively as 5. The moderation analysis was significant ($F[1, 2] = 5.96\times10^{14}$, $p < .001$), suggesting that specific ERP contributed to the heterogeneity in effect sizes. Individual estimates did not find evidence that any other specific ERP differed from the LDAEP effect ($b = 0.331$, $p = .002$), suggesting that specific ERP contributes to significant heterogeneity in effect sizes, but that no other ERPs have a significantly different relation with SI than the LDAEP.

Moderation of SI by Scoring Method

We tested whether the ERP scoring method contributed to the heterogeneity in effect sizes observed in our meta-analysis. In the end, we only had three different scoring methods: (1) raw, (2) difference score, and (3) slope procedure used to score the LDAEP. Thus, we coded raw = 0, and difference score and slope procedure as 1. The moderation analysis was not statistically significant ($F[1, 6] = 0.07$, $p = .798$). Thus, we did not find evidence that ERP scoring method contributed to the heterogeneity observed in our effect sizes.

Moderation of SI by Sample Age

Our analysis examining age as a moderator did not find evidence of age as a significant contributor to the heterogeneity in our effect sizes for SI ($F[1, 5] = 2.67$, $p = .163$).

Overall SA Results and Publication Bias

After excluding three outlier effect sizes, our SA meta-analysis consisted of 12 studies with 49 effect sizes ($M = 4.08$ effect sizes per study). The difference in ERPs between those with a previous suicide attempt and those without a previous suicide attempt was significant, with an average weighted Hedges' $g = 0.40$ (95% CI [0.26, 0.54]). Our model did not find evidence of significant heterogeneity in effect sizes ($Q[45] = 42.93$, $p = .560$, $I^2 = 19.91\%$). For a forest plot

of our suicide attempt results, see Figure 4. Regarding publication bias, visual inspection of the funnel plot (see Figure 5) suggested small-sample publication bias, with smaller samples consistently having larger effect sizes than the pooled effect size. We tested this observation by examining sample size as a moderator. The analysis was not statistically significant ($F[1, 10] = 3.22$, $p = .103$). Therefore, we did not find clear evidence that sample size contributed to differences in effect size estimates.

Moderation of SA by Specific ERP

For this analysis, ERPs were coded similarly as it was in the corresponding analysis with SI. For this analysis, the moderation analysis was significant ($F[4, 7] = 31.90$, $p < .001$), suggesting that specific ERPs contributed to the heterogeneity in effect sizes of SA. Individual estimates suggested that the LPP ($b = -0.268$, $p = .029$) and RewP ($b = -0.321$, $p = .014$) each had significantly smaller effect size estimates than the LDAEP ($b = 0.560$, $p < .001$).

Moderation of SA by Scoring Method

Our analysis did not find evidence that ERP scoring method contributed to the heterogeneity in effect sizes ($F[1, 9] = 0.70$, $p = 0.424$).

Moderation of SA by Sample Age

Our analysis examining whether age moderated the relation between ERPs and SA was statistically significant ($F[1, 6] = 26.11$, $p = .002$), suggesting that the relation between ERPs and SA is smaller in older samples compared to younger samples ($b = -0.019$, $p = .002$; see Figure 6).

Overall Suicide Risk Results and Publication Bias

We did not find any outliers for our suicide risk meta-analysis, resulting in six studies with 38 effect sizes ($M = 6.33$ effect sizes per study). The difference in ERPs between those with higher suicide risk/suicidality and those with lower suicide risk/suicidality was significant, with

an average weighted Hedges' g = 0.33 (95% CI [0.18, 0.48]). Our model did not find evidence of significant heterogeneity in effect sizes (Q[37] = 20.93, p = .385, I^2 = 12.27%). For a forest plot of our suicidality results, see Figure 7. Visual inspection of the funnel plot (see Figure 8) suggested small-sample publication bias, with smaller samples consistently having larger effect sizes than the pooled effect size. Results of the analysis examining study sample size as a moderator was not statistically significant (F[1, 4] = 0.26, p = .636); therefore, we did not find evidence that sample size contributed to differences in effect size estimate in this meta-analysis.

Moderation of Suicide Risk by Specific ERP

For this analysis, the moderation analysis was significant (F[3, 2] = 47.97, p = .021), suggesting that measuring different ERPs contributed to the heterogeneity in effect sizes of suicide risk. However, no individual estimates were statistically significant, suggesting that no other ERP's effect sizes significantly differed from the average effect size of the LDAEP.

Moderation of Suicide Risk by Scoring Method

Our analysis did not find evidence that ERP scoring method contributed to the heterogeneity in effect sizes (F[1, 4] = 2.22, p = 0.210).

Moderation of Suicide Risk by Sample Age

Our analysis examining whether age moderated the relation between ERPs and suicide risk was not statistically significant (F[1, 4] = 8.82, p = .059); therefore, we did not find evidence that the relation between ERPs and suicide risk differs as a function of the study sample age.

Sensitivity Analyses

SI Sensitivity Analyses

In our SI meta-analysis without outlier exclusion, the pooled effect size increased slightly to Hedges' g = 0.28 (95% CI [0.14, 0.41]). In our SI meta-analysis excluding effect sizes from

unpublished studies, the pooled effect size estimate increased slightly to Hedges' g = 0.30 (95% CI [0.13, 0.47]).

SA Sensitivity Analyses

In our SA meta-analysis without outlier exclusion, the pooled effect size increased significantly to Hedges' g = 0.53 (95% CI [0.32, 0.75]), which is nearly outside the 95% CI of our meta-analysis that excluded these outliers. Excluding these outliers but only using published studies also resulted in a larger pooled effect size of Hedges' g = 0.45 (95% CI [0.28, 0.62]).

Suicide Risk Sensitivity Analysis

Because we did not find any outliers for the suicide risk variable, we did not conduct a sensitivity analysis reintroducing outliers. A meta-analysis analysis using only published studies resulted in a much larger pooled effect size of g = 0.42 (95% CI [0.21, 0.63]).

Discussion

Scientists have proposed that suicidal thoughts and behaviors (STBs) are at least in part the result of differences in neural architecture and functioning (Mann, 2003; Van Heeringen & Mann, 2014). Evidence from fMRI studies has led to divergent conclusions, with some papers concluding that there are neural differences between those with and without STBs, and others suggesting that there is not enough evidence to conclude that there are differences in neural functioning between individuals with and without STBs (Huang, Rootes-Murdy, et al., 2020; Schmaal et al., 2019). Event-related potentials (ERPs) offer an alternative approach to quantifying neural functioning in those with STBs that is more cost-effective, provides excellent temporal resolution, and directly measures neurophysiological processes. However, the effectiveness of ERPs at differentiating individuals with versus without STBs was unknown.

The current meta-analysis revealed a significant small-to-moderate relationship between ERPs and STBs. On average, those with STBs exhibit differences in neural functioning that can be measured using ERPs. Though these effects were significant, the potential clinical utility of ERPs to predict SI or SA is unknown. In our review of the ERP and STB literature, we found no longitudinal studies examining the ability of ERPs to predict changes in STBs. Moreover, in light of recent meta-analyses and the size of the cross-sectional effects in our study, it is unlikely that ERPs used in isolation can provide enough clinically meaningful information to predict STBs (Franklin et al., 2017). However, ERPs may provide useful and, importantly, unique information that can increase the predictive value of machine-learning algorithms (Gibb & Tsypes, 2019). This concept is supported by work that has shown that adding self-report measures to administrative data can increase prediction accuracy of perpetrating violence or being a victim of violence among United States Army personnel (Bernecker et al., 2018). Moreover, ERPs may be used in conjunction with other measures to improve the predictive ability of linear models (Hajcak et al., 2019). For example, combining ERPs and self-report measures has been used successfully to predict the development of depression and anxiety (Meyer et al., 2018; Nelson et al., 2016).

This meta-analysis also sought to examine whether specific ERPs had stronger effects for different STBs. For SI and suicide risk, we found no evidence that any specific ERP was significantly better at differentiating those with versus without SI or differentiating those with or without suicide risk. However, we found that the late positive potential (LPP) and the reward positivity (RewP) are both significantly *weaker* than the loudness dependence of auditory evoked potentials (LDAEP) in differentiating between those with versus without previous SAs. Because our suicide-risk meta-analysis may have been driven by differences in SI, our results may

suggest that differences in severity of SI can be due to disruptions in neural systems. This suggestion aligns with recent work suggesting that the number of paths leading to SI is indeterminate (Huang, Ribeiro, et al., 2020; Ribeiro et al., 2019). Another possibility is that what has been termed the general factor of psychopathology, or *p* factor, is driving this lack of differences (Caspi et al., 2014; Lahey et al., 2012). Specifically, in addition to more specific factors such as internalizing and externalizing factors, the *p* factor may cause disruptions across neural systems, thereby increasing risk for SI and causing differences across various ERPs. For now, though, these ideas are speculative and point toward potential future studies.

Regarding our SA results, we see at least two possibilities accounting for the LPP and RewP having smaller effect sizes. First, the LPP and RewP may be better at detecting other STB constructs, such as SI, than at detecting SA. This possibility is underscored by work showing that the LPP and the RewP independently relate to depression (Klawohn et al., 2020), and research has shown that accounting for depression reduces SI's integrity as a construct (Rogers et al., 2016). Therefore, the LPP and RewP may better relate to depression/SI. Another possibility is that smaller effect sizes were driven by larger samples and unpublished work that used the LPP and RewP. For example, the mean sample size of studies in our SA analyses that used the LPP was 235, compared to a mean sample size of 38.9 for the LDAEP. Thus, these lower effect sizes for the LPP and RewP may reflect greater accuracy in detecting the true effect of the relation between the ERP and SA, whereas other ERP's effect sizes may be inflated due to small-sample publication bias.

We also found that the mean age of the sample moderated the relation between ERPs and SA history, such that older samples corresponded with smaller effect sizes. One explanation for this result is that large differences in neural functioning early in life are markers of particularly

high risk for suicide. Over time, these differences may diminish as those with the largest neural differences die by suicide, restricting the range of ERPs in older samples with STBs[1]. However, given that death by suicide is relatively rare, this effect, if it exists, may be relatively small. Another possibility is that being younger generally serves as a protective factor that can only be overridden by large perturbations in neural functioning, leading to increased risk for SAs. Indeed, while suicide rates see a large increase in late childhood and early adolescence, even very young children can exhibit STBs (CDC, 2017; Rosenthal & Rosenthal, 1984).

Though we found significant differences in ERPs between various STB groups, these results should be interpreted within the context of possible small-sample publication bias across STB outcomes. Specifically, all three funnel plots (i.e., for suicide risk/suicidality, SI, and SA) suggested that smaller studies had inflated effect sizes and that many nonsignificant effect sizes might be missing from the published literature. In our SI meta-analysis, we also found that study sample size moderated the relation between ERPs and SI, such that studies with larger samples had significantly smaller effect size estimates compared to studies with smaller samples (see Figure 3). Though we did not find this significant moderation in our SA and suicidality meta-analyses, we may have been underpowered to detect moderation effects in these meta-analyses.

Future of the Study of STBs Using ERPs

The results of our meta-analysis show that ERPs have promise in aiding our understanding of the neural functioning of those with STBs. ERPs are relatively cheap to collect and can be used in myriad settings, increasing the possibility of measuring ERPs in more ecologically valid settings (Shamay-Tsoory & Mendelsohn, 2019). Capitalizing on the strengths

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[1] The authors thank Keanan Joyner for making us aware of this possibility.

of ERPs can complement the spatial resolution of fMRI to give a fuller picture of the neural functioning of those with STBs. However, as with the fMRI literature, where a meta-analysis found a median sample size of 45 (Huang, Rootes-Murdy, et al., 2020), most studies using ERPs to investigate STBs suffer from small sample sizes. In our review, the mean sample size across studies was 72.95 (*SD* = 63.36), with most studies across the different STB categories having fewer than 60 participants (see Figure 9). Low statistical power increases the frequency of both false negatives and false positives, which limits the replicability of studies of STBs (Button et al., 2013). There are likely many factors contributing to low statistical power in the neuroimaging and ERP literature, including institutional incentives (Smaldino & McElreath, 2016), the high financial cost to conduct neuroimaging studies, and the relatively low base-rate of STBs (Fazel & Runeson, 2020). To address low statistical power, consortia have been developed to construct large neuroimaging datasets (e.g., Thompson et al., 2014). A similar consortium using ERPs, as well as greater collaboration in general, would substantially move the field forward in understanding the neurobiology of STBs.

Conclusions

Our results indicate that event-related potentials (ERPs) have a small-to-moderate relationship with suicidal thoughts and behaviors (STBs), such that ERPs generally reveal differences between those with versus without suicidal thoughts, previous suicide attempts, and suicide risk/suicidality. These findings suggest that ERPs can complement neuroimaging in studies of the neurobiology of STBs. Our review revealed that all research to date has examined the relation between ERPs and STBs cross-sectionally, with no attempts at prediction (e.g., longitudinal studies were absent from the available literature). Therefore, it remains to be seen whether ERPs can be used in conjunction with other measures to create suicide risk algorithms

that can more accurately predict STBs, including suicidal ideation (SI) and suicide attempts (SA). For suicidal ideation and suicide risk/suicidality, we did not find that any single ERP had a significantly stronger relationship with SI or with suicide risk/suicidality than other ERPs. Therefore, future research may consider using multiple ERPs, or use ERPs with other measures, to predict STBs. Moreover, we found that the late positive potential (an index of the neural response to emotional salience) and the reward positivity (an ERP that measures response to rewards) each had a significantly smaller relationship with suicide attempt status than other ERPs, suggesting an important area for future research. Our results suggest that the extant literature examining ERPs and STBs may be suffering from small-sample publication bias, with smaller samples having much larger effect sizes. We also found that the modal study on ERPs and STBs is likely underpowered to estimate the expected effect size. Thus, future researchers should consider collaborating to obtain larger, more representative samples in order to better detect effects and elucidate the neurobiology of STBs using ERPs.

*References marked by * indicate studies included in meta-analysis before outliers removed.*

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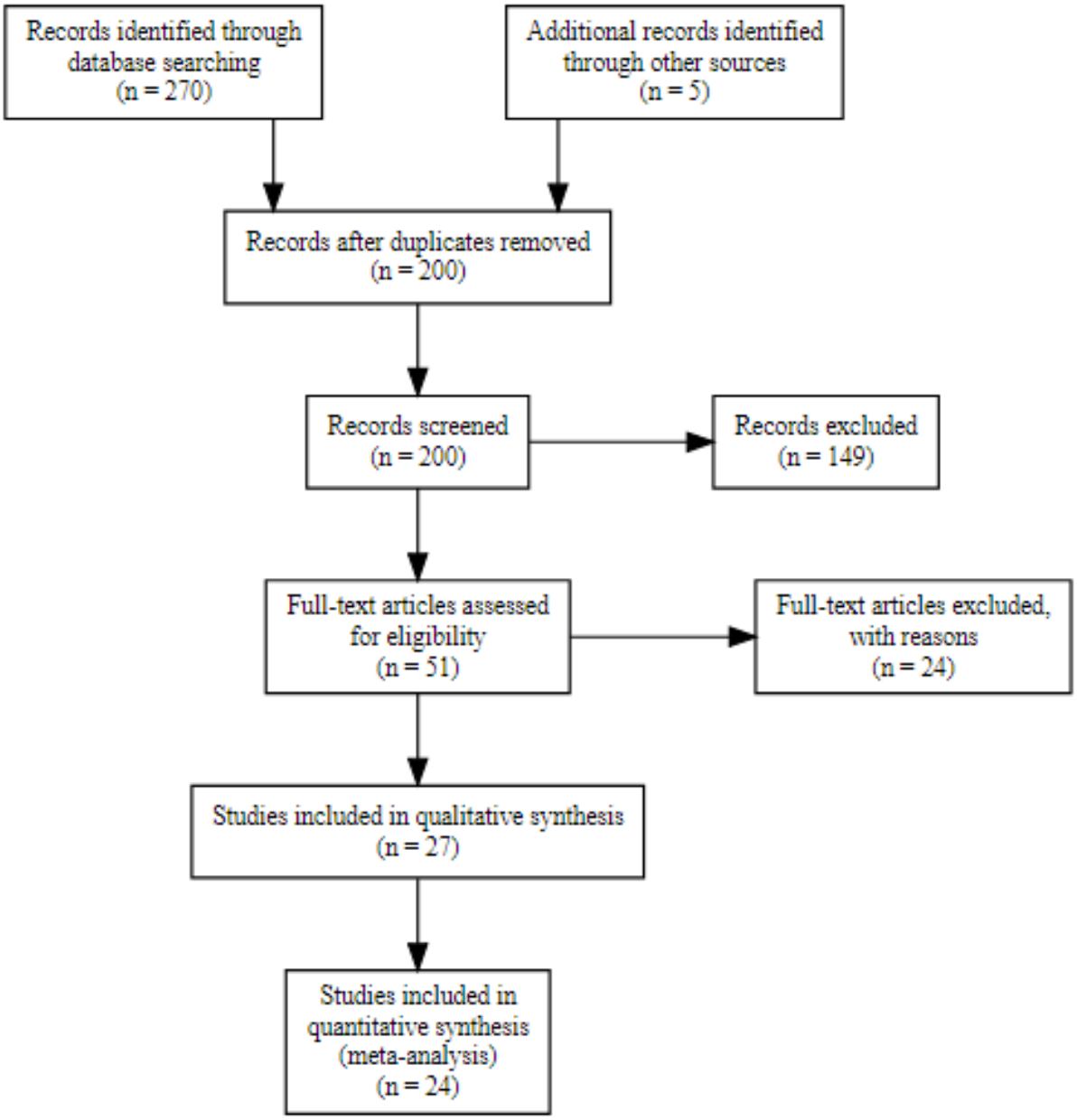

Figure 1. PRISMA diagram for the selection of studies for the present meta-analysis.

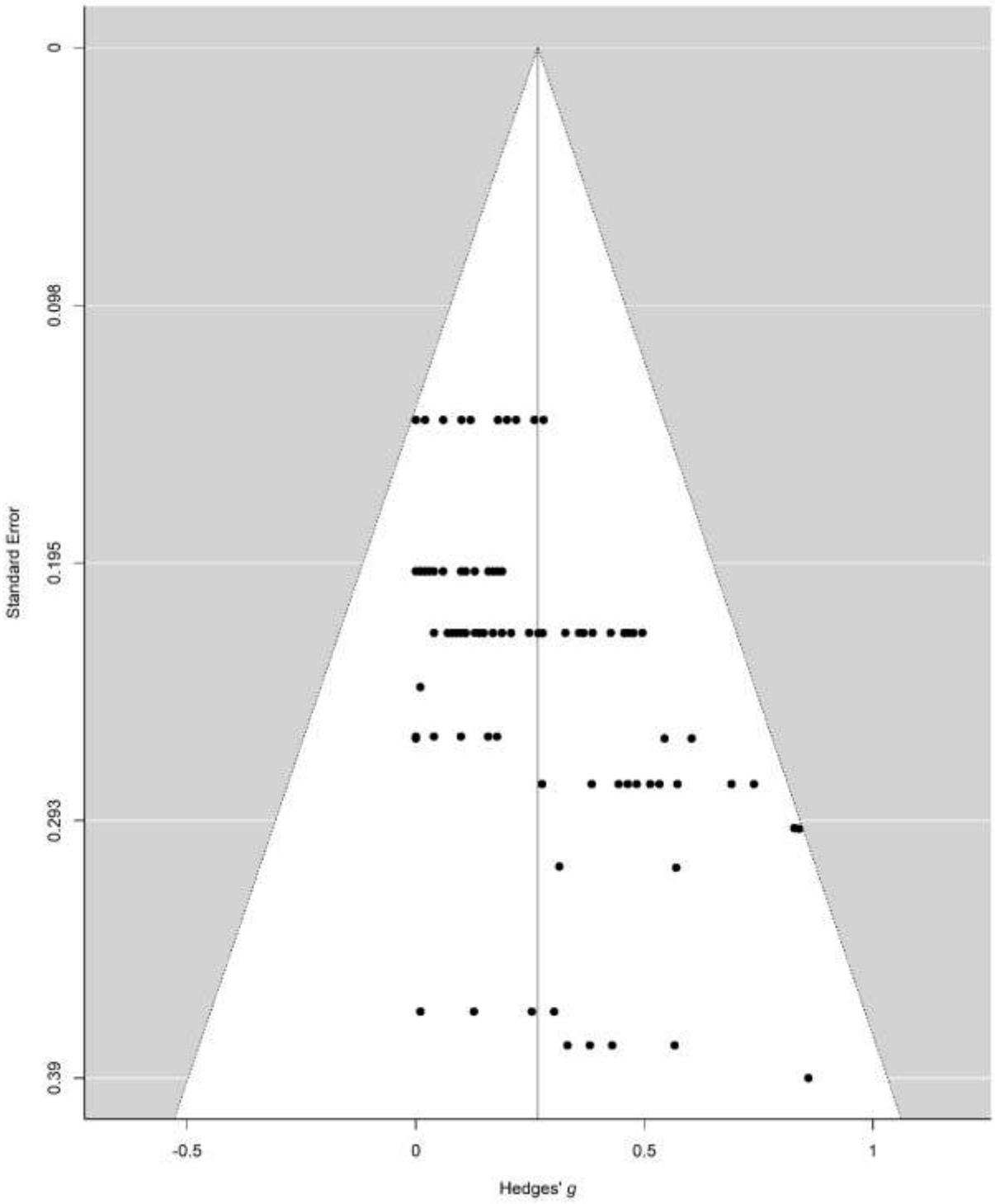

Figure 2. Funnel plot for the suicidal ideation (SI) meta-analysis.

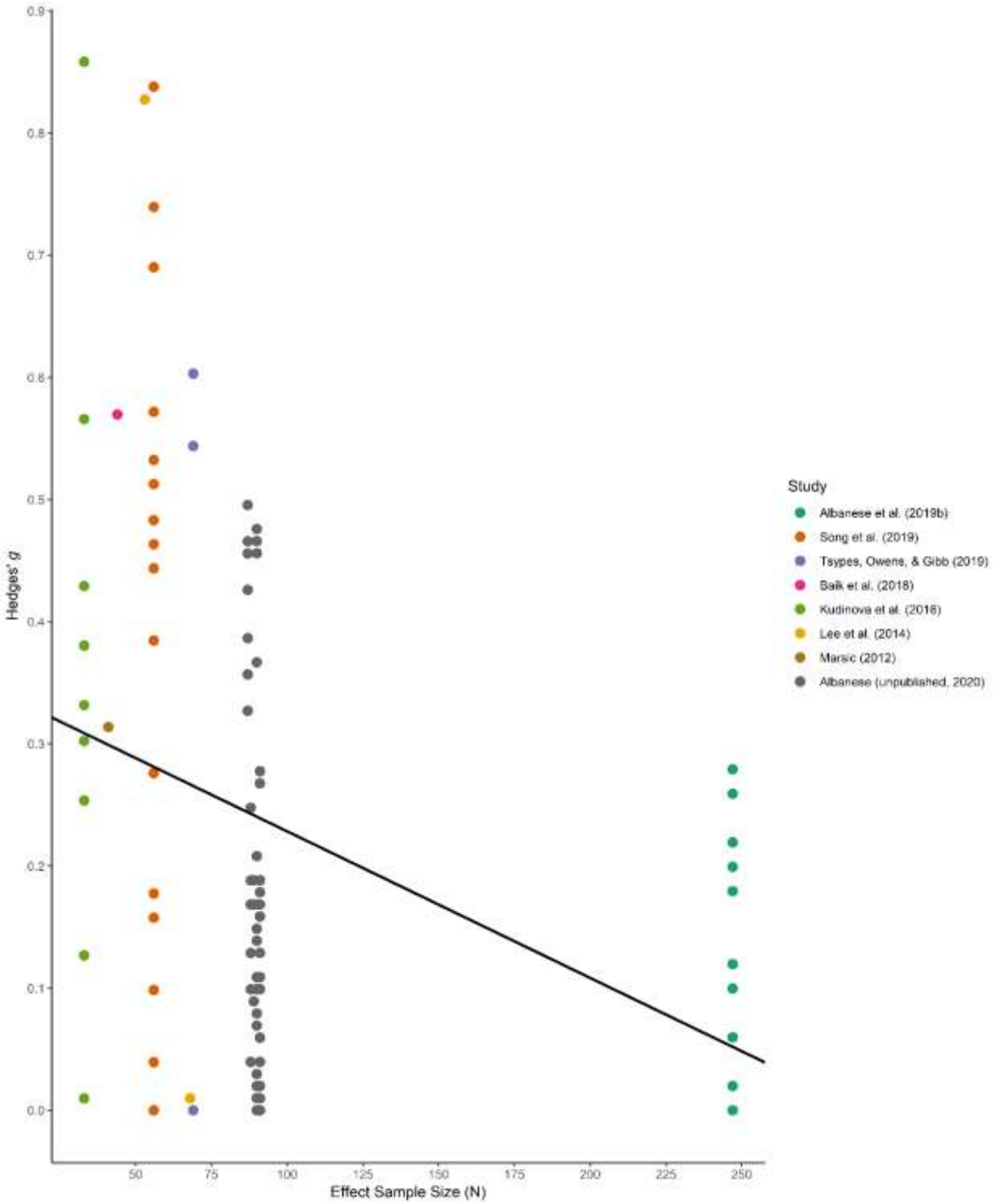

Figure 3. Scatterplot illustrating moderation of average suicidal ideation (SI) effect size by effect sample size.

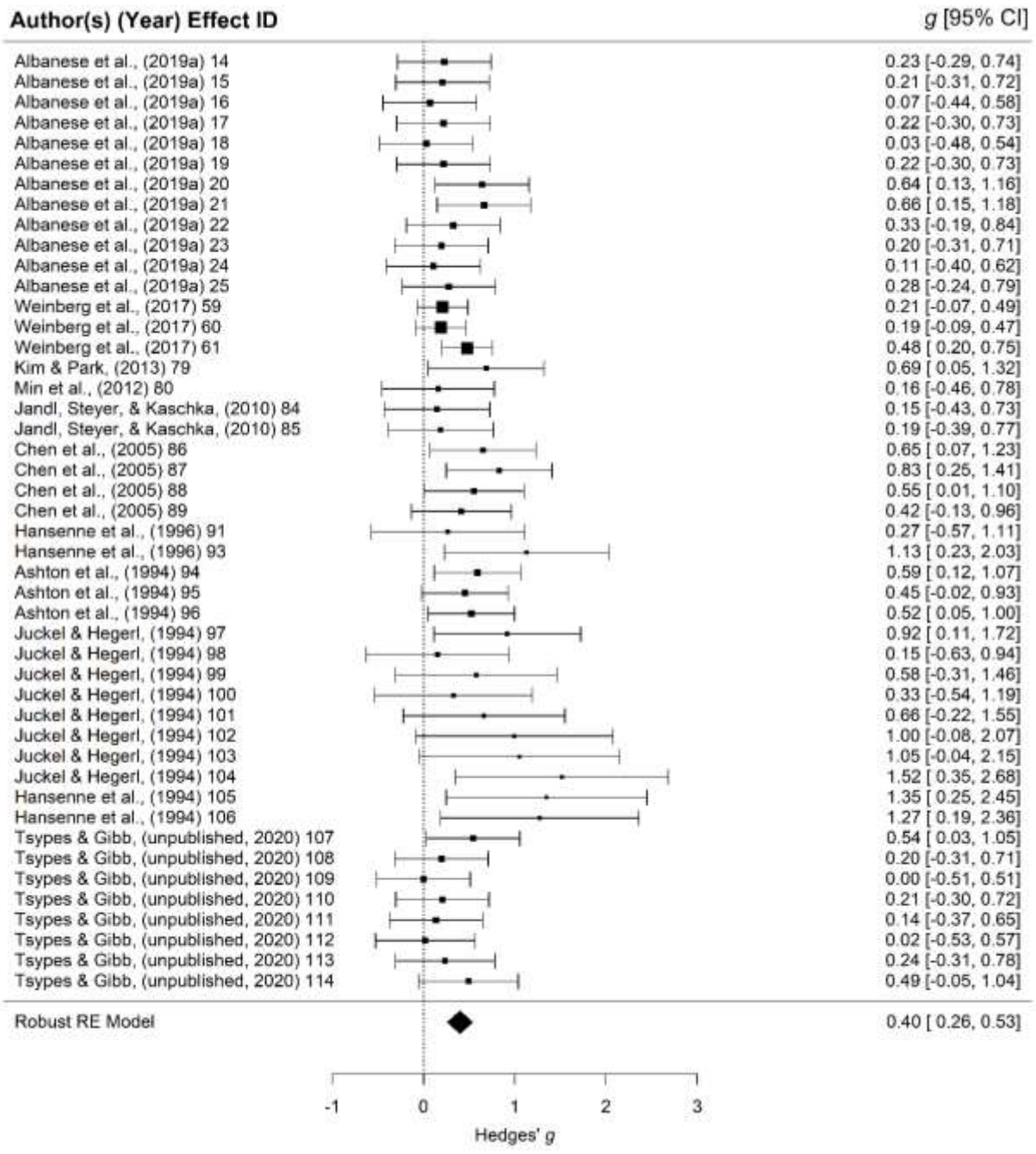

Figure 4. Average difference (Hedges' *g*) in event-related potentials (ERPs) between those with and those without a previous suicide attempt.

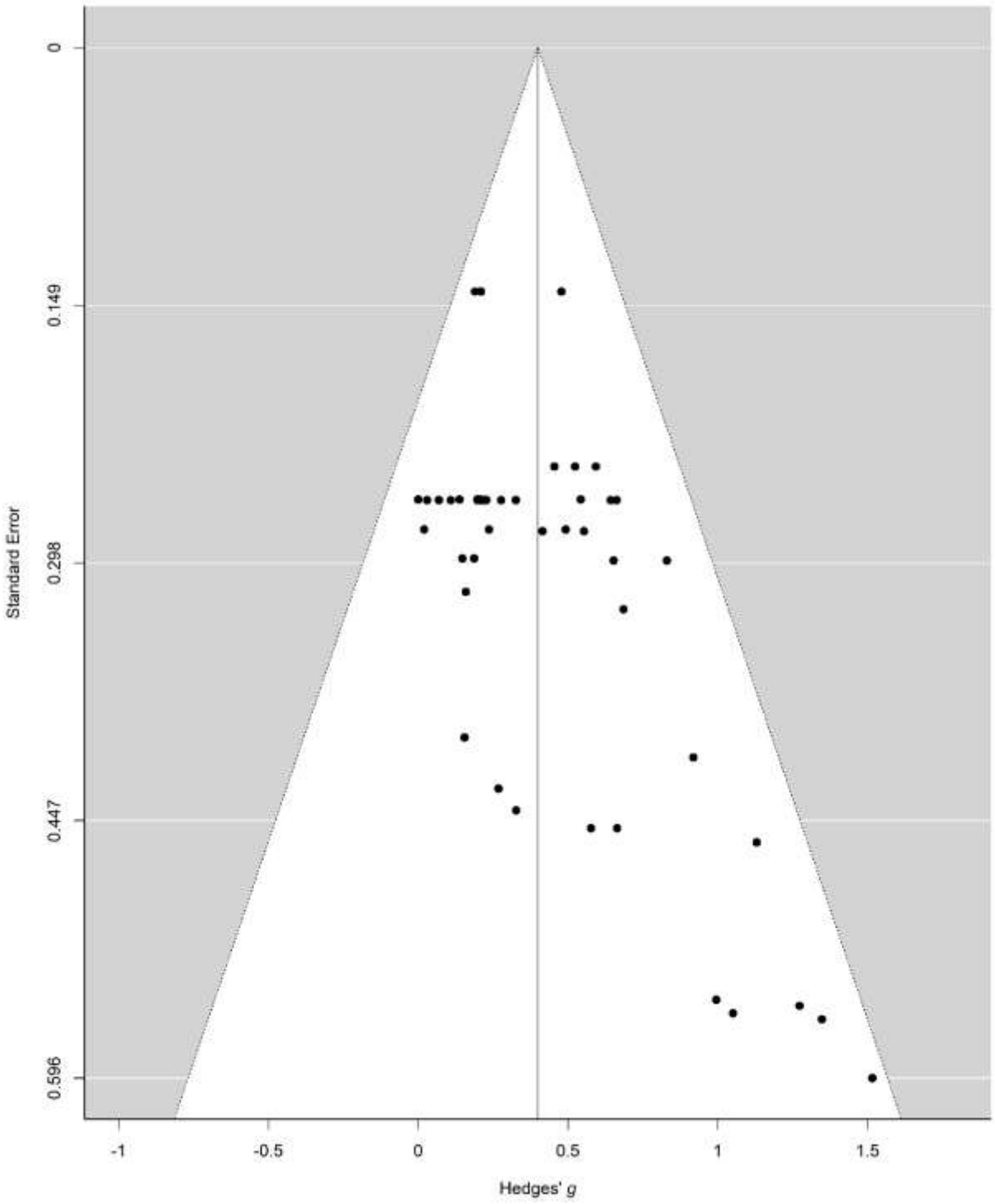

Figure 5. Funnel plot for the suicide attempt meta-analysis.

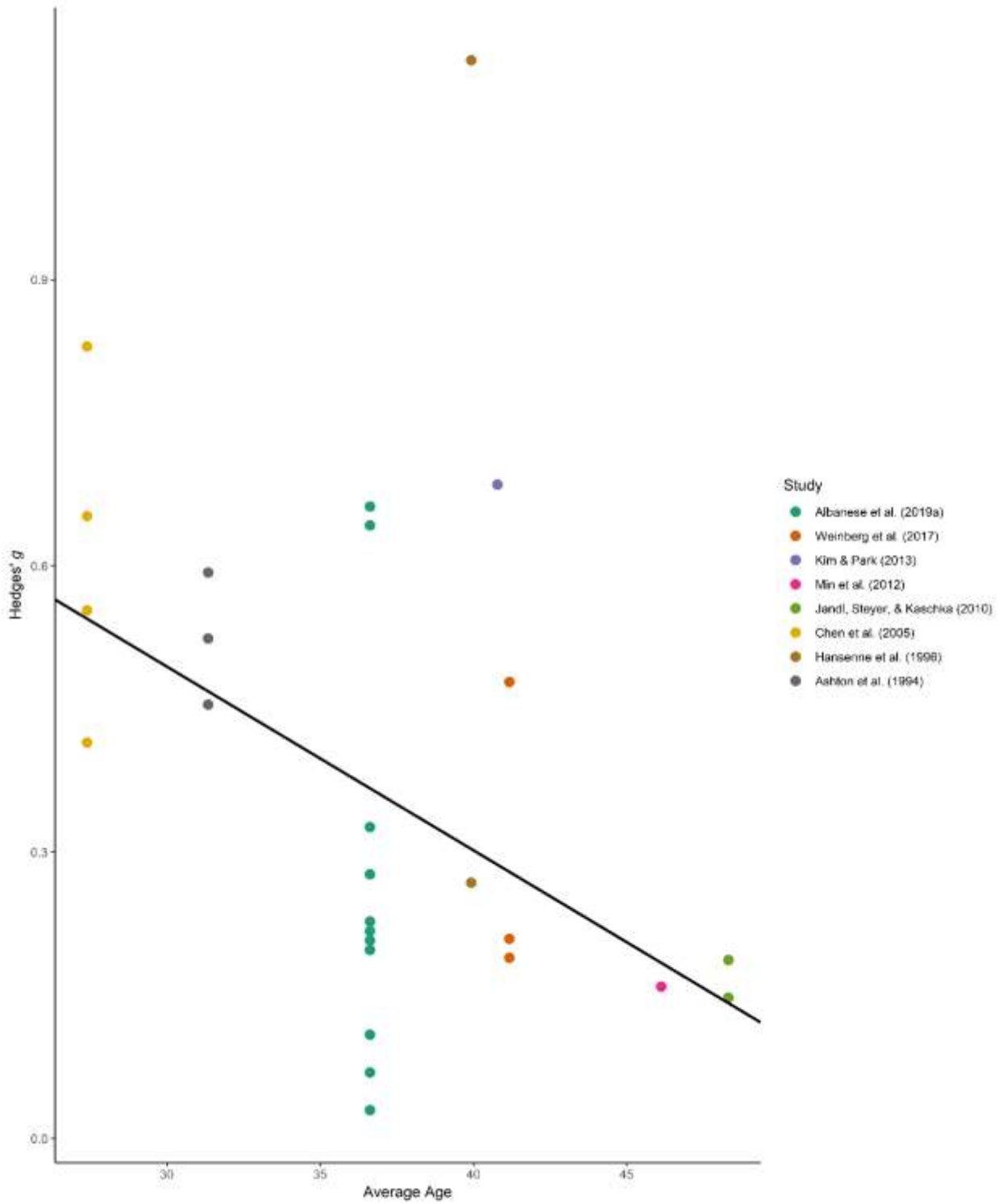

Figure 6. Scatterplot illustrating moderation of average suicide attempt (SA) effect size by effect sample age.

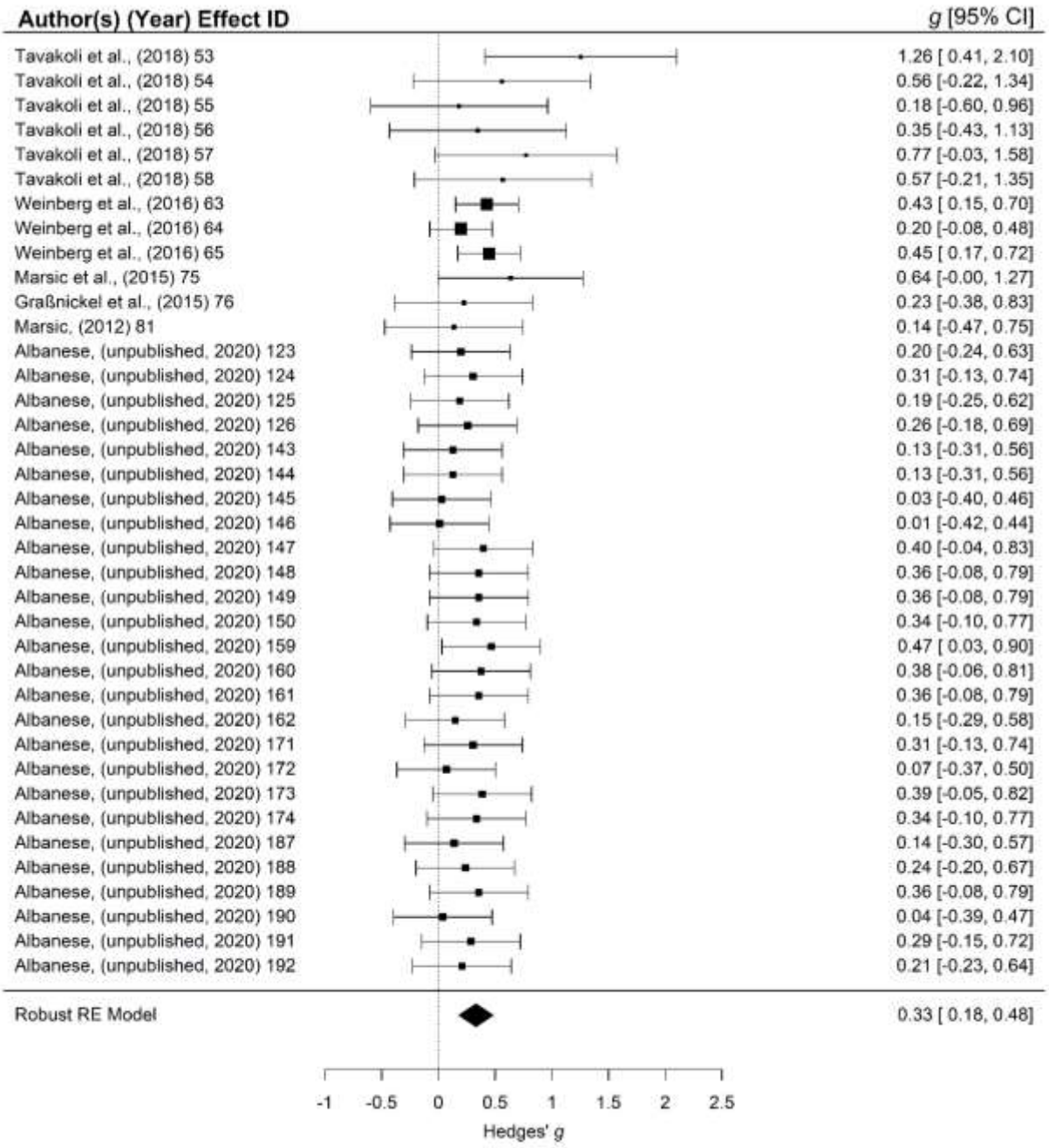

Figure 7. Average weighted absolute difference Hedges' *g* in event-related potentials (ERPs) between those at lower risk for suicide and those at higher risk for suicide.

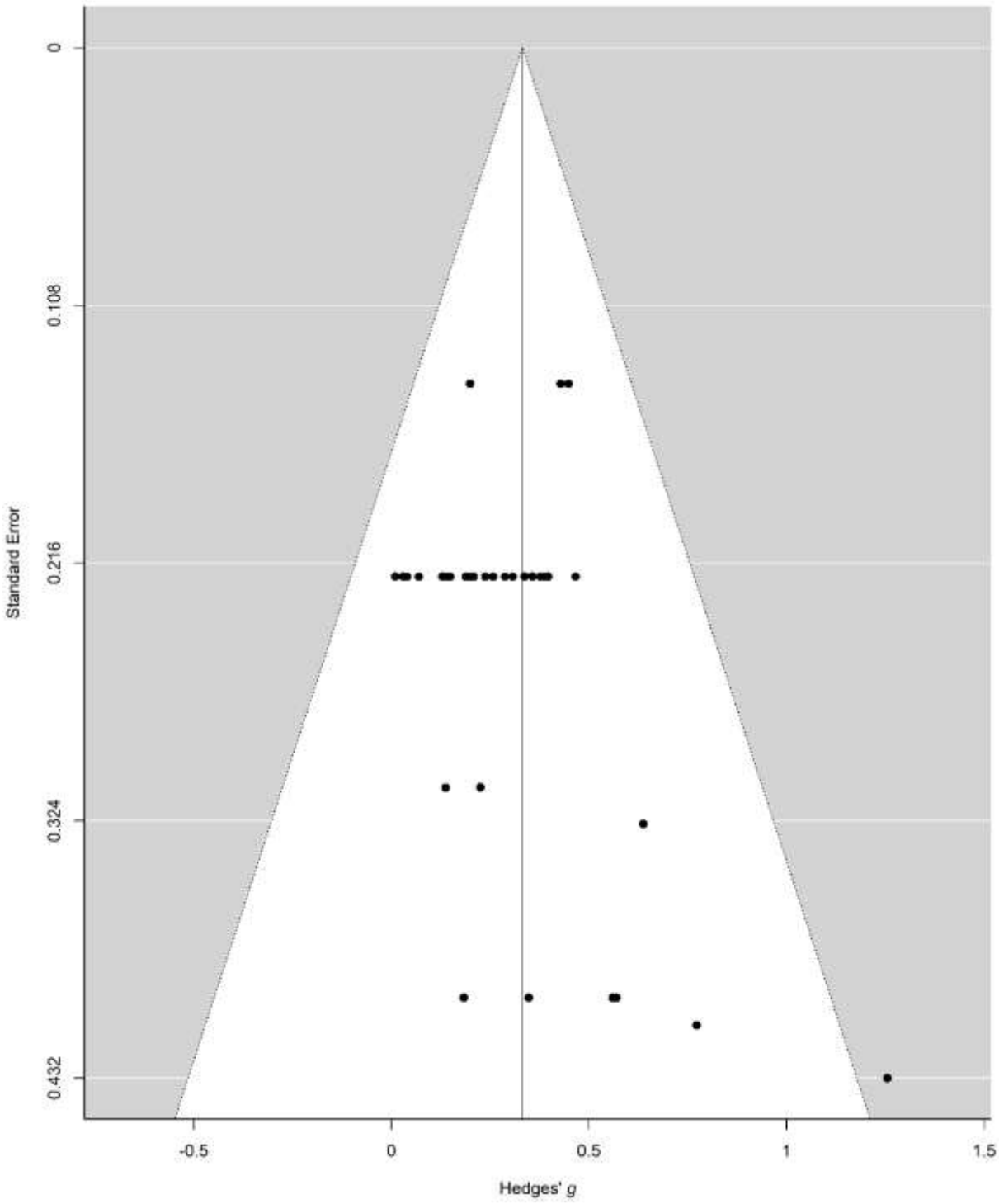

Figure 8. Funnel plot for the suicide risk/suicidality meta-analysis.

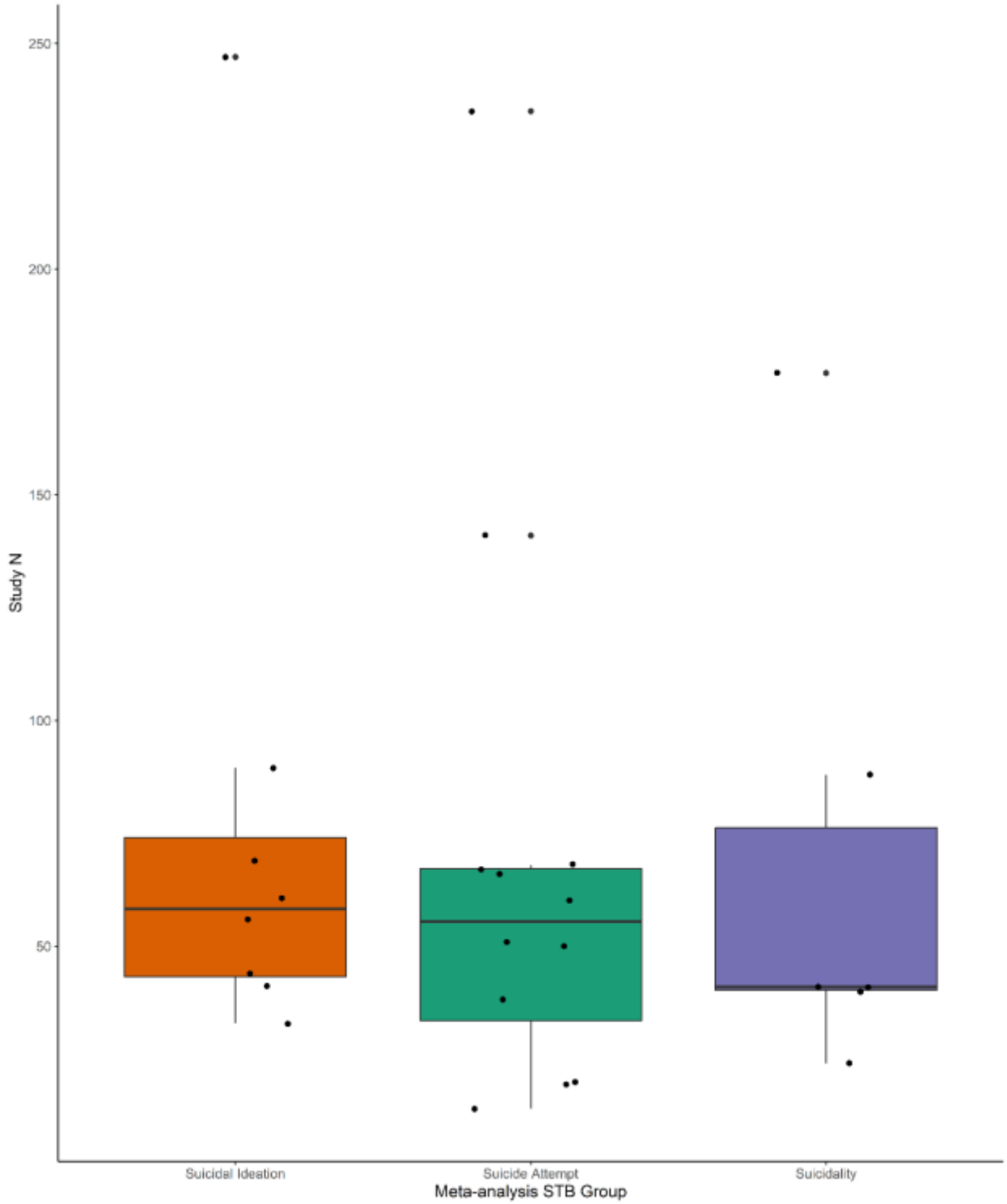

Figure 9. Distribution of study sample sizes across the three suicidal groups in the present study.