Individual differences do not mask effects of unconscious processing

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Author note

All data except for the datasets from Machado et al., 2007, 2009, for which participants did not consent to having their data shared online, and all analysis code are available at https://github.com/mufcItay/NDT. This study's analysis was not pre-registered.

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Abstract

A wave of criticisms and replication failures is currently challenging claims about the scope of unconscious perception and cognition. Such failures to find unconscious processing effects at the population level may reflect the absence of individual-level effects, or alternatively, the averaging out of individual-level effects with opposing signs. Importantly, only the first suggests that consciousness may be necessary for the tested process to take place. To arbitrate between these two possibilities, we tested previously collected data where unconscious processing effects were not found (26 effects from 470 participants), using four frequentist and Bayesian tests that are robust to individual differences in effect signs. By and large, we found no reliable evidence for unconscious effects being masked by individual differences. In contrast, when we examined 135 non-significant effects from other domains, a novel non-parametric sign consistency test did reveal effects that were hidden by opposing individual results, though as we show, some of them might be driven by design-related factors. Taken together, four analysis approaches provide strong evidence for the restricted nature of unconscious processing effects not only across participants, but also across different trials within individuals. We provide analysis code and best-practice recommendations for testing for non-directional effects.

Keywords: unconscious processing; individual differences; consciousness

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Introduction

Our brains simultaneously perform complex information processing functions and yet, at any given moment in time, only a small subset of these functions is accompanied by conscious experience. This raises the question: which brain functions depend on consciousness, and which functions can take place without it?

One approach to investigating the scope and limits of unconscious processing is to measure the effect of different stimulus features on behaviour, while making sure that the stimulus itself is not consciously perceived (for review, see Kouider and Dehaene, 2007; Reingold and Merikle, 1988). If a stimulus feature affects behaviour even when the participant is not aware of the stimulus, being conscious of the stimulus cannot be necessary for processing that feature.

For example, Vorberg and colleagues (2003) studied the role of consciousness in motor preparation. In a series of experiments, they presented an arrow stimulus (henceforth, the prime) which was followed by an arrow-shaped metacontrast target stimulus, rendering it invisible (Breitmeyer and Ganz, 1976; see Figure 1A). Unconscious motor preparation priming was demonstrated by showing that participants responded faster to the target stimulus when its direction was congruent with the direction of the prime. This suggests that the direction of the prime has been represented unconsciously, triggering a motor plan. In similar studies, participants were reported to unconsciously perform high-level functions such as arithmetic operations (Sklar et al., 2012), extract and integrate word meanings (Damian, 2001; Sklar et al., 2012; Van Gaal et al., 2014), or scenes and objects (Mudrik et al., 2011), detect errors (Charles et al., 2013), and exert inhibition over responses (Van Gaal et al., 2008) to stimuli that were masked from awareness. Findings of high-level processing in the absence of consciousness served to inform and reform theories of consciousness (Dehaene & Naccache, 2001; Lamme, 2020; Lau & Rosenthal, 2011; Oizumi et al., 2014).

However, more recent work has called into question some of these previous findings and their interpretations. First, many of the original results do not replicate when tested in independent samples of participants (using direct replications, e.g., Biderman and Mudrik, 2018; Moors and Hesselmann, 2019; Stein et al., 2020, or conceptual replications, e.g., Hesselmann et al., 2015; Hesselmann et al., 2016; Rabagliati et al., 2018). Second, some of these findings might be driven by residual consciousness in a subset of trials due to unreliable awareness measures (Meyen et al., 2022; Moors & Hesselmann, 2018; Rothkirch & Hesselmann, 2017; Shanks, 2017; Zerweck et al., 2021). Indeed, when re-analyzed to properly control for this possibility, some of these effects disappear (Meyen et al., 2022; Shanks, 2017). As a result, the scientific pendulum seems to be receding back to a narrower account of unconscious processing, consistent with a functional role of consciousness in most aspects of cognition (Balota, 1986; Meyen et al., 2022; Moors et al., 2017; Peters et al., 2017).

Overall, the field is still far from reaching a consensus regarding the scope and limits of unconscious processing. Although progress has been made in recent years toward improving methodology in unconscious processing studies, revealing the functional role of consciousness in cognition and perception remains difficult. Here we consider a largely neglected limitation of unconscious processing studies: by focusing on the average of signed (i.e., directional) single-participant summary statistics (for example, subtraction of reaction times between two conditions), previous investigations require not only that unconscious processing should leave a trace on behaviour, but also that this trace should be qualitatively similar across different participants (i.e., that the experimental manipulation would affect most participants in the same direction). We note that though this second requirement is intuitive, it is orthogonal with the theoretical question at stake; our main concern is whether a given stimulus feature can affect behaviour in the absence of consciousness, yet this does not necessarily imply that it affects all participants in the same way. This way, previous analyses of unconscious processing may have been too *conservative,* potentially missing effects that happen to vary between different participants (for a similar argument regarding cognitive science in general see Ince et al., 2022).

On the face of it, pronounced individual differences in unconscious processing effects on cognition and perception seem possible, even likely. Indeed, previous investigations revealed heterogeneity in susceptibility to the attentional blink (Martens et al., 2006), in the effects of stimulus onset asynchrony (SOA) on metacontrast masking (Albrecht et al., 2010), the speed of breaking perceptual suppression (Sklar et al., 2021), both in the breaking continuous flash suppression paradigm (b-CFS; Jiang et al., 2007) and the breaking repeated mask suppression one (b-RMS; Abir & Hassin, 2020), and in the effects of visual imagery on conscious perception in a binocular rivalry setting (Dijkstra et al., 2019). Some qualitative differences have been linked to variability in processing speed (Martens et al., 2006), genetics (Maksimov et al., 2013), and brain anatomy and physiology (Boy, Evans, et al., 2010; Van Gaal et al., 2011). Critically, in other behavioural paradigms, unconscious stimuli had opposite effects on different participants. Bolger and colleagues (2019) showed that while most participants responded faster to upright faces in a b-CFS task, some responded faster to upside-down faces. Other findings from several different study groups have repeatedly revealed that masked priming effects changed in magnitude and even flipped in sign as a function of the interval between prime and target (Boy & Sumner, 2010; Boy & Sumner, 2014; Parkinson & Haggard, 2014; Schlaghecken & Eimer, 2004). Moreover, different hypotheses were laid out over the years regarding the driving mechanisms of the counter-intuitive 'negative' priming effects. Among others, response inhibition of initial prime activations (Boy, Husain, et al., 2010; Eimer & Schlaghecken, 2003), or neural habituation (Jacob et al., 2021) were suggested. Taken together, it is not clear if, and to what extent, unconscious effects are subject to meaningful individual variability. Crucially, if they are, then some previously reported null results might actually be true effects, masked by such variability.

The paper proceeds as follows. We first simulate a setting where a strong effect of unconscious processing on behaviour is entirely missed in standard analysis, due to pronounced inter-individual differences. We then show that the same effect is revealed when using three tests that are robust to population variability: the global null prevalence test (Donhauser et al., 2018), Bayesian hierarchical modelling (Haaf & Rouder, 2019), and a test based on analysis of variance (ANOVA; Miller & Schwarz, 2018). Importantly, unlike common measures of reliability which are used to directly estimate individual differences (see Parsons et al., 2019), the above tests do not quantify individual differences, but *measure group effects in a way that is robust to such differences*. Hence, they provide researchers with the appropriate tools for detecting unconscious effects even if pronounced individual differences exist, without depending on that being the case.

We then apply these tests to data gathered from eight unconscious processing studies (reporting 26 non-significant effects), and show that the same three tests support the null hypothesis according to which the behaviour of individual participants is unaffected by unconscious cognition and perception. This strengthens claims for a true absence of an effect in these studies. Finally, we propose a non-parametric alternative that provides improved sensitivity and specificity, avoiding potentially unjustified statistical assumptions regarding the data-generating process. Our test successfully reveals effects on multisensory integration, visual search, and confidence ratings that could not be detected using standard directional analysis. However, similar to the three other approaches, it reveals no effects when applied to the studies of unconscious processing examined here. We conclude that existing data are most consistent with the absence of influences of unconscious stimuli on cognition and perception, not only at the population, but also at the single-participant level.

Simulating non-directional unconscious effects

To provide a conceptual demonstration of how true causal effects of unconscious processing can be masked by inter-individual differences in effect signs, we simulated a typical experiment using a within-participants manipulation (Figure 1). Specifically, we generated trial-by-trial data from a standard unconscious priming experiment. For each simulated participant, we generated reaction time data from two conditions (corresponding to congruent and incongruent primes in unconscious processing studies). Individual-level effect sizes (in milliseconds) were sampled from a normal distribution centred at zero ($e_i \sim \mathcal{N}(0, \sigma_b)$, where e_i denotes the true effect size of the i^{th} participant and σ_b the between-participant standard deviation. Then, the trial-by-trial reaction times (RTs) of each participant and condition were generated according to each participant's true effect score (e_i), the relevant condition ($c \in \{1,0\}$, where $c = 1$ denotes the incongruent condition, and $c = 0$ denotes the congruent condition), and the within-participant standard deviation (σ_w) ($RT_{i,c} \sim \mathcal{N}(0, \sigma_w) + c * e_i$).[1]

[1] Similar results were obtained with more realistic Wald RT distributions as detailed in Appendix A.

In two simulations, we manipulated two factors: the between-participant standard deviation (SD) over effect sizes (σ_b), and the within-participant SD over RTs within each condition (σ_w). This resulted in two distinct scenarios under this framework: (1) a *qualitative* or *non-directional differences* scenario, where all individuals show an effect, but individual-level effects largely vary in magnitude and sign (σ_b=15, σ_w=30; Figure 1B)), and (2) a *global null* scenario (Allefeld et al., 2016; Nichols et al., 2005), where no single participant is affected by the experimental manipulation (σ_b=0, σ_w= 100; Figure 1C). We simulated N_t=200 trials from N_p=15 participants per scenario, noting that the general principle holds for other sample sizes and number of trials.

First, we analyzed this simulated data using a two-sided paired t-test on the differences in mean RTs between the two conditions. This is the standard protocol for testing if unconscious processing took place. In both simulations, we obtained a null result, revealing no evidence for a difference in RT between the congruent and incongruent conditions (*non-directional differences*: $M = 5.52$, 95% CI $[-5.49, 16.54]$, $t(14) = 1.08$, $p = .300$; *global null*: $M = -2.78$, 95% CI $[-12.09, 6.53]$, $t(14) = -0.64$, $p = .532$). Importantly, in the *non-directional differences* simulation, all participants were affected by the experimental manipulation (that is, their true effect sizes were different from zero). Thus, this commonly used approach systematically misses true causal effects of the experimental manipulation whenever they are inconsistent between participants.

To reiterate, a standard t-test misses existing individual-level effects because, operating on individual-level summary statistics, it is oblivious to within-participant variability in the dependent variable. In recent years, researchers sought to address this limitation, advocating for the use of statistical methods that incorporate both within and between-participant variability.

Specifically, three approaches were proposed. First, the *prevalence global null* approach (Donhauser et al., 2018; henceforth GNT) tests if the prevalence of individual-level effects in a given population (the proportion of individuals showing an effect) is greater than zero. The prevalence approach relies on a two stages procedure. In the first stage, effects are tested at the individual level using a standard hypothesis-testing approach. In the second stage, the proportion of observed individual-level effects is tested against the alpha level, or type-1 error rate, using a binomial test. A significantly higher prevalence means the *global null* hypothesis, according to which no individual shows a true effect, can be rejected. Second, the *qualitative individual differences* approach (Rouder and Haaf, 2020; Rouder and Haaf, 2021; Haaf and Rouder, 2019; henceforth QUID) quantifies the relative support for the presence of "qualitative differences" in effects, that is, inter-individual differences in effect signs, by performing a Bayesian model comparison over a family of hierarchical models with different constraints (Haaf & Rouder, 2019). Third, Miller & Schwarz (2018) introduce a parametric and frequentist test, based on ANOVA. Specifically, their Omnibus ANOVA test (henceforth OANOVA) probes the joint null hypothesis that there are no systematic differences neither between experimental conditions across individuals, nor within individuals and across trials. Together, this is equivalent to the *global null* scenario we presented above.

We applied the tests to our simulated data. For QUID, we used the default priors from the original publication (Rouder & Haaf, 2021). For GNT and OANOVA, we used an α of 0.05 to examine individual-level and group-level effects. For QUID, we considered $BF > 3$ as evidence for an effect, $BF < \frac{1}{3}$ as evidence for no effect (*global null*), and values between these thresholds ($\frac{1}{3} \leq BF \leq 3$) as inconclusive (Jeffreys, 1998). Reassuringly, all tests were able to differentiate between the two simulated scenarios, providing very strong evidence for an effect in the *non-*

directional differences scenario, but not in the *global null* one. Specifically, According to GNT, the prevalence of effects on RT was clearly above zero in the *non-directional differences* simulation (using a two-sided t-test for the individual-level test; 80% of significant effects, one-sided CI_{95} = [56.02 100], p < .001), but this proportion was not higher than α in the *global null* simulation (6.67% of significant effects, one-sided CI_{95} = [0.34 100], p =.537). Using the QUID method, a random effects model with individual-level effects was overwhelmingly preferred in the *non-directional differences* simulation (BF= 9.27e+53), but a null model was preferred in the *global null* simulation (BF= 0.12). Similarly, the OANOVA test revealed significant results in the *non-directional differences* scenario (F(15, 2970) = 21.38, p < .001), and a non-significant effect in the *global null* simulation (F(15, 2970) = 1.30, p =.190).

The simulations above demonstrate that adopting a non-directional approach, that is, an approach that takes into account the potential for opposite true effect signs among different participants, has the potential to reveal individual-level effects that would otherwise be missed due to high between-participant variability. Equipped with these validated tools, in the next section we use the QUID, GNT, and OANOVA tests to ask whether null results in the field of unconscious processing are driven by such inter-individual variability, or alternatively, whether they reflect the true absence of a causal effect.

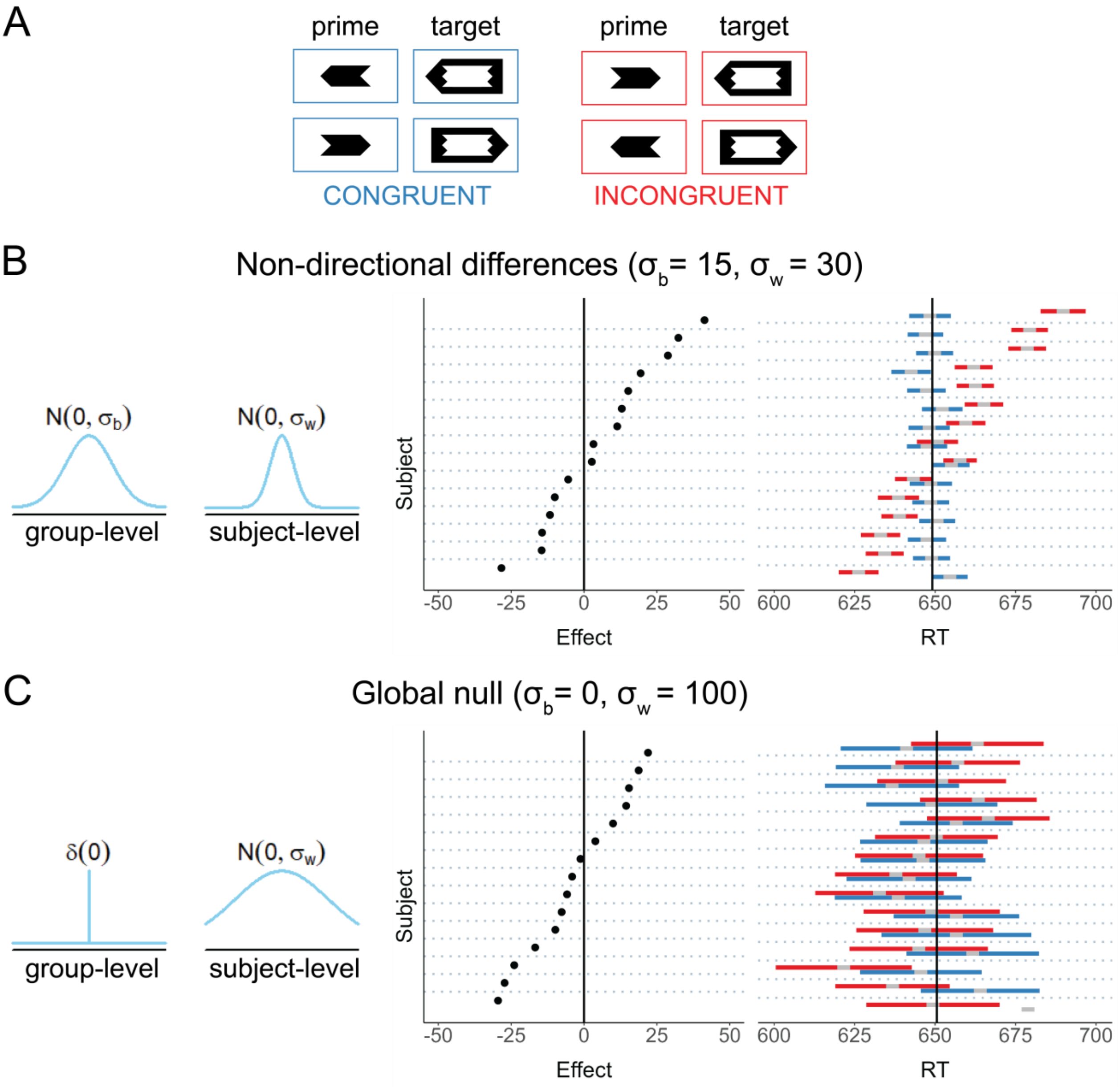

Figure 1. Simulated data demonstrating how true effects of unconscious priming can be masked by heterogeneity at the population level. Panel A: stimuli in a typical unconscious processing experiment (based on Vorberg and colleagues, 2003). Participants make speeded decisions about a consciously perceived target stimulus (for example, the direction of an arrow: right or left). The presentation of the target stimulus is preceded by a prime stimulus, which is masked from awareness. Decision time is measured as a function of prime-target agreement: congruent (blue) or incongruent (red). Panels B, C: Left: simulation parameters controlling the within (σ_w) and between (σ_b) participant SD. Right: the

results that were generated using the simulation parameters. Each point depicts the measured individual-level summary statistics for the difference between the mean RTs of each condition (congruent and incongruent), and the blue and red segments depict the 95% confidence interval (CI) around the average of RTs (the grey segment in the middle of each CI) in the congruent and incongruent conditions, respectively. A constant of 650ms was added to the RTs in both panels for presentation purposes. Panel B: a *non-directional differences* scenario (simulated using the parameters σ_b=15, $\sigma_w = 30$). Panel C: a *global null* scenario (no effect of the experimental manipulation; simulated using the parameters σ_b=0, $\sigma_w = 100$). Since standard directional tests rely on individual-level summary statistics, they cannot arbitrate between the scenarios described in the two panels.

Reexamining unconscious effects

To examine whether inter-individual differences masked true unconscious priming effects in previously reported studies, we collected and tested data from eight studies that reported null results (Benthien & Hesselmann, 2021; Biderman & Mudrik, 2018; Faivre et al., 2014; Hurme et al., 2020; Skora et al., 2021; Stein & Peelen, 2021; Zerweck et al., 2021; Chien et al. 2022; all datasets and analysis scripts are publicly available online: https://github.com/mufcItay/NDT).

We had three inclusion criteria: first, since all probed tests require trial-level data, only open-access datasets providing such data were included. Second, the independent variable of all studies had to be manipulated within single participants. And third, at least one non-significant effect was reported in the original study. Overall, this search strategy yielded data associated with 26 null effects (see Supplementary Table 1 for details about all effects), 21 focusing on differences in RT and 5 on differences in signal detection sensitivity, d' (Green & Swets, 1966). We used the criteria set by the original authors for demonstrating unawareness (e.g., using objective and/or subjective measures of awareness), and a two-sided non-parametric sign-flipping test on the population mean for filtering out significant priming effects[2]. Finally, we excluded participants with fewer than five trials per experimental condition and/or zero variance in the dependent variable (e.g., when accuracy was measured). Together, these data allowed us to reexamine null unconscious processing effects using a non-directional approach that takes into account the potential for differences in effect signs when testing for group-level effects. We accordingly asked whether true effects of unconscious processing were masked by population heterogeneity in effect signs.

To that end, the effects of interest were tested using GNT, QUID, and the OANOVA tests (see Supplementary Figure 1 for an analysis of the significant directional effects which were excluded). GNT was applied to all 26 effects. In contrast, QUID and OANOVA were used on subsets of 20 and 21 of these effects, respectively (omitting five effects of signal detection sensitivity, d', from both tests, and one additional RT interaction from the QUID analysis, as its current implementation only supports simple RT effects). All tests agreed on finding no reliable evidence for non-directional unconscious effects. According to GNT, the prevalence statistic was zero in 50% of the effects (maximal observed prevalence = 15.79%; see Fig. 2A), and the 95% one-sided CI included $\alpha = 5\%$ in all of them. Hence, for all effects the prevalence of effects did not exceed the expected rate under the global null hypothesis. Similarly, for both QUID and the OANOVA tests, no single BF or p-value revealed evidence for an effect (maximal BF_{10} = 0.75 and all p-values > 0.05; see Figure 2B, C). Notably, QUID obtained moderate evidence for the

[2] Across all RT effects, our analysis used raw RT scores, and thus our results diverged from the original results when log transformations were used (see the notes column in Supplementary Table 1 for details).

global null model in 70% of the cases (see Fig. 2B). The remaining effects were inconclusive. Hence, for the effects collected here, in the case of unconscious processing, the three tests revealed a highly similar pattern of results, consistent with a strong interpretation of previously reported null results as revealing the genuine absence of a causal effect of unconsciously perceived stimuli on behaviour.

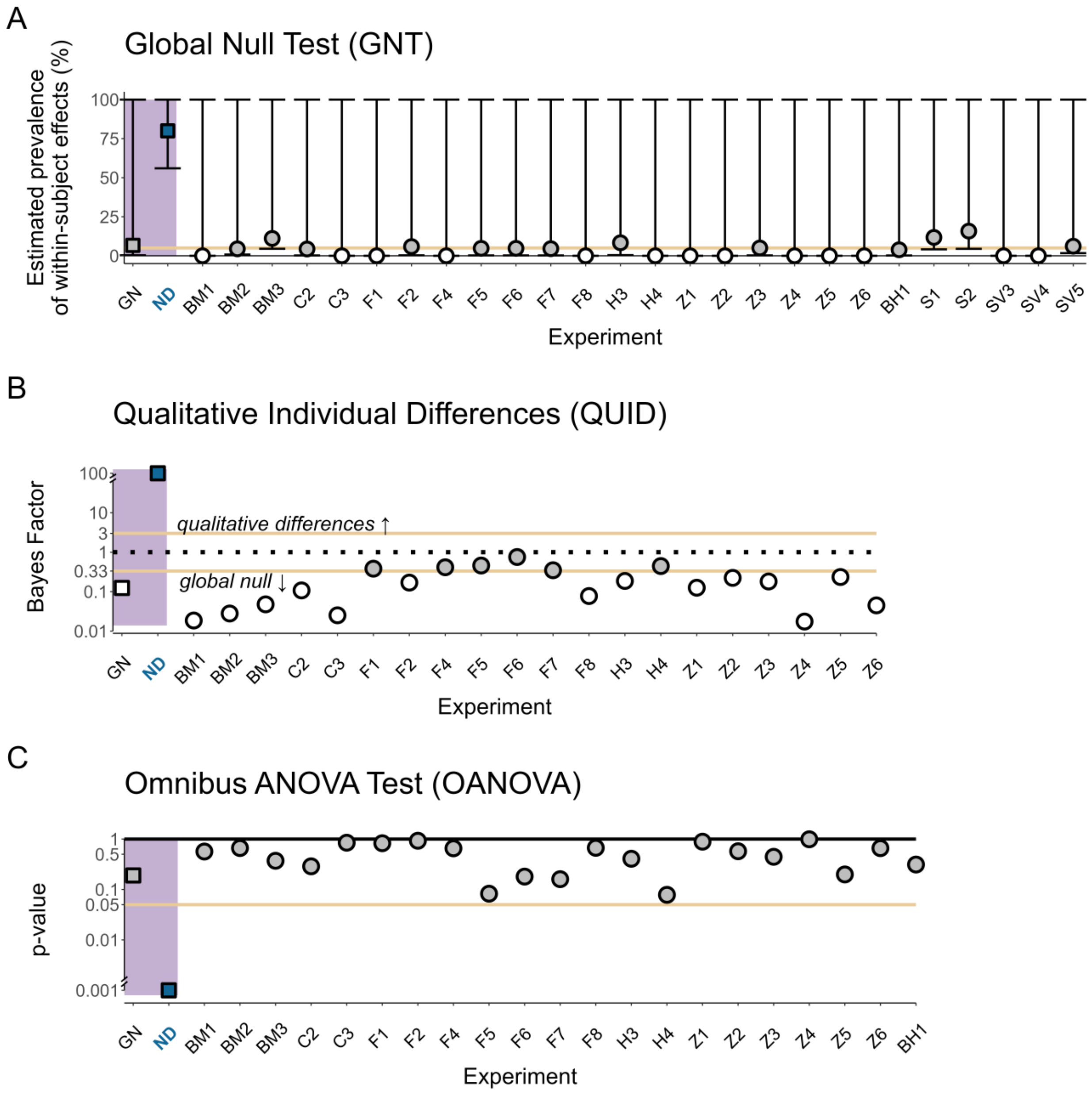

Figure 2. The results of applying the GNT (A), QUID (B), and OANOVA (C) tests to effects that produced null results in a non-parametric directional test and to simulated data (the Non-directional effect (ND) and Global Null (GN) simulations described above, presented as square-shaped markers). Effect labels[3] appear on the x-axis. Panel A: the estimated prevalence of an unconscious effect in each of the cases, using GNT (Donhauser et al., 2018). Segments depict the one-sided 95% CI (CI_{95}) for the prevalence estimate. The solid orange line indicates the expected prevalence of 5% of significant individual-level effects, given that individual effects were tested using $\alpha = 0.05$. Panel B: Bayes factors for the comparison between a random effects model that takes into account potential differences in effect signs and the global null model. White markers depict cases where moderate evidence for the global null model was found, while grey markers indicate inconclusive results. The dashed black line indicates a BF of 1 (no preference for either model), and the solid orange lines indicate a BF cutoff of 3. Panel C: p-values obtained by the OANOVA test (Miller & Schwarz, 2018). Blue and grey markers indicate significant and non-significant results, respectively. For illustration purposes, BF and significance values are presented on a logarithmic scale on the y-axis.

Yet, the reviewed approaches also have some limitations that make it harder to draw firm conclusions based on their results. First, in contrast to frequentist tests within the Null Hypothesis Statistical Testing (NHST) tradition, QUID provide no control over long-term error rates (the

[3] Effect labels abbreviations (sorted alphabetically): BH = Benthien and Hesselmann (2021), BM = Biderman and Mudrik (2018), C = Chien et al. (2022), F = Faivre et al. (2014), H = Hurme et al. (2020), S = Skora et al. (2021), SV = Stein and Peelen (2021), Z = Zerweck et al. (2021). For all labels, numbers denote effect indices within each study (see Supplementary Table 1 for the full mapping between labels and effects).

probability of finding a false positive result or missing a true result over an infinite number of tests, with the former being more critical to our point here). Such error control promises a much-needed 'fool-proof' method to infer the existence of unconscious processing effects without making too many mistakes in the long run (Lakens et al., 2020). To illustrate, while an alpha level of 0.05 guarantees that only one in 20 tests will generate a significant result when there is no true difference between the conditions, using a Bayes Factor cutoff of 3 provides no such guarantee.

Second, both the model comparison approach used in QUID and the OANOVA test necessarily assume a parametric model of the data, making specific assumptions of normality and equal within-individual variance. In simulations, we find that violations of this second assumption can have dramatic effects on the specificity and sensitivity of both tests (see Appendix B). This can be addressed by more complex models that are capable of handling different distribution families, but as model complexity grows, unwanted effects of assumption violations may become harder to spot and quantify. Hence, taking a non-parametric approach provides safer inferences when the form of the data-generating process is not fully known.

Lastly, since GNT is focused on the prevalence of effects, it begins with testing the significance of effects at the single subject level, thereby dichotomizing a continuous test statistic into one bit of information: significant or not. This dichotomization results in information loss and introduces an additional free parameter — the individual alpha level. This step is well justified when estimating population prevalence, but it is unnecessary for our purpose of detecting a non-directional effect at the population level. As we describe below, using a continuous participant-level statistic makes our test more sensitive (see Appendix C for a direct comparison between the two approaches).

In the next section, we introduce a novel non-directional test that takes into account population heterogeneity to infer group-level effects. The test is both frequentist and non-parametric, which addresses the above issues. Similarly to the OANOVA test, it promises a control for long term error-rates, but unlike it, our test does not assume a parametric model of the data-generating process. Using a continuous within-participant summary statistic, it is also more statistically powerful than approaches that focus on a dichotomous notion of effect prevalence (see Appendix C).

Sign Consistency: a non-parametric test that is robust to qualitative differences

Our test assumes that a within-participant effect is convincing if it is consistently evident across different trials. To test this, we can split the trials of an individual into two random halves, and ask whether both halves show the same qualitative effect (e.g., for both halves, the performance in the congruent condition is higher than in the incongruent condition; see Fig. 3A). By doing this many times, we can measure how often the two halves agree. Following this strategy, we estimate the consistency of effect signs within each individual by measuring the frequency of consistent results across splits. Then, we compare the group-mean consistency score against a null distribution: 10,000 samples of group-level consistency scores, obtained after randomly shuffling the experimental condition labels within participants (here, to speed up the computational process, for each participant, 100 permutations were created, from which we randomly sampled a single permutation in each null distribution sample; Stelzer et al., 2013). Hence, our null distribution reflects the expected consistency of within-participant effects when the dependent variable of no single participant is sensitive to the experimental manipulation. An easy-to-use implementation of the sign consistency test is available as part of the signcon R package (https://github.com/mufcItay/signcon; see Appendix D for extensions of the test to use cases that diverge from simple mean difference between conditions).

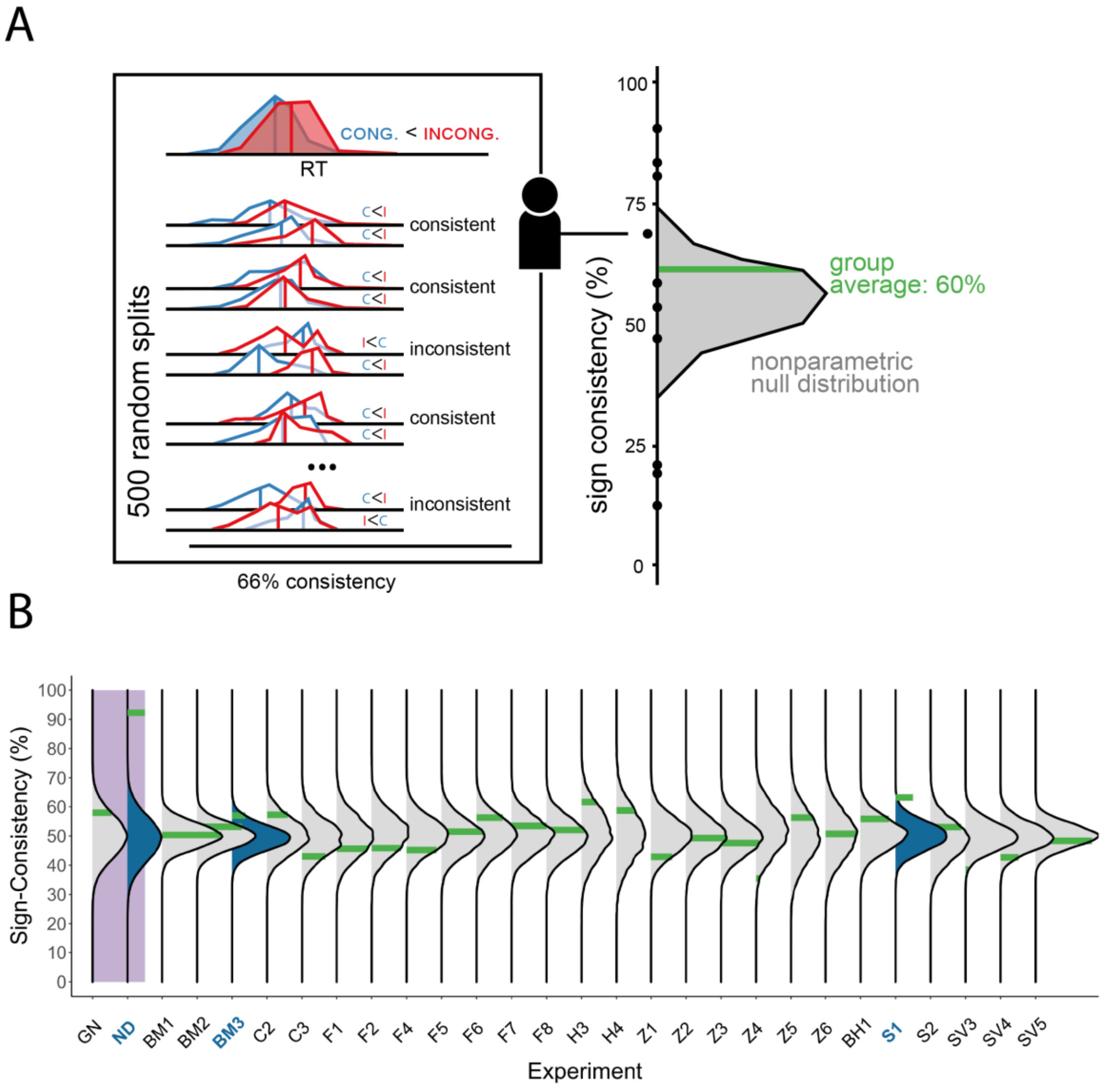

Figure 3. A frequentist, non-parametric, test for sign consistency. Panel A: a schematic illustration, using the same conventions as in Figure 1 (C = congruent, I = incongruent). Participant-wise sign consistency is quantified as the proportion of random splits of experimental trials, for which both halves display the same qualitative effect (C>I or I>C). Group-level sign consistency is compared against a non-parametric null distribution to obtain a significance value. The left panel illustrates a subset of random splits from a hypothetical participant. The upper row illustrates the overall RT data for that participant, and each row below shows one split of the data, where for each half we compare the mean of congruent and

incongruent RT distributions, to test if the direction of the difference in the two halves is consistent or not. Then, to determine if the group shows evidence for non-directional effects, the averaged consistency score *across participants* (plotted in green), which is the proportion of consistent splits across all splits, is compared to the null distribution (right panel). In this hypothetical case, the group does not show an effect, as the average score is well within the null distribution. Panel B: the results of applying the sign consistency test to effects that produced null results in a non-parametric directional test (N = 26). Significant results, for which the estimated mean sign consistency score is greater than 95% of the null distribution, are marked in blue. As in Figure 2, the x-axis lists effect labels.

We quantified the average within-participant sign consistency of effects for which a directional test did not produce significant results (the same effects reported in Fig. 2). For each individual, sign consistency was defined as the percentage of consistent signs across 500 random splits. Effect scores were calculated using a predefined summary function (i.e., taking the average RT or calculating signal detection sensitivity, d’, in each condition, depending on the effect of interest). The results revealed a similar picture to the one provided by the previous analyses (see Figure 3B). First, for the simulated datasets, the sign consistency test obtained non-significant results in the *global null* scenario (M = 58%, p = .138), and detected an effect in *non-directional differences* scenario (M = 92%, p < .001). Second, for the empirical datasets, the vast majority of cases did not show significant sign consistency, with two exceptions: first, an effect of an unconsciously presented cue on wagering decisions (Skora et al., 2021; M = 63%, p = .003), and second, a scene-object congruency effect (Biderman and Mudrik, 2018; M = 57%, p = .041). Although the two effects were not detected by GNT, the prevalence of observed proportion of individual-level effects was above zero for both (11.76% and 11.11%, respectively). Thus, despite some evidence for sign consistency, the overall picture remained the same, hinting at minimal qualitative inter-individual differences in unconscious processing.

Together, four different analysis methods support the conclusion that by and large, unconscious priming effects are not masked by individual differences. Yet one can still claim that these statistical tests are simply not sensitive enough to detect qualitatively variable, non-directional effects, even when those exist. To test this claim, we conducted two additional analyses: First, we used simulations to estimate the sensitivity of our solution to non-directional effects with various effect sizes, determined according to previous analyses on unconscious processing (Meyen et al., 2022) and cognitive control (Rouder et al., 2023). The results corroborated the concerns for lack of power when using common unconscious processing settings of the number of participants and trials (see Baker et al., 2021, for a detailed analysis of the contribution of both factors to power). Yet, we conducted further analysis showing that given the (low) power estimate we found, the number of significant effects obtained by the sign consistency test would be surprisingly low if an effect existed in all or even half of the datasets (see Appendix F). Second, to provide positive-control for these methods and show that they can be used to reveal such hidden effects in other fields, we collected additional, openly accessible, datasets from studies conducted in different fields of research within experimental psychology. We then used our non-parametric test on these datasets, demonstrating its potential benefit in determining whether a null result at the group level hides true, but variable, effects at the individual participant level.

Positive control: Testing within-participant sign consistency across experimental psychology studies

We used the sign consistency test to expose hidden effects that were not revealed by standard directional tests in various fields of research (see Appendix E for the same analysis using the three other tests). To that end, we exhausted all data from different open-access databases (the Confidence Database (Rahnev et al., 2020), the Reproducibility Project (Open Science Collaboration, 2015), and the Classic Visual Search Effects open dataset (Adam et al., 2021)). We also used social media to ask for previously reported null effects, using the same inclusion criteria from the unconscious processing studies analysis, detailed above. Again, effects that were significant according to a non-parametric, directional sign-flipping test on the population mean were filtered out. Overall, we collected data associated with 135 non-significant effects (120 from the Confidence Database, four from the Reproducibility Project, eight from the Classic Visual Search Effects open dataset and three from the social media query). In all cases, participants were excluded for having fewer than five trials per experimental condition and/or zero variance in the dependent variable.

We grouped the different effects into three categories, according to research topics and the analysis we used to test them: first, we tested for effects of participants' responses in 2-alternative forced choice tasks on their confidence ratings in all datasets from the Confidence Database (Rahnev et al., 2020; retrieved on 23/1/2023), by comparing the mean confidence ratings between two different responses. Second, we used the same Confidence Database datasets to test for metacognitive sensitivity effects of response. Metacognitive sensitivity, that is, the agreement between objective accuracy and subjective confidence, was quantified as the area under the response-conditional type-2 Receiver Operating Characteristic curve (Meuwese et al., 2014; here we also excluded datasets that did not include accuracy scores; the remaining 47 effects were analyzed). Third, we grouped effects from the Reproducibility Project (Open Science Collaboration, 2015), the Classic Visual Search Effects open dataset (Adam et al., 2021), and a single study from the social media query (Battich et al., 2021) under a more general "Cognitive Psychology" category. For these studies, we tested the sign consistency of the effect tested by the original authors (averaged difference or interaction effects).

Across the entire sample, including all analyzed effects (N = 135), most effects (62.22%) showed significant sign consistency. This trend was further explored within each category, revealing significant effects in 90.41% 27.66%, and 33.33%, of the Confidence, Metacognitive Sensitivity, and Cognitive Psychology effects (two visual search effects and all three effects from Battich et al., 2021), compared with only 7.69% of the unconscious processing effects, as reported above (see Figure 4). These results validate the potential of using sign consistency to reveal effects on cognition and perception. In striking contrast to the absence of hidden effects in the field of unconscious processing, we found compelling evidence for pronounced inter-individual differences that mask group-level effects in other domains.

However, special care should be taken when interpreting non-directional test results, and when designing experiments targeting non-directional effects (see Box A for best-practice recommendations). A case in point can be found in Battich et al. (2021), who examined the hypothesis that joint attention affects multisensory integration. Critically, this hypothesis was tested by comparing two social conditions that were counterbalanced across participants, such that for half of the participants a joint attention condition was performed before a baseline condition where participants performed the same task individually, and vice versa for the other half. As a result, contrasting the two conditions within participants is identical to contrasting early and late trials. Thus, although the interaction between social condition and multisensory integration showed significant sign consistency (M = 62.39%, p < .001, M = 58.53%, p < .001, and M = 66.73%, p < .001, for the three effects that showed sign consistency effects paralleled with null results according to directional analysis), we cannot unambiguously interpret these results as suggesting a causal, non-directional, effect of the social manipulation. This is because, under this design, the social setting condition and the order of experimental conditions are perfectly correlated within individual participants, rendering both potential drivers behind the observed effect.

Similarly, the great majority of experiments in the Confidence Database showed significant non-directional effects of response on confidence, such that individual participants were more confident in making one response or the other. Here, order effects are not a concern, as the two responses are expected to be equally distributed within a block. However, since stimulus-response mapping was not counterbalanced within participants, we are unable to tell whether these effects reflect individual differences in stimulus preferences (e.g., enhanced sensory encoding for right-tilted gratings) or in response priming (e.g., reports of high confidence are primed by reporting a decision with the right finger).

As a general principle, counterbalancing of confounding experimental variables can be done either between participants (for example, using a different response-mapping for odd and even participants) or within participants (for example, changing the response-mapping between experimental blocks for all participants). While both approaches are effective in protecting against confounding of the mean tendency of the dependent measures, only within-subject counterbalancing is effective when testing for non-directional effects. Accordingly, unless all confounding variables (e.g., condition order or response-mapping) are randomized within participants, the interpretation of non-directional effects cannot be uniquely linked to causal effects of the experimental manipulation.

Importantly, although we cannot conclusively attribute these non-directional effects to social setting versus condition order in the first example, or to response versus stimulus in the second, they both constitute examples of true effects that were masked by inter-individual differences. The absence of a directional effect in Battich et al. is indicated by the fact that on average, participants showed similar levels of multisensory integration in the first and second parts of all three experiments showing non-directional sign consistency effects ($M_D = 0.03$, 95% CI $[-0.02{,}0.09]$, $t(48) = 1.22$, $p = .228$, $M_D = 0.03$, 95% CI $[-0.01{,}0.08]$, $t(48) = 1.47$, $p = .149$, and $M_D = -0.02$, 95% CI $[-0.06{,}0.03]$, $t(48) = -0.69$, $p = .493$). In the case of confidence effects, response mapping was not counterbalanced across participants in many of the considered datasets. This way, the absence of a directional effect of response is also indicative of the absence of a directional effect of stimulus. Together, these previously hidden non-directional findings make the absence of significant non-directional effects in unconscious processing a more convincing indication of the true absence of such effects at the individual-participant level.

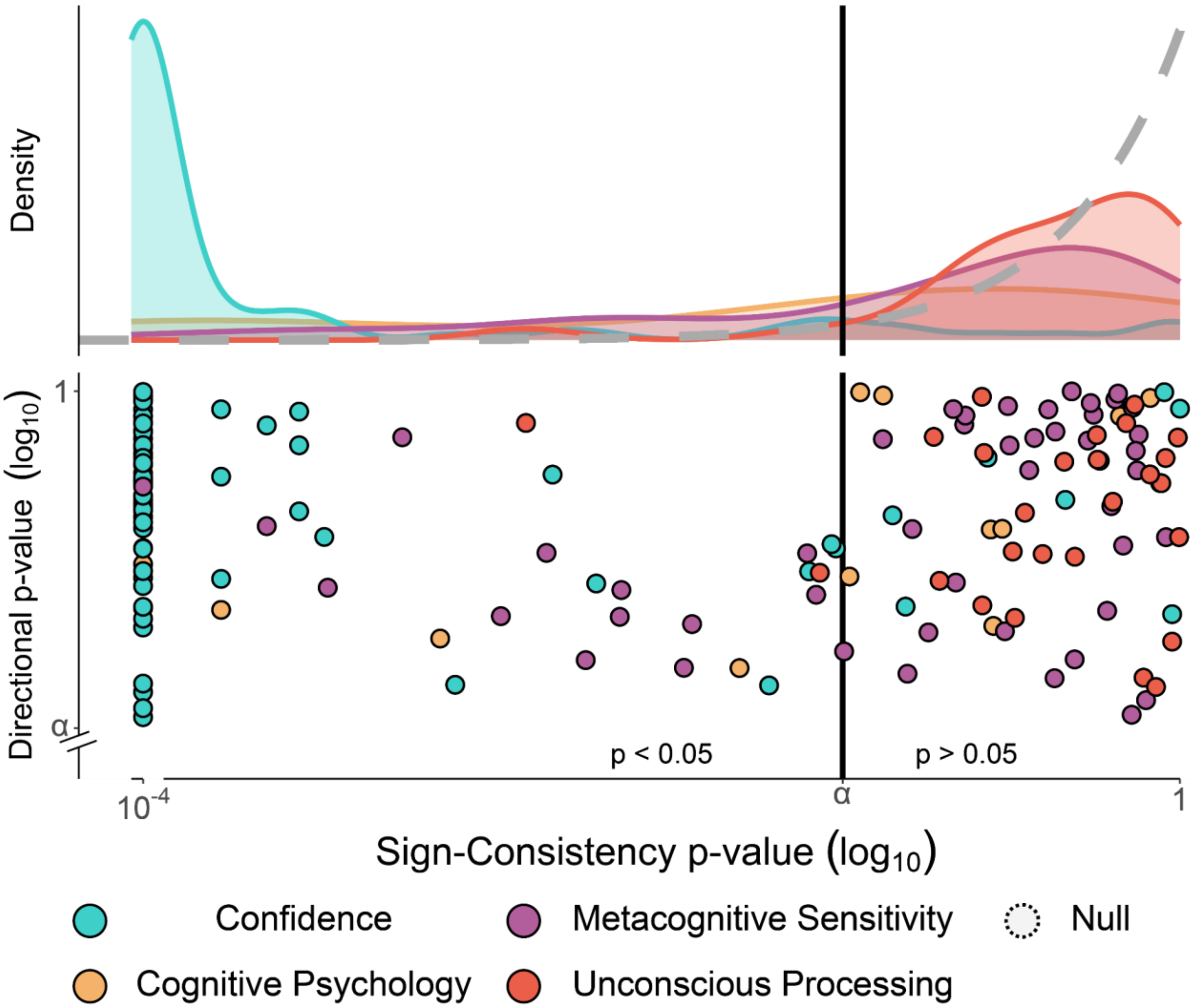

Figure 4. Sign consistency test results for null directional effects from different cognitive psychology fields. Turquoise and purple markers indicate the outcomes for datasets from the Confidence Database (Rahnev et al., 2020) that were analysed to reveal differences in confidence and metacognitive sensitivity between responses, respectively. Orange markers indicate the outcomes for effects from various cognitive psychology studies. Finally, for comparison purposes, we also plot here in red the results of the studies on unconscious processing (N=26), reported in the previous section, and the expected null plotted as a gray dashed line where p-values are sampled from a uniform distribution. Lower panel: each point depicts the log_{10} transformed p-values obtained by the sign consistency test (x-axis) and a directional sign-flipping test (y-axis; datasets were filtered to exclude significant directional effects, hence the minimal directional p-value for all datasets is $\alpha = 0.05$). Upper panel: The p-values density distributions that summarize the results in the lower panel for datasets in each field.

Discussion

What is the scope and depth of unconscious processing? Previous claims about high-level unconscious processing effects have recently been criticized for methodological reasons (Meyen et al., 2022; Rothkirch & Hesselmann, 2017; Shanks, 2017), and for lack of replicability (Biderman & Mudrik, 2018; Hesselmann et al., 2015; Moors et al., 2016; Moors & Hesselmann, 2018; Stein et al., 2020). Here, we point out that testing for effects that are consistent across individuals may be overly conservative for the question at stake. Instead, we examined if these null results might still be underlied by an effect, yet a non-directional one. That is, we tested the hypothesis that individual differences in unconscious processing mask true unconscious effects in individual participants. Adopting a non-directional approach that is robust to inter-individual differences in effects, we used a Bayesian test (Rouder & Haaf, 2021), two frequentist tests based on prevalence assessment and ANOVA (Donhauser et al., 2018; Miller & Schwarz, 2018, respectively), and a novel non-parametric frequentist test. We examined previously reported non-significant results (N = 26), and showed they cannot be explained by inter-individual differences in effects. All tests converged on a similar picture: besides two effects that were picked up by one of the four methods, unconscious processing effects were not masked by substantial inter-individual differences.

It is important to note that our claim here is not about the presence of individual differences in unconscious processing in general, but about the likelihood that such differences in effect signs may be responsible for null group-level findings. Indeed, previous studies revealed inter-individual differences in the magnitude of unconscious processing effects (Boy, Evans, et al., 2010; Cohen et al., 2009; Van Gaal et al., 2011). For example, Van Gaal et al. (2011) used fMRI and a meta-contrast masked arrows-priming task, to show that grey matter density is correlated with the size of unconscious motor priming effects. Yet importantly, in this experiment effects were defined according to the assumption that *incongruent* trials are performed slower than *congruent* trials (trials in which primes and targets pointed to opposing and the same direction, respectively). This assumption of group coherence in effect signs is prevalent in consciousness science, and in cognitive science more broadly, with few exceptions (for example, see Bolger et al., 2019, for a study where the direction of face orientation effects was not assumed in advance). Here, in contrast, we asked whether relaxing the assumption of effect sign uniformity could reveal unconscious effects that remain undetected using standard directional approaches.

Overall, a sign consistency test detected an effect that was missed by a standard, directional test only in two out of 26 datasets. However, even these two effects should be examined cautiously. First, both the effect found for the third experiment in Biderman & Mudrik (2018) (M = 57%, uncorrected p = .041), and the significant sign consistency d' effect in the first experiment of Skora et al., (2021) (M = 63%, uncorrected p = .003) did not survive a correction for false discovery rate among unconscious processing effects (Benjamini & Hochberg, 1995; corrected p-values: .530 and .078, respectively). Hence, it is likely that this effect reflects a type-1 error. Furthermore, the former effect was not detected by the three other tests, and for the latter effect, the authors expressed concerns regarding possible contamination of their measured effect by conscious processing due to regression to the mean (Shanks, 2017). Thus, we suggest that our findings should be interpreted as suggesting no masking of unconscious processing effects by population heterogeneity.

While our focus here was on unconscious processing, a non-directional analysis approach can be useful in many fields of investigation where individual differences are expected. A null finding in a standard t-test or an ANOVA may indicate the true absence of an effect or a lack of statistical power, but it may also be driven by qualitative heterogeneity in participant-level effect signs. In the field of neuroimaging, the adoption of information-based, non-directional approaches famously revealed such effects that were otherwise masked by heterogeneity in neural activation patterns and fine brain structure (Gilron et al., 2017; Ince et al., 2021, 2022; Kriegeskorte & Kievit, 2013; Norman et al., 2006). In the context of this investigation, we found considerable evidence for cases where inter-individual differences mask group-level effects. These cases carry theoretical significance both in uncovering previously missed effects, and in revealing aspects of human cognition that are subject to considerable population variability (Bolger et al., 2019; Rouder & Haaf, 2020, 2021).

Previously, Rouder & Haaf (2021) suggested that such qualitative individual differences may be expected in preference or bias-based effects (e.g., Schnuerch et al., 2021; Rouder and Haaf, 2021), but not in effects that are driven by low-level perceptual and attentional processes. Consistent with this proposal, the absence of substantial evidence for variability in effect signs in unconscious processing was paralleled with strong evidence for such qualitative inter-individual differences in subjective confidence ratings (e.g., some participants are more confident in classifying a grating as oriented to the right, while others show the opposite preference)[4].

[4] As we note above, since in most of these studies responses and stimuli are closely correlated, these effects cannot be unambiguously attributed to stimulus preferences or response priming effects. Relatedly, more recent work reveals that such inter-individual differences in preference for specific responses or stimuli can be traced back to heterogeneity in sensory encoding Rahnev (2021).

However, robust participant-level effects were masked by qualitative individual differences in other domains too, not all of them relate to higher-level preferences or biases. For example, non-directional effects of distractor presence were found in two visual search experiments (Adam et al., 2021; sign consistency > 62.17%, p <.020, for two out of eight measured effects). These findings echo the non-directional effects of distractor-target compatibility on action planning that were revealed by Miller and Schwarz, (2018). These effects were not detected when using standard directional analysis yet show significant sign-consistency (M = 77.44%, p < .001, for a target-distractor SOA of 350ms in Machado et al., 2007, and M = 63.41%, p = .015, for an SOA of 650ms in Machado et al., 2009). Thus, aside from shedding light on previous non-significant results, our preliminary findings inform previous claims regarding the plausibility of population heterogeneity in effect signs in perceptual and attentional effects in general, providing some indication that such effects may be more prevalent than previously assumed.

To facilitate the adoption of this non-directional approach in experimental psychology, we release with this paper an R package with a simple-to-use implementation of our error-controlled and non-parametric sign consistency test (https://github.com/mufcItay/signcon). We note that unlike directional tests, the validity of the sign consistency test (and more generally, non-directional tests) depends on counterbalancing of confounding variables not only across participants, but also across trials within a single participant. We recommend using this test to complement standard, directional tests, taking into account the effect of additional tests on the family-wise error rate. Furthermore, although the test revealed effects in various domains, special attention should be given to statistical power when collecting data for a non-directional test, considering both the number of participants and the number of trials per participant. This is especially important when the effect size of interest is small, as is clearly the case in unconscious processing studies (more generally, when the relation between true variability between participants and measurement error is small; see Rouder et al., 2023, and Appendix F). Given proper use, the test should be particularly useful in interpreting null findings at the group level (see Box A for a more detailed description of best-practice recommendations for non-directional testing). This seems highly relevant to the field of unconscious processing, where null results are becoming more prevalent, and carry theoretical significance as hinting at possible functional roles for conscious processing.

Conclusions

Experimental demonstrations of unconscious processing have been reported for nearly 150 years now (e.g., Peirce and Jastrow, 1884), yet their reliability and robustness have repeatedly been put into question (e.g., Holender, 1986 and Shanks, 2017). Here, we examined the possibility that some of the findings against such processing, reporting null results, might hide effects at the individual level, yet in opposing directions. We employed four non-directional tests to re-examine 26 null effects. Our findings suggest no role for individual differences in explaining non-significant effects at the group level. Furthermore, by expanding our exploration outside the domain of unconscious processing, we found compelling evidence for effects that were shadowed by individual differences in effect signs, nuancing views about the universality of cognitive and perceptual effects. We provide a user-friendly implementation of the non-directional sign consistency test, and recommend its use for interpreting null results.

Data and code availability

All data except for the datasets from Machado et al., 2007, 2009, for which participants did not consent to having their data shared online, and all analysis code are available at https://github.com/mufcItay/NDT, using R (Version 4.3.2; R Core Team, 2023) and the R-packages *BayesFactor* (Version 0.9.12.4.4; Morey & Rouder, 2022), *coda* (Version 0.19.4; Plummer et al., 2006), *data.table* (Version 1.14.8; Dowle & Srinivasan, 2023), *dplyr* (Version 1.1.2; Wickham, François, et al., 2023), *extraDistr* (Version 1.9.1; Wolodzko, 2020), *foreach* (Version 1.5.2; Microsoft & Weston, 2022), *ggh4x* (Version 0.2.5; van den Brand, 2023), *ggplot2* (Version 3.4.2; Wickham, 2016), *ggpubr* (Version 0.6.0; Kassambara, 2023), *ggridges* (Version 0.5.4; Wilke, 2022), *ggtext* (Version 0.1.2; Wilke & Wiernik, 2022), *gridExtra* (Version 2.3; Auguie, 2017), *groundhog* (Version 3.1.2; Simonsohn & Gruson, 2023), *MASS* (Version 7.3.60; Venables & Ripley, 2002), *Matrix* (Version 1.6.0; Bates et al., 2023), *MCMCpack* (Version 1.6.3; Martin et al., 2011), *nleqslv* (Version 3.3.4; Hasselman, 2023), *papaja* (Version 0.1.2; Aust & Barth, 2023), *patchwork* (Version 1.1.2; Pedersen, 2022), *pracma* (Version 2.4.2; Borchers, 2022), *scales* (Version 1.2.1; Wickham & Seidel, 2022), *signcon* (Version 0.1.0; Yaron & Mazor, 2024), *stringr* (Version 1.5.0; Wickham, 2022), *tidyr* (Version 1.3.0; Wickham, Vaughan, et al., 2023), *tinylabels* (Version 0.2.4; Barth, 2023), and *xfun* (Version 0.39; Xie, 2023).

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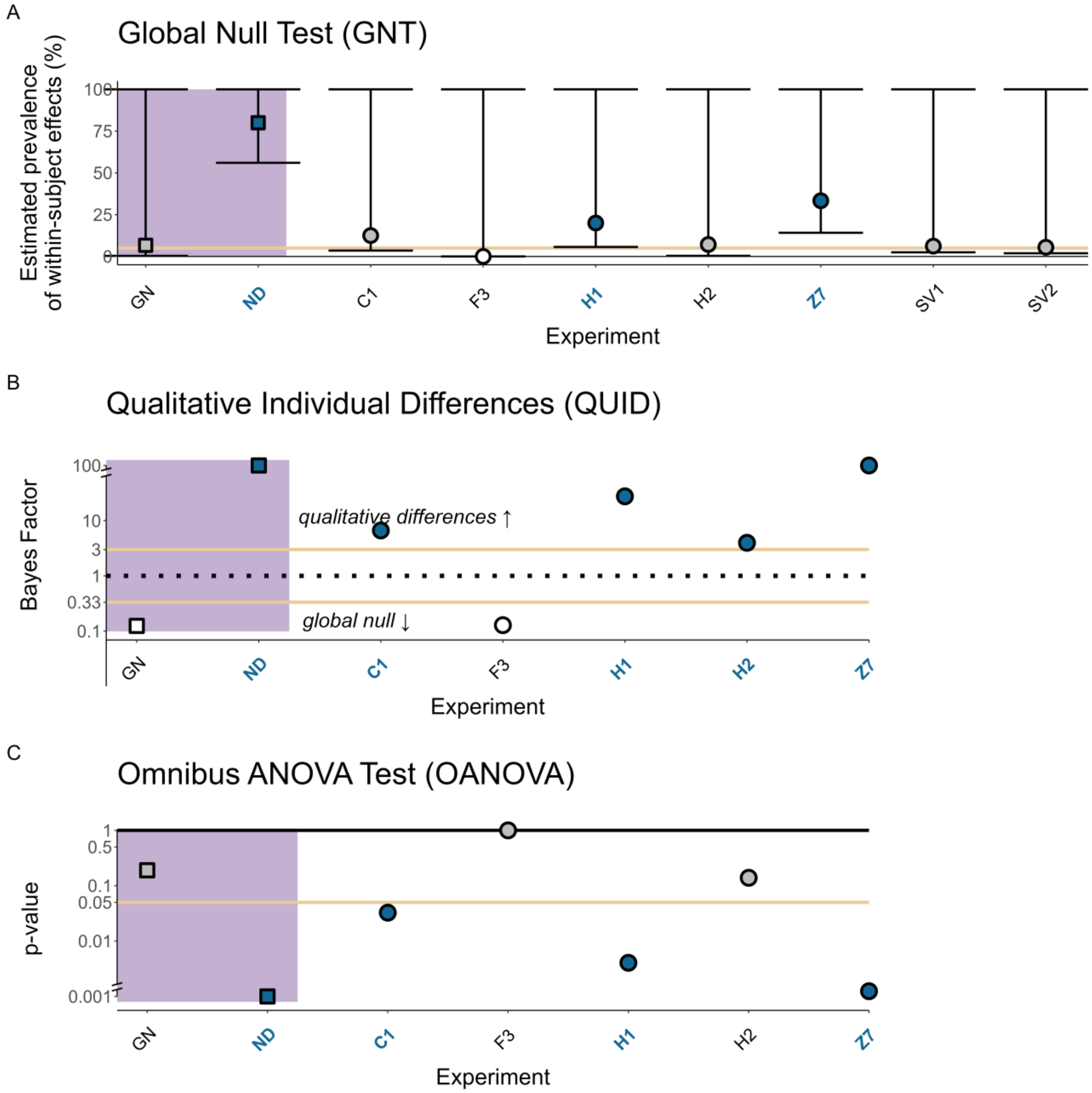
Supplementary Table 1

Unconscious processing effects metadata

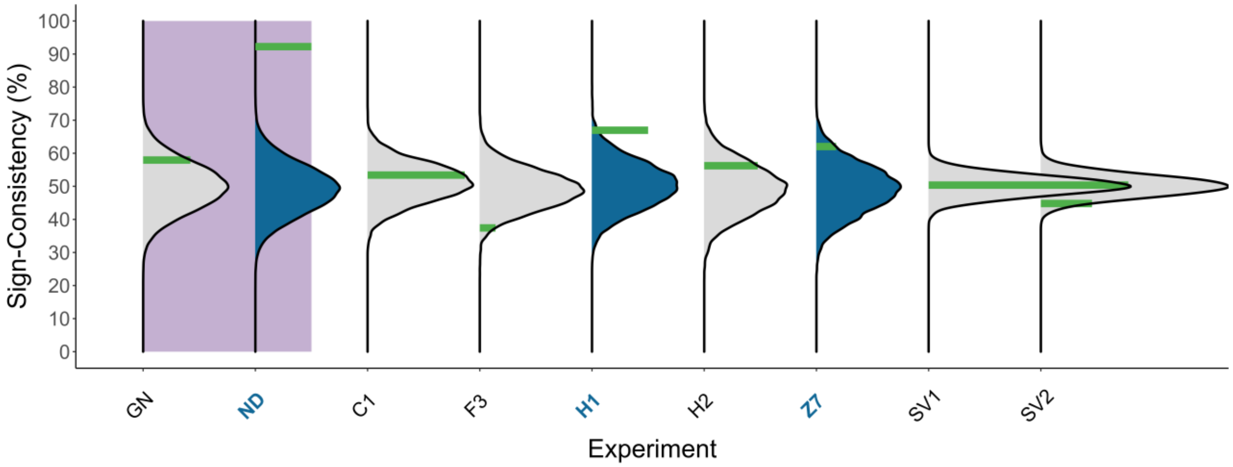
Study	Labels	Topic	Paradigm	DV	Notes
Biderman & Mudrik, 2018	BM1-3	Scene congruency	Masking	RT	Replication study. For all experiments, log(RT) was used in the original analysis
Faivre et al., 2014	F1-8	Multisensory integration	Masking	RT	Four experiments, with two effects in each experiment (identical/different targets). For all experiments, log(RT) was used in the original analysis
Stein & Peelen, 2021	SVP1-5	Location effects + PAS (detection)	CFS	d’	Two experiments (3 and 4 in the paper), measuring effects in different prime-mask SOAs
Zerweck et al., 2021	Z1-7	Numerical Priming	Masking	RT	Two experiments (2 and 3 in the original paper), measuring effects in different SOA / Contrast conditions
Benthien & Hesselmann, 2021	BH1	Numerical Priming	CFS	RT	Interaction effect - prime congruency X location certainty
Hurme et al., 2020	H1-4	Colours	TMS + Metacontrast Masking	RT	Redundant target effect (TMS / Masking X Blue / Red)
Skora et al., 2021	S1-2	Instrumental Learning	Masking	d’	Regression to the mean as a confound according to authors
Chien et al., 2022	C1-3	Semantic priming	CFS	RT	Word, Picture, and trait discrimination tasks

Supplementary Figure 1 - GNT, QUID and OANOVA results for datasets showing a directional effect



Supplementary Figure 1. The results of applying the GNT (A), QUID (B) and OANOVA (C) tests to effects that produced significant results in a non-parametric directional test. Same conventions as Fig. 2.

Supplementary Figure 2 - Sign consistency test results for datasets showing a directional effect



Supplementary Figure 2. The results of applying the sign consistency test to significant directional effects (N = 7). The x-axis lists effect labels. Same conventions as Fig. 3.

Appendix A. Simulating non-directional unconscious processing effects with Wald distributions

To complement the simulation of normally distributed RTs reported in the main text (under the section titled ‘Simulating non-directional unconscious effects’), we ran an additional simulation using more realistic Wald distribution. Importantly, unlike normal distributions and similarly to RT distributions, Wald distributions are strictly positive and right-skewed. Again, we simulated a *non-directional differences* scenario, and a *global null* scenario, which differed by the within-participant shape parameter λ (λ=101250 and λ=9,112.50 in the former and later scenarios, respectively). Accordingly, RTs were sampled from shifted Wald (SW) distributions ($RT_{i,c} \sim \mathcal{SW}(\mu + c * e_i, \lambda, \tau)$, where μ was set to 450ms and τ was set to 200ms, to mimic typical RT distributions).

First, as in the original analysis, a t-test did not find an effect in neither scenario (*non-directional differences*: $M = 5.03$, 95% CI $[-5.16,15.21]$, $t(14) = 1.06$, $p = .308$; *global null*: $M = 0.48$, 95% CI $[-7.79,8.75]$, $t(14) = 0.12$, $p = .903$). More crucially, the results of all four probed tests were similar to those obtained with normally distributed RTs. In the *non-directional effect* scenario, an effect was found (GNT: 73.33% of significant effects, one-sided CI_{95} = [48.92 100], p < .001), QUID: BF= 2.43e+46, OANOVA: F(15, 2970) = 18.64, p < .001, and for the sign-consistency test: M = 91%, p < .001), while finding no evidence for an effect in the *global null* scenario (GNT: 0% of significant effects, one-sided CI_{95} = [0 100], p > .999, QUID: BF= 0.29, OANOVA: F(15, 2970) = 1.06, p =.386, and for the sign-consistency test: M = 53%, p = .327).

Appendix B. Violating the equal within-individuals variance assumption

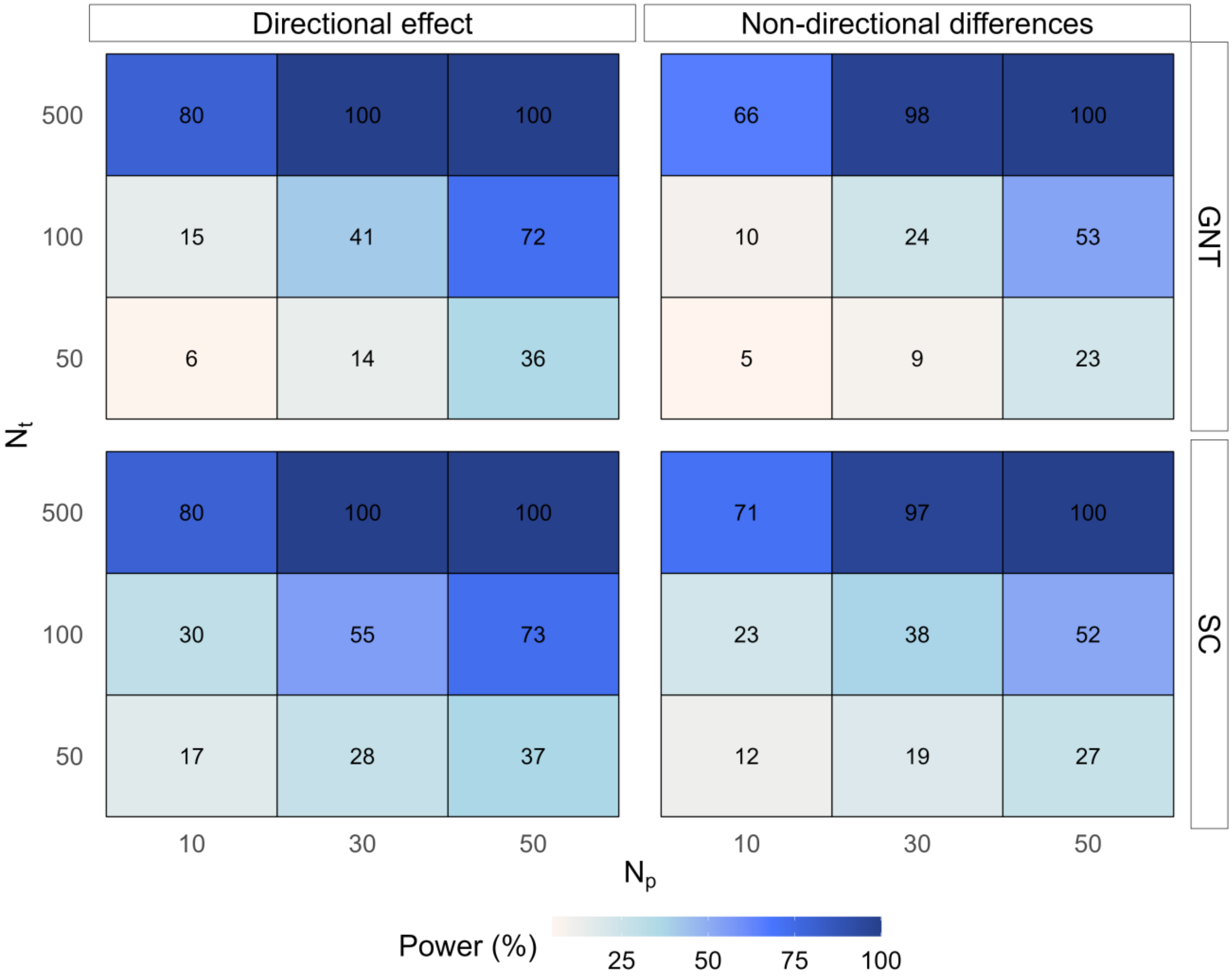
We used the simulation scheme described in the main text (see section ‘Simulating non-directional unconscious effects’), to test the consequences of violating the equal within-individuals variance assumption for both QUID and the OANOVA test. We compared the distribution of Bayes factors and p-values obtained by applying QUID and the OANOVA test to generated data meeting and violating the equal within-participants variance assumption. In the first, equal-variance case, the within-individual standard deviation was low ($\sigma_w = 1$) for all participants. In the second, unequal-variance case, the within-individual standard deviation was low ($\sigma_w = 1$) for all participants except one, for whom it was set to a high value ($\sigma_w = 1000$). As in the main simulation, the effect sizes of each participant were sampled from a normal distribution centred at zero ($e_i \sim \mathcal{N}(0, \sigma_b)$; where e_i denotes the effect size of the i^{th} participant). Within this framework, examined two scenarios: a *non-directional differences* scenario where participants are differentially affected by the experimental manipulation ($N_p = 30$, $\sigma_b = 15$), and a *global null* condition where all participants are unaffected by the experimental manipulation ($N_p = 100$, $\sigma_b = 0$). In both scenarios, we simulated random data in 250 iterations, and used the same number of trials per condition (the total number of trials, $N_t = 200$).

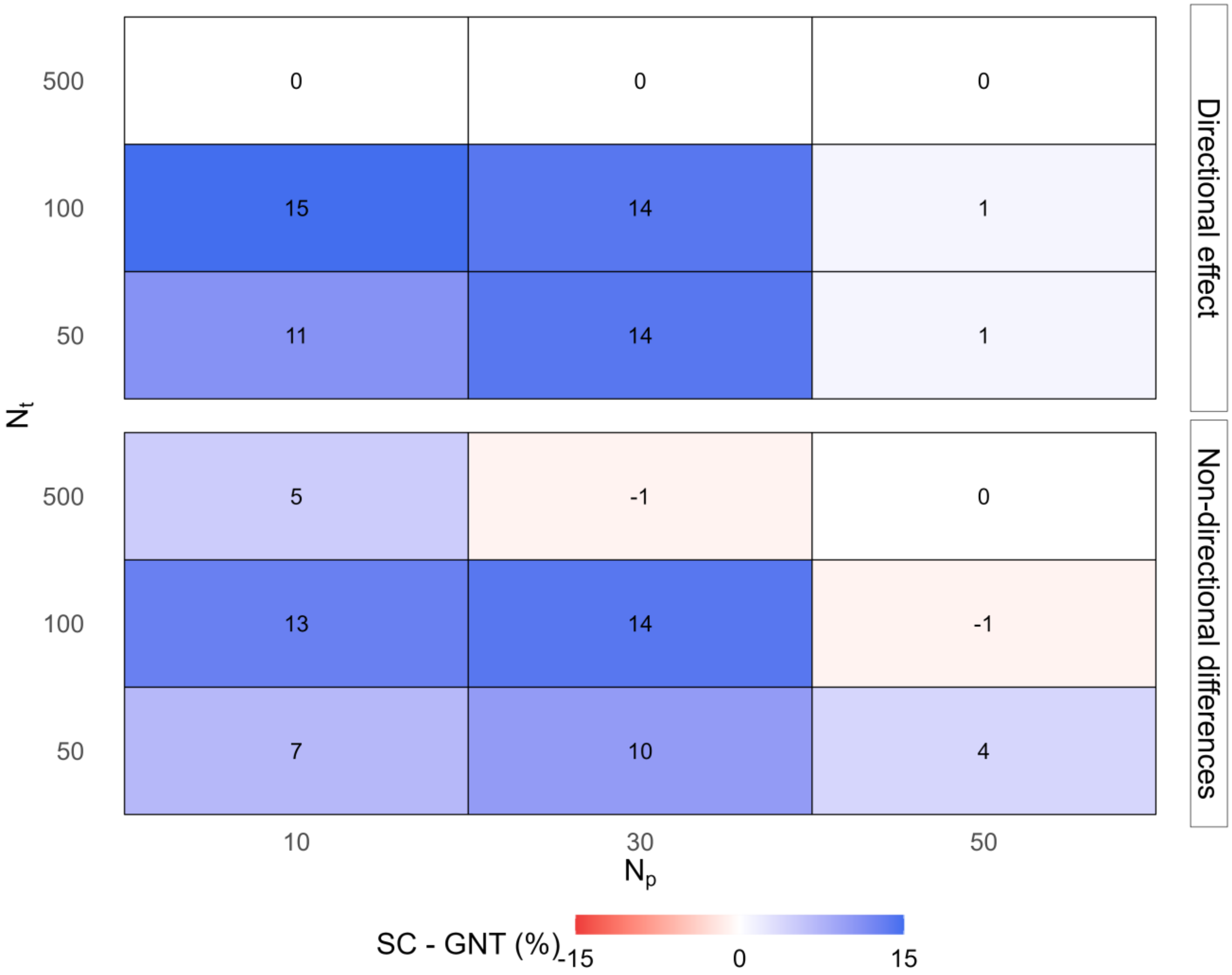
To examine the tests’ specificity, we measured the proportion of iterations where evidence for an effect was erroneously found in the global null condition. In the equal-variance case, all iterations provided evidence for the lack of an effect according to QUID (all BFs < $\frac{1}{3}$). Similarly, non-significant results were found by the OANOVA test in 95% of the iterations. However, in the unequal-variance case, false-positives were obtained in 13% of the QUID Bayes Factors (BF > 3), and 1% showed inconclusive evidence. Again, the OANOVA test showed a similar pattern, detecting falsely significant effects in 22% of the iterations. Thus, we show that the specificity of these tests is compromised by violations of the equal-variance assumption.

We then analyzed the tests' outcomes in the non-directional differences scenario to examine their sensitivity. When the equal-variance assumption was met, both tests found evidence for an effect (all BFs > 3, and all p-values < 0.05). In contrast, in the unequal-variance case, only 19% of QUIDs BFs showed evidence for an effect, whilst 76% showed evidence for no effect (the remaining 6% were inconclusive). Similarly, the OANOVA test found significant effects in only 28% of the iterations. Hence, both tests missed true effects when the assumption was not met, demonstrating that their sensitivity is compromised by violations of the equal-variance assumption.

Appendix C. Comparing the power of the GNT and sign consistency test

To examine the differential sensitivity of GNT and the sign consistency tests, we conducted a power analysis, simulating two scenarios under the simulations scheme described in the main text (see section ‘Simulating non-directional unconscious effects’): First, a *non-directional differences* scenario where an effect exists for each participant but it is inconsistent within participants ($e_i \sim \mathcal{N}(0, \sigma_b)$; where σ_b=1.5). Second, a *directional effect* scenario, with individual variation around a positive mean effect size ($e_i \sim \mathcal{N}(1, \sigma_b)$; where σ_b=1.5). For each scenario, we manipulated the number of simulated participants (N_p=10/30/50) and trials (N_t=50/100/500) across 1000 random iterations, with the within-participant SD (σ_w) set to 10 in both scenarios. Statistical power was defined as the proportion of significant results for both tests ($\alpha = .05$). While both tests were similarly sensitive when applied to well-powered datasets (e.g., when N_p=50 or N_t=500), the sign consistency test proved to be more sensitive in the remaining conditions (see Baker et al., 2021) for a more comprehensive power analysis of a directional test in the *directional effect* scenario).


Directional effect
Non-directional differences
GNT
SC
500
100
50
80
100
100
66
98
100
15
41
72
10
24
53
6
14
36
5
9
23
500
100
50
80
100
100
71
97
100
30
55
73
23
38
52
17
28
37
12
19
27
N_t
10
30
50
10
30
50
N_p
Power (%)
25
50
75
100



Appendix C-figure 1. Power analysis for the sign consistency (SC) and the global null (GNT) tests for simulated datasets. Top panel: Each cell depicts the percent of iterations where SC and GNT resulted in significant effects (upper and lower panels, respectively). Rows and columns correspond to the number of simulated participants (N_p), and the number of simulated trials per participant (N_t), respectively. Left panel: the results of the GNT and SC in the non-directional differences scenario. Right: the results of the GNT and SC in the directional effect scenario. The number in each cell denotes the % of significant effects (power) in each simulated condition (across 1000 iterations), and darker blue colors indicate higher power. Bottom Panel: the difference between power estimates in each cell (sign consistency power - GNT power). Red to blue colors indicate higher power for GNT vs. the sign consistency test.

Appendix D. Extending the sign consistency test to additional use cases

We provide two code examples to demonstrate how to extend the sign-consistency test implemented in the signcon R package (https://github.com/mufcItay/signcon) to common use case: D.1. A 2 X 2 interaction, and D.2. calculating SDT’s d’. For both examples we will use simulated trial-level data, mimicking a 2X2 within-participant design.

```
##   idv iv iv2 dv_response    dv_RT
## 1   1  0   0           0 500.9610
## 2   1  0   1           0 528.2344
## 3   1  0   0           0 413.6181
## 4   1  0   1           0 497.6549
## 5   1  0   0           0 571.0572
## 6   1  0   1           0 604.1898
```

Appendix D.1: 2X2 interction effect:

To test for an interaction effect we override the default test-consistency summary function. In this example, we use a function that summarizes RTs (‘dv_RT’) by calculating the mean difference between the two conditions of the second variable (‘iv2’). This summary function will be applied to the dependent variable (‘dv_RT’) of different splits of the data, under each condition of the independent variable (‘iv’), when calculate sign-consistency scores per participant.

```
# the interaction summary function for an interaction effect
interaction_summary_function <- function(data) {
  if(length(unique(data$iv2)) != 2) {
    return(NA)
  }
  # we use mean to summarize the RT under each level of 'iv2'
  res <- mean(data[data$iv2 == 1,]$dv_RT) -
    mean(data[data$iv2 == 0,]$dv_RT)
  return(res)
}
# run the sign-consistency test
sc_interaction <- test_sign_consistency(data, idv = 'idv', iv = 'iv', dv = c(
'iv2', 'dv_RT'), summary_function = interaction_summary_function)
```

Appendix D.2: d’ effect:

To test for an effect on sensitivity (d’) we override the default test-consistency summary function, to compute the normalized rate of responses given for a reference stimulus (here, the reference stimulus is encoded as ‘1’). As explained above, since this summary function is applied to each condition under the independent variable (‘iv’) when calculating sign consistency scores, the sign-consistency test would test for consistent d’ sign between different splits of the data.

```
# since in this use case there is only one dependent variable, the 'data' arg
ument
# is a vector containing all of the dv_response values for the sampled split
dprime_summary_function <- function(data) {
  # count how many '1' responses were given
  cnt <- sum(data)
  # get the total number of trials in this split
  len <- length(data)
  # correction for edge cases where participants only give one response (0 /
1)
  floor_rate <- 1/(2*len)
  ceiling_rate <- 1 - 1/(2*len)
  # calculate the observed rate of 1 responses
  rate <- ifelse(cnt == 0, floor_rate,
                 ifelse(cnt == len, ceiling_rate,
                        cnt / len))
  return (qnorm(rate))
}
# run the sign-consistency test
sc_dprime <- test_sign_consistency(data, idv = 'idv', iv = 'iv', dv = 'dv_response', summary_function = dprime_summary_function)
```

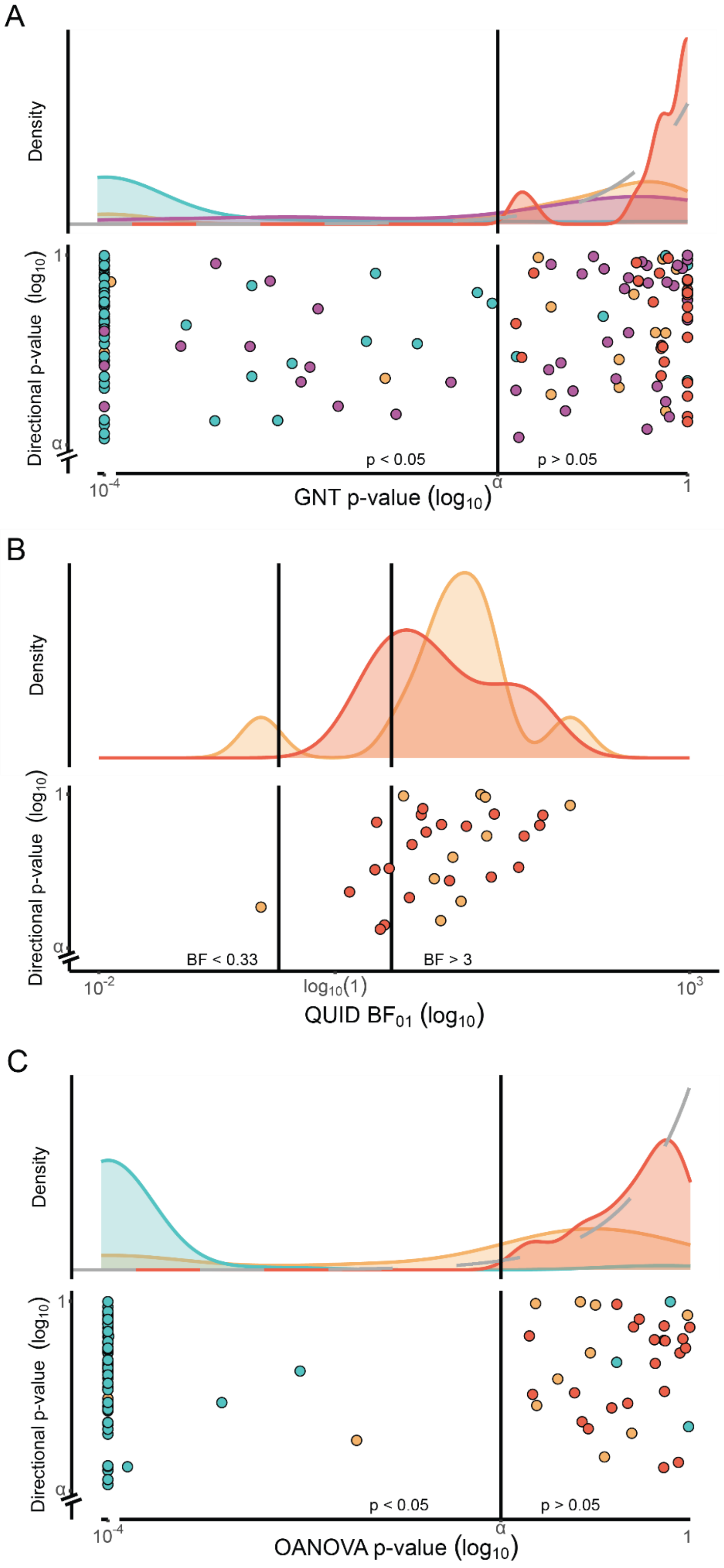
Appendix E. Testing for effects from other domains with the altenative tests

For completeness, we report here the results of the GNT, QUID, and OANOVA tests for the all datasets outside the domain of unconscious processing reported on the main text, which were non-significant effects according to a directional test[5] (see section 'Positive Control: Testing within-participant sign consistency across experimental psychology studies' for the same analysis using the sign consistency test). Crucially, this analysis should be interpreted with caution given the results we report in Appendix B and C, showing potential issues with the sensitivity and/or specificity of these tests.

Overall the results were similar to the one found with the sign consistency test: First, the vast majority of datasets from the confidence database showed non-directional effects (93% and 96%, for GNT and OANOVA, respectively). Similarly, GNT found metacognitive sensitivity effects in 28% of the datasets. Lastly, within the 'Cognitive Psychology' datasets category, both GNT and OANOVA were significant for all three effects from Battich et al. (2021) on multisensory integration (since all of these effects involve interactions, they were not analyzed using QUID), while obtaining significant results for only one of the two visual-search sign consistency effects by OANOVA and QUID, or none of them for GNT (overall cognitive

[5] Notably, since both QUID and OANOVA were developed for continuous dependent variables, with the default prior settings of QUID were set according to expected patterns for RTs, we did not use either test to analyze metacognitive sensitivity effects, and also excluded confidence effects from the QUID analysis. Similarly, QUID was not used for analyzing interaction effects, because its current implementation does not allow for such analysis.

psychology datasets, GNT, QUID and OANOVA found 20%, 10%, and 29% of significant effects, out of 15, 10, and 14 effects examined by each test).


A
Density
Directional p-value (log10)
1
α
p < 0.05
p > 0.05
10^{-4}
α
1
GNT p-value ($\log_{10}$)
B
Density
Directional p-value (log10)
1
α
BF < 0.33
BF > 3
10^{-2}
$\log_{10}(1)$
10^{3}
QUID BF_{01} ($\log_{10}$)
C
Density
Directional p-value (log10)
1
α
p < 0.05
p > 0.05
10^{-4}
α
1
OANOVA p-value ($\log_{10}$)

Appendix E-figure 1. The results of applying the GNT (A) (N=161), QUID (B) (N=30), and OANOVA (C) (N = 102) tests to for null directional effects from different cognitive psychology fields. Same conventions are used as in Figure 4 in the main text. Effects that are incompatible with OANOVA or QUID were excluded from this analysis. In panel B the two black vertical indicate BF criteria of 3.

Appendix F. Empirically informed power sign-consistency test power estimation

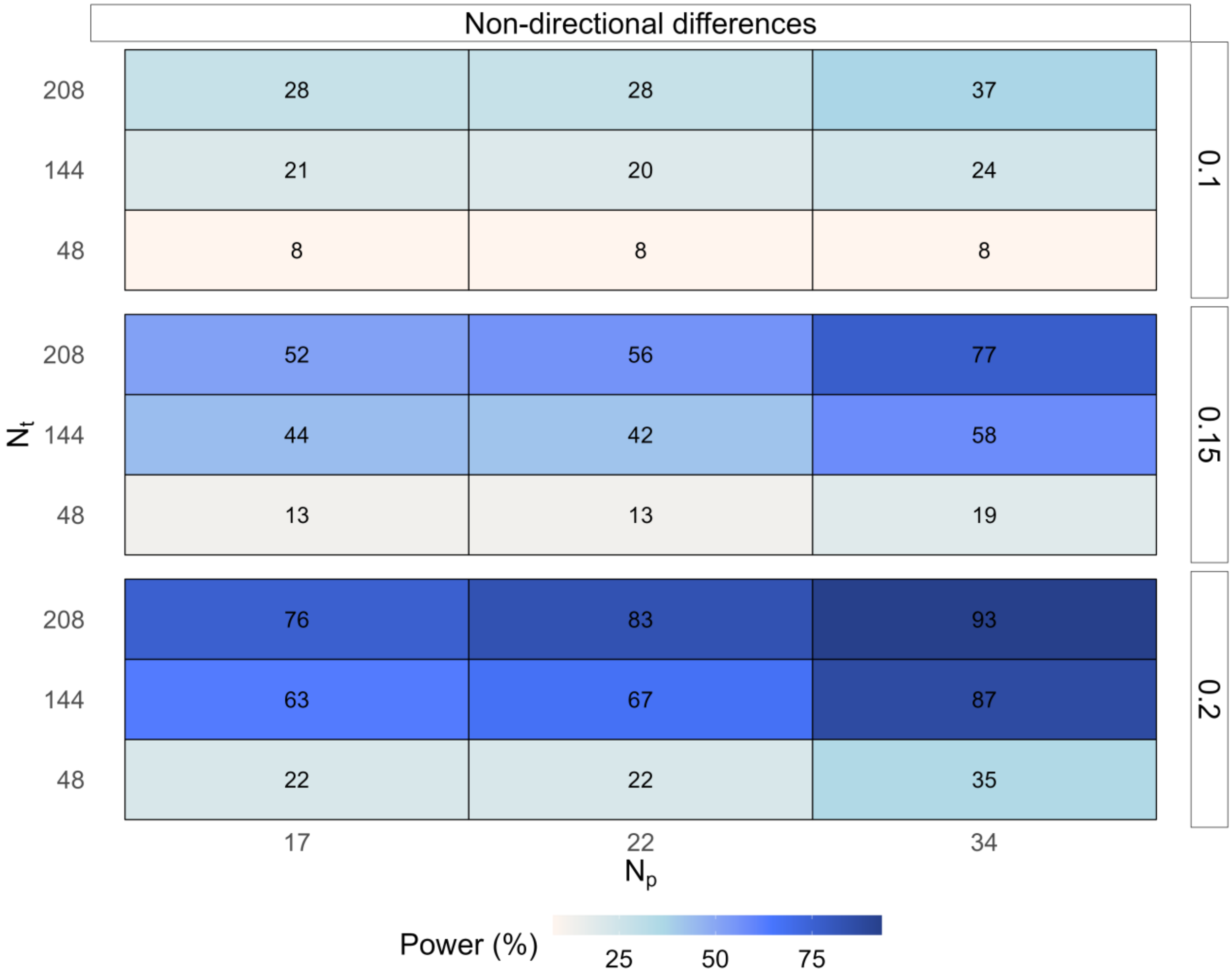
To examine whether lack of power can explain not finding convincing evidence for non-directional unconscious processing effects (Fig. 3), we examined the sensitivity of the sign-consistency test in detecting effects of empirically relevant studies. To that end, we simulated *non-directional differences* scenarios with different degrees of true between participants variance ($\sigma_b \in \{1,1.5,2\}$) and fixed amount of within participant variability ($\sigma_w = 10$). These parameters were chosen based on previous works where the ratio $\frac{\sigma_b}{\sigma_w}$ was estimated to values ranging between .04 and .15 (M = .1, SD = .04) in six unconscious processing datasets (Meyen et al., 2022), while in another work estimating the same parameter in 24 cognitive control studies (Rouder et al., 2023; where no unconscious manipulation was used) values ranged between .05 and .36 (M = .14, SD = .08). Then, we determined the number of trials and participants in the simulated datasets according to the parameters used in the unconscious processing datasets we obtained by calculating the 25%, 50%, and 75% percentile of both parameters. This resulted in additional simulation conditions where the number of participants was set to $N_p \in \{17,22,34\}$ and the total number of trials was set to $N_t \in \{48,144,208\}$. All other simulation parameters were the same as detailed in Appendix C.

From the results of this power simulation we obtained an estimate for the power of the sign consistency test, in common sample size settings, for an effect of interest of $\frac{\sigma_b}{\sigma_w} = .15$[6]. We

[6] Importantly, this decision incorprates the fact that the sign-consistency test may also detect small directional effects that remain undetected using standard tests, due to heterogeneity in individual-level

then used a prevalence test to test the obtained power estimate of 42% is compatible with the low observed prevalence of unconscious processing effects we found (0.08%). Specifically, we tested if the observed proportion of significant sign consistency effects is lower than the expected prevalence according to our power estimate (42%, as stated above). Indeed, this was the case when comparing the observed rate of significant effects with the expected rate if all, or even half of the effects exist, yet were not detected due to a lack of power (CI_{95} = [0 22.29], and p = < .001, p = .037, respectively). Hence, we interpret these results as suggesting that for an effect size of $\frac{\sigma_b}{\sigma_w} = .15$ the results are unlikely to be explained simply by lack of power.

effects. In this case, estimating the power of the test based solely on the ratio of between and within participant variability might underestimate the true power of the test for the obtained datasets. Hence, we used the same effect size as was done in Meyen et al. (2022), who used it as part of a “benefit of a doubt” approach for a different set of analyses on unconscious processing effects.



Appendix F-figure 1. Power analysis for the sign consistency (SC) test in various non-directional differences scenarios. Each panel depicts the results for different effect size ($\frac{\sigma_b}{\sigma_w} \in \{.1, .15, .2\}$). Within each panel, the x and y axes depict different settings for the number of participants (N_p) and the total number of trials across two conditions (N_t), both determined according to the 25, 50 and 75 percentiles of these parameters in the unconscious processing datasets we collected. The number in each cell denotes the % of significant effects (power) in each simulated condition (across 250 iterations), and darker blue colors indicate higher power.

BOX A: Non-directional testing: best practice recommendations

- **When should we use the non-directional approach?**
  - Not all hypotheses are suitable for examination under the non-directional approach. Since the non-directional approach is targeted at detecting the presence of effects rather than their direction, it cannot be used to establish average differences between conditions at the group level (e.g., when comparing memory performance for items presented first and later in an experiment, rejecting a non-directional hypothesis does not entail evidence for an overall primacy or recency effect on recollection). In the case of unconscious processing, the theoretical question is regarding the presence or absence of a difference between the two conditions at the single-participant level, and as such, it lends itself to non-directional testing. Thus, selecting whether to use the non-directional or directional approach is directly linked to the theoretical question at stake.
- **Which test should be used?**
  - When testing whether the experimental manipulation affects the dependent variable (e.g., either main or interaction effects on reaction times, accuracy, brain activity etc.), unless normality and equal variance of within-participant variability can be assumed with high certainty, we recommend using the sign consistency test.
  - When these assumptions hold, QUID or OANOVA can be used for effects that are measured on a trial-by-trial basis (as opposed to effects measured by summarizing data from multiple trials, e.g., d' or correlation effects). Specifically, when prior data is available, we advise incorporating it into the analysis using QUID, and when examining an interaction effect, OANOVA provides an easy-to-use solution.
  - To test for the prevalence of individual-level effects, rather than the mere existence of an effect at the group level, we recommend using the prevalence approach (Ince et al., 2021, 2022). More specifically, we recommend using GNT (Donhauser et al., 2018) to test whether the data provide evidence for the presence of an effect for at least a single individual.
- **Non-directional tests require within-participant counterbalancing of confounding variables**
  - As we discuss in the text, special care should be given to counterbalancing of confounding variables when using the non-directional approach. Specifically, unlike standard directional tests, the effects of confounders are not averaged out at the group level when counterbalanced across participants. Thus, counterbalancing should be done not only across participants but also across trials within participants.
- **How to interpret non-directional effects?**
  - In contrast to directional tests, where signal is measured relative to variability across individuals, in non-directional tests it is measured relative to variability

across different trials, within an individual. Hence, a positive result of a directional test indicates that effects are consistent between participants, while a non-directional test reveals the presence of an effect on the dependent variable within participants, regardless of the alignment of within participants effects across participants.

- A significant non-directional effect without a corresponding directional effect suggests reliable variability in effect signs across individuals. Whether this variability reflects transient or stable individual differences can be further tested by correlating individual effect scores from two experimental sessions: stable differences should result in a positive correlation. Whenever stable individual differences are observed, further research may be needed to identify the relevant personal traits that interact with the experimental manipulation.