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Accurately Measuring Nonconscious Processing Using a Generative Bayesian Framework

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Despite considerable interest in subliminal effects, fundamental questions about the proper way of examining them remain unanswered, sowing doubts regarding the veracity of published results. A central question is whether observed effects result from nonconscious processing rather than from some stimuli being consciously perceived by participants which are missed due to error in the awareness measurement. Here, we suggest a solution that implements a Bayesian modeling approach to measure the behavioral effects due to nonconscious stimuli accurately. Our solution relies on a Bayesian estimate of the correlation between variables that accounts for measurement error by modeling their uncertainty. We use simulations to show that this method accurately estimates nonconscious effects. The method we suggest is easy to use, and we describe its implementation on a relevant data set. We recommend that researchers in the field of nonconscious processing employ this method to estimate the effects of nonconscious processing more accurately.

Keywords: subliminal perception, hierarchical Bayesian framework, awareness test

The study of nonconscious cognitive abilities is a long-standing tradition in empirical psychology. Since the end of the 19th century, researchers have been exploring the scope of the nonconscious mind (Abrams et al., 2002; Dehaene, 2018; Dehaene et al., 2017, 2001; Marcel, 1983; Peirce & Jastrow, 1884; Sidis, 1898; Solomon & Howes, 1951; Van den Bussche et al., 2009; Wokke et al., 2011). Yet, despite more than a century of research, there is still no consensus regarding the scope of nonconscious capabilities. Instead, there is an ongoing debate regarding methodology, the outcome of which is a wide disagreement about the validity of empirical findings purporting to

provide evidence for nonconscious processing (Goldstein & Hassin, 2017; Hassin, 2013; Hesselmann & Knops, 2014; Hesselmann & Moors, 2015; Holender & Duscherer, 2004; Rabagliati et al., 2018; Shanks, 2017; Sklar et al., in press). The critical issue in this debate can be phrased in terms of a simple methodological question: How can we conclude with confidence that an observed effect is the result of nonconscious processing? Here, we attempt to resolve this debate by proposing a new method employing generative Bayesian models. This method settles previously raised methodological and statistical issues with experiments exploring nonconscious processes.

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Code and scripts described in Appendix B and Appendix C.

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A common way to explore nonconscious processes is to test the influence of subliminal stimuli on participants' behavior. To examine these nonconscious processes, many researchers combine two measures (Reingold & Merikle, 1988). One measure is the *awareness* measure, which quantifies participants' awareness of the subliminal stimuli. The other measure is the *effect* measure, which quantifies the behavioral change (e.g., faster reaction time) induced by the subliminal stimuli. These two measures are then combined to examine whether nonconscious processing occurred: If the *effect* measure indicates that stimuli were processed, and the *awareness* measure indicates that stimuli were not consciously perceived, one can conclude that stimuli were processed nonconsciously. This logic has been used in establishing nonconscious processing of different types of stimuli, and different kinds of processes, including the processing of single words (Armstrong & Dienes, 2014; Dehaene et al., 1998; Marcel, 1983; Payne et al., 2016; Van den Bussche et al., 2010), phrases (Armstrong & Dienes, 2013; Nakamura et al., 2018; Sklar et al., 2012; van Gaal et al., 2014), numbers (Kouider & Dehaene, 2009), simple arithmetic equations (Garcia-Orza et al., 2009; Sklar et al., 2012), pictures and images (Van den Bussche et al., 2012), and abstract shapes (Kunst-Wilson & Zajonc, 1980) among others.

A typical subliminal experiment consists of effect and awareness measurements (Reingold & Merikle, 1988). The effect measurement is done by presenting subliminal stimuli followed by supraliminal targets and measuring responses to the targets. Suppose different subliminal stimuli (e.g., control stimuli vs. critical stimuli) lead to differences in responses to the supraliminal target. In that case, the researcher can conclude that there is evidence for an *effect* of the subliminal stimuli (sometimes referred to as the *subliminal priming effect*). The awareness measurement is necessary to establish that the presumably subliminal stimuli are indeed subliminal.

There are two main distinctions between awareness measures: subjective versus objective and trial-by-trial versus block design. In subjective awareness measurement, participants are asked to report to what degree they perceive a given stimulus (Dienes, 2007; Dienes & Seth, 2010; Overgaard et al., 2010; Sandberg et al., 2013). While, in objective awareness measurement, participants are asked to perform a forced-

choice test regarding some aspect of the subliminal stimulus (e.g., asking participants to decide whether a subliminal stimulus appeared above or below a fixation cross; e.g., Cheesman & Merikle, 1984; Kouider & Dehaene, 2009; Sklar et al., 2012). The debate regarding which method of awareness measurement is preferable is vibrant and ongoing (Dienes, 2021; Rosenthal, 2019; Sandberg, et al., 2010; Van den Bussche et al., 2013).

Usually subjective awareness measurements are obtained during the same trials as the effect measurement by asking participants to both respond to the target and rate the visibility of the subliminal stimulus. Thus they are termed trial-by-trial measures. Objective awareness measurement can be implemented on a trial-by-trial basis (Oxner et al., 2018) or in a separate block (Cheesman & Merikle, 1984; Goldstein et al., 2020; Kouider & Dehaene, 2009; Sklar et al., 2012). When administered as a separate block, the same supposedly subliminal stimuli as those in the effect measurement block are presented under identical conditions, and participants' only task in such blocks is the forced-choice discrimination task that comprises the objective awareness measurement.

When using objective awareness measures, researchers often define a threshold to classify participants as aware or unaware (Heerey & Velani, 2010; Kawakami & Yoshida, 2015; Muscarella et al., 2013; Pessiglione et al., 2007; Sklar et al., 2012). When researchers employ this method, participants who score significantly above chance level on an objective measure are considered aware of the stimuli and are removed from the analysis that estimates the nonconscious effect. Thus, only participants that are not classified as aware are included in the final analysis from which evidence for nonconscious processing (or lack thereof) is drawn. Despite the prevalence of this methodological strategy, it has two serious caveats.

First, it is unclear how one should determine the proper threshold to use to detect all aware participants. Every method suggested for setting a threshold carries some risk of erroneously classifying conscious participants as nonconscious (Morey & Rouder, 2011; Rabagliate, 2017). This issue led Shanks (2017) to conclude that many (if not most) previous results obtained by choosing an awareness threshold cannot conclusively be shown to not be the outcome of a statistical bias due to regression to the mean

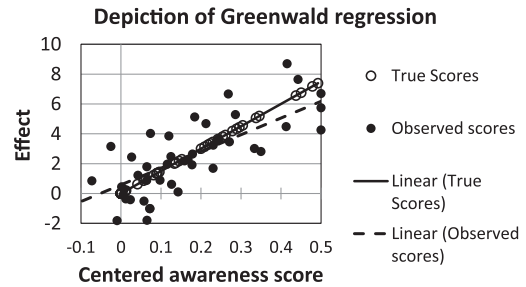
(i.e., underestimation of the awareness scores), thus calling into question their scientific merit (but see Sklar et al., in press). This conclusion urgently calls for valid methods of analyzing data gathered in such designs without using thresholds.

Second, this procedure excludes from the analysis participants who were aware of any portion of the trials. This means that even a participant who was aware of a tiny portion of trials, and as such was, in fact, unaware of the stimuli in the majority of the experiment, will still be excluded from analysis, leading to a loss of potentially informative data. This, in turn, reduces statistical power.

A way of avoiding these two caveats is to use a regression-based strategy suggested by Greenwald et al. (1995). In this approach (hereafter referred to as *Greenwald regression*), the *effect* scores are predicted in a simple regression model from *awareness* scores centered so that zero indicates “no awareness.” Thus, the predicted variable is the *effect* and is defined as the difference in performance between the control and critical conditions. The predictor is the centered awareness score. Practically, the centering of the awareness score is done by subtracting the chance level from the actual performance values, so that chance-level (e.g., “no awareness” point) performance is at 0. For example, in a two-alternative forced-choice (2-AFC) design, 0.5 will be subtracted from the awareness scores. Given this centering, the regression intercept represents the predicted *effect* for a participant whose awareness score is at chance level (e.g., a participant who scored 50% correct in a 2-AFC measure). Thus, an intercept significantly larger than 0 is evidence for an *effect* resulting from nonconscious processing (see Figure 1). Importantly, this analysis avoids the need to adopt an awareness threshold and includes data from all participants, thus potentially circumventing the two major drawbacks of the threshold method.

While this method has theoretical advantages, subsequent work showed that the intercept in Greenwald regression is a biased estimate of the actual nonconscious effect (Doshier, 1998; Klauer et al., 1998; Miller, 2000; Sand & Nilsson, 2016). This bias emerges because, like any behavioral measurement, the awareness measurement includes measurement error. Critically, in a regression analysis, error in the predictor variable leads to underestimating the slope coefficient—a well-established issue known as

Figure 1
Depiction of Greenwald Regression



Note. Each circle represents a hypothetical participant. The y-axis shows the *effect* measured (i.e., the difference between control and critical conditions). The x-axis is the centered awareness score: raw awareness score (where 0.5 represents complete unawareness—and 1 represents full awareness) minus 0.5 (chance level). Thus, complete unawareness is reflected by the value 0 and complete awareness by 0.5. Empty circles represent the participants’ true scores, while full circles represent participants’ observed scores (which include measurement error). The intercept is the performance expected for subjects with complete unawareness. Note that due to error in awareness measurement, observed awareness scores could be negative (i.e., observed scores below chance level). As can be seen by the different intercepts for true scores and observed score, measurement error leads to an underestimation of the slope and therefore overestimation of the intercept.

regression attenuation or dilution (Spearman, 1904)—and hence to possible overestimation of the intercept.¹ For example, consider a situation where there is a positive correlation (and hence, slope) between true awareness levels and an effect. Because of measurement error, the estimated slope is most likely underestimated compared to the true slope. Due to the inherent dependence of the intercept and the slope in regression analysis, the intercept will now be *overestimated* (see Figure 1); hence the estimated effect under “zero awareness” may be estimated as higher than it is (for mathematical description see Appendix A).

To adjust the biased estimation, Klauer et al. (1998) suggested an alternative regression approach that corrects for the intercept overestimation induced by the error in measurement. However, some objections to their suggestion were raised (Miller, 2000; but see Klauer &

¹ This is true in the most common case in which the mean awareness measurement score, the mean behavioral effect, and the slope coefficient are all positive. Other cases may lead to under- or overestimation.

Greenwald, 2000). First, Klauer et al. explicitly assume that the errors in the awareness measurement are independent of the true awareness value. This assumption is often violated, as awareness measures most often rely on the number of correct responses in a 2-AFC task, where the true awareness value ($N \times P$) is by definition related to variance, or measurement error [$N \times P \times (1 - P)$]. In other words, common awareness measures are inherently more accurate for participants with higher awareness scores, and one cannot assume independence of error variance from true values (Miller, 2000). More generally, Klauer et al. were criticized for not demonstrating robustness to violations of assumptions (Miller, 2000).

The disagreement regarding Klauer's correction led to the only partial adaptation of their method. While some researchers used this method (Bermeitinger et al., 2012; Eckstein & Henson, 2012; Spruyt et al., 2012), often acknowledging the debate regarding this correction, others use the original Greenwald regression (Lin & Murray, 2013; Naccache & Dehaene, 2001; Reber et al., 2012; Van Opstal et al., 2005) or, most often, rely on an awareness threshold despite the issues it incurs (Shanks, 2017). Here, we propose a new method inspired by Greenwald regression. This method employs Bayesian generative modeling to accurately estimate the intercept in the presence of measurement error while avoiding the assumptions made by Klauer et al. (1998). Further, as we detail below, our approach offers a flexible framework for testing alternative assumptions.

Bayesian Generative Models

In developing the current method, we take a Bayesian generative modeling approach. In this approach, one has to specify a model of how a series of unobserved variables generated a set of observed variables (most commonly, an experiment's results, along with other known design parameters) and define priors for the unobserved parameters in the model (reflecting the researcher's prior beliefs regarding them). Then, given the model's architecture, the priors, and the observed data, posterior distributions are estimated for each unobserved parameter, reflecting the researcher's current beliefs regarding the parameters in question. Several software packages are currently available for building such Bayesian generative models (e.g., winBUGS, JAGS, STAN).

In practice, since in increasingly complex models, there is no simple analytical solution for computing posterior distributions, these software use Monte Carlo Markov Chain (MCMC) algorithms in the process of their estimation.

Here, we estimate the intercept of Greenwald's regression from a Bayesian model, which aims to resolve the overestimation issue described above. The procedure first specifies a model that details which variables influence which and how (described below). It takes as input the data from an experiment: the number of correctly identified trials in the objective awareness measurement (from which the awareness score is calculated) and the effect estimate of each participant. As an output, the model estimates a posterior distribution for each of the unobserved variables—including, in particular, the intercept. These distributions represent the researchers' current beliefs regarding the parameters of interest given the observed data and the model, from which we can estimate central tendency measures (e.g., mean, median) and measures of dispersion (e.g., standard deviation and density intervals). Centrally for our purposes, we will focus on examining the posterior distribution of the (centered) intercept, which reflects the extent of nonconscious processing (for a thorough discussion of the Bayesian estimation approach, see Dienes, 2021).

Accurate Intercept Estimation in Light of Measurement Error—An Overview

Our approach builds upon a recent work by Matzke et al. (2017), who proposed a Bayesian generative model to correct for measurement error in the estimation of correlations. Here, we adapt their model specifically to the issue of nonconscious processing by estimating the intercept in a regression model while accounting for the error in the awareness and effect measurements.

It is generally reasonable to assume that every psychological measurement includes some degree of measurement error, quantified as the measure's (un)reliability. The expected value of a measurement thus represents not only the actual value that we try to measure ("true score") but also some error noise. For example, when we try to measure the awareness level of a participant in an objective awareness measurement, we take the portion of trials she reported correctly as an indicator of awareness, but this measurement

includes some measurement error. Matzke et al. (2017) suggest that within a Bayesian modeling framework, the measurement error is reflected in the *uncertainty* we have regarding the estimation of a parameter. In other words, the uncertainty of an estimate can be used as a proxy for measurement error. Importantly, in a Bayesian generative modeling framework, uncertainty is well defined and can be computed from the posterior distributions of the variables in the model.

The procedure of estimating the corrected intercept consists of three stages detailed below: First, for each participant, we estimate the true value of the awareness measure along with its uncertainty, which we take as an estimate for the measurement error in the awareness measurement. Second, for each participant, we estimate the true value of the behavioral effect and its uncertainty. Third, we estimate the posterior distribution of the intercept (along with other population-level parameters including the correlation between the awareness score and the effect) while crucially accounting for the uncertainty reflecting measurement error.

Accurate Intercept Estimation—in Practice

Practically, once the data are acquired, a single script implements all three steps and approximates a posterior distribution for the intercept, 95% credible interval, and a Bayes factor (BF) comparing the evidence for a null model (an intercept of zero indicating no nonconscious effect) to the evidence for a model in which the intercept is different from zero (drawn from the prior specified for the intercept in the Bayesian model, see Figure 5). This script takes as input the data from each trial in the effect measurement part of the experiment and each participant's number of correctly identified trials in the objective awareness measurement (for an explanation on how to format input data, run the model online, and interpret the results see Appendix B).

Figure 2 describes the model's output using data from a recent study by Goldstein et al. (2020). The data used are taken from 30 participants and from two conditions in Experiment 1. The participants performed a 2-AFC recognition task regarding a conscious target. The conscious target was either congruent ($M = 629$ ms, $SD = 248$ ms) or incongruent ($M = 669$ ms, $SD = 274$ ms) with the direction of a masked moving stimulus. Each condition consisted of 32 trials.

The awareness measurement part consisted of 64 2-AFC trials.

Relevant to the current discussion, the authors refrained from presenting their results in terms of subliminal presentation due to the issue of potential measurement error. Our claim here is that by using our correction, which directly corrects for measurement error, a direct estimation of nonconscious processing can in fact be made (a point we return to in the General Discussion section).

Accurate Intercept Estimation—Full Model

Step One

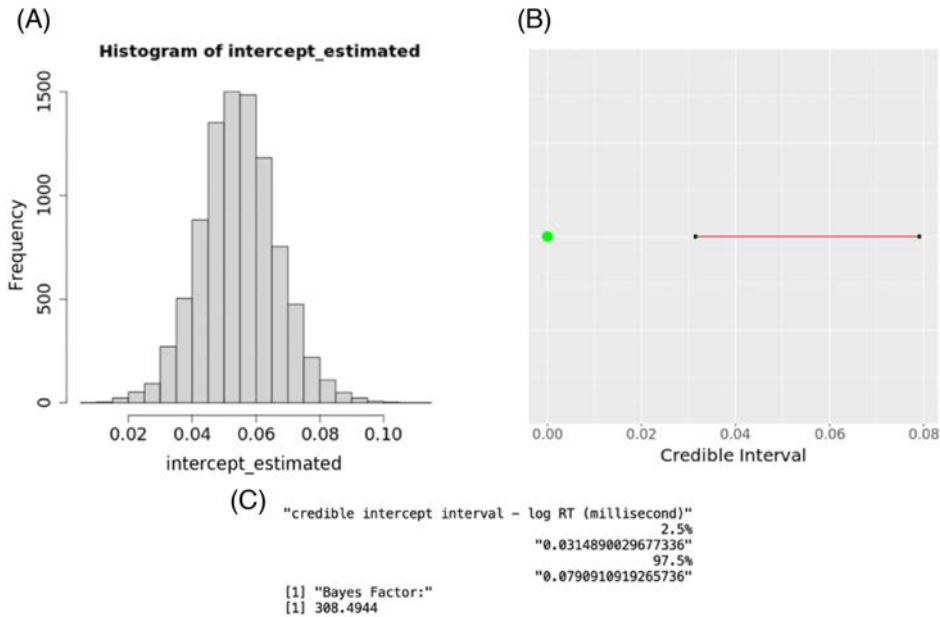
To calculate the awareness measurement score and its uncertainty for each participant, we must first specify a generative model that presumably gave rise to the observed data in this task. A reasonable view of the awareness score holds that there are, in fact, two different subpopulations of participants: one, masked (or nonconscious) participants, who are not aware of the masked stimuli. Thus, their expected (i.e., true) value in the awareness measurement test is 0.5 (in a 2-AFC awareness test). Second, partially aware participants, whose expected values range between 0.5 and 1 (with 1 representing a participant who was aware of the subliminal stimuli on all of the trials).

In the Bayesian modeling framework, one can simulate a mixture of two subpopulations using a latent-mixture model, which estimates the probability of each participant to belong to one of the two populations and the true score of a subject given their membership status to these subgroups (Lee & Wagenmakers, 2014; Nakamura et al., 2018; Siegelman et al., 2019). Using this framework, we formulate two subgroups of participants: a subgroup of masked participants (who have an expected value of 0.5 (ψ) in the awareness task) and partially aware participants (whose awareness scores (ϕ_i) are drawn from a uniform distribution that ranges from 0.5 to 1).² The

² An alternative model would involve a hierarchical structure, where the awareness scores of participants in the partially aware subsample come from some predefined distribution with parameters estimated based on the data (e.g., a normal distribution across awareness scores with estimation of a group-level mean and standard deviation). Barring a clear hypothesis regarding the shape of this distribution, however, we chose instead to use a more conservative subject-by-subject estimation of awareness scores assumed to originate from a uniform distribution.

Figure 2

The Output of the Bayesian Model on the Data From an Experiment That Included Two (Within Participant) Conditions and a Separate Objective Measure Block



Note. (A) Histogram of the posterior estimation of the intercept (in log RT units). (B) Credible interval (2.5, 97.5) for the estimation. (C) The values for the credible interval as well as the Bayes factor comparing a null model where the intercept is set to zero (i.e., no nonconscious processing) to a model where it is drawn from wide normal distribution. Bayes factor is a measure of how much more likely the data are to be observed under an alternative hypothesis (H1) than under a null hypothesis (H0; i.e., $p(\text{Data} | H1)/p(\text{Data} | H0)$; see, e.g., Hoijtink et al., 2019, for details). As a guideline, a Bayes factor > 3 is considered moderate evidence supporting the alternative model (H1), while Bayes factor > 10 is considered strong evidence. See the online article for the color version of this figure.

latent-mixture parameter (z_i)—a Bernoulli trial which in each MCMC iteration for each subject can be either 1 or 0—determines whether a participant's true score (θ_i) is drawn from the masked subgroup or the partially aware subgroup. The proportion of subjects belonging to each of the two subgroups at the population level is determined by the base rate parameter (BR), which can a priori take any value between 0 and 1. Finally, the model estimates a posterior distribution for the true awareness score of each participant (θ_i), according to the number of correct responses in the awareness measurement of that participant (k_i) out of the number of trials in the task (n). See Figure 3 for full model specification.

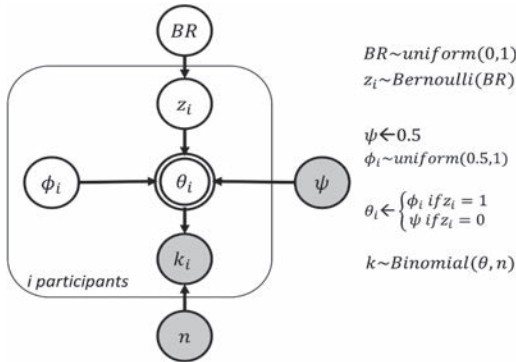
For our purposes, we focus on each participant's posterior distribution for the awareness score. Thus, from the posterior distribution of each θ_i , we take for each participant their estimated awareness measurement score (the mean of the posterior distribution) and its standard

deviation (representing the uncertainty in this estimation). In the third step of our process, we will use this mean estimation of each participant's true score and its uncertainty estimate (which serves as a proxy for measurement error) as input to a Bayesian model that estimates the regression coefficients quantifying the link between awareness measurement and behavioral effects.

Step Two

Next, for each participant (i), we estimate the true behavioral effect (δ_i) and its uncertainty. As an example, here we deal with a common design. The behavioral effect is the difference in Reaction Time (RT) between a target stimulus following a critical subliminal stimulus and one following a control subliminal stimulus. While the resulting model here is more complicated than the model in the previous step, it follows the same principles (see Figure 4). We assume that each response

Figure 3
Model of the Awareness Estimation



Note. The number of trials in the awareness measurement part (n) and the number of correct responses for each participant (k_i) are shaded in gray as they are observed. Because it is the sum of multiple Boolean (true/false) outcomes, k is drawn from a binomial distribution which depends on the likelihood of the participant to respond correctly on a given trial (θ_i) and the overall number of trials (n). The true awareness score (θ_i) is estimated per participant i , given a latent-mixture architecture that assumes two subsamples in the data (masked participants whose true values in the awareness measurement are at chance and partially aware participants): One subsample where members' true awareness scores (ψ) are bound to be 0.5 (i.e., unaware participants), and another subsample where true awareness scores (ϕ_i) come from a uniform distribution between 0.5 and 1 (i.e., partially aware participants).

latency (x_{ij} ; participant i , trial j) is generated from one of two normal distributions of log-transformed RT. Log RT is often distributed normally (Baayen, 2008), and thus the normality assumption seems plausible. One distribution includes RTs of trials in which a critical stimulus appears, and the other includes trials in which a control stimulus appears. Then, the model estimates the difference between the critical and control distributions, which is the parameter of interest, marked δ_i . This represents the behavioral effect for each participant. As such, from the posterior distribution of this parameter (δ_i) for each participant i , we estimate the mean of the effect and its uncertainty (again, uncertainty serves as a measure of measurement error), to be used in Step 3 of the process.

Step Three

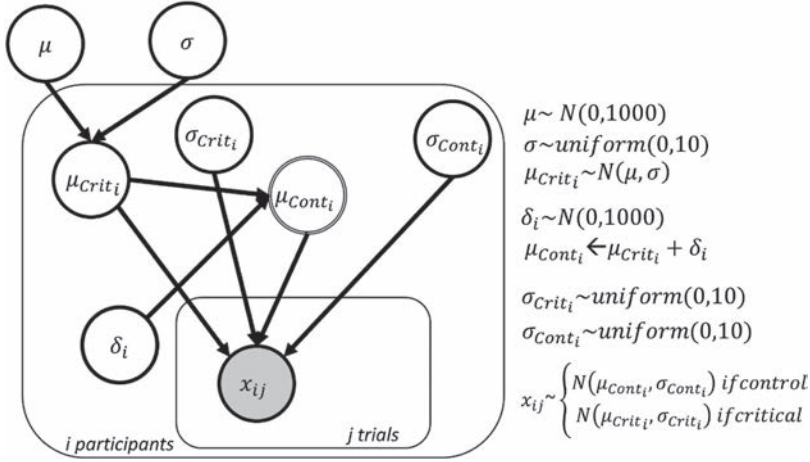
The third step of the process is estimating the regression coefficients of the relation between the estimated awareness score and the effect, while using uncertainty to correct for measurement error (see Figure 5). This step follows closely

recent work by Matzke et al. (2017) that describes the calculation of a true bivariate correlation (ρ) under noisy measurement. In our extension of this work, the model uses the outputs of the two models presented before (specifically, the mean of the posterior distributions—taken as a best estimate, and the standard deviation of these distributions—taken as measures of uncertainty in the estimations), to produce corrected regression coefficients that account for measurement error as reflected by uncertainty. Critically, these corrected coefficients aim to provide unbiased estimates of the true relation between the *awareness* and *effect* values (see Matzke et al., 2017 for discussion in the context of correlation coefficients; and see simulations showing empirical evidence for this claim below). Note that Matzke et al.'s (2017) method (and by extension, our model) assumes that the true values are sampled from a bivariate normal distribution. In the current context, this assumption is likely to be violated, at least in regards to the awareness scores which often have a restricted range and are thus not normally distributed. However, our simulations (see below) indicate that the model is robust to this violation of the assumption. Centrally to our purpose, our model derives the (*centered*) *intercept* of a regression model (α_c) predicting the true *effect* from the true *awareness* scores—that is, the estimated *effect* for an *awareness* score indicating no awareness. Practically, our model is parameterized such that it applies a wide normal prior on the central centered intercept parameter which includes all reasonable expected effect sizes, $N(0, 0.14)$ in log space which corresponds to a standard deviation of 91 ms assuming a baseline of 600 ms. The model uses uninformative priors for the correlation between the effect and the awareness scores, the mean of the awareness score, and the standard deviations of the awareness and effect scores. It then derives other parameters via standard formulas (e.g., deriving the slope from the correlation and the standard deviations via the formula $\beta = \rho \frac{\sigma_\alpha}{\sigma_\theta}$). Please refer to Figure 5 below and the online code (see Appendices B and C) for complete details regarding the model specification.

Simulation

To test whether our model indeed produces an unbiased estimate of the intercept, we simulated

Figure 4
Model Estimating the Effect



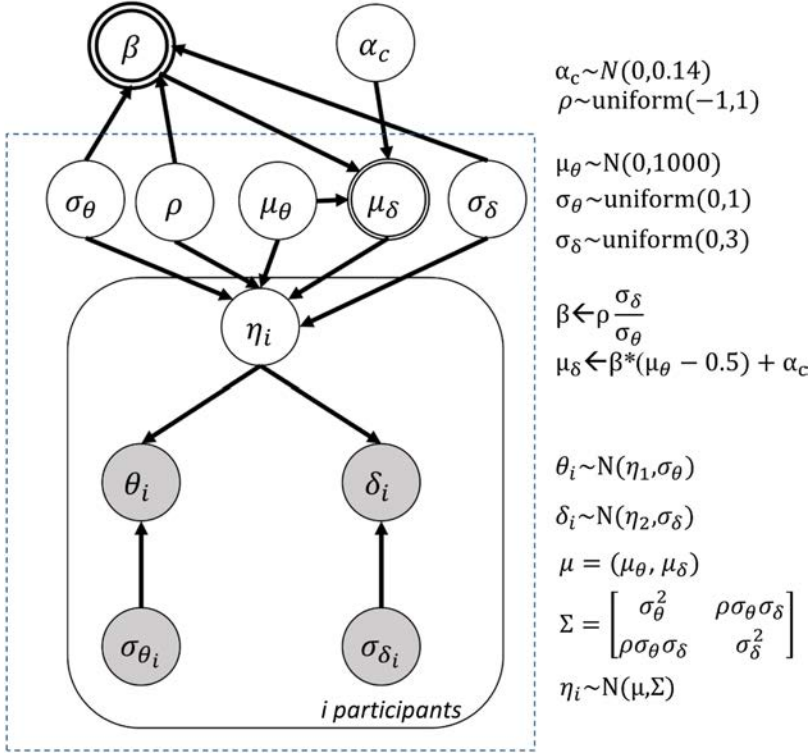
Note. That all Reaction Times (RTs) in this model are log transformed. The RT of participant i in trial j (x_{ij}) is determined by the condition: That is, RTs of critical and control trials are assumed to follow two normal distributions. The expected values of RTs in the critical condition (μ_{Crit_i}) are assumed to follow a normal distribution, $N(\mu, \sigma)$, indicating individual differences in baseline. The expected values of RTs in the control condition (μ_{Cont_i}) are the summation of the expected values of RTs in the critical condition and the effect (δ_i). As we do not have strong priors regarding the parameters, we chose either uniform or wide normal distributions. For simplicity, we assume equal variance in the critical and control conditions.

possible results of two types of experiments testing nonconscious processing: High-power experiments with 100 simulated participants and 200 trials in each data set and (relatively) low-power experiments with 30 simulated participants and 100 trials in each data set.³ For more simulations, see Appendix D. For each type, we simulated 1,250 data sets in total, combining different nonconscious and conscious processing effects. We included five simulated levels of nonconscious effect (i.e., intercept values) that correspond effects of 0, 12, 24, 37, 50 ms (the effect in the simulations are in log RT difference using an RT baseline of 600 ms), and five values of the slope predicting a participant's *effect* measure from their true *awareness* score: 0, 0.06, 0.12, and 0.18, corresponding to expected correlations of 0, 0.27, 0.49, 0.64, and 0.81 between the *effect* and *awareness* measures. We simulated 50 data sets for each of the 25 combinations. The mean RT of high-powered experiments across all conditions is 707 ms ($SD = 385$) and of the low-powered experiments is 934 ms ($SD = 1,056$). Importantly, the data sets simulating no nonconscious effect (i.e., an intercept value of 0) and no conscious processing effect (i.e., a correlation of 0

between *awareness* and *effect*) indeed yielded very small differences between control and critical conditions for both high- and low-power experiments (0.19 ms and 1.34 ms, respectively).

Trials for each participant were sampled from two normal distributions simulating critical and control conditions. The *effect* was defined as the difference between the mean of the critical condition and control condition. Note that due to the skewed nature of RT distributions, sampling from a normal distribution means assuming that RT data have undergone a preprocessing procedure (e.g., log transformation) to render them normal prior to analysis. Half of the simulated participants were fully nonconscious participants with an expected value of 0.5 on the awareness score (i.e., chance). The other half of the simulated participants (conscious participants) each had an expected value drawn from a uniform distribution between 0.5 and 1 (for other portions of conscious participants, see Appendix D).

³ To run the simulation, please visit: <https://codeocean.com/capsule/4196748/tree> and press the "Reproducible Run" button on the top left.

Figure 5
The Model Estimating the Corrected Correlation Coefficient and Intercept


Note. In the dashed rectangle, we depict the parameters included in Matzke et al.'s (2017) model. For each participant, the observed data are the estimated awareness score θ_i and the uncertainty of the awareness score ($\sigma_{\theta i}$), taken from Step 1, and the estimate of the effect δ_i and its uncertainty ($\sigma_{\delta i}$), taken from Step 2. Note that the uncertainty in these distributions serves as an estimate for measurement error. The estimates are assumed to be sampled from a bivariate normal distribution with expected values (μ) and from the covariance matrix we can estimate the true correlation (ρ ; see Matzke et al. 2017). Given the estimation of the awareness measurement score (μ_θ), its standard deviation (σ_θ), the effect score (δ_i), and unbiased correlation estimate (ρ), the intercept of the regression of the centered awareness score (α_c) is estimated. See the online article for the color version of this figure.

For each iteration, we calculate the centered intercept per our approach, as well as the estimation for the “standard” Greenwald regression.

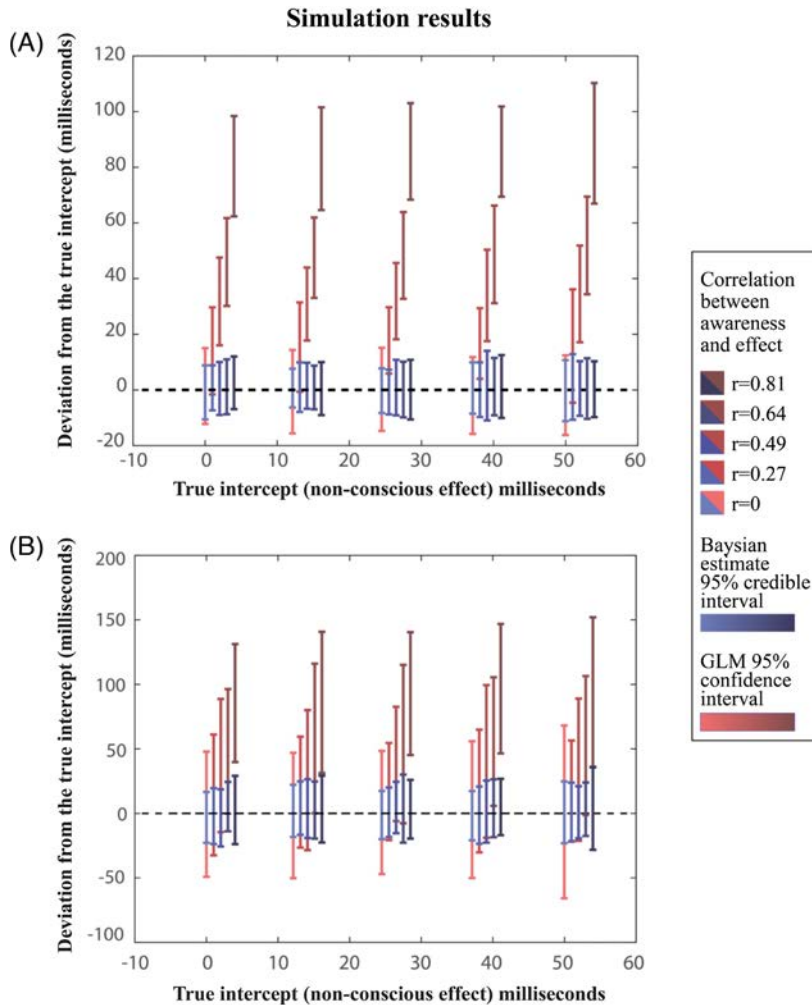
The results of the simulation, presented in Figure 6, clearly show the limits of the standard approach presented by Greenwald et al. (1995). When there is no effect of conscious processing (i.e., the correlation between *awareness* scores and the *effect* is zero) both the Greenwald and Bayesian estimations are accurate, with intervals that are centered around zero deviation from the actual simulated (i.e., true) intercept. This means that when there is no effect of conscious processing, no correction is required (i.e., there is no attenuation to correct for). When the correlation is

larger than 0, however, Greenwald’s approach overestimates the intercept, as expected, with increasingly greater overestimation for stronger correlations between the *awareness* score and the *effect*. In contrast, the Bayesian model correctly estimates the intercept, as reflected by zero mean deviance from the true intercept, overcoming the influence of measurement error, regardless of the correlation between the *awareness* score and the *effect*.

In addition to the intercept estimation, the Bayesian framework also allows for model comparison via BFs. In the current context, we use BFs to compare the model specified above (where the centered intercept is taken from a wide normal

Figure 6

The Results of the Simulation for High-Power Experiments (A) and Low-Power Experiments (B) Comparing the Bayesian Approach to Greenwald's Regression (a Genral Linear Model; GLM-Based Approach)



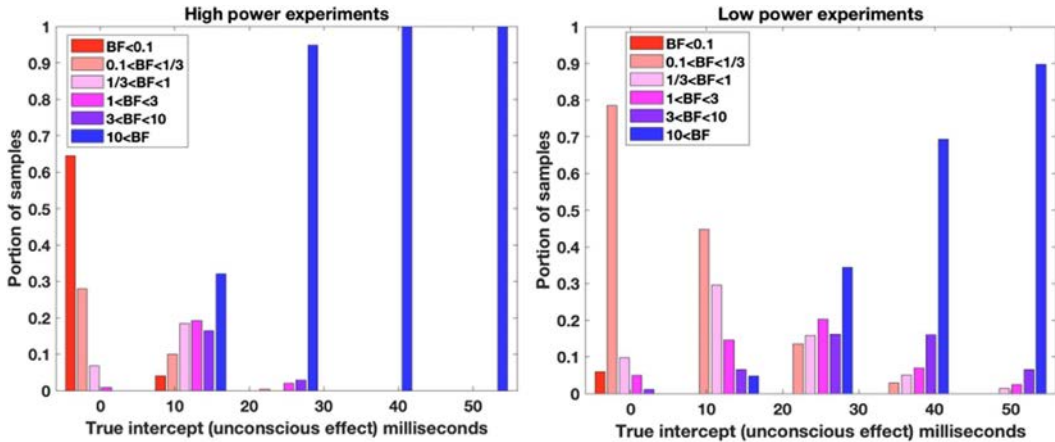
Note. Each simulation (for a given combination of conscious and nonconscious effects) yields two bars (blue and red). The red bars represent the 95% confidence intervals calculated using Greenwald et al. (1995). The blue bars represent 95% credible intervals calculated using our procedure. The y-axis represents the deviation from the true intercept. Bars which do not include the 0-error line show overestimation of the intercept. These include all red bars simulating a conscious effect above 0 (i.e., a positive correlation between the awareness score and the effect) when using Greenwald's method. Bars in which the 0-error line is included in the 95% credible interval indicate unbiased estimation of the intercept. This is the case for all of the blue bars which are the results of the Bayesian model. See the online article for the color version of this figure.

distribution) to a null model where the centered intercept is set to zero (i.e., no unconscious effect). Thus, in each iteration of the simulation, we examined the evidence in favor of the two models when compared to each other,

quantifying the evidence for the presence versus absence of an unconscious effect. For a comprehension overview of how to compute BFs with respect to nonconscious effects, see Dienes (2021). Practically, and for comparability with

Figure 7

The Results of the Simulation for High-Power Experiments (A) and Low-Power Experiments (B)



Note. For each level of a true nonconscious effect (horizontal axis), the proportion (vertical axis) of the simulated data sets that had strong evidence for the absence of a nonconscious effect ($\text{Bayes factor} < 0.1$), weak evidence for the absence of a nonconscious effect ($0.1 < \text{Bayes factor} < 1/3$), inconclusive evidence ($1/3 < \text{Bayes factor} < 3$), weak evidence supporting the nonconscious effect ($3 < \text{Bayes factor} < 10$), and strong evidence supporting the nonconscious effect ($\text{Bayes factor} > 10$) is plotted. See the online article for the color version of this figure.

Matzke et al. (2017), BFs were computed using the Savage–Dickey approximation. Figure 7 presents the distribution of BFs as a function of the experiment’s power (high- vs. low-power experiments) and the true effect size.

Overall, the results presented in Figure 7 show that our model overwhelmingly supports the existence of nonconscious processing effects when such effects are present and these effects are moderate or larger. As could be expected, this support is greater when the simulated experiments have higher statistical power (i.e., a larger sample size). Importantly, the portion of samples that supported the existence of a nonconscious effect ($\text{BF} > 3$) when this effect was absent (a true intercept of 0 ms) was only 1.1% of the data sets of the low-powered simulated experiments and 0% of the data sets of the high-powered simulated experiments. However, note that for a small nonconscious effects (10 ms), 44.75% of the low-power simulated experiments showed some evidence supporting the null hypothesis ($\text{BF} < 1/3$). Thus, the results indicate the importance of doing high-powered experiments when the effects of interest are small—though results also indicate reasonable performance for low-powered experiments when effects are larger.

In order to examine the robustness of our tool, we added another type of simulation with 30

participants and 30 trials, which simulates higher measurement error (Appendix D). We also manipulated the portion of truly unaware participants to reflect different type of experimental outcomes. For completion, we repeated the simulation for different portions of truly in unaware participants for the high-power experiment as well. The results clearly indicate robustness of the tool for the values manipulated.

General Discussion

Psychological studies of consciousness attempt to empirically tackle questions that were debated solely in the philosophical arena for centuries (Hume, 1739; Husserl, 1913; Leibniz, 1720; Locke, 1688; Mill, 1829). One of the fundamental questions in this field is what is the functional advantage of consciousness (Block, 1995; Flanagan & Polger, 1995; Lombardi et al., 1987). It is a common belief that consciousness equips conscious beings with some adaptive skills (Eccles, 1994; Kotchoubey, 2018; Macphail, 1998). One way to examine this issue empirically is to chart the scope and limitations of nonconscious cognition. Given an accurate understanding of nonconscious capabilities, one can gain insights about which processes do or do not require conscious processing. From this perspective, the study

of nonconscious cognition is the empirical intellectual infrastructure for one of the most daunting questions regarding human existence—why are we conscious.

The study of nonconscious cognition is rife however with methodological and statistical obstacles, including in particular outstanding questions regarding the proper ways of inferring whether a measured behavior indeed provides evidence for nonconscious processing. These obstacles yielded differing approaches, which led to different and often contrasting interpretations of existing results (Holender & Duschner, 2004; Kouider & Dehaene, 2009; Moors & Hesselmann, 2018). Here, we suggest an approach that combines the principles of a Bayesian generative modeling framework with the regression-based method suggested by Greenwald et al. (1995). Our approach maintains the advantages of Greenwald's method, namely using the data from all participants and avoiding the need to choose an awareness threshold. Critically, unlike Greenwald's analysis, our method does not lead to an overestimation of nonconscious effects as it corrects for measurement error. Therefore, we believe that it is a useful analytical tool for any experiment where stimuli are masked, and awareness is measured using an objective test (whether done in a separate block or on a trial-by-trial basis).

One of the assumptions in our model is that the relation between participants' awareness and observed effect is linear. This is reflected by the fact that the current method estimates the intercept of a linear regression as evidence for nonconscious effect. This assumption seems warranted as both the awareness score and the contribution of conscious processing to the observed effect rely on a single parameter—the percent of trials that a given participant is aware of. As such, these values should be linearly related, with an increase in the percent of aware trials leading to both a proportional increase in the *awareness* score and proportional change in the observed *effect*.⁴ Alternatively, if one assumes a nonlinear relation between awareness scores and participants' observed effect, an alternative specification of their relation can be implemented using the same approach.

Notably, the linearity assumption in our model means that it is technically possible to extrapolate based on the linear trend of the regression model. In practice, this means that as long as participants are not aware of the subliminal stimuli on some

portion of the trials, the effect of nonconscious processing can be estimated even if all participants were aware of some (but not all) of the subliminal stimuli. However, conclusions regarding values that are outside the range of values used to compute the model are less certain and should be treated with caution. Thus, we caution against using our model to estimate the effect of nonconscious processing from samples in which few participants were entirely unaware of the subliminal stimuli.

A major advantage of the Bayesian generative framework is its flexibility for exploring other models and the robustness of results against alternative models. Practically, if one wishes to use an alternative model for awareness scores, they should replace the current model for estimating awareness (Figure 3) with an alternative model, while other components (described in Appendix C) should not be changed. We encourage researchers to test their own data using different models of awareness (such as those described in this article and others) to ensure the robustness of their findings. We also encourage researchers to revisit the assumptions we made here as reflected in the architecture and priors of the model and to refine them as knowledge in the field accumulates.

Our method is directly applicable to any experiment that used a standard design where the *effect* is computed as the difference in performance between two conditions (i.e., critical and control), and awareness is measured in a forced-choice paradigm. As forced-choice awareness measures are widely used (either as a separate block or on the same trials of the effect block), our model is applicable to a large number of data sets (e.g., Goldstein et al., 2020; Heerey & Velani, 2010; Kawakami & Yoshida, 2015; Kouider & Dehaene, 2009; Muscarella et al., 2013; Pessiglione et al., 2007; Sklar et al., 2012). Importantly, as we do not use a threshold, our method does not exclude participants whose data were not used in a threshold-based analysis and thus may change the interpretation of already

⁴ The change in the observed effect may be an increase (if conscious processing leads to a larger observed effect), a decrease (if the effects of conscious and nonconscious processing operate in opposite directions), or it may be no change at all (if awareness does not contribute to the observed effect). All three cases would be represented by possible slopes (with a positive, negative, or zero value) of the linear relationship between *awareness* and *effect* scores.

obtained results. In addition, because the current approach uses more data, one should have more confidence in its outcomes.

Shanks (2017) emphasized the error in measurement problem in threshold-based awareness tests, casting doubt on whether past published work indeed showed effects due to the processing of truly subliminal stimuli. In light of this criticism, and due to the lack of an accepted solution, some researchers avoided interpreting their results as induced by subliminal presentation (Goldstein et al., 2020). The method we describe above directly tackles the error in measurement issue which significantly limits the possible interpretation of results, thus allowing researchers to more confidently make conclusions regarding both previously collected data as well as new data sets.

The method we describe here is, to our knowledge, the first to use generative Bayesian modeling to directly assess the scope of nonconscious processing by focusing on the regression intercept. However, several other Bayesian methods have previously been proposed for exploring nonconscious processing in different ways (e.g., Dienes, 2021; Dienes & Overgaard, 2015; Malejka et al., 2021; Rouder et al., 2009).

One suggested method models the null hypothesis that an effect fully depends on awareness by creating a linear prediction based on the effect observed when participants are fully aware and the 0,0 point (i.e., the point at which there is no awareness and hence, ex hypothesis, no effect; Dienes, 2021; Dienes & Overgaard, 2015). However, this method requires gathering additional data (a condition in which participants are aware of priming stimuli), and it relies on the assumption that the changes to experimental procedure needed to render participants aware do not affect the relationship between awareness and the effect in question. As such, its application may be limited to specific experimental designs in which it can be reasonably implemented.

Another method using generative Bayesian modeling to address the problem posed by error in measurement for experiments examining nonconscious processing was recently put forward by Malejka et al. (2021). Malejka et al. (2021) propose that researchers use Matzke et al.'s (2017) model (which also forms the basis for the model presented here) to estimate the correlation between the *effect* and *awareness* measures while accounting for the influence of measurement error. This estimate can then be used to

compare the evidence for a null correlation hypothesis (i.e., there is no correlation between awareness and the effect in question) compared to a positive correlation hypothesis (i.e., more awareness is linked to larger effect) to calculate a BF. If this BF shows strong evidence for the null hypothesis, researchers can conclude, according to Malejka et al.'s (2021) suggestion, that there is evidence that the effect in question is independent from awareness.

Notably, as this analysis focuses on the correlation between awareness and the effect, it examines a different research question than the one commonly considered by researchers conducting experiments regarding nonconscious processing. As such, the conclusions of this analysis may be orthogonal to the question most often posed by such experiments—is there evidence for nonconscious processing. Indeed, an effect may theoretically be dependent on awareness (i.e., larger the more a participant is aware) but still present even when participants are fully unaware. As such, although both rely on similar statistical tools and may be applied to the same data sets, the correlation analysis proposed by Malejka et al. (2021) fits different research questions and leads to different theoretical conclusions than the regression intercept analysis presented here.

Bayesian approaches are geared toward an explicit estimation of the uncertainty in the estimation, which is reflected in the width of the posterior distribution of the estimated parameters. Thus, in the current case, researchers can directly examine the degree to which they are certain regarding the existence of a nonconscious processing effect by examining the full posterior distribution of the centered intercept. Importantly, in cases where the results are still characterized by substantial uncertainty, the Bayesian framework allows for a continuous aggregation of data across experiments. Practically, this can be done simply by running the models on the aggregated data of multiple experiments. As long as the design of the different studies is identical—no further modifications to the model are needed; in cases where the design differs across studies, some straight forward adaptations may be required (e.g., allowing for different amount of trials across studies). In both cases, as data accumulate, researchers should expect to see a decrease in the estimation uncertainty.

The core principle in Bayesian models is that they require researchers to explicitly formulate their assumptions regarding the sources of the

observed data. This stands in contrast to frequentist statistics (e.g., Genral Linear Model), in which the assumptions are mostly implicit, and unfortunately rarely put to a test (e.g., Hoekstra et al., 2012). This requirement may bring to surface components that were implicitly assumed and often not addressed properly. Part of the assumptions that one needs to specify in Bayesian models are the priors of the parameters in the model. When there is no previous knowledge as to what these priors should be, as is the case of many of the parameters in the current models, it is recommended to choose weakly informative or uninformative priors, typically wide normal or uniform distributions (Chung et al., 2015; Gelman et al., 2017). The increasing prevalence of open science initiatives and data sharing will allow future researchers to adopt more informative priors that will in turn increase the sensitivity of the models. The more data are shared the more accurate the assumed priors will become, leading to gradually more accurate estimations of the parameters of interest (Lee et al., 2019; Poldrack et al., 2019). Bayesian modeling inherently benefits from data sharing and offers an efficient way to accumulate empirical data. In parallel, refinement of theories is also expected to lead to improvements in the architecture of the model.

Bayesian models are a well-defined computational model. A Bayesian model stands as a testable theory in which the different components are explicitly defined and the relations between them are specified. Adopting such mathematically defined theories will aid in making the field of consciousness and nonconscious processes science more precise and testable, thus leading to faster cumulative scientific advancement. Eventually, models that explain vast bodies of data, gathered from different time points and different labs, could be formulated. Such models would inherently be more robust and more likely to lead to replicable and conclusive findings.

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Appendix A

Intercept Overestimation in the Frequentist Framework

Cases where both the predictor variable mean and the regression slope are positive lead to an overestimation of the intercept due to regression attenuation. Regression attenuation is the phenomenon where, if a predictor variable is measured with error, the observed regression coefficient is attenuated by the measurement (un)reliability (Spearman, 1904):

$$b_{\text{observed}} = b_{\text{true}} \times r_{xx}. \quad (\text{A1})$$

This leads to misestimation of the observed intercept such that $a_{\text{observed}} = \bar{y} - \bar{x} \times b_{\text{true}} \times r_{xx}$.

Therefore, the observed intercept is a biased estimate of the true intercept ($a_{\text{true}} = \bar{y} - \bar{x} \times b_{\text{true}}$). This bias is the multiplication of the variable mean, the regression slope and one minus the predictor variable's reliability ($a_{\text{observed}} - a_{\text{true}} = (1 - r_{xx}) \times \bar{x} \times b_{\text{true}}$), and will thus be positive in the common case in which higher levels of awareness lead to larger observed effects.

(Appendices continue)

Appendix B

Running the Intercept Posterior Estimation Model Online

Data Formatting

Running the model on a new set of data requires formatting the data in a specific way. The data should be saved in CSV format that has four columns. Each row in the file describes a trial in the experiment.

The first column (“subject”) includes the participant ID/number.

The second column (“Condition”) describes the condition (1—critical trials/0—control trials). This column should be sorted in a descending manner.

The third column (“RT”) includes the RT in milliseconds. Missing values should be marked as NA.

The fourth column (“OT_score”) describes the performance at the Awareness Measurement part (i.e., the number of trials the participant classified correctly). Note that each participant has the same value in this column for all trials (i.e., same value for all rows from the same participants).

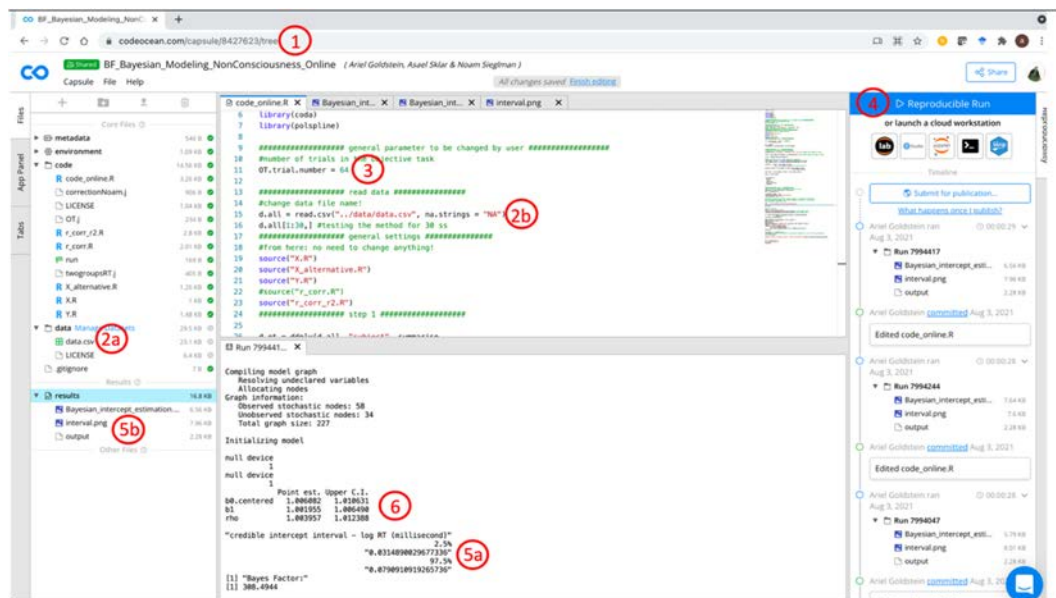
Running Procedure

Log-in (sign in the first time) to CodeOcean.

1. Go to the BF_Bayesian_Modeling_Non-Consciousness_Online capsule: <https://codeocean.com/capsule/8427623/tree> (see Figure B1). Upload the new data set in one of two options (see below the data formatting structure):
 - a. Name the data set file data.csv and upload. This will rewrite the current example file (needed to reproduce the results described in Figure 2) or
 - b. Go to code_online.R file, and change the name of the file in line 11 (do not delete “./data/”).
2. If the number of trials in the Awareness Measurement block is different than 64, line 13 should be changed (variable OT.trial.number).

Figure B1

The CodeOcean Website Allows Us to Provide the Environment Necessary to Reproduce the Results Reported in This Article As Well As Apply the Model to New Data Sets



Note. The numbers match the description below. See the online article for the color version of this figure.

(Appendices continue)

3. Press Reproducible Run button (top-right position).
4. After a few minutes, the results will appear in two places:
 - a. In the center-bottom, the credible values of the intercept and the Bayes actor will be displayed.
 - b. In the bottom-left screen under the “results” folder, there will be a “Bayesian_intercept_estimation.png” file with the histogram of the intercept.
5. The full samples from the posterior distributions of the estimated correlation, intercept, and slope, Gelman–Rubin diagnostic measures of convergence (Gelman &

Rubin, 1992), and the Bayes factor estimate are stored in variables for further inspection.

Interpreting the Results

The model generates the posterior histogram for the intercept, as well as a credible interval for the centered intercept in units of log of milliseconds. The script also stores in variables the full samples from the posterior distributions of the estimated correlation, intercept, and slope, estimates of convergence using the Gelman–Rubin diagnostic measure (Gelman & Rubin, 1992), and the estimated Bayes factor.

Appendix C

Running the Intercept Posterior Estimation Model in R with rjags

Below are instructions on how to set up and run the Bayesian corrected estimation script in R.

Installation

To run the script, you will need to install both JAGS (a separate sampling program) and the rjags, coda, and plyr R packages.

To install JAGS, go to <http://mcmc-jags.sourceforge.net/> and follow instructions for downloading.

To install R packages, type `install.packages("rjags")`, `install.packages("coda")`, and `install.packages("plyr")` into the R command line.

These scripts were developed in JAGS (4.3.0) sampling software and rjags package in R (4.3).

data.csv—A csv file in the format described in Data Formatting section in Appendix B. The data that are provided are from Goldstein et al.’s (2020) Experiment 1.

r_corr.R—An R function that calculates the posteriors for the correlation, the intercept, and slope, which is called by Main.R.

X_alternative.R—Estimates the awareness measurement and its uncertainty according to the mixture model (Figure 3). Is being used by Main.R.

Y.R—Estimates the effect measurement and its uncertainty. Is called by Main.R.

After running Main.R, several .j files will be created by the script.

Running the Model Locally

All of the files mentioned in the Files section should be in the folder from which the model is run. The scripts are written in R and should be run from the R environment. First, one should edit line 9 in Main.R to the number of trials in the awareness measurement part (this code assumes the awareness measure is a two alternatives forced choice with chance-level performance of 50%). Second, one should edit line 13 to match the name of the data file. By default, the name is data.csv.

Note, running this script is likely to take up to several minutes (though you should see progress information while it is running).

Setting up the Folder

Download the scripts here (or copy–paste the following link: https://zenodo.org/record/5169879#.YQ_iGINKhBU)

To run this script, the following files should all be in the same folder:

Main.R—this is the R script that runs the model.

Before running a model on a data set the number of trials in the awareness measurement should be changed in line 8 (the default, 64, is true for the example data set, but should be changed to the number in *your* experiment). If your data file is not called data.csv, change the filename of the input data set in line 12.

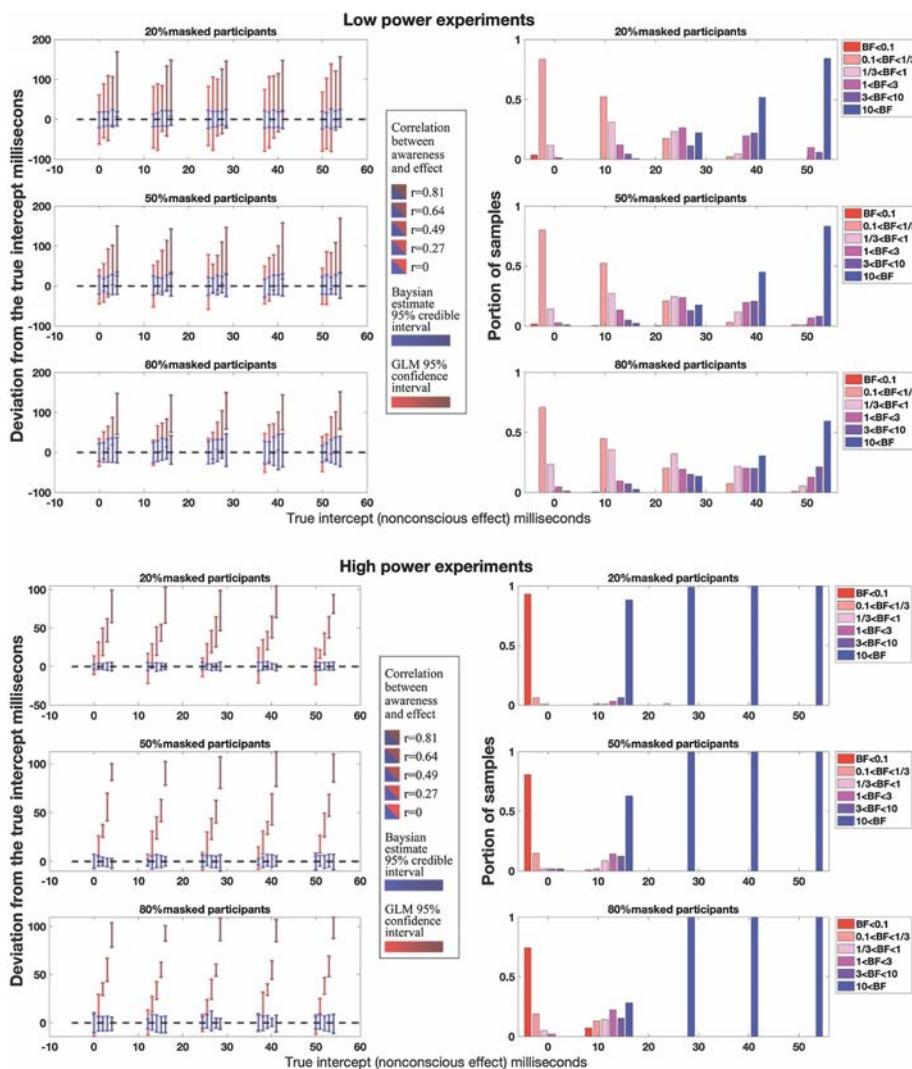
(Appendices continue)

Appendix D

Robustness to Portion of Participants Masked and Number of Participants

Figure D1

In Order to Test the Robustness of Our Suggested Method, We Conducted Multiple Simulations for Low-Power Experiments (30 Participants and 30 Trials), Which Simulate High Measurement Error, With Different Portions of Truly Masked Versus Partially Aware Participants (20%, 50%, or 80% of Participants Sampled From the Unaware Subsample; see Figure D1)



Note. The results of these additional simulations are presented in the top portion of the figure: These results clearly indicate that even for these conditions, the tool correctly estimates the nonconscious effect as reflected both by the estimation of the deviation from the true intercept, and the Bayes factors examining the hypothesis that there is a nonconscious effect (intercept > 0). For completion, we also ran the same simulations manipulating the percentage of aware versus unaware participants (100 participants and 200 trials) and replicated the results (see the bottom part of figure). See the online article for the color version of this figure.