Theoretical Article

Regression to the Mean Does Not Explain Away Nonconscious Processing

A Critical Review of Shanks 2017

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Abstract. In studies that use subliminal presentations, participants may become aware of stimuli that are intended to remain subliminal. A common solution to this problem is to analyze the results of the group of participants for whom the stimuli remained subliminal. A recent article (Shanks, 2017) argued that this method leads to a regression to the mean artifact, which may account for many of the observed effects. However, conceptual and statistical characteristics of the original publication lead to overestimation of the influence of the artifact. Using simulations, we demonstrate that this overestimation leads to the mistaken conclusion that regression to the mean accounts for nonconscious effects. We conclude by briefly outlining a new description of the influence of the artifact and how it should be statistically addressed.

Keywords: regression to the mean, nonconscious processes, subliminal

> "The universal phenomenon of regression toward the mean is just as universally misunderstood." Campbell and Kenny (1999, pp. xiii)

Examinations of the capacities and capabilities of nonconscious processes have been part of experimental psychology from the late 19th century (e.g., Peirce & Jastrow, 1885; Sidis, 1898) throughout the 20th century (e.g., Bruner, 1957; Dehaene et al., 1998; Greenwald, 1992; Greenwald et al., 1996; Marcel, 1983) and are still flourishing in the second decade of the 21st century (e.g., Abir et al., 2017; Faivre et al., 2014; Lei et al., 2017; Moors et al., 2017; Salomon et al., 2017). In recent decades, the modal view suggests that nonconscious mental processes are an inherent part of human psychology (e.g., Bargh et al., 2012; Breitmeyer & Öğmen, 2006; Capa et al., 2011; Dehaene et al., 2006; Dijksterhuis et al., 2006; Faivre et al., 2014; Goldstein & Hassin, 2017; Hassin, 2013; Hassin & Sklar, 2014; Lamy et al., 2008; Sklar et al., 2018; Van Opstal et al., 2010; Zacks et al., 2007). Thus, theories that posit both conscious and nonconscious processes form the basis for much of modern cognitive and social psychology (e.g., Evans & Stanovich, 2013; Kahneman, 2011; Sherman et al., 2014; but see Keren & Schul, 2009; Newell & Shanks, 2014).

In a subset of this vast literature, empirical demonstrations of nonconscious processes rely on subliminal presentations of stimuli (e.g., Dehaene et al., 1998; Greenwald et al., 1996; Hassin et al., 2007; Marcel, 1983; Reingold & Merikle, 1988). To verify that stimuli are indeed subliminal, researchers must use measures of stimulus awareness. Using these measures, experimenters usually exclude from analyses participants who are aware of the stimuli and/or trials in which participants were aware of the stimuli (e.g., Merikle & Reingold, 1992; Ramsøy & Overgaard, 2004; Sandberg et al., 2010; see Table 1 in Shanks 2017 for many examples[1] After

[1] An underlying assumption of this analysis is that the differences in awareness detected by awareness measures are due to actual differences in how aware participants are on a given task (or trial). If the differences detected by awareness measures represent measurement artifacts such as response bias (Schmidt, 2015), this assumption is not valid. On the other hand, when there is strong individual variance in the effectiveness of masking paradigms, such as in the case of continuous flash suppression (Gayet & Stein, 2017; Sklar et al., 2021) or long duration backwards masking (Repeated Masked Suppression (RMS); Sklar et al., 2021), and measurement artifacts are accounted for, this assumption is valid.

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excluding these participants and trials, researchers analyze their dependent variables examining evidence for nonconscious processing (e.g., reaction time difference between two conditions). For ease of writing, we follow Shanks (2017) in referring to these dependent variables of processing as participants' *performance*.

In a recent article, Shanks (2017) argued that this strategy, which he refers to as "post hoc data selection" introduces an inflation of apparent nonconscious performance.[2] This inflation, in turn, may lead researchers to erroneously conclude that there is evidence for nonconscious processing even in cases where no nonconscious processing occurs. Shanks (2017) then suggests that one can tease apart true nonconscious processing from the artifact created by the regression to the mean, using a regression analysis in standardized scores. Finally, Shanks (2017) presents simulations that purportedly show how this bias, in itself, can lead to results equivalent to those obtained by a previous study reporting evidence in line with nonconscious processing.

We concur with the novel and important assertion made in Shanks (2017) that utilizing a priori selection rules can lead to potential inflation of observed performance due to regression to the mean. Yet, we contend that issues in the conceptualization and the statistical procedures inevitably lead Shanks (2017) to systematically and profoundly underestimate the evidence for nonconscious processing. His dire conclusions regarding the evidence for nonconscious processing, then, seem unjustified and may hinder future research on consciousness and nonconscious processes.

Below we delineate the two major issues in Shanks (2017). We begin by explaining how regression to the mean influences apparent nonconscious performance. Critically, this influence depends on the relation between awareness and performance. Taking this dependence into consideration means that many findings of nonconscious processing, including examples used in Shanks (2017), are unlikely to be attributable to regression to the mean. Next, we examine the statistical procedure Shanks (2017) uses to predict the expected consequence of regression to the mean. Using simulations that are highly similar to those used by Shanks (2017), we show that this procedure leads to sever underestimation of nonconscious processes. Our simulations show that the procedure leads to the conclusion that there is no evidence for nonconscious processing even when there is very strong evidence for nonconscious processing in the data.

Section 1: When Does Regression to the Mean Influence Performance

Utilizing a priori selection rules, scientists focus on analyzing the data of participants who score low on awareness measures, that is, they analyze the data of participants who are categorized as unaware. By definition, the mean awareness score of this subsample is lower than that of the entire sample. As such, regression to the mean implies that these participants' true awareness scores should be, on average, higher than their observed scores. In other words, participants in the unaware group are, on average, more aware than their awareness scores suggest. Thus, some participants may actually be aware of some of the stimuli. Shanks (2017) correctly argues that the aforementioned underestimation of awareness scores may lead to an overestimation of participants' nonconscious performance.

Crucially, however, this is only true if *awareness increases performance*. When awareness increases performance, participants whose observed awareness score is lower than their true awareness are likely to perform better than their score suggests. This inflation can be quantified: It is the amount of true awareness in the unaware group multiplied by the effect of awareness on performance.[3] *The nature of multiplication means that this inflation will happen if, and only if, performance is positively increases with awareness*. If performance is not influenced by awareness, then the performance of aware and unaware participants is the same. In such a case, including aware participants in the unaware group will not inflate (or deflate) the average performance in the group. Thus, when there is no true correlation between awareness and performance, there is no inflation of the nonconscious effect. Moreover, in cases where awareness is negatively correlated with

[2] Note that the term post hoc data selection is easily confusable with the term post hoc analyses. Notably, there is a crucial difference. Post hoc analyses are analyses' choices that are made after data are collected and in light of what is found in them. In "post hoc data selection," however, all choices, including the inclusion criteria for the subsample, should be determined a priori (and preregistered). Critically, the limitations of post hoc analyses, such as Type I error inflation due to multiple comparisons, do not apply to post hoc data selection. We will therefore refrain from using this term here and instead will refer to it as employing a priori selection rules.

[3] This calculation assumes the effect of awareness on performance is linear. Note that this assumption is also made by Shanks (2017), where linear regression models relying on this assumption are heavily employed. Indeed, in cases where the effect of awareness on performance is all-or-none in a given trial, and both awareness and performance are averaged across multiple trials, this assumption should be maintained. However, in cases where the relationship between awareness and performance is more complex, both Shanks's (2017) statistical modeling and the current treatment fail to account for this complexity.

performance, that is, when aware participants perform worse than unaware participants, the regression artifact will actually yield underestimation of nonconscious effects.

These assertions may be more easily understandable in an example using different theoretical constructs than awareness and performance. Suppose we were interested in whether people tend to wear any cloths on hot days. We would perform a simple experiment, going outside on a random sample of days and counting how many articles of clothing a random sample of people we met were wearing. Then, we would apply a criterion for what constitutes a hot day (e.g., 30 °C) and only look at the data from those days. The correlation between the temperature outside and the amount of clothing is negative (people wear more clothing when it is cold outside), but not perfect. Because the correlation is negative, regression to the mean predicts that the number of clothing articles on our sample of hot days would be more extremely low compared to the mean number of clothes worn than the temperature is extremely high compared to the mean temperature. In this case, regression to the mean could not lead us to overestimate the amount of clothing worn on hot days, but only underestimate it. Similarly, nonconscious performance can only be underestimated due to regression to the mean if the true correlation between awareness and performance is negative. Likewise, if instead of temperature we measured a variable that has no correlation with how many articles of clothing people wear (e.g., the number of fire hydrants in the same street), then there would be no influence of regression to the mean for picking an extreme group on this variable (e.g., asking whether people wear any cloths on streets with no fire hydrants). In these examples, where the true correlation is clearly either negative or nonexistent, it is clear that the statistical phenomenon of regression to the mean could not lead us to erroneously conclude that people in the extreme subsample wear more cloths than they actually do. Likewise, if the true correlation between awareness and performance is negative or nonexistent, regression to the mean cannot lead us to conclude that there is more nonconscious performance than there actually is.

This analysis highlights the fact that the scope of the problem depends heavily on the prevalence of true positive, zero, and negative correlations between awareness and performance. Shanks (2017) has not addressed this issue at all. Logically, positive correlations are only a subset of the entire range, and hence failing to consider the entire range necessarily leads to overestimation of the number of results impacted by regression to the mean. Interestingly, in two of the most prominent examples discussed by Shanks (2017), Sklar et al. (2012), and Clark & Squire (1998), the evidence for nonconscious processing comes from samples in which observed awareness–performance correlations are small and nonsignificant ($-.2 < r$ -.200<r<.200, p>.150). Thus, in these examples, there is no significant evidence for a positive correlation (though an absence of evidence is not evidence for an absence of a true correlation).

The Influence of Measurement Reliability

There is a very specific case, which Shanks (2017, pp. 757) highlights, in which regression to the mean is a valid threat even though awareness–performance correlation appears negligible: *When the correlation only seems to be negligible*. This is the case when awareness is measured using a highly unreliable measure (e.g., a coin toss). Because the reliability of a measures creates an upper bound for its correlation with any other measure (Spearman, 1904), the awareness–performance correlation is bound to be negligible. Moreover, because unreliability drives regression to the mean, the regression to the mean artifact would be maximal.

Yet, while low reliability leads to a low awareness–performance correlation, one cannot simply assume that a low correlation means low reliability (to do so is an affirmation of the consequent). Reliability of awareness measures can, and should, be directly estimated from the observed empirical data through common reliability estimation procedures (e.g., split-half correlation). In experiments in which the reliability of the awareness measure is high, a low awareness–performance correlation indicates true minimal correlation between awareness and performance.

Take just a couple of examples discussed at length in Shanks (2017): In Sklar et al. (2012) Experiments 6 and 7, the reliability of the awareness measure was very high (Spearman–Brown corrected split-half reliability $r = .926$ and $r = .840$ in Experiments 6 and 7), while the awareness–performance correlations were negligible ($r = .202$, $p = .200$ and $r = -.174$, $p = .166$, respectively). Likewise, we have no reason to assume that the reliability of the awareness measure in other experiments used as main examples by Shanks (2017) was low. In Clark and Squire's (1998) case, awareness was measured in a 17-question memory test. The exact same awareness test was used in a different condition by Clark and Squire (1998). In this condition, the awareness–performance correlation was substantial ($r = .74$; $p < .01$) and could therefore not be limited by measure unreliability.[4] Thus, in many cases, including main examples used in Shanks (2017), there is

[4] It is unlikely that the same measure would be reliable in one of Clark and Squire's (1998) conditions and unreliable in a second, highly similar, condition.

direct or indirect evidence that awareness measures are reliable. In these cases, negligible awareness–performance correlations cannot be attributed to unreliability of the awareness measure.

To conclude, when awareness measures are reliable and yet they do not correlate with performance, inflation of the observed nonconscious performance due to regression to the mean is not a major concern and should not seriously impact our interpretation of the results.

Section 2: An Incorrect Use of Simple Regression

Shanks (2017) presented one statistical method designed to test directly whether observed nonconscious performance can be attributed to regression to the mean.[5] This method is a simple regression, in standardized scores,[6] which predicts the mean performance in the unaware group from the mean awareness score in that group. This simple regression procedure is treated in Shanks (2017) as providing the expected consequence of regression to the mean. Critically, though, it is not a plausible interpretation of this statistical procedure.

Simple regression is a fairly common and straightforward statistical procedure. The result of simple regression is a regression line, a simple equation that provides for each predictor value Xi the predicted value Yi most likely to be associated with it (assuming a linear relationship between X and Y). Shanks (2017) uses a simple regression in which the predictor variable, X, is the awareness measure score and the predicted variable, Y, is the performance score.[7] From this simple regression equation, he computes the predicted performance for the hypothetical participant whose awareness score is the average awareness score in the unaware group. Shanks (2017) treats this value as the predicted influence of regression to the mean on performance. He compares the observed performance in the unaware group to this value using a single sample *t*-test. If the observed performance is not significantly different from the predicted performance, he concludes there is no sufficient evidence to rule out regression to the mean.

However, despite its suggested use, what the predicted value Shanks uses gives us, like any predicted value in a simple regression, is the best estimate for the true *performance* (predicted Yi) given the specific awareness value (Xi). This value does not represent regression to the mean in performance. It is an estimate of the overall performance in the unaware group, given the observed mean awareness in this group. As such, the statistical procedure proposed by Shanks (2017) appears to be inapplicable to addressing the concern of regression to the mean.

Critically, the consequence of using the predicted value as a comparison benchmark quantifying the influence of regression to the mean (as Shanks, 2017, pp. 764 and 769, proposes) is grave: Datasets in which the awareness–performance relationship is strictly linear (or nonexistent) will almost always to lead to the conclusion that there is no evidence for nonconscious effect, *regardless of the actual evidence*.

The veracity of our previous statement is easily demonstrated by using simulations. We applied the procedure used in Shanks (2017) to three simulated example datasets. Dataset 1, taken from Shanks (2017), is a simulation of a case where there is no true nonconscious performance.[8] It was simulated from a model in which both performance and awareness are based on a single underlying value S (see Appendix for full details regarding all simulation models). In this case, when S is zero, both awareness and performance will have a value of zero, on average. In other words, this is a case where there is no nonconscious processing.

Dataset 2 is closely modeled after Dataset 1. The only change is the addition of true unaware performance

5 Shanks (2017) also presented several additional tools such as the Galton squeeze plot, using relative ordering of means or conducting multiple awareness tests, one can use to examine a given dataset for evidence of regression to the mean. However, none of these tools allow one to determine whether regression to the mean actually inflates the observed unaware performance. As we explain above, observing, for example, that awareness and performance are uncorrelated (which would result in robust evidence for regression to the mean according to a Galton squeeze plot or the relative ordering of means) does not mean that regression artifacts account for observed unaware performance. As such, we focus here on the one statistically veridical test proposed in Shanks (2017).

6 Note that standardization is a linear transformation and as such changes the scale, but not the meaning, of values. The statistical significance of the difference between performance in the unaware subsample and the predicted value is unaffected by standardization.

7 In Shanks (2017), the predictor variable is designated as Y and the predicted variable is designated as X. Following the common convention for designating predicting and predicted variables in regression analysis, we reverse these designations.

8 Although it was initially reported as a simulation of a dataset similar to Sklar et al. (2012) Experiment 6, this dataset contains a critical difference – the mean awareness score of the unaware group (55.19%) is significantly larger than the 50% chance score one would expect in an unaware group ($t(78) = 14.29$, $p < .001$). Thus, this simulation fails to replicate a crucial aspect of the experimental procedure – obtaining an unaware group that does not show, on the group level, evidence for awareness. In fact, given the significant evidence for awareness on the group level analysis in the supposedly unaware group, if these were true results, they would not be accepted as suggesting nonconscious processing. This difference however has no influence on this dataset's use as a general example.

Table 1. Procedure with standardized values

	Mean standardized awareness	Awareness–performance correlation	Predicted standardized performance	Observed standardized performance	Significance test
Dataset 1	−1.018	.300	−0.305	−0.276	$t(78) = 0.283, p = .778$
Dataset 2	−0.899	.287	−0.258	−0.276	$t(85) = -0.168, p = .867$
Dataset 3	−0.899	.270	−0.243	−0.256	$t(87) = -0.145, p = .885$

Note. Summary of results for each of the 3 datasets. Columns, in order, are as follows: mean standardized awareness score in the unaware subsample. The correlation between awareness and performance in the full sample. The predicted standardized performance in the unaware subsample (equal to the mean standardized awareness multiplied by the awareness–performance correlation). The average standardized performance observed in the unaware subsample, and a significance test compering observed standardized performance scores to the predicted standardized performance score (equivalent to the confidence interval procedure used in Shanks (2017) to show that empirical results are not significantly different from the supposed regression to the mean artifact).

through a slight change in the formula by which performance is generated: We added a constant (10) to all performance values. The addition of this constant means that even when the value underlying awareness, S, equals zero, that is – even when the simulated participants are nonconscious – there is performance equal to this constant (i.e., 10). The original simulation in Shanks (2017) was scaled to mimic empirical results in which the effect was measured in milliseconds. As such, this can be thought of as realistic evidence for nonconscious processing – equivalent to a 10-ms effect on performance. This dataset allows us to see if using the procedure proposed by Shanks (2017) allows us to detect a small nonconscious effect.

Dataset 3 is similar to Dataset 2, but instead of adding small-yet-quite-realistic evidence for nonconscious processing (i.e., a constant equivalent to a 10-ms effect), we now include highly exaggerated and unrealistic evidence – adding a constant equivalent to a 1,000-ms effect. As such, Dataset 3 is an extreme example. A procedure that fails to indicate evidence for nonconscious performance in this dataset is very likely to miss the vast majority, if not simply all, real-life nonconscious effects.

The results of these simulations are summarized in Table 1. For all three datasets, the procedure proposed by Shanks (2017) concludes that there is *no evidence for nonconscious processing*, despite the fact that Datasets 2 and 3 include realistic and even extreme evidence of nonconscious processing. We can thus conclude that the procedure proposed by Shanks (2017) fails to detect highly robust nonconscious effects. In other words, the proposed method *indicates that evidence of nonconscious processing is explained by regression to the mean, regardless of whether this is the case*. Employing this procedure is bound to lead one to a profound underestimation of nonconscious effects.

Having concluded that the procedure proposed by Shanks (2017) to estimate the influence of regression to the mean is not satisfactory, how *should* we estimate this influence? Briefly, our suggestion is that we rely on the multiplication we discussed in Section 1: The influence of regression to the mean on the observed performance in a given unaware group is the amount of true awareness in that unaware group multiplied by the true effect of awareness on performance.

To compute this value, we suggest using unbiased estimates that correct for the (un)reliability of the awareness measure. Specifically, an unbiased estimate of the *true amount of awareness in the unaware group* would correct for regression to the mean by using the formula proposed by Campbell and Kenny (1999, pp. 50) to estimate the true mean awareness score in the unaware group. An estimate for the *effect of awareness on performance* could be based on the regression coefficient from a simple regression predicting performance from the awareness score. This coefficient would then be corrected for regression attenuation (i.e., the influence of measurement unreliability; Spearman, 1904) to create an unbiased estimate. Finally, multiplying the two unbiased estimates should result in an unbiased estimate for the influence of undetected awareness in the unaware group on performance (i.e., the regression to the mean bias). This unbiased estimate can then be used in the same way the estimate proposed by Shanks (2017) was intended to be used – as a null hypothesis to which observed results would be compared. Importantly, both corrections are very simple and only rely on the reliability of the awareness measure, which can easily be computed so long as the awareness measure is based on multiple trials.

Conclusions

Shanks (2017) highlighted an important issue; studies employing the a priori selection strategy may, under certain conditions, find inflated evidence for nonconscious processing due to a regression to the mean artifact. Importantly, though, conceptual and statistical inadequacies in the methods developed in the original paper lead Shanks (2017) to seriously overestimate the impact of this artifact. As we have shown, the impact of regression to the mean critically depends on two factors: the awareness–

performance relationship in the population and the (un)reliability of the awareness measure. Our analyses clearly show that Shanks' claim that "once regression is considered, the results of many of these studies may turn out not to require postulating distinct unconscious processes at all" (pp. 773) is unjustified and, at best, premature. It is unclear how many (if any) published results are in fact qualitatively influenced by a regression to the mean artifact. In the specific cases explicitly discussed by Shanks, this threat is nonexistent, and hence, their original interpretation still holds.

Nonetheless, empirical science is always improved by accurate quantification of statistical artifacts and statistical tools that correct such artifacts' influence. As such, Shanks (2017) does the field a great service in highlighting a potential danger. Statistical tools can address this and other issues that arise from the use of awareness measures that are less than perfectly reliable. Employing tools like the one we briefly described at the end of Section 2 as well as more advanced ones (e.g., Goldstein et al., 2021) would allow the field to advance with greater confidence in the veracity of results. This, we hope, will lead to more cumulative and accurate science and therefore to faster progress in what is one of the most intriguing questions in psychology.

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Open Data
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Appendix

Dataset 1

As reported by Shanks (2017) who generated this dataset, scores in this dataset are based on a "internal representation score" S, which is taken from a normal distribution with a *M* of 1.0 and a *SD* of 0.5. S is then translated into both an awareness score and a performance score. Each score also includes an independent error term *e*. For the performance score, error values e_p are taken from a normal distribution with a *M* of 0 and a *SD* of 24. For the awareness score, error values e_x are taken from a normal distribution with a *M* of 0 and a *SD* of 0.04. Final scores are computed using the following formulas:

$$\text{Performance scores} = 18 * S + e_p$$
$$\text{Awareness score} = 0.12 * S + e_x \quad (1)$$

Dataset 2

In creating Dataset 2, exactly the same parameters and distributions were used as previously discribed for Dataset 1 exepting the calculation of performance scores. To simulate true unaware performance, a constant of 10 was added so that the performance when S is 0 would be 10. The new formula was therefore:

$$\text{Performance scores} = 10 + 18 * S + e_p \quad (2)$$

Dataset 3

In creating Dataset 3, exactly the same parameters and distributions were used as previously discribed for Dataset 1 exepting the calculation of performance scores. To simulate exagerated true unaware performance, a constant of 1,000 was added so that the performance when S is 0 would be 1,000. The new formula was therefore:

$$\text{Performance scores} = 1{,}000 + 18 * S + e_p$$

For the full simulated datasets, see Sklar (2021). (3)