Regression to the mean does not explain away non-conscious processing: 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 non-conscious effects. We conclude by briefly outlining a new description of the influence of the artifact, and how it should be statistically addressed.

“The universal phenomenon of regression toward the mean is just as universally misunderstood.” Campbell and Kenny (1999, p. xiii)

Examinations of the capacities and capabilities of non-conscious 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, Draine, & Abrams, 1996; Marcel, 1983) and are still flourishing in the second decade of the 21st century (e.g., Abir, Sklar, Dotsch, Todorov, & Hassin, 2017; Faivre, Mudrik, Schwartz, & Koch, 2014; Lei et al., 2017; Moors, Wagemans, & de-Wit, 2017; Roy et al., 2016; Sklar et al., 2012). In recent decades the modal view suggests that non-conscious mental processes are an inherent part of human psychology (Bargh, Schwader, Hailey, Dyer, & Boothby, 2012; Breitmeyer & Ögmen, 2006; Capa, Bustin, Cleeremans, & Hansenne, 2011; Dehaene, Changeux, Naccache, & Sergent, 2006; Dijksterhuis, Bos, Nordgren, & van Baaren, 2006; Faivre et al., 2014; Goldstein & Hassin, 2017; Hassin, 2013; Hassin & Sklar, 2014; Lamy, Mudrik, & Deouell, 2008; Sklar, Deouell, & Hassin, 2018; Van Opstal, Gevers, Osman, & Verguts, 2010; Zacks, Speer, Swallow, Braver, & Reynolds, 2007). Thus, theories that posit both conscious and non-conscious processes form the basis for much of modern cognitive and social psychology (e.g. Evans & Stanovich, 2013; Kahneman, 2011; Sherman, Gawronski, & Trope, 2014; but see Keren & Schul, 2009; Newell & Shanks, 2014).

In a subset of this vast literature, empirical demonstrations of non-conscious processes rely on subliminal presentations of stimuli (e.g., Dehaene et al., 1998; Greenwald et al., 1996; Hassin, Ferguson, Shidlovski, & Gross, 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, Timmermans, Overgaard, & Cleeremans, 2010; see Shanks, 2017, Table 1 for many examples). After excluding these participants and trials, researchers analyze their dependent variables examining evidence for non-conscious 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 non-conscious performance¹. This inflation, in turn, may lead researchers to erroneously conclude that there is evidence for non-conscious processing even in cases where no non-conscious processing occurs. Shanks (2017) then suggests that one can tease apart true non-conscious 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 Sklar et al. (2012).

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 non-conscious processing. His dire conclusions regarding the evidence for non-conscious processing, then, seem unjustified and may hinder future research on consciousness and non-conscious processes.

Below we delineate the two major issues in Shanks (2017). We begin by explaining how regression to the mean influences apparent non-conscious performance. Critically, this influence depends on the relation between awareness and performance. Taking this dependence into consideration means that many findings of non-conscious 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 severe underestimation of non-conscious processes. Our simulations show that the procedure leads to the conclusion that there is no evidence for non-conscious processing even when there is very strong evidence for non-conscious 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

¹ 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, are determined a-priori**. 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.

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' non-conscious 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 performance². *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 non-conscious effect. Moreover, in cases where awareness is negatively correlated with performance, i.e., when aware participants perform **worse** than unaware participants, the regression artifact will actually yield underestimation of non-conscious effects.

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) doesn't address this issue at all. Logically, positive correlations are only a subset 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 and Squire, 1998, the evidence for non-conscious processing

² 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 on 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.

comes from samples in which observed awareness-performance correlations are small and non-significant ($-0.2 < r < 0.2$, $p > 0.15$).

The influence of measurement reliability

There is a very specific case, which Shanks (2017, p.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 measure 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.

To 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 $r = 0.93$ and $r = 0.84$ in Experiments 6 & 7), while the awareness-performance correlations were negligible ($r = 0.198$, $p = 0.21$ and $r = -0.18$, $p = 0.16$ 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 questions 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 ($r = 0.74$; $p < 0.01$) and could therefore not be limited by measure unreliability³. Thus, in many cases, including main examples used in Shanks (2017), there is 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.

³ 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.

To conclude, when awareness measures are reliable and yet they do not correlate with performance, inflation of the observed non-conscious 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 non-conscious performance can be attributed to regression to the mean⁴. This method is a simple regression, in standardized scores⁵, 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 X_i the predicted value Y_i 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 score⁶. 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

⁴ 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).

⁵ 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.

⁶ In Shanks (2017) the predictor variable is designated Y and the predicted variable is designated X . Following the common convention for designating predicting and predicted variables in regression analysis, we reverse these designations.

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 Y_i) given the specific awareness value (X_i). 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 linear (or non-existent) will almost always lead to the conclusion that there is no evidence for non-conscious 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 non-conscious performance⁷. 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 non-conscious processing.

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

⁷ Although it was initially reported as a simulation of a data set similar to Sklar et al. (2012) Experiment 6, this dataset contains a critical difference invalidating any conclusions drawn from this simulation about the Sklar et al. experiment. Specifically, the mean awareness score of the unaware group (55.19%) is significantly bigger than the 50% chance score one would expect in an unaware group ($t(78)=14.29$, $p<0.001$). Thus, this simulation fails to replicate a crucial aspect of Sklar et al.'s design – obtaining an unaware group. In fact, if these were true results, no reasonable research would claim they suggest non-conscious processing, because the unaware group was simply aware. This difference however has no influence on this dataset's use as a general example.

thought of as realistic evidence for non-conscious processing – equivalent to a 10 milliseconds effect on performance. This dataset allows us to see if using the procedure proposed by Shanks (2017) allows us to detect a small non-conscious effect.

Dataset 3 is similar to Dataset 2, but instead of adding small-yet-quite-realistic evidence for non-conscious processing (i.e., a constant equivalent to a 10 milliseconds effect) we now include highly exaggerated and unrealistic evidence – adding a constant equivalent to a 1000 milliseconds effect. As such, Dataset 3 is an extreme example. A procedure that fails to indicate evidence for non-conscious performance in this dataset is very likely to miss the vast majority, if not simply all, real-life non-conscious 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 non-conscious processing*, despite of the fact that Datasets 2 and 3 include realistic and even extreme evidence of non-conscious processing. We can thus conclude that the procedure proposed by Shanks (2017) fails to detect highly robust non-conscious effects. In other words, the proposed method *indicates that evidence of non-conscious processing are explained by regression to the mean, regardless of whether this is the case or not*. Employing this procedure is bound to lead one to a profound underestimation of non-conscious effects.

Table 1 – Procedure with standardized values

	Mean standardized awareness	Awareness- performance correlation	Predicted standardized performance	Observed standardized performance	Significance test
Dataset 1	-1.018	0.300	-0.305	-0.276	t(78)=0.283, p=0.78
Dataset 2	-0.899	0.287	-0.258	-0.276	t(85)=-0.168, p=0.87
Dataset 3	-0.899	0.270	-0.243	-0.256	t(87)=-0.145, p=0.89

Table 1. Summary of results for each of the 3 datasets. Columns, in order, are: 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 comparing 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).

Conclusions

Shanks (2017) highlighted an important issue; studies employing the a-priori selection strategy may, under certain conditions, find inflated evidence for non-conscious 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" (p. 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 non-existent, and hence their original interpretation still holds.

Nonetheless, empirical science is always improved by accurate quantification of statistical artifacts and statistical tools which 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 such tools (e.g., Goldstein, Siegelman, & Sklar, in preparation; Sklar, in preparation) 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.

References

- Abir, Y., Sklar, A. Y., Dotsch, R., Todorov, A., & Hassin, R. R. (2017). The determinants of consciousness of human faces. *Nature Human Behaviour*.
- Bargh, J. A., Schwader, K. L., Hailey, S. E., Dyer, R. L., & Boothby, E. J. (2012). Automaticity in social-cognitive processes. *Trends in Cognitive Sciences*, 16(12), 593–605.
- Breitmeyer, B., & Öğmen, H. (2006). *Visual masking: Time slices through conscious and unconscious vision*. Oxford University Press.
- Bruner, J. (1957). On perceptual readiness. *Psychological review*, 64(2).
- Capa, R. L., Bustin, G. M., Cleeremans, A., & Hansenne, M. (2011). Conscious and unconscious reward cues can affect a critical component of executive control. *Experimental psychology*, 58(5), 370–5.
- Clark, R. E., & Squire, L. R. (1998). Classical Conditioning and Brain Systems: The Role of Awareness. *Science*, 280(5360), 77–81.
- Dehaene, S., Changeux, J., Naccache, L., & Sergent, C. (2006). Conscious , preconscious , and subliminal processing: a testable taxonomy. *Trends in Cognitive Sciences*, 10(5), 204–211.
- Dehaene, S., Naccache, L., Le Clec, H. G., Koechlin, E., Mueller, M., Dehaene-Lambertz, G., van de Moortele, P. F., et al. (1998). Imaging unconscious semantic priming. *Nature*, 395, 597–600.
- Dijksterhuis, A., Bos, M. W., Nordgren, L. F., & van Baaren, R. B. (2006). On making the right choice: the deliberation-without-attention effect. *Science (New York, N.Y.)*, 311(5763), 1005–7.
- Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science*, 8(3), 223–241.
- Faivre, N., Mudrik, L., Schwartz, N., & Koch, C. (2014). Multisensory Integration in Complete Unawareness: Evidence From Audiovisual Congruency Priming. *Psychological Science*, 25(11), 2006–2016.
- Goldstein, A. Y., & Hassin, R. R. (2017). Commentary: Definitely maybe: can unconscious processes perform the same functions as conscious processes? *Frontiers in Psychology*, 8(MAY), 2011–2014.
- Goldstein, A. Y., Siegelman, N., & Sklar, A. Y. (in preparation). Bayesian methods for estimating non-conscious performance. *In preparation*.

- Greenwald, A. G. (1992). New look 3. Unconscious cognition reclaimed. *The American psychologist*, 47(6), 766–79.
- Greenwald, A. G., Draine, S. C., & Abrams, R. L. (1996). Three cognitive markers of unconscious semantic activation. *Science*, 273, 1699–1702.
- Greenwald, A. G., Klinger, M. R., & Schuh, E. S. (1995). Activation by marginally perceptible (“subliminal”) stimuli: dissociation of unconscious from conscious cognition. *Journal of experimental psychology. General*, 124(1), 22–42.
- Hassin, R. R. (2013). Yes It Can: On the Functional Abilities of the Human Unconscious. *Perspectives on Psychological Science*, 8(2), 195–207.
- Hassin, R. R., Ferguson, M. J., Shidlovski, D., & Gross, T. (2007). Subliminal exposure to national flags affects political thought and behavior. *Proceedings of the National Academy of Sciences of the United States of America*, 104(50), 19757–61.
- Hassin, R. R., & Sklar, A. Y. (2014). The Human Unconscious A Functional Perspective. *Dual-Process Theories of the Social Mind*. (pp. 299–313).
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.
- Keren, G., & Schul, Y. (2009). Two is not always better than one. *Perspectives on Psychological Science*, 4(6), 533–550.
- Lamy, D., Mudrik, L., & Deouell, L. Y. (2008). Unconscious auditory information can prime visual word processing: a process-dissociation procedure study. *Consciousness and cognition*, 17(3), 688–98.
- Lei, Y., Dou, H., Liu, Q., Zhang, W., Zhang, Z., & Li, H. (2017). Automatic processing of emotional words in the absence of awareness: The critical role of P2. *Frontiers in Psychology*, 8(APR), 1–9.
- Marcel, A. (1983). Conscious and unconscious perception: Experiments on visual masking and word recognition. *Cognitive psychology*, 15, 197–237.
- Merikle, P. M., & Reingold, E. M. (1992). Measuring unconscious perceptual processes. In R. F. Bornstein & T. S. Pitman (Eds.), *Perception without awareness: Cognitive, clinical, and social perspectives* (pp. 55–80). New York: Guilford Press.
- Moors, P., Wagemans, J., & de-Wit, L. (2017). Causal events enter awareness faster than non-causal

events. *PeerJ*, 5, e2932.

Newell, B. R., & Shanks, D. R. (2014). Unconscious influences on decision making: A critical review. *Behavioral and Brain Sciences*, 38(01), 1–19.

Peirce, C. S., & Jastrow, J. (1885). On Small Differences in Sensation. *Memoirs of the National Academy of Sciences*, 3(1885), 73–83.

Ramsøy, T. Z., & Overgaard, M. (2004). Introspection and subliminal perception. *Phenomenology and the Cognitive Sciences*, 3(1), 1–23.

Reingold, E. M., & Merikle, P. M. (1988). Using direct and indirect measures to study perception without awareness. *P&P*, 44(6), 563–575.

Roy, S., Noel, J.-P., Łukowska, M., Faivre, N., Metzinger, T., Serino, A., & Blanke, O. (2016). Unconscious integration of multisensory bodily inputs in the peripersonal space shapes bodily self-consciousness. *Cognition*, 166, 174–183.

Sandberg, K., Timmermans, B., Overgaard, M., & Cleeremans, A. (2010). Measuring consciousness : Is one measure better than the other ? *Consciousness and Cognition*, 19(4), 1069–1078.

Shanks, D. R. (2017). Regressive research: The pitfalls of post hoc data selection in the study of unconscious mental processes. *Psychonomic Bulletin & Review*, 24(3), 752–775.

Sherman, J. W., Gawronski, B., & Trope, Y. (2014). *Dual-process theories of the social mind*. Guilford Publications.

Sidis, B. (1898). *The psychology of suggestion*. D. Appleton & Company.

Sklar, A. Y. (preparation). Accounting for regression to the mean in unaware subsample analysis. *In preparation*.

Sklar, A. Y., Deouell, L. Y., & Hassin, R. R. (2018). Integration despite Fractionation: Continuous Flash Suppression. *Trends in Cognitive Sciences*, 22(11), 956–957.

Sklar, A. Y., Levy, N., Goldstein, A., Mandel, R., Maril, A., & Hassin, R. R. (2012). Reading and doing arithmetic nonconsciously. *PNAS*, 109(48), 19614–19619.

Spearman, C. (1904). The Proof and Measurement of Association between Two Things. *The American journal of psychology*, 15(1), 72–101.

Van Opstal, F., Gevers, W., Osman, M., & Verguts, T. (2010). Unconscious task application. *Consciousness and cognition*, 19(4), 999–1006.

Zacks, J. M., Speer, N. K., Swallow, K. M., Braver, T. S., & Reynolds, J. R. (2007). Event Perception : A Mind – Brain Perspective, 133(2), 273–293.

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 mean of 1.0 and a standard deviation 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 mean of 0 and a standard deviation of 24. For the awareness score, error values e_x are taken from a normal distribution with a mean of 0 and a standard deviation of 0.04. Final scores are computed using the following formulas:

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

$$\text{Awareness score} = 0.12*S + e_x$$

Dataset 2

In creating Dataset 2, exactly the same parameters and distributions were used as previously described for Dataset 1 excepting the calculation of performance scores. In order 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:

$$\text{Performance scores} = 10 + 18*S + e_p$$

Dataset 3

In creating Dataset 3, exactly the same parameters and distributions were used as previously described for Dataset 1 excepting the calculation of performance scores. In order to simulate exaggerated true unaware performance, a constant of 1000 was added so that the performance when S is 0 would be 1000. The new formula was therefore:

$$\text{Performance scores} = 1000 + 18*S + e_p$$