Journal of Experimental Psychology:
Human Perception and Performance
1997, Vol. 23, No. 6, 1813–1818

Dependence by Any Other Name Smells Just as Sweet: Reply to van der Velde and van der Heijden (1997)

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The hypothesis that people selectively attend to entire objects predicts that all attributes of an object will be reported either very accurately (if the object was attended) or very inaccurately (if it was unattended). Hence, reports of object attributes should show positive dependence. M. Monheit and J. Johnston (1994) have confirmed this prediction. F. van der Velde and A. H. C. van der Heijden (1997), however, have argued that dependence in the overall data is spurious. They advocate a model that partitions the data into 2 subsets, 1 for perception trials and 1 for guessing trials, each of which separately exhibits independence. Here, the authors argue that this treatment of guessing is misguided because, in effect, guesses are discarded rather than treated as failures of perception. The Monheit and Johnston analysis, on the other hand, is fundamentally sound and demonstrates precisely the kind of dependence predicted by the spatial attention hypothesis.

Monheit and Johnston (1994, hereafter M&J) reexamined performance in a paradigm studied by Nissen (1985) and Isenberg, Nissen, and Marchak (1990) in which participants reported the color and form of one of several briefly presented objects. M&J argued that they had confirmed strong dependence in the probability of correctly perceiving the color and form of an object, as predicted by the hypothesis that participants selectively attend to some entire objects and not to others. van der Velde and van der Heijden (1997, hereafter referred to as V&H) argued that the conclusions of M&J are incorrect, mainly because M&J failed to properly handle guessing. On the basis of a reanalysis of M&J's data with an alternative computational method, V&H concluded that those data actually support independence of color and form perception.

In this reply we briefly review the findings and conclusions of the original M&J (1994) article. We first explain why M&J's data analysis followed correctly from their underlying conceptual model and supported the substantive conclusion that the report of object features in multiobject displays is highly dependent. We then discuss the criticisms of V&H (1997). We argue that the V&H discussion rests on a misunderstanding of M&J's objectives in correcting for guessing. M&J's goal was to determine the underlying perceptual dependence in the entire data set. To achieve that goal, they adjusted the obtained proportion correct over all trials to take into account guessing (reclassifying lucky guesses as failures of perception). The goal of V&H, on other hand, was apparently to analyze dependence over a subset of trials not influenced by guessing, and to achieve that goal they partitioned the data into subsets. We argue that given the substantive questions at issue, M&J's adjustment of the data was appropriate, whereas V&H's partitioning was not appropriate. This wrong turn sets the entire V&H effort off on a wrong course from which it never recovers.

We follow this discussion with treatments of dependence, independence, and guessing. We do not have major objections to the V&H (1997) computational model itself; in fact, it differs from M&J's only in minor assumptions. However, our analysis shows that the V&H independence model can fit the M&J (1994) data successfully only because it actually embodies dependence. We conclude that the V&H analysis provides no reason for one to doubt the substantive conclusion of M&J: The data show strong dependence, just as expected from the hypothesis of selective attention to entire objects in multiobject arrays.

Monheit and Johnston (1994) Analysis

M&J (1994) attempted to resolve a perplexing disagreement between theories of selective attention and empirical data obtained by Nissen (1985) and Isenberg et al. (1990). These investigators gave participants a brief glimpse of an array of four multidimensional objects (colored shapes) and then immediately asked them to report both properties of one of the objects (the "probed" object). Nissen and Isenberg et al. reported that performance on two properties of the same object showed "remarkable independence" (Nissen, 1985, p. 876). What is perplexing about these results is that they appear to disconfirm predictions from the theory of selective attention—namely, that participants should selectively attend to some objects in the arrays but not to others. In that case one would expect high performance on both properties when the probed object had been attended and low performance on both properties when the probed object had not been attended. This stratification

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would inevitably lead to strong dependence across trials between color and form performance. Nissen and her colleagues explicitly noted that their finding of independence appeared to be inconsistent with the hypothesis of selective attention to objects.[1]

It thus appeared that either the theory of selective attention to objects (cf. Duncan, 1984) is wrong, that it does not apply to the Nissen paradigm, or that there is something wrong with the empirical claim that data from that paradigm show independence. M&J (1994) argued that there is very strong support for the theory of selective attention to objects and that there is every reason to believe that the theory should apply to the Nissen paradigm. M&J therefore concluded that the validity of empirical claims from that paradigm should be reexamined.

Before attempting to replicate the Nissen results, M&J (1994) carefully analyzed how much dependence could be expected in the Nissen paradigm. M&J's quantitative modeling showed that it was unreasonable to expect more than a modest degree of dependence in the data because the effects of guessing reduce the observable level of dependence to below the true level of dependence in the underlying perceptual performance. Their modeling allowed them to calculate an "adjusted dependence limit" for the expected level of objective accuracy in correctly reporting both properties ("correct conjunction reports"), assuming maximum dependence in perception.

Guided by this analysis, M&J (1994) proposed a much more sensitive design to test the dependence model. In four experiments, M&J found strong evidence for positive deviations from independence in almost every participant's data. Out of a total of 65 participants, 60 showed statistically significant deviations (53 of them significant at or beyond the .001 level). M&J compared the observed levels of dependence they found with the expectations from several quantitative models of selective object attention. The data show about as much dependence as predicted by models with essentially complete dependence at the perceptual level.

In summary, M&J (1994) attempted to measure the level of dependence in reporting both the color and form of one probed object from an array of multidimensional objects. Their analysis showed that there was as much dependence in the data as could be expected, given the attenuating effects of guessing on the observable level of dependence. Whereas Nissen and her colleagues asserted that the dependence glass was empty, M&J found that it was actually full to the brim.

Criticism of Monheit and Johnston (1994)

V&H (1997) strongly criticized M&J's (1994) analysis and conclusions. They argued that M&J's data analysis was flawed because of an improper treatment of guessing. Because M&J stated that the observed level of dependence is contaminated by the effects of guessing, V&H asserted that the obvious solution to that problem is to determine the level of dependence on the subset of trials not contaminated by guessing. Hence, proper data analysis requires a decomposition of the observed data matrix into two component matrices, one for guessing trials and another for perception trials.

V&H (1997) presented a method for accomplishing such a putative decomposition of the data. They found that the M&J (1994) data, which as a whole show dependence, can be decomposed into a perception data subset and a guessing data subset, each of which separately exhibits statistical independence. V&H argued that the success of this decomposition means that the overall dependence model in the M&J data is "spurious" (p. 1842), a "polluted" version of a true underlying independence (p. 1842). Thus, this decomposition provides the basis for V&H's claim that M&J's conclusions about dependence were wrong.

It also follows from the V&H (1997) analysis that M&J (1994) were wrong in their assertion that guessing masks true perceptual dependence. In fact, V&H argued that guessing readily produces spurious dependence in the observed data because of Simpson's paradox: The pooled combination of two independent data sets is likely to produce a combined data set with substantial dependence. Such spurious dependence is especially likely when accuracy is very different for the two data sets, as when a high-performance perception matrix is combined with a low-performance guessing matrix. V&H argued that any such dependence is spurious.

In summary V&H (1997) showed that M&J's data can be fit by a procedure that decomposed the data into separate perception and guessing matrices, each of which exhibits independence. For this reason, they argued that M&J's claim to have confirmed dependence in color–form performance is wrong.

The Key Dispute

The key differences between M&J (1994) and V&H (1997) flow from a single point of dispute. V&H argued that the theoretical model of M&J implies a need to decompose the data into subsets—typically one for perception and one for guessing—and then to look for dependence within the perception data subset. This claim is in accord neither with what M&J said nor what M&J meant. Moreover, we will show that this claim is ultimately misguided.

M&J (1994) did assert that correct guessing created problems with the overt data and that therefore an adjustment was needed, but nowhere did they say or imply that analyzing subsets of the data separately for dependence was the proper remedy. In the introduction to their article, M&J stated clearly (and in italics for emphasis) that the topic of study was overall performance: "*Stratification of overall performance, regardless of the cause, is incompatible with independence*" (p. 692). In the section where the M&J computational model for dependence was presented (pp. 693–695), parameters for the proportion of correct responses (P_A and P_B) clearly referred to proportions of all trials. The

[1] In the Nissen paradigm there is a one-to-one relation between objects and locations, so it does not matter whether one hypothesizes attention to objects or attention to locations. The results are equally mysterious under either hypothesis.

M&J correction for guessing attempted to adjust (not partition) the observed proportion of correct responses on all trials for the effects of guessing, deriving the underlying proportion of all trials on which each feature was correctly perceived.

In summary, from the many comments in M&J (1994) about how guessing distorts the data, V&H (1997) incorrectly supposed that M&J wished to remove the trials with guessing from the analysis. M&J actually were trying to remove the effects of guessing (on correct performance) from the analysis. This goal sounds similar, but it requires adjusting the observed data (i.e., reclassifying correct guessing responses as failures of perception) to better estimate the true probability of success versus failure of perception across all trials.

Having settled the question of what M&J (1994) intended, we can address the question of whether what they did was appropriate or what V&H (1997) did was appropriate. We cannot emphasize enough the common sense of the M&J position that dependence can be meaningfully assessed only across the full data set. The reason guessing trials should not be excluded is that trials on which guessing occurs are trials on which perception has failed. It is nonsensical for the key analysis of dependence in the success versus failure of perception to be carried out within a data set that excludes most of the failures! Note that substantively, these are just the trials for which M&J hypothesize that spatial attention has failed to be allocated to the probed object. Throwing out guesses in the present context is as sensible as throwing out guesses on a multiple-choice test when trying to estimate a test taker's knowledge.

In their model M&J assumed, for the sake of simplicity, that successful perception would always result in a correct report. V&H (1997) do not make this high-threshold assumption; in their model perceiving a feature can produce a mistaken value for that feature. Because the mistake is unknown to the participant, the participant will report the mistaken feature, and no guessing will occur. Without the high-threshold assumption, V&H advocate a more complex model which has separate parameters for the probability that features will be perceived and for the probability that the features, if perceived, will be correct. So far, so good. What does not make sense is segregating for analysis the trials on which perception occurred rather than failed outright. V&H typically exclude over 40% of all trials from the perception subset without ever satisfactorily addressing what might be causing all of these failures to perceive. The remaining trials that are included in the perception subset show extremely high performance, unrepresentative of the overall difficulties participants faced. Showing independence within this special subset of high-performance trials says little about the nature of overall performance.

By computing dependence separately within the perception subset and within the guessing subset, V&H (1997) beg the key question: Why or how do some trials come to be in a subset where the model allows both features to be perceived with very high (although not quite perfect) performance, and other trials come to be in a separate subset where performance is terrible? The joint assignment of two variables to states with either very high or very low performance produces stratified performance, leading to dependence between the two variables. Just this kind of stratification of performance is predicted by the hypothesis of selective attention to objects: When the probed object has been attended, performance is very good, and when the probed object has not been attended, performance is poor.

Fortunately, there is no need to partition the data at all. The proper correction for guessing in accuracy experiments does not involve partitioning. The proper goal of a correction for guessing is to adjust the observed proportion of successful reports (which include lucky guesses) back to the true proportion of underlying perceptual successes. In the present context, the goal is to determine on what proportion of all trials correct perception of each feature has occurred so that one can analyze whether those correct perceptions of each feature did or did not occur independently. M&J (1994) followed this procedure, but V&H (1997) did not.

Having identified the fundamental cause of the dispute, we address three specific topics of contention: modeling dependence, modeling independence, and modeling the influence of number of response alternatives.[2]

Modeling Dependence

One of the more curious aspects of the V&H (1997) article is that the authors appeared to dispute whether the M&J (1994) model of dependence, which virtually defines what kind of dependence M&J were seeking, actually counts as real dependence. This dispute emerges from V&H's decision to partition the data into two subsets and to assess dependence only within each subset.

Let us first review M&J's (1994) model of maximum dependence in the perception of two features of an object. Because M&J did not wish to assume that perception of the two features was equally likely, they simply labeled the better perceived feature as B (with perception probability β) and the other feature as A (with perception probability α). In this general case, M&J argued that the highest possible level of dependence in perception that can be imagined is that whenever Feature A is perceived correctly, so is Feature B. Because M&J adopted an all-or-none high-threshold assumption, in their model all features not perceived correctly must be guessed.

When V&H (1994) subjected this model to their type of analysis, they found that they could match the performance of the model by decomposing the overall data matrix into three independent matrices: one for guessing on both features, one for perceiving B but guessing A, and one for perceiving both. Because the determinants of all three matrices are zero, they count as independent. V&H believed

[2] In this short reply we have insufficient space to deal separately with each specific instance where V&H asserted that M&J were mistaken. Lest our failure to deal with any such charge be taken as agreement, we wish to make it clear that we do not agree with any of V&H's complaints. As far as we can tell, they all stem from the same underlying dispute about the proper understanding of the concept of dependence.

that the relevant test for dependence should be carried out only within matrices, so they concluded that even the dependence model of M&J (1994) actually exhibits independence!

All of this notwithstanding, the common sense of the matter is that the M&J (1994) model exhibits precisely the kind of dependence that is of theoretical interest. The M&J dependence model directly embodies the hypothesis that spatial attention to objects causes a dependence in the probability of correctly perceiving each feature. Across trials, either the probabilities of perceiving the color and form features are both very high or they are both very low. This model virtually defines what the substantive issue of dependence is about. That V&H (1997) challenged whether this dependence model exhibits any nonspurious dependence is a sign of how far off the course they have veered.

Modeling Independence

M&J (1994) derived the implications of guessing for modeling dependence but did not discuss the implications of guessing for modeling independence because they supposed that in the case of independence no corrections for guessing were needed. If perceptions of the attributes of an object were independent, then the overall data should also exhibit independence, regardless of the amount of guessing. We believe that the nature of the independence hypothesis compels this conclusion. The independence hypothesis asserts that all of the mental processing of one attribute (perception, guessing, etc.) is independent of the processing of the other attribute. No matter how complicated the processing of each feature, it must in the end produce a single probability of correct report for each feature that is independent of the other.

This logic notwithstanding, V&H (1997) made the counterintuitive claim that independent perception of features, combined with guessing, can result in dependence in the overall data. How did V&H end up with such a counterintuitive conclusion? To answer this question, we will attempt to analyze an independence model—including the effects of guessing—with the same analytical framework that V&H used. Insofar as we can, we will make the same assumptions that V&H made. In so doing we believe we can show where V&H went awry.

We first assume that Attributes A and B are processed independently of each other on each trial. Attributes A and B are either perceived—with probabilities α and β, respectively—or guessed. Following V&H (1997) we make the low-threshold assumption that perceiving an attribute does not guarantee a correct report. When perceived, Attributes A and B are reported with accuracy A_C and B_C, respectively. When guessed, Attributes A and B are reported with an accuracy equal to the expected guessing success rate,[3] g (which is equal to 1 divided by the number of response alternatives).

On each trial one of four states must occur: (1) Both A and B are perceived, (2) A but not B is perceived, (3) B but not A is perceived, or (4) neither is perceived. From the independence hypothesis, trials of type a (when both are perceived) occur with probability $\alpha \times \beta$. Similarly, the other three types of trials occur with probabilities $\alpha \times (1 - \beta)$, $\beta \times (1 - \alpha)$, and $(1 - \alpha) \times (1 - \beta)$, respectively.

For each of these four states, we can use a separate matrix to show the probabilities of correct or incorrect reports of Features A and B. In each of these matrices the left and right columns correspond to correct and incorrect reports of A, respectively. The top and bottom rows correspond to correct and incorrect reports of B, respectively. Thus, the four entries indicate the proportion of trials on which (1) both attributes are correctly reported, (2) A but not B is reported correctly, (3) B but not A is reported correctly, and (4) neither is reported correctly. We should then have for the both-perceived matrix

$$\begin{bmatrix} A_C \times B_C & (1 - A_C) \times B_C \\ A_C \times (1 - B_C) & (1 - A_C) \times (1 - B_C) \end{bmatrix},$$

for the A-only perceived matrix

$$\begin{bmatrix} A_C \times g & (1 - A_C) \times g \\ A_C \times (1 - g) & (1 - A_C) \times (1 - g) \end{bmatrix},$$

for the B-only perceived matrix

$$\begin{bmatrix} g \times B_C & (1 - g) \times B_C \\ g \times (1 - B_C) & (1 - g) \times (1 - B_C) \end{bmatrix},$$

and for the neither-perceived matrix

$$\begin{bmatrix} g_2 & g \times (1 - g) \\ (1 - g) \times g & (1 - g)^2 \end{bmatrix}.$$

To derive the formulas for the probability for each of the four entries in the observed outcome matrix, we mixed these four matrices according to the relative frequencies with which the four perceptual states occur, namely, $\alpha \times \beta$, $\alpha \times (1 - \beta)$, $\beta \times (1 - \alpha)$, and $(1 - \alpha) \times (1 - \beta)$, respectively. The probabilities can now be multiplied through with matrix algebra to produce the observed data matrix. It can easily be shown that the resulting matrix has a determinant of zero. Therefore, the model produces a matrix of observed data outcomes that shows independence in the accuracy of reporting Features A and B. Thus, this more complex analysis confirms our earlier assertion that independent feature perception combined with independent guessing must produce independence in the observable data.

[3] M&J referred to the probability of success in guessing a feature as the "guessing rate." In this article we refer to this quantity as the guessing success rate to reduce the possibility of confusion with another quantity, the probability that on any trial a feature will have to be guessed.

Why does our analysis lead to a different conclusion from that of V&H? In the above presentation, we used all four perceptual state matrices and assigned trials to them, assuming that the two features in an object were processed independently. In constrast, V&H (p. 1803) formulated a model with only two of these four state matrices, corresponding to our first matrix (for both features perceived) and our last matrix (for neither feature perceived). The V&H model assumes that all trials go into one of these two states, mixed in proportion with Q and 1–Q, where Q is a free (fitted) parameter. The other two matrices, corresponding to states where one of the two features is perceived but not the other, are nowhere to be found. Thus, without any discussion, *V&H have implicitly assumed perfect dependence across trials in the assignment of features to perception states.* Either both features go into the "perception" matrix, where performance for both is very high, or both go into the not-perceived (guessing) matrix, where performance for both is very low. As noted by M&J (1994), this kind of stratification of performance levels is exactly the kind of dependence predicted by the hypothesis of selective attention to entire objects.

There is nothing wrong with the model V&H (1997) have arrived at, *but it embodies dependence.* If one believes in selective attention to objects, then the joint assignment of features to either a both-perceived or a neither-perceived state is precisely the consequence one should expect from attending to objects.[4]

Although the M&J (1994) method provides a clear way to determine how much dependence is present in the overall performance, it does not provide any way to determine which internal stages or processes produce the dependence. M&J were careful to state that they had shown that the prediction of dependence from the hypothesis of selective attention to objects was confirmed. To the extent that other hypotheses also predict strong dependence, they are also consistent with M&J's data and analyses.

Guessing Success Rates

We next deal with an ancillary aspect of the main dispute between M&J (1994) and V&H (1997): whether it is advantageous in studies of dependence to have lower or higher guessing success rates. The guessing success rate is the probability that if participants must guess a feature, they will guess it correctly. Both M&J and V&H have assumed that participants have no partial information about a feature when it must be guessed. In the experiments at issue there are always n equally likely alternatives for any feature, and n is the same for both features, so the guessing success rate can be represented by a single parameter g with the value $1/n$.

Therefore, the question is, whether it is better to have a larger number of alternatives so that g is smaller or a smaller number of alternatives so that g is larger. We believe that the standard received wisdom in studies of the accuracy[5] of perception of single features is that if one wants to estimate the proportion of correct perceptions, it is advantageous to have as small a guessing success rate as possible. Correct guesses result in trials on which the failure of perception produces the same outcome as a success of perception, blurring the distinction of interest to us. Corrections for guessing are possible, and they ameliorate the problem to some extent, but they are necessarily imperfect. The proper adjustment for guessing involves reassigning some trials on which the observed data showed a correct response into the incorrectly perceived category.[6] Such a reassignment is necessarily imprecise because it requires estimating two unknowns, the number of trials on which guessing occurred and the actual guessing success rate (which need not be exactly equal to its expectation g). Because such an adjustment can be only approximately accurate, the fewer trials that have to be reassigned due to the guessing correction, the better. Note that if the guessing success rate could be reduced to zero, the observed proportion correct would simply be the underlying proportion of correct perceptions, and no adjustment would be required.

M&J (1994) argued that this simple received wisdom can be readily extended to studies of the perception of multidimensional stimuli. Once again, successful guesses blur our ability to measure perceptual accuracy. M&J showed that, even if there were no errors in estimating the actual guessing success rate, the lower the expected guessing success rate (i.e., the larger the number of alternatives), the larger the

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[4] In the original simple model of M&J, all feature perception was correct, so it did not make sense to ask the question of whether performance was dependent within the "both-good" state (the attended state, by hypothesis). If this high-threshold assumption were relaxed, and the more complex parameterization in this section were adopted, then this question could be posed sensibly. We do not, however, see much basis for an answer. The data are precise enough to permit rejection of models without any source of dependence, but it seems doubtful that the goodness of fit depends much on the level of dependence within the "both-good matrix." Note that M&J could account for the data without assuming any errors in perception at all, and that V&H produced good fits only by assuming extremely high accuracy in the "both-good matrix." At these performance levels the difference between independence and dependence within this matrix would depend on only a tiny proportion of the overall number of trials. It seems unlikely that the present data will permit discrimination between models with such small differences. In any case, the point of M&J is that something (attention, by hypothesis) is causing extreme dependence in the quality of perception of the two features. We cannot, of course, rule out the possibility that something other than spatial attention might also be contributing to dependence.

[5] It is, of course, common practice in studies of response time to discard trials (usually small in number) on which perception went awry (errors). In these response time studies the subject of interest is the time it takes to accomplish a computation, and there is reason to believe that those computations were not completed successfully on error trials. However, when accuracy is the dependent variable of interest, and the conditions are arranged deliberately so that such errors will occur, one is most interested in the proportion of all trials on which perception succeeded or failed. This proportion cannot be estimated sensibly if failures are excluded from analysis.

[6] See, for instance, Loftus & Ruthruff (1994). To solve for the level of true perception, p', as a function of the observed proportion correct (p) and the guessing success rate (g), one can first set up the formula for the probability of an overt error: $(1-p) = (1-g)(1-p')$. Solving for p', one arrives at $p' = (p-g)/(1-g)$.

expected difference in performance between dependence and independence (see Monheit & Johnston, Figure 1)[7] and the easier it would be empirically to detect dependence in the data. Although not reported explicitly, M&J also confirmed that the smaller the guessing success rate, the lower the adjustment required between the nominal Yule's Q measure of association based on the observed data and the adjusted Yule's Q based on estimated underlying perceptual states. Thus, M&J found that the received wisdom—correct characterization of underlying perceptual performance is promoted by arranging for lower guessing success rates—applies in a straightforward way to the estimation of dependence in the perception of component features of multidimensional stimuli.

In contrast, V&H (1997) argue that higher guessing success rates produce the least distorted estimates of perceptual dependence. That this conclusion is the reverse of the usual received wisdom should by itself raise the suspicion that their analysis has gone off course somewhere. There is no disagreement between M&J (1994) and V&H about the mathematics. Everyone is agreed *that the lower the guessing success rate, the higher the level of nominal dependence found in the overall observed data.* However, V&H contend that all of the observed dependence is spurious, so that more observed dependence means a worse mistake. M&J, on the other hand, assert that the observed data underestimate the true level of dependence so that more observed dependence means a closer approximation to the truth. We hope that anyone who has a lingering doubt about the larger issue will have an additional chance to appreciate from this auxiliary consequence that V&H have gone off course. It is counterintuitive in the extreme that studies of perceptual accuracy should purposely strive to produce a larger contamination of correct reports by guessing.

Conclusion

In conclusion, V&H (1997) have not provided any valid reasons to question the soundness of either the methods or the substantive findings of M&J (1994). In fact, the formalism proposed by V&H, when properly understood, provides a handy way to compute a new exemplar of the class of dependence models advocated by M&J. The fairly good fit of the V&H model is consistent with strong positive dependence in the overall data, as predicted by models of selective attention to objects.

[7] It was in this context, long after their formal presentation of their model, that M&J attempted to provide an intuitive motivation for why higher guessing success rates reduce observed dependence (cf. Figure 2 of Monheit & Johnston). In the low guessing rate section, M&J wrote "Better success at guessing means a smaller proportion of correct responses will be due to perception, and it is only these responses that produce dependence" (p. 694). V&H stated "This quote shows that Monheit and Johnston incorrectly assumed that statistical dependence only depends on the correct responses instead of the overall contingency matrix as expressed by the determinant" (p. 1833). It is absurd to suggest that M&J advocated calculating dependence based only on correct responses. M&J were, of course, aware that all four cells of the observed data matrix contribute to dependence and thus correctly used all four cells in all calculations of dependence. Having presented the proper calculations earlier, M&J were merely trying to informally motivate why a higher guessing success rate was undesirable. Their point was that correct reports due to successful guessing can only (barring better than chance guessing) serve to dilute the degree to which the dependence in the underlying perception states shows through in the observed data. Hence, the lower the guessing success rate, the better.

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Received December 30, 1996
Revision received May 2, 1997
Accepted May 31, 1997 ■