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Response Bias Correction in the Process Dissociation Procedure: Approaches, Assumptions, and Evaluation

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Buchner, Erdfelder, and Vaterrodt-Plunnecke (1995) advocated an exposition of the process dissociation procedure within the framework of multinomial modeling. Among the misleading aspects of this exposition is its tendency to obscure the overlap between processes. In contrast, clarifying these crucial interactions leads to a general classification of response bias corrections to the process dissociation procedure. This scheme, in which corrective models are classified on the basis of process interactions, clarifies the assumptions underlying previously proposed corrections. As an illustration of the framework, three such corrections are derived. These corrective models are evaluated by applying them to the data reported by Buchner et al. (1995).

The process dissociation procedure (henceforth referred to as the PDP) was introduced by Jacoby (1991) as a framework for separating consciously controlled and unconscious influences on task performance. To date, this emerging paradigm has generated a substantial amount of empirical research, as well as theoretical controversy. One focal point for the controversy has been the relational assumptions made about the interaction of conscious and unconscious processes (e.g., Cowan & Stadler, in press; Curran & Hintzman, 1995; Gardiner & Java, 1993; Jacoby, Begg, & Toth, in press; Jacoby, Toth, & Yonelinas, 1993; Jacoby, Toth, Yonelinas, & Debner, 1994; Jacoby, Yonelinas, & Jennings, in press; Joordens & Merikle, 1993; Reingold & Toth, 1995; Richardson-Klavehn, Gardiner, & Java, 1994, 1996). In addition, several recent publications have discussed the issue of response bias in the context of the PDP (e.g., Buchner, Erdfelder, & Vaterrodt-Plunnecke, 1995; Cowan, 1995; Graf & Komatsu, 1994; Reingold & Toth, 1996; Yonelinas & Jacoby, in press; Yonelinas, Regehr, & Jacoby, in press). In a recent paper, Buchner et al. (1995) addressed both the issue of relational assumptions and the response bias problem. By rederiving the PDP as a multinomial model, they claimed to have produced an exposition of the PDP that does not require specifying a relational assumption. Thus, they argued that the controversy surrounding relational assumptions can be completely sidestepped. Turning to the response bias issue, Buchner et al. (1995) sought to incorporate a correction for guessing into the PDP. This correction for guessing was also presented within the framework of multinomial modeling. In this paper, we strongly argue against the notion that the multinomial approach leads to a model that is free of relational assumptions. Instead, we highlight the necessity of explicitly considering

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relational assumptions and demonstrate that such consideration reveals a general class of response bias corrections to the PDP. Accordingly, we begin by contrasting the standard derivation of PDP with the multinomial derivation advocated by Buchner et al. (1995). Next, we demonstrate that the issue of relational assumptions is not adequately addressed within the response bias correction proposed by Buchner et al. (1995). An explicit consideration of the overlap between processes reveals that this correction is but one member of a larger class of corrective models. We therefore present a general classification scheme of PDP extensions and illustrate it by specifying the relational assumptions underlying previously proposed corrective models (Buchner et al., 1995; Cowan, 1995; Jacoby et al., 1993; Komatsu, Graf, & Uttl, 1995; Roediger & McDermott, 1994; Toth, Reingold, & Jacoby, 1994; Yonelinas et al., in press). We provide a preliminary evaluation of these models by applying them to the data reported by Buchner et al. (1995). Although no single model emerges as clearly superior, other corrective models perform at least as well as the model proposed by Buchner et al. (1995).

STANDARD DERIVATION OF THE PDP

The process dissociation procedure comprises an inclusion and an exclusion condition. To illustrate these two conditions, consider their use in a word stem completion task (e.g., Jacoby et al., 1993). In this task, word stems (e.g., DEF ______) with multiple completions (e.g., DEFEND, DEFECT, DEFINE, DEFEAT) serve as retrieval cues at test. For each stem, one completion (e.g., DEFEND) is designated the target completion. In the test phase, study cues are word stems for which the designated target completion was presented during study. The baseline cues are word stems for which no possible completion was presented during study. During test, there are two possible sets of instructions, corresponding to the inclusion and exclusion conditions. In inclusion, participants are instructed to complete the stem with a previously studied word (i.e., in this case with DEFEND). On the other hand, the exclusion condition requires them to complete stems with new, unstudied words (e.g., DEFINE, DEFEAT, DEFECT).

The PDP begins by acknowledging that task performance in the inclusion and exclusion conditions can be sensitive to both conscious and unconscious influences. The goal of the PDP is to separate and quantify the contributions of these processes to task performance. Below, we derive general equations for the PDP. In order to derive these equations, it is helpful to consider the processes in terms of sets. Specifically, let C represent the set of all trials in which conscious influences act to produce ‘‘old’’ or target responses and let U represent the set of all trials in which unconscious influences act to produce ‘‘old’’ or target responses. The two sets C and U are represented in the Venn diagram in Fig. 1. Note that Fig. 1 incorporates no assumptions about the overlap ($C\&U$), where consciously controlled and unconscious influences occur together. For instance, this overlap could be an empty set.

Inclusion is an example of a *facilitation* condition because consciously controlled and unconscious influences act in concert, both resulting in ‘‘old’’ or target completions. Let I represent inclusion performance: the proportion of ‘‘old’’ completions in the inclusion condition. In general, ‘‘old’’ or target completions in inclusion occur when conscious *or* unconscious influences act. Therefore, we have the equation

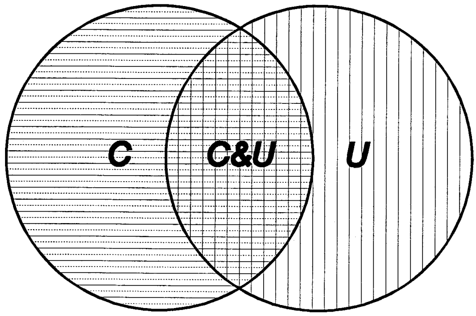

FIG. 1. A Venn diagram depicting conscious influences (C) and unconscious influences (U). $C\&U$ denotes the overlap between conscious and unconscious influences.

$$I = p(C \text{ or } U)$$

where $p(C \text{ or } U)$ denotes the probability of C or U. In terms of Fig. 1, this probability (of C or U) corresponds to the entire area covered by circles C and U. Furthermore, by examining Fig. 1, the reader can verify the identity

$$I = p(C \text{ or } U) = p(C) + p(U) - p(C\&U). \tag{1}$$

The overlap term ($C\&U$) is subtracted so as not to be counted twice. Thus, we have derived the first of the two general PDP equations.

In the exclusion condition, consciously controlled and unconscious processes are placed in opposition. As in inclusion, unconscious processes result in stem completions with ‘‘old’’ or target words. On the other hand, consciously controlled processes result in new, unstudied words being used as completions. Since exclusion is an *interference* condition, it is important to specify the outcome of overlap ($C\&U$) trials, where consciously controlled and unconscious influences occur together. In overlap trials, the conscious influence overrides the unconscious influence, and consequently, the stem is completed with a new, unstudied word. Let E represent the proportion of ‘‘old’’ or target completions in exclusion. Target word completions in exclusion occur only when unconscious influences occur *in the absence* of consciously controlled influences:

$$E = p(U) - p(C\&U). \tag{2}$$

In terms of Fig. 1, this set corresponds to only part of the U circle—in particular, to the part obtained after eliminating the overlap $C\&U$ from the set U. Equation (2) is the second of the two general PDP equations.

The PDP asserts that by comparing a participant’s performance under instructions to include versus instructions to not include (i.e., to exclude), an estimate of conscious influences may be obtained. This comparison amounts to subtracting Eq. (2) from Eq. (1), which yields the familiar PDP estimate for conscious influences[2]

$$p(C) = C = I - E. \tag{3}$$

[2] A remark concerning notation: if X is a set, then $p(X)$ denotes the probability of X. The notation X will be used as a shorthand for $p(X)$.

Noteworthy is the fact that Eq. (3) is valid irrespective of the relational assumption (e.g., redundancy, independence, exclusivity, or otherwise) made about conscious and unconscious processes (Joordens & Merikle, 1993; Reingold & Toth, 1996).

Solving for $p(U)$ proves more involved. If there were an independent empirical estimate of the proportion of overlap trials (i.e., $p(C\&U)$, then an estimate of $p(U)$ would follow immediately from a rearrangement of Eq. (2):

$$p(U) = U = E + p(C\&U). \tag{4}$$

The absence of such an independent estimate of the overlap necessitates consideration of relational assumptions between C and U. These relational assumptions serve as a chisel to break open the overlap $C\&U$ and express it in terms of its constituents C and U. The overlap between processes C and U may be envisaged as a continuum (but see Cowan & Stadler, in press). Along this continuum, certain relations about the overlap are more amenable to mathematical treatment than others. Several relations possessing clean mathematical descriptions were exposited by Jones (1987). At one extreme of the continuum, the overlap set ($C\&U$) could be assumed to be empty, in which case, $p(C\&U) = 0$. This relation is known as exclusivity. At the other extreme, it could be assumed that C is a subset of U, in a relation termed redundancy. In this case, $C\&U = C$ and therefore, $p(C\&U) = p(C)$. Applying these assumptions in turn to Eq. (4) yields the following two estimates of unconscious processes:

$$\text{(i)}\quad U_{\text{exclusivity}} = E \tag{4E}$$

$$\text{(ii)}\quad U_{\text{redundancy}} = E + C = E + (I - E) = I. \tag{4R}$$

Equations (4E) and (4R) are the estimates of $p(U)$ under the assumptions of exclusivity and redundancy, respectively.

Finally, C and U could be assumed to be partially overlapping, and a relation of stochastic independence could hold for the overlap. Then, by definition, $p(C\&U) = p(C)*p(U)$. From Eq. (2), we may write

$$E = p(U) - p(U)*p(C) = U*[1 - C].$$

Therefore, assuming that C is not equal to 1, we have

$$U_{\text{independence}} = E/[1 - C], \tag{4I}$$

that is, the familiar estimate of unconscious processes under the assumption of stochastic independence.

Thus, computing an estimate of unconscious processes requires that an explicit C–U relational assumption be made. In the standard version of the PDP (Jacoby, 1991; Jacoby et al., 1993), a relation of stochastic independence of C–U is adopted. However, as Reingold and Toth (1996) argued, one of the most important contributions of the PDP, quite independent of the specific relational assumption embraced, is in highlighting the importance of specifying the relation between consciously controlled and unconscious influences on task performance. Prior to the introduction of the PDP, this issue had been largely ignored in the study of the relationship between consciousness and cognition. In the next section, we refute the claim of Buchner et al. (1995) that their multinomial rederivation of the PDP eliminates the necessity of considering relational assumptions. We then explore some of the problems that arise from neglecting to consider the interactions between processes.

THE PDP AS A MULTINOMIAL MODEL?

It is from within the framework of multinomial modeling (Hu & Batchelder, 1994; Riefer & Batchelder, 1988) that Buchner et al. (1995) approached the process dissociation procedure. By viewing this procedure as a particular example of a multinomial model, Buchner and his coauthors set out to achieve a general formulation of the PDP that subsumes the independence model (Jacoby, 1991), as well as the redundancy (Joordens & Merikle, 1993) and exclusivity (Gardiner & Java, 1993) variants. Initially, this multinomial modeling exposition of the original PDP is quite appealing because it seems graced with a rare combination of ease and generality. The simple procedure of following branches in a processing tree yields two equations that appear quite general because they integrate all current variants (independence, redundancy, exclusivity) of the PDP. However, examination of the ordered treatment of processes reveals that the exposition is not as general as it may appear. In multinomial processing trees, distinct processes are considered at different levels of the tree (Riefer & Batchelder, 1988). As a consequence, a fixed ordering of processes must be specified. In their PDP exposition, Buchner et al. (1995) implied that the order in which the two processes (conscious and unconscious) are considered is irrelevant. Thus, although they chose to place conscious processes at the first level followed by unconscious processes at the second level (as in Fig. 2A), they intimated that the converse ordering of processes (shown in Fig. 2B) could just as easily be used. In contrast, we claim that the ordering of processes in their exposition is nonarbitrary. In fact, the apparent generality of the exposition stems from exploiting a particular sequential order in processes.

To illustrate this order dependence, we contrast the two systems of equations generated by each of the possible orderings of processes. To begin, consider the ordering in Fig. 2A. Multinomial modeling assumes that branches at one level of a processing tree are conditional upon the levels above it (Riefer & Batchelder, 1988). This stricture implies that all cognitive processes below the first level are designated as conditional probabilities. It also means that in following branches of a processing tree, the probabilities at different levels combine by multiplication. Incorporated in the processing tree in Fig. 2A are two parameters for unconscious processes, both of them conditional probabilities.

The first parameter, U_{c+}, is the conditional probability of unconscious influence given that conscious influence occurs; the counterpart U_{c-} is the conditional probability of unconscious influence given that conscious influence does not occur. As before, let I and E represent the proportion of ‘‘old’’ responses in inclusion and exclusion, respectively. Denote by C the unconditional probability of consciously controlled influence and by U the unconditional probability of unconscious influence. In the processing trees shown in Fig. 2, only the branches or ‘‘cognitive states’’ that lead to ‘‘old’’ responses contribute to inclusion (or exclusion) performance. By following these ‘‘old’’ branches and multiplying parameters at each level, one obtains an expression for the probability of that particular contribution to inclusion (or exclusion)

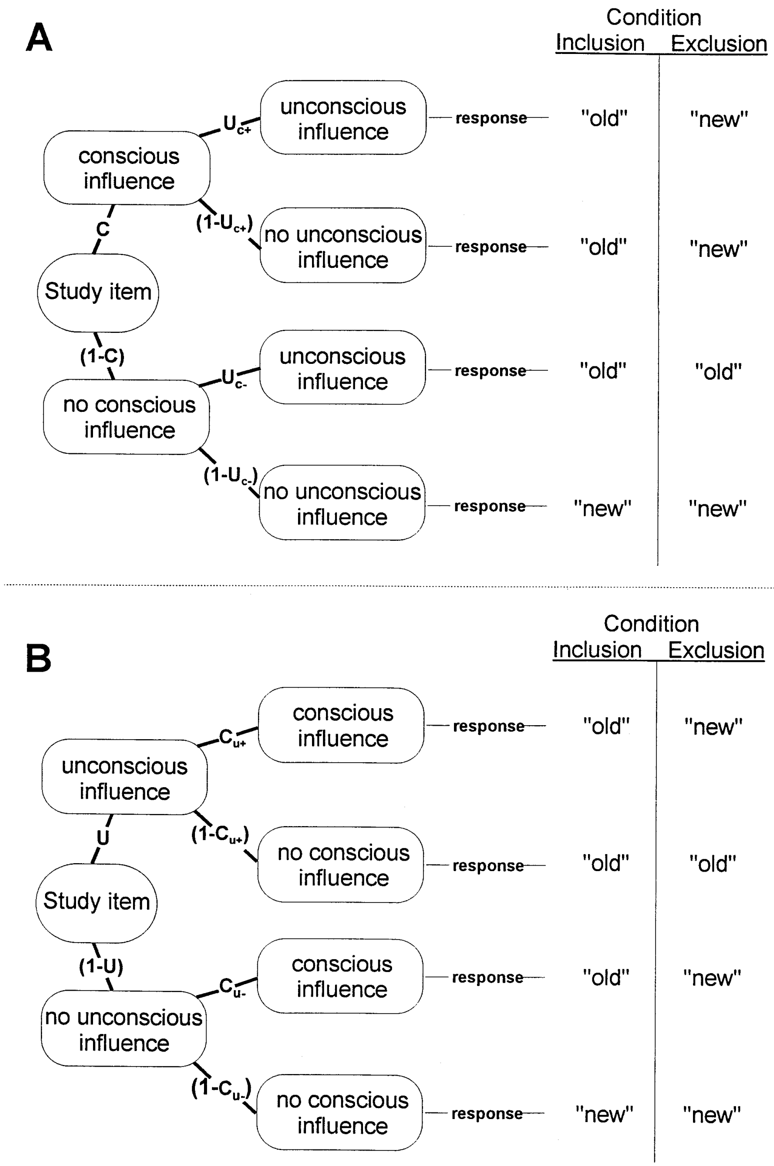

FIG. 2. Multinomial processing trees under the two orderings of conscious and unconscious influences with the corresponding responses in inclusion and exclusion. (A) Conscious influence preceding unconscious influence; (B) unconscious influence preceding conscious influence. The probability of a response is provided by multiplying the parameters along the branches leading to it.

performance. Because all of these contributions are mutually exclusive, their probabilities combine additively. In this way, the processing tree in Fig. 2A yields the following pair of equations:

$$I = C*U_{c+} + C*(1 - U_{c+}) + (1 - C)*U_{c-} = C + (1 - C)*U_{c-} \quad (5)$$

$$E = (1 - C)*U_{c-}. \quad (6)$$

Note that U_{c+} disappears from Eq. (5) by fortuitous cancellation; moreover, it does not figure in Eq. (6). Hence, this parameter is not identifiable in the model. Only the conditional probability U_{c-} figures in the resulting equations for the PDP. Although the three PDP variants may be obtained by imposing suitable restrictions on U_{c+} (see Buchner et al., 1995; Eq. (4), p. 140; see also Cowan & Stadler, in press), making such relational assumptions seems superfluous because the system may be solved for C and U_{c-}. Due to this apparent generality, the formulation is quite attractive initially. Indeed, the exposition permits the computation of estimates for conscious and unconscious processes without having specified their interaction. In this way, it seems to neatly sidestep the consideration of relational assumptions, an issue which has been the focus of considerable controversy (e.g., Cowan & Stadler, in press; Curran & Hintzman, 1995; Gardiner & Java, 1993; Jacoby et al., in press; Jacoby et al., 1993, 1994, in press; Joordens & Merikle, 1993; Reingold & Toth, 1996; Richardson-Klavehn et al., 1994, 1996). As Buchner et al. (1995; p. 141) wrote, ''one benefit of using this measure [U_{c-}] is that we may dispense with (more or less problematic) assumptions about the unidentifiable parameter U_{c+}.'' Thus, this exposition using U_{c-} appears to be free of assumptions.

However, the conclusions obtained upon considering the converse ordering of processes shown in Fig. 2B are substantially different. In this case, two analogous conditional probabilities (C_{u-} and C_{u+}) must be specified. As before, the following equations are obtained from the processing tree in Fig. 2B:

$$I = C_{u-} + U - U*C_{u-} \quad (7)$$

$$E = U - U*C_{u+}. \quad (8)$$

Observe that this new system of *two* equations contains *three* distinct variables (U, C_{u-}, and C_{u+})—implying that this system, unlike the earlier one, is underspecified. Therefore, the converse ordering of processes does not yield a set of equations that may be solved in general for all three variants of the PDP. Rather, in order to solve this system of equations, a relational assumption between conscious and unconscious processes must be specified immediately. The two conditional probabilities are related to the overall unconditional probability of conscious influence (C) via the equation

$$C = U*C_{u+} + (1 - U)*C_{u-}. \quad (9)$$

The restriction $C_{u+} = C_{u-}$ generates the independence variant of the PDP. Similarly, $C_{u+} = 0$ is the defining condition for the exclusivity variant. For the redundancy case, there is no suitable restriction on the parameter C_{u+}; however, requiring that $C_{u-} = 0$ does yield this variant. That these ''more or less problematic'' relational assumptions *must* be specified reflects the fact that the second system, unlike the first system, is not generally soluble. Therefore, reordering of processes entails a crucial loss of generality. This loss indicates that, contrary to Buchner and coauthors' (1995; see p. 140) intimations, the ordering of processes in their exposition is *not arbitrary.*

Thus, we have established that presenting the PDP as a multinomial model achieves an illusory generality only because it exploits a nonarbitrary ordering of conscious and unconscious processes. Even if the PDP is formulated as a multinomial model, the relations between processes must still be specified. This fact highlights a conceptual disadvantage of a multinomial modeling exposition of the PDP: the sequential ordering of processes obscures rather than clarifies the interaction between processes. It is important that this interaction between processes be addressed by any multiple process theory (see Cowan, 1995; Reingold & Toth, 1996). Indeed, the value of explicitly considering the overlap between processes will become clear in the next section, when we seek response bias corrections to the PDP.

RESPONSE BIAS CORRECTION IN THE PDP

Previous applications of the PDP have acknowledged that the estimate of unconscious influences reflects both unconscious influences of the study episode as well as baseline performance (see Jacoby et al., 1993; Toth et al., 1994). It is only factors not related to the study episode that contribute to baseline performance. These two effects—pure unconscious influences and baseline influences—were assumed to be additive. Under this assumption, pure unconscious influences of the study episode may be assessed by subtracting the baseline from the original PDP estimate of unconscious processes (see Toth et al., 1994; p. 292). In actual practice to date, no correction for response bias has been required because researchers have been careful to avoid differences in baseline across inclusion and exclusion (see Reingold & Toth, 1996; Yonelinas et al., in press). However, situations may arise in which the base rates differ across the inclusion and exclusion conditions (e.g., Komatsu et al., 1995) or across other experimental conditions (e.g., Verfaellie & Treadwell, 1993). Desirable therefore, are extensions of the PDP that can compensate for response bias differences. The objective of response bias corrections is to obtain pure estimates of conscious and unconscious processes. Hence, it is necessary to make a sharp distinction between consciously controlled and unconscious influences of the study episode, versus preexperimental factors not related to the study phase. The latter influences contribute to baseline performance. In developing correction methods, baseline influences are embodied in the action of guessing. A critical implication is that conscious and unconscious processes are *necessarily* those related to the specific study episode. Consequently, a word of caution is in order: previous applications of the PDP included baseline performance in the estimate of unconscious influence. In contrast, in the context of corrective models extending the PDP, the unconscious estimate does not include the baseline. It is the latter interpretation of the unconscious estimate that must be taken from here onward.

From within their multinomial modeling framework (Hu & Batchelder, 1994; Riefer & Batchelder, 1988), Buchner and colleagues developed a response bias correction for the PDP. The action of guessing is considered at the third level of a processing tree, preceded by the usual ordering of conscious and unconscious processes (see Fig. 3). Of course, other orderings of the three processes ($3! = 6$ in

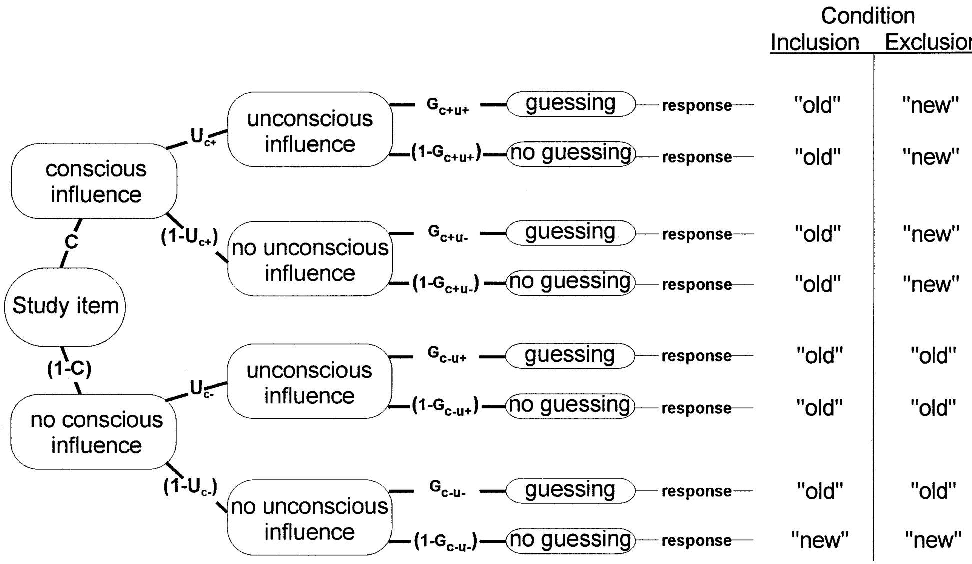

FIG. 3. A tri-level multinomial processing tree depicting conscious influences, unconscious influences, and guessing and the corresponding responses in inclusion and exclusion. The probability of a response is provided by multiplying the parameters along the branches leading to it.

total) are possible. Consequently, the same criticisms regarding the exploitation of a particular ordering apply *a fortiori* to this extended model. Rather than belabor this point, we focus instead on the interactions between processes. The inclusion of a guessing process necessitates the consideration of two additional relations—the first between conscious processes and guessing (C–G) and the second between unconscious processes and guessing (U–G). By explicitly considering these relational assumptions, we reveal that the extended model of Buchner et al. (1995) contains a curious inconsistency between an assumption made in computing estimates and statements about the relations between processes.

Buchner et al. (1995; Fig. 2, p. 144) placed the guessing parameters at the third level of a processing tree, and they ‘‘denote[d] the probability of guessing *old* given that an item is neither recollected nor familiar to the individual by g_i in the inclusion test condition and by g_e in the exclusion test condition.’’ (Buchner et al., 1995; p. 143). Therefore, these parameters are a particular type of *conditional* probability. For clarity, we index this conditional probability by G_{c-u-}, where the subscripts denote that neither conscious nor unconscious processing occurs. Observe that in addition, three other conditional probabilities of guessing G_{c+u+}, G_{c+u-}, and G_{c-u+} appear in Fig. 3. Recall that in multinomial processing trees, all parameters below the first level are conditional probabilities. These conditional probabilities may be contrasted with the overall *unconditional* probability of guessing, which shall be denoted by G. (See Eq. (20) in Appendix A for the relation between G and the four conditional parameters). Note that all of these guessing parameters may vary between inclusion and exclusion conditions. To distinguish these cases, superscripts will be used as necessary (e.g., G^i and G^e denote the unconditional probability of guessing in inclusion and exclusion, respectively). The distinction between unconditional and conditional probabilities of guessing is pertinent only to studied items. In study conditions, conscious and unconscious processes are both free to operate and thus may serve as antecedents for distinguishing conditional probabilities (such as G_{c-u-}). The situation is markedly different for distractor items. As explained earlier, in the context of correction methods, both conscious and unconscious mnemonic processes apply only to studied items; therefore, new items are not subject to either of these two processes. Essentially, the action of conscious or unconscious processes is *logically precluded* for distractor items—implying that neither conscious nor unconscious influences may serve as conditional antecedents. Consequently, there are no conditional probabilities of guessing in the distractor condition; rather, there is only the unconditional probability G. Now, if the extended model is to yield computable estimates for C and U, then as Buchner and his coauthors argued, baseline performance must serve as a constraint for guessing parameters. Since only the unconditional parameter figures in the distractor condition, then *by definition*, the baselines can be used to estimate only this unconditional parameter G. In contrast, Buchner et al. (1995; Eqs. (10) and (12), p. 143) used the base rate to estimate the conditional parameter G_{c-u-}. Such an estimation procedure is tantamount to equating G_{c-u-} with the unconditional G. This equation of G with G_{c-u-} is consistent with assumptions of stochastic independence of the C–G and U–G relations. Indeed, when such independence assumptions are explicitly adopted (see Cowan, 1995; Yonelinas et al., in press), the resultant independent guessing model yields corrected estimates that are numerically identical to the Buchner et al. (1995) model.

It is important to note that Buchner et al. (1995) did not explicitly state assumptions of independence. Rather, they appear to adopt the assumption of exclusivity in the C–G and U–G relations: ‘‘We assume that people guess if and only if both conscious and unconscious mental processes fail to give evidence for responding.’’ (Buchner et al., 1995; p. 143). That is, if either conscious or unconscious influences occur, then guessing does not occur. Therefore, the conditional probabilities G_{c+u+}, G_{c-u+}, and G_{c+u-} are all equal to zero. In Fig. 3, there are four branches that lead to guessing at the final level. Under assumptions of exclusivity, only the branch with G_{c-u-} remains, because the other three conditional probabilities are zero. Thus, the unconditional probability of guessing G is obtained by multiplying the parameters along the G_{c-u-} branch. Therefore, if assumptions of exclusivity in the relations C–G and U–G are made, then $G = (1 - C)*(1 - U_{c-})*G_{c-u-}$ (see also Eq. (20) in Appendix A). Thus, Buchner et al. (1995) appear to have made two contradictory assumptions: (a) $G = G_{c-u-}$, consistent with assumptions of independence but not exclusivity of $C - G$ and $U - G$, and (b) $G = (1 - C)*(1 - U_{c-})*G_{c-u-}$, following from exclusivity but inconsistent with independence of $C - G$ and $U - G$. This confusion clearly highlights the importance of explicitly specifying the relational assumptions underlying any corrective model. This inconsistency aside, the model proposed by Buchner et al. (1995), in its current form, yields estimates that are identical to the independent guessing model (Cowan, 1995; Yonelinas et al., in press) and hence can be considered functionally equivalent to the independent guessing correction.

In summary, we have established that a multinomial modeling approach to the PDP tends to obscure the interactions between processes. Failure to explicitly consider relational assumptions may result in logical inconsistencies, such as that embedded in the exposition of the corrective model proposed by Buchner et al. (1995). A more unfortunate consequence, however, is that the multinomial modeling exposition conceals the existence of a host of response bias corrections to the PDP. It is to the derivation of such alternative extensions of the PDP that we now turn.

CLASSIFICATION BY RELATIONAL ASSUMPTIONS

An explicit consideration of the *C–U, C–G,* and *U–G* relational assumptions leads to a multitude of possible response bias corrections for the PDP. Rather than derive each of these models individually, we undertake the more general derivation of an entire class of corrections to the PDP. We illustrate this classification scheme by specifying the relational assumptions underlying other suggested response bias corrections of the PDP (Buchner et al., 1995; Cowan, 1995; Jacoby et al., 1993; Komatsu et al., 1995; Toth et al., 1994; Roediger & McDermott, 1994; Yonelinas et al., in press). Readers not inclined to pursue this somewhat technical development may refer directly to Table 1, in which the various models are displayed along with the relational assumptions that underlie them.

As before, let *C* represent the set of all trials where conscious influences act to produce target or ‘‘old’’ responses, and let *U* represent the set of all trials where unconscious influences act similarly. Let G^i represent the set of all trials where target or ‘‘old’’ responses in inclusion are produced by guessing, and let G^e be the counterpart in the exclusion condition. Consider first the inclusion condition. The three sets *C, U,* and G^i are represented by circles in the Venn diagram shown in Fig. 4. Note that this representation implies nothing about the various overlaps (e.g., *C&U,* $U\&G^i$, $C\&U\&G^i$, etc.). These overlaps could be empty, nonempty, or could satisfy other more complex relations. In other words, this representation is general because it makes no relational assumptions about the overlaps.

As in the original PDP, contributions to inclusion occur if conscious or unconscious influences act. In addition, guessing is assumed to contribute to inclusion. Overall, ‘‘old’’ or target responses in inclusion performance (denoted by *I*) are provided if and only if conscious processes *or* unconscious processes *or* guessing act. In terms of the sets in Fig. 4,

$$I = p(C \text{ or } U \text{ or } G^i),$$

where $p(C \text{ or } U \text{ or } G^i)$ denotes the probability of any of the three processes acting. This probability corresponds simply to the area covered by all three circles in Fig. 4. The following equation, which expresses the probability $p(C \text{ or } U \text{ or } G^i)$ in terms of the overlaps between component processes, may be verified with the help of Fig. 4. The various overlaps are added and subtracted so as to count every part exactly once.

$$I = p(C \text{ or } U \text{ or } G^i) = [p(C) + p(U) - p(C\&U)] + [p(G^i) - p(C\&G^i) - p(U\&G^i)] + p(C\&U\&G^i).$$

The first cluster of terms represents the union of *U* and *C,* which in Fig. 4 is the area covered by the two circles *U* and *C*. This cluster of terms should be familiar from the original PDP inclusion Eq. (1). The second cluster of terms represents the circle G^i with the overlap areas with *C* and *U* (i.e., $C\&G^i$ and $U\&G^i$) subtracted because

TABLE 1
Model Equations by Correction Method and PDP Variant

Correction method	Variant (C–U)	Model equations
Independent guessing (C–G = Independence; U–G = Independence)	Independence	$I = C + U - U*C + (1 - C)*(1 - U)*G^i$ $E = U - U*C + (1 - C)*(1 - U)*G^e$ $C = [(I - r*E) + (r - 1)]/r$ $U = [1/(1 - B^e)]*\{[E/(1 - C)] - B^e\}$
	Exclusivity	$I = C + U + G^i - C*G^i - U*G^i$ $E = U + G^e - C*G^e - U*G^e$ $C = [(I - r*E) + (r - 1)]/r$ $U = [E - B^e + B^e*C]/(1 - B^e)$
	Redundancy	$I = U + (1 - U)*G^i$ $E = U - C + (1 - U)*G^e$ $C = [(I - r*E) + (r - 1)]/r$ $U = (I - B^i)/(1 - B^i)$
HITS-FA (C–G = Exclusivity; U–G = Exclusivity)	Independence	$I = C + U - C*U + G^i$ $E = U - C*U + G^e$ $C = I - E - d$ $U = (E - B^e)/(1 - C)$
	Exclusivity	$I = C + U + G^i$ $E = U + G^e$ $C = I - E - d$ $U = E - B^e$
	Redundancy	$I = U + G^i$ $E = U - C + G^e$ $C = I - E - d$ $U = I - B^i$
Additive (C–G = Independence; U–G = Exclusivity)	Independence	$I = C + (U + G^i) - C*(U + G^i)$ $E = (U + G^e) - C*(U + G^e)$ $C = (I - E - d)/(1 - d)$ $U = [E/(1 - C)] - B^e$
	Exclusivity	$I = C + U + G^i - C*G^i$ $E = U + G^e - C*G^e$ $C = (I - E - d)/(1 - d)$ $U = E - B^e + C*B^e$

Note. I, proportion of ''old'' responses in inclusion; *C,* estimate of conscious influences; *E,* proportion of ''old'' responses in exclusion; *U,* estimate of unconscious influences; G^i, probability of guessing in inclusion; B^i, base rate from inclusion; G^e, probability of guessing in exclusion; B^e, base rate from exclusion; $r = (1 - B^i)/(1 - B^e)$; $d = B^i - B^e$.

they were already counted in the first cluster. The final term is simply the three-way overlap ($C\&U\&G^i$), which is added back because it was subtracted off twice in the second cluster of terms. Thus, we have derived the first of two equations for the general classification scheme.

Consider now the exclusion condition, where guessing is represented by G^e. In the original PDP, unconscious influences lead to ''old'' or target responses in exclusion condition, but only in the absence of conscious influences. Now in addition, guessing

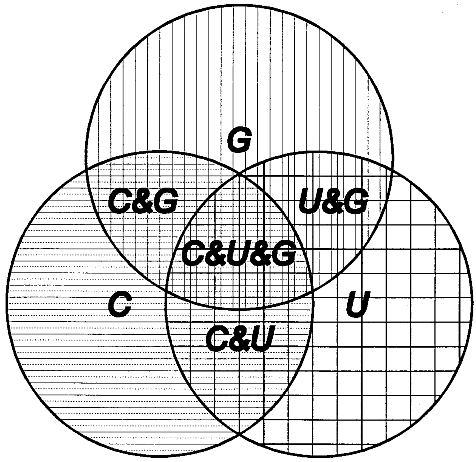

FIG. 4. A Venn diagram depicting conscious influences (C), unconscious influences (U), and guessing (G: denotes G^i in inclusion and G^e in exclusion). $C\&U$ = the overlap between conscious and unconscious influences; $C\&G$ = the overlap between conscious influences and guessing; $U\&G$ = the overlap between unconscious influences and guessing. All two-way overlaps include the three-way overlap $C\&U\&G$.

contributes to exclusion but only in the absence of conscious influences. When consciously controlled influences act, they override the effects of guessing (or unconscious influences); consequently, a new or unstudied response is given. Therefore, ''old'' or target responses in exclusion (denoted by E) occur if and only if unconscious processes *or* guessing act but *in the absence* of consciously controlled influence. In set-theoretic terms

$$E = p(U \text{ or } G^e) - p((U \text{ or } G^e) \,\&\, C).$$

In Fig. 4, this probability corresponds to the area covered by circles U and G^e, with the parts that overlap with C removed. The following equation, which may be verified with the aid of Fig. 4, expresses this area in terms of these various overlaps:

$$E = [p(U) - p(C\&U)] + [p(G^e) - p(C\&G^e)] - [p(U\&G^e) - p(C\&U\&G^e)].$$

The first cluster in this equation corresponds to the contributions of U in the absence of C, which should be familiar from the original PDP exclusion Eq. (2). Similarly, the second cluster reflects the contributions of G in the absence of C. The final cluster is subtracted because it was counted twice in the first two clusters. Thus, we have derived the second of two general equations for a class of PDP corrections.

ALTERNATIVE EXTENSIONS OF THE PDP

We are now equipped with the following pair of equations:

$$I = p(C) + p(U) - p(C\&U) + p(G^i) - p(C\&G^i) - p(U\&G^i) + p(C\&U\&G^i) \quad (10)$$

$$E = p(U) - p(C\&U) + p(G^e) - p(C\&G^e) - p(U\&G^e) + p(C\&U\&G^e). \quad (11)$$

There are three separate relational assumptions to be considered: between conscious and unconscious influences (labeled by C–U), between conscious influences and guessing (termed the C–G relation), and the corresponding U–G relation between unconscious influences and guessing. A plethora of different corrections to the original PDP (as well as to its redundancy and exclusivity variants) may be elegantly distinguished along the dimensions of these relational assumptions. Such a profusion renders impractical an exhaustive exposition. In lieu, we undertake the derivation of three models previously suggested as corrections to the PDP (Buchner et al., 1995; Cowan, 1995; Jacoby et al., 1993; Komatsu et al., 1995; Toth et al., 1994; Roediger & McDermott, 1994; Yonelinas et al., in press). The swift derivation of these models suffices to illustrate both the power and applicability of Eqs. (10) and (11). Since all of these corrections were applied to the independence variant, we initially assume, for the sake of clarity in exposition, that C–U is a relation of stochastic independence. These corrections may also be applied to the exclusivity variant and, except for the additive method, to the redundancy variant as well. Presented in Table 1 are the equations describing all of these corrections.[3]

First, we rederive the independent guessing model, earlier shown to be functionally equivalent to the model proposed by Buchner et al. (1995). As previously elucidated, underlying the independent guessing model are assumptions of stochastic independence in C–G and U–G. These independence assumptions allow the probabilities of overlap between C–G and U–G to be broken down multiplicatively. That is, $p(C\&G) = p(C)*p(G)$; $p(U\&G) = p(U)*p(G)$; as well, it is assumed that $p(C\&U\&G) = p(C)*p(U)*p(G)$ (where G denotes G^i in Eq. (10) and G^e in Eq. (11)). Substituting these expressions for the overlaps into Eqs. (10) and (11), rearranging and factoring yields the independent guessing model:

$$I = C + U - U*C + (1 - C)*(1 - U)*G^i \quad (12)$$

$$E = U - U*C + (1 - C)*(1 - U)*G^e. \quad (13)$$

It is the *unique* contributions (i.e., those that occur in the absence of both conscious and unconscious influences) of guessing that are represented in the tacked-on terms of the form $(1 - C)*(1 - U)*$[guessing parameter]. Indeed, the multiplicative structure of these terms reflects the latent assumptions of independence.

Second, as an alternative to stochastic independence, assume that both C–G and U–G are relations of exclusivity. In this case, all the overlap sets between C–G and U–G are empty, implying that the corresponding probabilities are all zero: that is, $p(C\&G) = p(U\&G) = p(C\&U\&G) = 0$, in both Eqs. (10) and (11). Therefore, these two equations immediately simplify:

$$I = C + U - C*U + G^i \quad (14)$$

[3] Before proceeding, a few remarks regarding notation: in all of the following derivations, we will use C as shorthand for $p(C)$ and similarly U for $p(U)$. Furthermore, G will always denote $p(G)$, the unconditional probability of guessing (or more generally, of response biases). Since this unconditional probability G may vary from the inclusion to exclusion conditions, superscripts will be used, as necessary, to distinguish these two cases. The baselines (B^i and B^e in the inclusion and exclusion conditions, respectively) are the empirical measures of G^i and G^e.

$$E = \quad U - C*U + G^e. \tag{15}$$

This model corresponds to the HITS-FA correction. In this method, the baselines (i.e., false alarms) are subtracted directly from the inclusion and exclusion scores (i.e., hits). Roediger and McDermott (1994) applied this correction in a re-analysis of Verfaellie and Treadwell's (1993) recognition memory data from amnesic patients and normal participants. Note that to assume that two processes are exclusive is equivalent to assuming that their effects are additive (see Jones, 1987). In the HITS-FA model, the effect of guessing combines additively with the effects of both conscious and unconscious processes. It is this additivity that is manifest in the appended guessing parameter in Eqs. (14) and (15).

Third, consider a mixed set of assumptions: let the *C–G* relation be stochastic independence, and let the *U–G* relation be exclusivity. In this case, the overlap sets *U&G* and *C&U&G* are both empty; hence, $p(U\&G) = 0 = p(C\&U\&G)$. Given the assumption of independence, the overlap between *C–G* may be split multiplicatively: i.e., $p(C\&G) = p(C)*p(G)$. Substituting these relations into Eqs. (10) and (11) and factoring yields the following pair of equations:

$$I = C + (U + G^i) - C*(U + G^i) \tag{16}$$

$$E = \quad (U + G^e) - C*(U + G^e). \tag{17}$$

This extended model is a slight elaboration of the additive correction originally applied to the PDP (Toth et al., 1994). The current model is elaborated in that it incorporates two (potentially different) parameters for guessing in inclusion versus exclusion. Again, the assumption that unconscious processes and guessing are exclusive is equivalent to assuming that their effects are additive (see Jones, 1987). This additivity assumption manifests itself in the terms $(U + G^i)$ and $(U + G^e)$.

All of these models may be solved for *C* and *U* in terms of *I, E,* and the baselines B^i and B^e. These solutions are presented in Table 1. Also displayed in the table are corrections to the redundancy and exclusivity variants of the PDP. There are several features of the corrections that warrant commentary. First of all, the additive correction is not applied to the redundancy variant. The cause of this omission is the incompatibility of the particular triad of relational assumptions. Specifically, if one assumes that *C–U* is a relation of redundancy (that is, *C* is a subset of *U*), then it is not possible to simultaneously assume that *C–G* is independent and that *U–G* is exclusive. To establish this incompatibility, suppose that *U–G* is exclusive: then by definition the set *U&G* is empty. To assume that *C–U* is redundant means that *C* is a subset of *U*. By extension, *C&G* is a subset of the empty set *U&G* and therefore it is empty as well. Consequently, $p(C\&G) = 0$. However, *C–G* was also assumed to be stochastically independent—implying that $p(C\&G) = p(C)*p(G)$. These two equations are inconsistent in all but the degenerate cases $p(C) = 0$ or $p(G) = 0$. Second, one simplification occurs uniformly for all the model estimates of *C*. If response bias is assumed to operate equivalently across conditions, then G^i is equal to G^e in Eqs. (10) and (11). Subtracting these two equations then yields the original PDP Eq. (3) for the estimate of conscious influences: that is, $C = I - E$. Thus, under the assumption of equivalent response bias across inclusion and exclusion, this simple estimate of *C* holds irrespective of any relational assumptions (i.e., about *C–U, C–G,* or *U–G*).

Under this assumption, analogous simplifications do occur for the estimate of U in Table 1. However, these simplifications are dependent upon the relational assumptions underlying the given model. In contrast, the invariance of C suggests a certain robustness, which could well be exploited in the investigation of conscious control (see Reingold & Toth, 1996).

All of these corrections were derived directly from the foundational Eqs. (10) and (11) of the present framework. By clarifying the interactions between processes, this framework revealed and classified a collection of corrective models. In contrast, the multinomial modeling framework, with its tendency to obscure interactions, masked the existence of these corrections. However, with the hindsight of our analysis, we can now translate assumptions about overlaps into strictures on the conditional probabilities of guessing (i.e., G_{c-u-}, G_{c+u+}, G_{c+u-}, and G_{c-u+}). Then, the various correction methods may be derived by using the complete processing tree in Fig. 3 and imposing restrictions on the conditional probabilities of guessing. The interested reader may consult Appendix A for details.

Although all of the corrections in the present framework are linear models, nonlinear corrections to the PDP have been proposed. Notably, Yonelinas et al. (in press) developed a nonlinear correction to the PDP, based on signal detection theory (see also Banks & Prull, 1994). Despite differences in the details of implementation, the relational assumptions underlying this signal detection model parallel those of the additive correction to the independence variant (see Jacoby et al., 1993; Toth et al., 1994). Specifically, conscious influences (recollection) are assumed to be independent of guessing, whereas unconscious influences (familiarity) and guessing are assumed to combine additively. Furthermore, Yonelinas et al. (in press) found that the additive correction often led to estimates very close to those of the dual-process signal detection method. By no means is the potential of linear models exhausted: from the multitude of model possibilities incorporated in the general Eqs. (10) and (11), only three corrections have been derived. Varying the combination of relational assumptions will generate other potential corrections. Moreover, we have considered only three possible relational assumptions: independence, exclusivity, and redundancy (Jones, 1987). Although these relations permit a straightforward mathematical treatment, they are merely points on the continuum representing the relationship between two processes. Another interesting possibility is that the interactions between processes may vary across inclusion and exclusion. In this situation, different relational assumptions would be specified across the two conditions, thereby yielding a hybrid model. In short, Eqs. (10) and (11) embody additional corrections other than the three models that we have derived for illustrative purposes.

EMPIRICAL EVALUATION

We have now illustrated the value of specifying relational assumptions by deriving three corrections to the PDP: the HITS-FA correction, the additive model, and the extension proposed by Buchner and his colleagues. It is in the context of empirically assessing correction methods that Buchner et al. (1995) made a unique contribution. In a series of three experiments, Buchner et al. (1995) sought to selectively manipulate response bias without influencing mnemonic processes. In the first experiment,

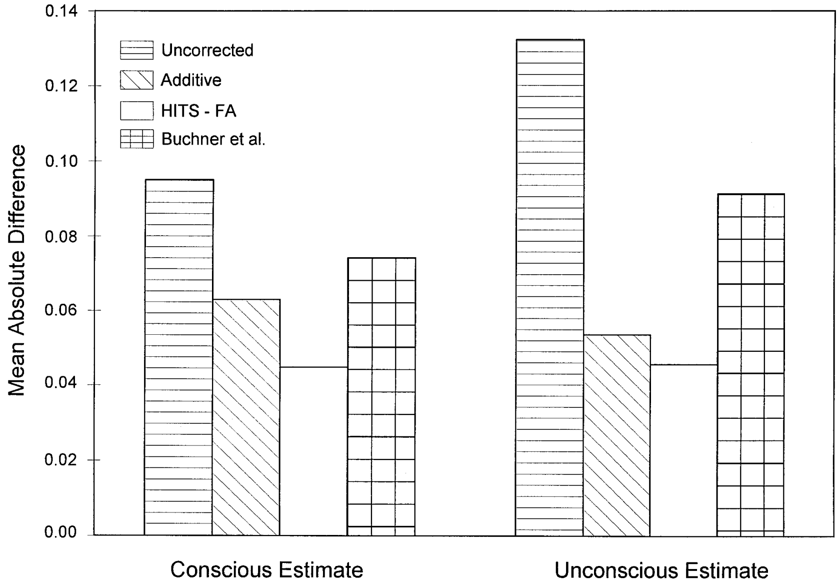

FIG. 5. Mean absolute differences in the estimates of *C* and *U* for the uncorrected PDP and the three corrective models. Absolute differences were aggregated across the read and anagram conditions and across all three experiments reported by Buchner et al. (1995). For the underlying data, see Appendix B.

Buchner et al. (1995) varied the proportion of new items by using standard and extended distractor sets. Experiment 2 featured two types of payoff matrices, liberal and conservative, which were intended to differentially influence participants' response criteria. In the third experiment, Buchner et al. (1995) used two different sets of instructions. One group of participants received the standard PDP instructions, whereas the ''base-rate'' groups received additional information about the proportion of required ''old'' and ''new'' responses in inclusion and exclusion, respectively. It was predicted that all of these manipulations would influence response bias exclusively. In each experiment, Buchner and his colleagues documented significant change in an index of response bias, coupled with a stable index of sensitivity, thereby supporting this prediction.

We made use of the data from these experiments in assessing the three previously derived corrections. The rationale of our evaluation was as follows: if a corrective model truly compensates for response bias, then experimental manipulations that selectively influence bias should not substantially affect the parameter estimates. From the frequency data in Buchner et al. (1995; Table A1, p. 160), we calculated estimates of *C* and *U* for each of the three correction methods, as well as for the uncorrected PDP. For each model, we computed the absolute differences in *C* and *U* estimates across the bias manipulations. All of these calculations are presented in Appendix B. The mean of absolute differences was aggregated across conditions and experiments, thereby constituting a measure of model performance.

Presented in Fig. 5 are the mean absolute differences in the estimate of *C* and *U* for the three correction methods and the uncorrected PDP. The first bar in each grouping corresponds to the uncorrected PDP. Observe that the mean absolute difference for the uncorrected model is greater than the mean absolute difference for each of the corrections. Represented by the fourth bar in each group is the correction proposed by Buchner et al. (1995). As they claimed, their correction results in estimates of consciously controlled and unconscious processes that are relatively unaffected by response bias, at least in comparison to the original PDP. In addition, the additive and the HITS-FA corrections performed just as well, if not better.

In their experiments, Buchner et al. (1995) set up the inclusion and exclusion conditions as a between-subjects rather than within-subjects manipulation, a fact that severely circumscribes the scope of our statistical analysis. Nonetheless, the present analysis has sufficed to highlight two key points. First of all, comparing a given correction method to the uncorrected PDP is not particularly informative. This is the case because the equivalence of baselines across inclusion and exclusion is one prerequisite of computing estimates in the original PDP. Therefore, applying the original PDP is inappropriate in cases when response bias has been selectively manipulated to cause differences in inclusion and exclusion baselines. Instead of contrasting a corrective model with the uncorrected PDP, different corrections must be compared to one another (see Yonelinas et al., in press). In fact, although the preceding analysis was only preliminary, the present results indicate that all three models merit further consideration. Furthermore, in a recent paper, Yonelinas and Jacoby (in press) performed a similar analysis on Buchner and colleagues' data, and they showed that the dual-process signal detection method performed as well as, if not better than, the correction proposed by Buchner et al. (1995). Additional sets of appropriate data and additional response bias corrections to the PDP are both required in order to further address the issue of response bias in the PDP.

GENERAL DISCUSSION

At the foundation of the process dissociation framework is a rejection of the process purity assumption (see Jacoby, 1991; Merikle & Reingold, 1991; Reingold & Merikle, 1988, 1990; Reingold & Toth, 1996). Rather than equating tasks with processes, the framework declares that all tasks are potentially sensitive to both consciously controlled and unconscious influences. Thus emphasized is the interaction of processes in the codetermination of task performance (Reingold & Toth, 1996). Herein lies one of the major contributions of the process dissociation framework: the focusing of attention on the delicate interplay between processes. From this perspective, the drawbacks of a multinomial modeling exposition of the PDP are clear. Although ostensibly free from assumptions, this exposition actually relies on a nonarbitrary ordering in the treatment of processes. This sequential ordering is misleading in shifting attention away from the overlap of processes. Hence, the multinomial processing tree framework diminishes rather than highlights the importance of explicitly specifying underlying assumptions.

In contrast, we advocate emphasis on the interplay between processes. In the PDP, it is precisely this careful consideration of the overlap between consciously controlled and unconscious processes that permits their estimation. In the current paper, this approach has paid further dividends in developing response bias corrections to the PDP. Focusing on the interaction of guessing with conscious and unconscious processes unveils a full class of corrective models. In contrast, the multinomial modeling approach masks the existence of these corrections. All of these models may be classified along three dimensions of relational assumptions. The three relevant interactions are between conscious and unconscious processes, between conscious processes and guessing, and between unconscious processes and guessing. Using this framework, we derived previously proposed corrections, including the HITS-FA method, the independent guessing model, and an additive correction. Although we do not champion any one of these corrections, deriving these models within the current taxonomic framework makes explicit the relational assumptions on which they are founded.

Worthy of reiteration is that the present empirical evaluation and the evaluation of Yonelinas and Jacoby (in press) are merely preliminary. Nonetheless, the clear formulation of these models paves the way for more stringent testing. One requirement is additional sets of appropriate data. To date, the recognition version of the PDP (Jacoby, 1991) has served as the empirical testing ground for response bias corrections (Buchner et al., 1995; Roediger & McDermott, 1994; Verfaellie, 1994; Yonelinas et al., in press). However, the correction models in the framework discussed in this paper are all applicable to other tasks to which the PDP has been applied. Among these tasks are stem completion (e.g., Debner & Jacoby, 1994; Jacoby et al., 1993; Reingold & Goshen-Gottstein, 1996, in press; Toth et al., 1994), as well as other tasks (e.g., Lindsay & Jacoby, 1994; Reingold, 1995). It is therefore vital that response bias be selectively manipulated in versions of the PDP other than recognition memory. The data from such experiments would then lead to continued and more rigorous testing of response bias corrections to the PDP.

Finally, although the original formulation of the PDP did not include explicit corrections for response bias, applications of this paradigm were based on careful comparison of inclusion versus exclusion baselines. The equivalence of these baselines constituted a prerequisite for computing estimates. In marked contrast, within the implicit memory framework, differences in baseline across indirect (implicit) and direct (explicit) tests have been largely ignored (see Reingold & Toth, 1996 for a review). It is imperative that corrections for response bias be implemented in paradigms based on task dissociations, as well as those based on process dissociations. Thus, rather than regarding the problem of response bias as specific to the PDP, this issue should be viewed in the broader context of investigating the relation between consciousness and cognition.

APPENDIX A

Derivation of Corrective Models within the Multinomial Modeling Framework

Herein, we rederive three response bias corrections to the PDP from within the multinomial modeling framework. At the foundation of these derivations is the complete tri-level processing tree drawn in Fig. 3. In this multinomial processing tree, C represents the unconditional probability of conscious influence. The parameter U_{c-} denotes the conditional probability of unconscious influence given that conscious influence does not occur, whereas U_{c+} is the conditional probability of unconscious influence given that conscious influence does occur. Define U as the unconditional probability of unconscious influence. Let G be the overall unconditional probability of guessing. One type of conditional probability of guessing is G_{c-u-}, the probability of guessing given that neither conscious nor unconscious influence occurs. Three other conditional probabilities of guessing also appear in Fig. 3. The counterpart of G_{c-u-}, denoted by G_{c+u+}, is the conditional probability of guessing given that both conscious and unconscious influences act. In analogous fashion, two mixed conditional probabilities may be indexed, in the spirit of our notation, by G_{c+u-} and G_{c-u+}. Note that all of these guessing parameters may vary across the inclusion and exclusion conditions; superscripts will be used as needed to distinguish between these cases.

Let I and E represent the proportion of ''old'' responses in the inclusion and exclusion conditions, respectively. By following the ''old'' branches in the tree in Fig. 3, the following pair of equations are derived:

$$I = C + U_{c-} - C*U_{c-} + (1 - C)*(1 - U_{c-})*G^{i}_{c-u-} \tag{18}$$

$$E = U_{c-} - C*U_{c-} + (1 - C)*(1 - U_{c-})*G^{e}_{c-u-}. \tag{19}$$

Note that only one of the four conditional probabilities of guessing (namely, G_{c-u-}) figures in these equations; the other three disappear by fortuitous cancellation. Also vanishing is the conditional parameter U_{c+}.

As this pair of equations stands, it is not soluble. It is necessary to use the base rates of performance (B) for new items to further constrain the model by serving as an estimate of guessing. We established above that the baselines may be used only to estimate the unconditional G. However, only the conditional parameter G_{c-u-} appears in Eqs. (18) and (19). The key link between G and the conditional probabilities is afforded by the equation

$$\begin{aligned} G = {} & C*U_{c+}*G_{c+u+} + C*(1 - U_{c+})*G_{c+u-} + (1 - C)*U_{c-}*G_{c-u+} \\ & + (1 - C)*(1 - U_{c-})*G_{c-u-}. \end{aligned} \tag{20}$$

Note that there are two such equations: one for each of the inclusion and exclusion conditions, with parameters of guessing distinguished by the appropriate superscripts.

In order to illustrate the use of Eq. (20), we derive the three corrections to the independence variant of the PDP. Of course, corrections to the other two variants could be derived just as easily. Under the independence assumption, $U_{c-} = U$ in Eqs. (18), (19), and (20). Denote by C–G the relation between conscious influences and guessing. Analogously, let U–G represent the relation between unconscious influences and guessing, and let C–U stand for the relation between conscious and unconscious influences. Various restrictions on the four conditional probabilities in Eq. (20) yield the desired corrections.

(a) In the independent guessing model, the C–G and U–G relations are both assumed to be stochastically independent and $G = G_{c-u-}$. When this equality is substituted into Eqs. (18) and (19), the model Eqs. (12) and (13) are obtained.

(b) In the HITS-FA model, C–G and U–G are assumed to be exclusive. This assumption is equivalent to $G_{c+u+} = G_{c+u-} = G_{c-u+} = 0$. Imposing these restrictions in Eq. (20):

$$G = (1 - C)*(1 - U)*G_{c-u-}.$$

After substituting this result into Eqs. (18) and (19), the defining equations (14) and (15) for the HITS-FA model are obtained.

(c) Third, in the additive model, C–G is assumed stochastically independent, whereas U–G is assumed exclusive. From the exclusivity assumption, we have the relations $G_{c+u+} = G_{c-u+} = 0$. From the exclusivity and independence assumptions, it follows that $G_{c+u-} = G_{c-u-}$. Substituting these expressions into Eq. (20) and simplifying yields

$$G = (1 - U)*G_{c-u-}.$$

By substituting this expression into Eqs. (18) and (19), and rearranging, one obtains the model equations [(16) and (17)] for the additive model.

APPENDIX B

Application of Correction Methods to the Data Reported by Buchner et al. (1995)

Using the frequency data from Buchner et al. (1995; Table A1, p. 160), estimates for conscious (*C*) and unconscious influences (*U*) are calculated for the independence variant of the PDP, as well as for three response bias corrections of this variant: the additive model, the HITS-FA model, and the correction proposed by Buchner et al. (1995). All of these computations are performed using the equations for *C* and *U* displayed in Table 1. Absolute differences in parameter estimates were taken across the manipulations of response bias.

Condition (R = read; A = anagram)	Estimated parameter	Uncorrected	Correction method		
			Additive	HITS-FA	Buchner et al.
Experiment 1					
R/Standard	*C*	0.520	0.385	0.300	0.429
R/Extended	*C*	0.417	0.274	0.220	0.311
	Absolute difference	0.103	0.111	0.080	0.118
A/Standard	*C*	0.802	0.747	0.582	0.766
A/Extended	*C*	0.735	0.670	0.537	0.688
	Absolute difference	0.067	0.077	0.045	0.078
R/Standard	*U*	0.401	0.230	0.157	0.278
R/Extended	*U*	0.305	0.195	0.163	0.219
	Absolute difference	0.096	0.035	0.006	0.059
A/Standard	*U*	0.418	0.243	0.000	0.295
A/Extended	*U*	0.330	0.215	0.081	0.243
	Absolute difference	0.088	0.028	0.081	0.052
Experiment 2					
R/Liberal	*C*	0.475	0.342	0.272	0.397
R/Conservative	*C*	0.515	0.378	0.295	0.424
	Absolute difference	0.040	0.036	0.023	0.027
A/Liberal	*C*	0.753	0.690	0.550	0.729
A/Conservative	*C*	0.775	0.712	0.555	0.731
	Absolute difference	0.022	0.022	0.005	0.002
R/Liberal	*U*	0.529	0.269	0.172	0.363
R/Conservative	*U*	0.361	0.249	0.202	0.280
	Absolute difference	0.168	0.020	0.030	0.083
A/Liberal	*U*	0.697	0.403	0.044	0.571
A/Conservative	*U*	0.333	0.228	0.096	0.254
	Absolute difference	0.364	0.175	0.052	0.317
Experiment 3					
R/Standard	*C*	0.318	0.254	0.232	0.275
R/Base-rate	*C*	0.545	0.359	0.255	0.426
	Absolute difference	0.227	0.105	0.023	0.151
A/Standard	*C*	0.602	0.566	0.517	0.580
A/Base-rate	*C*	0.712	0.595	0.422	0.651
	Absolute difference	0.110	0.029	0.095	0.071
R/Standard	*U*	0.388	0.275	0.241	0.310
R/Base-rate	*U*	0.407	0.236	0.178	0.285
	Absolute difference	0.019	0.039	0.063	0.025
A/Standard	*U*	0.453	0.334	0.207	0.379
A/Base-rate	*U*	0.513	0.312	0.165	0.390
	Absolute difference	0.060	0.022	0.042	0.011

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