Running head: MULTINOMIAL PROCESS MODELS

Multinomial Process Tree Models of Control and Automaticity in Weapon Misidentification

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Abstract

When primed with a Black face, people are more likely to misidentify a non-weapon as a weapon. Weapon misidentification may hinge on the distinction between controlled and automatic processes. Various relationships between controlled and automatic processes are cast in the form of five multinomial process models, which are illustrated and compared. It is shown that variants of the traditional Process Dissociation model and the Stroop model are nested within the Quad model. Across 4 different studies, various complexity corrected model performance measures converged to support the Process Dissociation account. This account suggests that the automatic association between race and weapons is subordinate to controlled processing. More generally, these results suggest that the weapon-bias might be alleviated without interventions that directly target stereotypes.

KEYWORDS: DUAL PROCESS, WEAPON, AUTOMATIC, PROCESS DISSOCIATION, QUAD MODEL

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When determining if a weapon is present, people sometimes falsely claim to have seen a weapon when they have seen only a harmless object and a Black person (Payne, 2001; also see Correll, Park, Judd, & Wittenbrink, 2002; Greenwald, Oakes, & Hoffman, 2003; Lambert, Payne, Ramsey, & Shaffer, 2005). Such split-second errors could be terribly important if the error means pulling a trigger rather than pressing a computer key. The goal of the current research is to compare different process accounts of this error, and specifically, process accounts that can be cast in the form of multinomial process tree models. To this end, first, a set of multinomial models will be illustrated, including process dissociation models and the quadruple process model. It will be shown that the models are connected not only conceptually, but also via a specific mathematical relationship (i.e., they are nested). Second, these models will be empirically compared in terms of their ability to account for weapon misidentification data.

Weapon misidentification may hinge on the distinction between controlled processing and automatic accessibility of the stereotype (Payne, 2001). We define controlled processing broadly, as the use of information most applicable to one's current goals or task set. In the case of weapon identification, controlled processing can take the form of discriminating between the perceptual characteristics of gun and non-gun objects, and using this information to respond within a limited amount of time. In contrast, the activation of automatic processes may reflect primed associations that do not necessarily aid the accurate completion of one's goals. In the case of weapon identification, the automatic process of most interest is the stereotypical association between African Americans primes and weapons.

Two decades of research on dual process theories have established the importance of distinguishing between automatic and controlled influences in social cognition (Chaiken & Trope, 1999). These theories describe distinct processes, but they rarely specify how the processes relate to each other. A “second generation” of research has recently begun doing so (Bargh, 2006). A complete dual process theory must explain not only when distinct processes are likely to drive behavior, but also how those processes interact. For example, when automatic and controlled responses conflict, how is that conflict resolved?

Some dual-process theories ascribe a relatively dominant role to controlled processing, with automatic processes influencing behavior only to the extent that controlled processing fails (Jacoby, 1991; Payne, 2001). Other theories treat controlled processing as relatively subordinate, as a means to adjust an initial impression or decision that was based on automatic processes (Devine, 1989; Gilbert, Pelham, & Krull, 1988; Kahneman, 2003; for discussion, see Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005; Jacoby, Kelley, & McElree, 1999).

The relative dominance of controlled and automatic processes may depend on the task at hand. In the weapon identification task, consider three possible relationships between controlled and automatic processes:

1. Control-Dominating Relationship: A nonweapon is misidentified as a weapon only when both controlled processing fails and automatic racial bias occurs.

2. Automaticity-Dominating Relationship: A nonweapon is misidentified as a weapon when an automatic racial bias occurs, regardless of controlled processing.
3. Probabilistic Relationship: If both controlled processing succeeds and the automatic influence occur on the same trial, the resulting conflict will be resolved probabilistically.

Note that these three possible relationships only refer to how conflict is resolved between control and automaticity. For example, even if the Control-Dominating Relationship were true, it would still be possible for automaticity to play an important role in determining behavior. Automatic processes would still be relied upon to make decisions so long as controlled processes failed. Thus, the relationship between controlled and automatic processes may be very difficult to intuit a priori for any given task or situation. Whether the relationship takes one form or another is an empirical question that can be addressed via mathematical modeling.

Multinomial Process Tree Models

The possible relationships between control and automaticity can be cast as multinomial process tree models. Multinomial models allow researchers to test theories of underlying processes in a way that traditional approaches like ANOVA cannot (Riefer & Batchelder, 1988). One reason for this is that multinomial models can have more than one process pathway or branch leading to the same response. To illustrate, consider a case where a person correctly identifies a gun after being primed with a Black face. According to the Process Dissociation Model, there are two process pathways that can lead to this event. In the first pathway, control constrains processing to relevant perceptual characteristics of the gun, thereby leading to a correct gun response. In the second pathway controlled processing fails, but the gun response is still given because of the automatic influence of the prime. Multinomial models can help disentangle underlying processes in such situations (for a review, see Batchelder & Riefer, 1999).

In multinomial models, each parameter ranges from 0 to 1 and represents the probability with which a process occurs. The top panel of Figure 1 shows the processes in the traditional Process Dissociation Model (Jacoby, 1991; Payne, 2001). In that model, when controlled processing succeeds with probability C, a correct response (+) is given in all conditions. When controlled processing fails with probability (1-C), the automatic influence of the prime determines the response. When the automatic influence is stereotype-consistent with probability A, the response is correct for the White-tool and Black-gun conditions, but incorrect (-) for the other conditions. With probability (1-A), the response is counter-stereotypical, with a tool response following Black primes and a gun response following White primes. Note that the A parameter is irrelevant whenever controlled processing succeeds. Thus, even though the automatic process operates faster, controlled processing dominates automaticity in the Process Dissociation model (see Payne 2001, 2005; Payne, Lambert, & Jacoby 2002, for evidence that C and A parameters represent controlled and automatic processes, respectively; for related evidence, see Klauer & Voss, 2008).

By contrast, in the bottom panel of Figure 1, automaticity dominates controlled processing. We refer to this as the “Stroop Model” because it is based on a model developed for the Stroop task (Lindsay & Jacoby, 1994), a task where the relatively automatic, unintended process of word-reading can dominate the intended process of color-naming. In the Stroop model, if the prime has an automatic influence, a stereotypic response is given, and this occurs regardless of the status of controlled processing. Only when an automatic influence does not occur (with probability 1-A) does controlled processing matter. Thus, Process Dissociation and Stroop models represent the Control-Dominating and Automaticity-Dominating relationships, respectively.

The third possible relationship can be represented by the Quad-Model (Conrey et al., 2005). The original depiction of the Quad-Model is shown in Figure 2. Parameter AC is analogous to parameter A in the previous models in that it represents the stereotypic effect of the prime. Parameter D is analogous to parameter C in the previous models in that it represents correct discrimination of the object (gun or tool).

Importantly, the Quad-Model also has precise relationships to variants of the Process Dissociation and Stroop models. Relabeling D as C, and AC as A, the Quad-Model can be rewritten into an algebraically equivalent form, shown in Figure 3 (for proof that Figures 2 and 3 are identical models, see Appendix A). Figure 3 shows that the Process Dissociation model with a guessing parameter (Buchner Erdfelder, & Vaterrodt-Plünnecke, 1995) and the Stroop model with a guessing parameter are both nested within the Quad-Model. These nested models will be referred to as Process Dissociation/G and Stroop/G. Although the OB parameter has sometimes been described as inhibitory (Conrey et al., 2005), Figures 3 reveals other possible interpretations. nother way of describing the Quad-Model is that, with probability OB, the Process Dissociation/G model is followed; with probability (1-OB), the Stroop/G model is followed. Therefore, when OB=1.0, the Quad-Model reduces to the Process Dissociation/G model; when OB=0.0, the Quad-Model reduces to the Stroop/G model.

To our knowledge, this nested relationship has not been previously reported in the literature. The nested relationship shows that the OB parameter in the Quad-Model may provide information about which processes dominate others. For control-dominating situations, OB should approach 1; for automaticity-dominating situations, OB should approach 0. Additionally, the nested relationship reveals that the interpretation of Quad-Model parameters critically depends on the value of OB. For example, AC has sometimes been described as a parameter distinct from the G parameter because only G measures response biases that occur when controlled processing fails (Sherman, 2006). However, as OB approaches 1 (as shown in the top half of Figure 3), both G and AC represent biases that matter only when control fails.

Comparing Models of Differing Complexity

There is only one previously published comparison of multinomial models of weapon misidentification. Using data from Lambert and colleagues (2003), Conrey et al. (2005) compared the Process Dissociation, Quad-Model, and Stroop Model. The Quad-Model showed the smallest G^2 value, and so it was concluded that the Quad-Model "provides a better description of the responses in the weapon identification task than less complex models" (Conrey et al., 2005; p. 482).

However, a major challenge to model comparison is that models that are complex (e.g., have a large number of free parameters) can capitalize on chance (Busemeyer & Wang, 2000; Pitt, Myung, & Zhang, 2002). That is, complex models can sometimes appear to fit well for spurious reasons. To take an extreme example, if a model were so complex that it had as many free parameters as there were data points, the model could spuriously provide a perfect fit to the data with a G^2 of 0. More generally, G^2 will tend decrease as the number of model parameters increases even if the model is inaccurate. This tendency is analogous to the tendency in multiple regression for R^2 to improve as the number of predictors increases even if those predictors are random and arbitrary.

Because the Quad-Model is more complex than other models, does the Quad-Model better account for the data, or just better capitalize on chance? Furthermore, is there a model that is generally supported by the data? We address these questions by using several model testing approaches that adjust for complexity differences, including nested tests to examine the OB parameter, goodness-of-fit tests relative to a saturated model, and more direct model comparison using both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

Nested Tests of the OB parameter. One approach is to compare two models to see if the model with additional free parameters fits significantly better than the model with fewer free parameters. This approach is only valid when the models are nested. For example, the Quad-Model can be compared to the Stroop/G model, because the latter is nested within the former. When OB=0, the Quad-Model reduces to the Stroop/G model, and so a significant difference from 0 would be taken as evidence against the Stroop/G model. Similarly, the Quad-Model can be compared to the Process Dissociation/G model by determining whether the OB parameter was significantly different from 1. Unfortunately, there are limitations to nested testing. One limitation is that the Process Dissociation and Stroop models *without* guessing parameters cannot be compared to other models. A second limitation is that the OB parameter can lack precision in the Weapon-Bias paradigm (e.g., Conrey et al., 2005), and so it may rarely be significantly different from either 1 or 0. Finally, while nested tests can potentially provide evidence against the Process Dissociation/G and Stroop/G models, the Quad-Model is insulated from falsification in such tests.

Goodness of fit: G^2 comparison to a saturated model. The G^2 statistic can be computed for each model of interest relative to a saturated model, with G^2 representing badness of fit (i.e., higher is worse). G^2 is biased to be low for models with more free parameters (e.g., the Quad-Model), and so models should not be directly compared to one another via G^2. Each model of interest can, though, be separately compared to the saturated model. Each model of interest has a particular critical value based on the model's degrees of freedom. When G^2 is below the critical value, the model of interest is said to "fit" the data. When a model of interest fits, the model did not perform significantly worse than the saturated model. G^2 is limited because, even when a model fits, all it indicates is a failure to reject the null hypothesis. Results can be ambiguous when multiple models fit the data. Furthermore, G^2 does not allow for direct comparisons among non-nested models.

Complexity Corrected Fit Statistics: AIC and BIC. To directly compare all models, two adjustments to G^2 that correct for complexity differences among models were examined. The two particular adjustments were chosen because they are known to have different biases. The first adjustment, AIC (Akaike, 1974), is biased to favor more complex models especially when the sample size is large. The second adjustment, BIC (Schwarz, 1978), is based on asymptotic principles from Bayesian model comparison. BIC tends to favor simpler models. Because AIC and BIC have opposing biases, when both complexity adjustments agree, there is good evidence that one model is performing better than another (Burnham & Anderson, 2004; Kuha, 2004). For both AIC and BIC, smaller values indicate better model performance.

Testing the Generality of Results

We extend previous work in three ways in order to thoroughly test the generality of results. First, we use four datasets (including the one used by Conrey et al.) in order to determine whether results are consistent across studies. The studies, described below, were selected because they included enough conditions to provide the degrees of freedom needed to directly compare all models. Second, we tested additional models that are nested within the Quad-Model: the Process Dissociation/G and Stroop/G models. These comparisons allow us to consider whether the use of an OB parameter or Guessing parameter (or both) are justified by the available data. Third, data are analyzed at both the group and the subject level. The group level collapses together all responses from all subjects in an experimental group. This approach is common in multinomial process tree models (for a review see Batchelder & Riefer, 1999), but it relies on the assumption that parameter values are identical across participants within a group. Alternatively, models can be fit separately to each subject, with each subject having his or her own set of unique parameter values. The two levels of analysis can produce very different results (e.g., Estes & Maddox, 2005) and so we examine both separately (for alternative approaches, see Klauer, 2006; Riefer & Batchelder, 1991).

Method

Lambert et al. (2003), Study 2.

Participants (N=127) were randomly assigned to a Private or Anticipated Public condition. Those in the Private condition were assured that their responses would be confidential. Participants in the Anticipated Public condition were told that, following the task, they would be asked to share and discuss their performance with other participants in the experiment session. The primes included four Black and four White faces, including two male and two female faces of each race. Target photos included four handguns and four hand tools. Each trial sequence included 1) a visual mask of black and white "noise," presented for 500 ms, 2) a prime face presented for 200 ms, followed by 3) a gun or tool target presented for 100 ms, and finally, 4) another visual mask, which remained until a response was made. The response window was 550 ms from the onset of the target item. Following 48 practice trials, participants completed 384 critical trials.

In multinomial models, some parameter constraints had to be used in order to achieve enough degrees of freedom. Table 1 shows the full list of model parameters across this and other experiments. In every experiment, the quad-model's D and AC parameters were allowed to vary in the same manner as the other models' C and A parameters, respectively. In describing parameter constraints, we use the label C to collectively refer to both C and D, and the label A to collectively refer to both A and AC.

Parameter constraints in this experiment were identical to those used in Conrey et al. (2005). Because race and gender of the prime are thought to primarily influence automatic processes (Payne, 2001; also see Conrey, 2005), we allowed for A to vary based on whether the prime was white or black, or male or female, but we did not allow C or OB to do vary by prime. We allowed for the possibility that public versus private context could affect either automatic or controlled processes, and so C, A, and OB were allowed to vary across that manipulation. The G parameter was intended to represent a general, experiment-wise guessing bias, and so G was constrained to be the same across all conditions (as in Conrey et al., 2005, Experiment 5). Note that, because the public versus private manipulation was between-subjects, models at the individual subject level of analysis required fewer free parameters (see Table 1). Further details about modeling methods can be found in Appendix B.

Lambert et al. (in prep.)

This study examined effects of public versus private performance using an actual, rather than anticipated public setting. Participants (N=151) were assigned to either a private condition (same as previous) or a public condition. In the public condition, an experimenter watched while the participant performed the weapons task. The trial sequence and timing were identical to Lambert et al. (2003). Model parameters were also free to vary in the same manner as before.

Payne (2005)

Participants (N=55) completed the weapons task using the same stimuli, trial sequences, and timing as described above (in the private conditions), except that the target items were presented for 200 ms rather than 100 ms. Participants completed 64 practice trials, followed by 320 critical trials. Because all responses were private in this experiment, model parameters were the same in this experiment as in the previous two except that there were fewer parameters for the group level of analysis (see Table 1).

Payne et al. (2002)

Participants (N=97) were randomly assigned to one of three instruction conditions. In a baseline control group, participants were instructed to focus on identifying the target items and ignore the prime photos. The "avoid race" group were instructed to try to avoid being influenced by race as they identified the target items. In the “use race” condition participants were instructed to use race as a clue to help them make their decisions. Targets were presented for 100 ms. A practice round of 64 trials allowed an 800 ms response window. Next subjects completed three blocks of trials with increasingly fast response windows from 750 ms, to 450 ms, to 200 ms. Each critical block included 128 trials, for a total of 384 critical trials.

As shown in Table 1, model parameter constraints in this experiment were the same as those in the previous experiment with three exceptions. First, based on the idea that controlled processes but not automatic processes would be affected by response deadline, C and OB (but not A) were allowed to vary across the 700, 450, and 200 millisecond deadlines. Second, the gender of the prime was not recorded in the available data, and so A was separated by race but not gender. Third, we allowed for the possibility that the instructional manipulation could affect either automatic or controlled processes, and so separate C, A, and OB parameters were used across the baseline, avoid race, and use race conditions.

Results

Group Level

OB Parameter. As shown in Figure 4, the OB parameter at the group level was sometimes significantly different from 0, suggesting that the Stroop/G model was inaccurate. Otherwise, the OB parameter was largely ambiguous.

Using nested comparisons, 5 of the 14 OB parameters were significantly different from 0, *p*s < .05. These 5 OB parameters are the same 5 in Figure 4 that do not have confidence intervals overlapping with 0. In contrast, none of the OB parameters were significantly different from 1.0, *p*s > .05. In other words, the Stroop/G model could sometimes be ruled out, but Process Dissociation/G model could not. A casual glance at Figure 4 might suggest that OB differed systematically across conditions, but additional nested comparisons revealed no significant differences in OB across conditions, all *p*s >.18 (For the interested reader, estimates of other parameters can be found in Appendix C).

G^2. In most studies, the G^2 values suggested that the Process Dissociation, Process Dissociation/G, and the Quad-Model were all plausible models, but the two versions of the Stroop model were not. An exception to this pattern occurred in the Payne (2005) data, where none of the models provided an adequate fit.

Group level G^2 is shown in the upper row of Figure 5. It would be inappropriate to compare G^2 values directly across models because not all models had the same number of free parameters. Rather, G^2 is tested against a critical value appropriate for each model based on the chi-squared distribution.

Examining from left to right in Figure 5, in Lambert et al. (2003), G^2 was below the critical value for Process Dissociation, $G^2(6)=6.71$, critical=12.59; Process Dissociation/G, $G^2(5)=7.27$, critical=11.07; Quad-Model, $G^2(3)=5.15$, critical=7.81; and Stroop/G model, $G^2(5)=9.42$, critical=11.07. G^2 was above critical value for the Stroop model, $G^2(6)=28.46$, critical=12.59.[1] Thus, only the Stroop model did not fit the data.

In Lambert et al. (in prep.), G^2 was below the critical value for Process Dissociation, $G^2(6)=6.62$, critical=12.59; Process Dissociation/G, $G^2(5)=7.12$, critical=11.07; and Quad-Model, $G^2(3)=6.21$, critical=7.81. G^2 was above critical value for both the Stroop/G model, $G^2(5)=12.42$, critical=11.07; and Stroop model, $G^2(6)=120.70$, critical=12.59.

In Payne (2005), G^2 was above critical value for all 5 models: Process Dissociation, $G^2(3)=10.79$, critical=7.81; Process Dissociation/G, $G^2(2) = 10.79$, critical=5.99; Quad-Model, $G^2(1)=7.00$, critical=3.84; Stroop/G, $G^2(2) = 7.00$, critical=5.99; and Stroop model, $G^2(3)=8.93$, critical=7.81.

Finally, in Payne et al. (2002), G^2 was below the critical value for Process Dissociation, $G^2(21)=18.98$, critical=32.67; Process Dissociation/G, $G^2(20) = 18.98$, critical=31.41; and the Quad-Model, $G^2(11)=10.11$, critical=19.68. G^2 was above critical value for both the Stroop/G model, $G^2(20)=37.09$, critical=31.41; and Stroop model, $G^2(21)=39.51$, critical=32.67.

Except for Payne (2005), where all models were rejected, the G^2 values suggested that only the Stroop models could be rejected. However, G^2 does not provide a means of discriminating among the remaining models. G^2 tended to be lowest in the Quad-Model, but this could be because the Quad-Model is the most complex model considered. AIC and BIC allow for complexity corrected comparisons.

AIC and BIC. In the majority of studies, AIC favored the Process Dissociation model. As can be seen in the middle row of Figure 5, AIC was lowest for Process Dissociation in 3 out of 4 datasets. Like with G^2, the Payne (2005) data was exceptional. For that data, the smallest AIC occurred in the Stroop model.

The Process Dissociation model was also favored by BIC in the majority of studies. As can be seen in the bottom row of Figure 5, BIC was lowest for Process Dissociation in 3 of the 4 datasets. The Payne (2005) data was again exceptional, with the smallest BIC in the Stroop model. With the exception of Payne (2005), the AIC and BIC generally converged to support the Process Dissociation model.[2]

Subject Level

OB Parameter. The OB parameter was ambiguous at the subject level. Across all subjects, 99% of OBs were not significantly different from 1, and 99% were not significantly different from 0, *p*s > .05.

G^2. The top row of Figure 6 shows mean G^2 across subjects. We examined the percentage of subjects where the model fit, as indicated by a G^2 below the appropriate critical value for each model. Across datasets, the process dissociation model fit the largest percentage of subjects: Process Dissociation=95.2%, Process Dissociation/G=87.6%, Quad-Model=74.8%, Stroop/G=89.0%, Stroop=73.3%. The percentage was significantly higher for the Process Dissociation model when compared to any other model, all *p*s < .001 by McNemar's (1947) test.

AIC and BIC. AIC and BIC were analyzed within each dataset by performing one-way repeated measures ANOVAs with Model as the factor (Levels=Process Dissociation, Process Dissociation/G, Quad-Model, Stroop/G, and Stroop). Group (e.g., Public vs. Private), was not included as a factor in our reported analyses because preliminary analyses showed that all main effects of Group and Group X Model interactions were nonsignificant, all *p*s > .23.

The AIC, as shown in the middle row of Figure 6, favored the Process Dissociation model in all 4 datasets. For each dataset, there was a significant main effect of Model, all *F*s > 21.7, *p*s < .001. Bonferroni comparisons showed that AIC was significantly lower for the Process Dissociation model than for any other model, all *p*s < .001. The Quad-Model performed significantly worse than all other models, *p*s < .001, except in the Lambert et al. (2003; in prep.) datasets, where the Quad-Model was not significantly different from the Stroop model, $p > .90$.

The BIC, as shown in the bottom row of Figure 6, also consistently favored the Process Dissociation model. For each dataset, there was a significant main effect of Model, all Fs > 100.4, ps < .001. In Bonferroni comparisons, BIC was significantly lower for the Process Dissociation model than for any other model, ps < .001. BIC was significantly higher for the Quad-Model than for any other model, ps < .001.

Discussion

Among the 5 multinomial models tested, the process dissociation model was best supported by the data. It was supported by AIC and BIC at both the group level and the subject level, and also G^2, particularly at the subject level, where more participants were successfully fit by the process dissociation model than by any other model. Analyses of OB parameters and the Group level G^2 were less clear, but generally suggested that the Stroop and Stroop/G models did not accurately represent the processes involved in the weapon-bias.

No analysis suggested that the process dissociation model was inaccurate, except for the Payne (2005) group level G^2 analysis, an analysis that suggested that *all* models were inaccurate. This discrepancy may be due to floor effects in error rates for that particular dataset. In that dataset, targets were presented for 200 ms rather than 100 ms. Perhaps due to the extended target presentation, error rates were lower in that dataset (10.3%) than in any other dataset (range=15.3% to 20.7%). Floor effects in error rates could violate the assumptions of all models. The power to detect such violations (i.e., reject the null) would be higher in group models than subject models because the number of data points is dramatically larger in group models.

Based on model comparisons, there was little evidence to support the use of a guessing parameter via the Process Dissociation/G or Stroop/G models. Of course, the manipulations in the studies here were not particularly relevant to the guessing parameter. Future experimental manipulations, for example, of the payoffs associated with responding guns versus tools, might make guessing parameters useful.

In the Quad-Model, the OB parameter was rarely informative because the parameter's confidence interval often spanned the entire range of the scale. Our reanalysis of the Lambert et al. (2003) dataset, as well as three other datasets, failed to identify a single reliable difference in OB across experimental condition. Previous analysis of OB using Lambert et al. (2003) data has focused on nonsignificant differences in point estimates, leading to the conclusion that bias is more likely to be overcome in public conditions than private conditions (see Conrey et al., 2005, p. 482; Sherman, 2006, pp. 176-177). It seems premature to draw such a conclusion considering the width of the confidence intervals of OB. Furthermore, the OB parameter was insensitive to instructional manipulations that specifically encouraged the use and avoidance of racial bias (Payne et al., 2002). Insensitivity to such a direct manipulation does not encourage faith in the parameter's construct validity.

The unreliability of the OB parameter may be the result of excessive model complexity. The Quad-Model often showed a small G^2, but when fit was corrected for complexity via AIC or BIC, the Quad-Model was outperformed by other models. This pattern could occur if the Quad-Model was achieving a small G^2 by capitalizing on chance.

The general convergence of support for the Process Dissociation model is consistent with a Control-Dominating relationship for the weapon-bias task. That is, racial stereotypes are used only if controlled processing fails. The Control-Dominating view has a practical implication. All of the models reviewed here suggest that bias could be reduced by either minimizing automatic influences or maximizing controlled influences. However, the relative potency of each strategy differs across models. In a Control-Dominating model, maximizing control is the most potent strategy because when control succeeds, automatic biases are irrelevant. According to this model, the weapon bias might be remediated via controlled processing even without intervention aimed at stereotype accessibility.

In the modeling here, parameter constraints were necessary in order to achieve at least one degree of freedom. Parameter constraints were chosen on the basis of theory and prior work (e.g., Conrey et al., 2005), but that provides no guarantee that results will generalize to other possible parameter constraints, even when using the same general multinomial trees.

The current research suggests a dominant role for controlled processing in the weapon identification task, but the relationship between processes may differ across situations and contexts. Even though the Process Dissociation model was generally favored in weapon identification experiments, other models may fit better in other tasks. An important issue for future research is to identify the relationship between experiment characteristics and relative model performance. Models that allow for a more dominant automatic component, such as the Quad-Model or the Stroop model, might provide better fits to data when inhibitory failures are common in a task or population. As one example from research on memory and aging, an automaticity-dominating model known as the "capture" model (Jacoby, Bishara, Hessels, & Toth, 2005) was required specifically when fitting the performance of older adults, perhaps as a consequence of an inhibitory deficit in that population.[3]

In conclusion, the available evidence from the weapon identification paradigm suggests that the process dissociation model provides a more accurate description of the existing data than do models in which automatic processes can dominate decisions. This finding suggests that the weapon-bias might be alleviated even without interventions that directly target stereotypes.

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Appendix A: Proof that Figures 2 and 3 are Algebraically Equivalent

In Figure 2, the Quad-Model's predicted probabilities of correct responses are:

$$p(\text{Correct}|\text{White \& Tool}) = AC + (1-AC)D + (1-AC)(1-D)G \quad \text{(A1)}$$

$$p(\text{Correct}|\text{White \& Gun}) = AC \cdot D \cdot OB + (1-AC)D + (1-AC)(1-D)(1-G) \quad \text{(A2)}$$

$$p(\text{Correct}|\text{Black \& Tool}) = AC \cdot D \cdot OB + (1-AC)D + (1-AC)(1-D)G \quad \text{(A3)}$$

$$p(\text{Correct}|\text{Black \& Gun}) = AC + (1-AC)D + (1-AC)(1-D)(1-G) \quad \text{(A4)}$$

In Figure 2, relabeling AC as A and D as C:

$$p(\text{Correct}|\text{White \& Tool}) = A + (1-A)C + (1-A)(1-C)G \quad \text{(A5)}$$

$$p(\text{Correct}|\text{White \& Gun}) = A \cdot C \cdot OB + (1-A)C + (1-A)(1-C)(1-G) \quad \text{(A6)}$$

$$p(\text{Correct}|\text{Black \& Tool}) = A \cdot C \cdot OB + (1-A)C + (1-A)(1-C)G \quad \text{(A7)}$$

$$p(\text{Correct}|\text{Black \& Gun}) = A + (1-A)C + (1-A)(1-C)(1-G) \quad \text{(A8)}$$

In Figure 3, the most apparent predicted probabilities of correct responses are:

$$p(\text{Correct}|\text{White \& Tool}) = OB \cdot C + OB(1-C)A + OB(1-C)(1-A)G + (1-OB)A + (1-OB)(1-A)C + (1-OB)(1-A)(1-C)G \quad \text{(A9)}$$

$$p(\text{Correct}|\text{White \& Gun}) = OB \cdot C + OB(1-C)(1-A)(1-G) + (1-OB)(1-A)C + (1-OB)(1-A)(1-C)(1-G) \quad \text{(A10)}$$

$$p(\text{Correct}|\text{Black \& Tool}) = OB \cdot C + OB(1-C)(1-A)G + (1-OB)(1-A)C + (1-OB)(1-A)(1-C)G \quad \text{(A11)}$$

$$p(\text{Correct}|\text{Black \& Gun}) = OB \cdot C + OB(1-C)A + OB \cdot (1-C)(1-A)(1-G) + (1-OB) \cdot A + (1-OB)(1-A)C + (1-OB)(1-A)(1-C)(1-G) \quad \text{(A12)}$$

For Equations A9 and A12 in Figure 3, OB can be factored out from the first three terms, and (1-OB) from the last three:

$$p(\text{Correct}|\text{White \& Tool}) = OB[C + (1-C)A + (1-C)(1-A)G] + \quad \text{(A13)}$$

$(1\text{-}OB)[A+ (1\text{-}A)C + (1\text{-}A)(1\text{-}C)G]$

$$p(\text{Correct}|\text{Black \& Gun}) = OB[C + (1\text{-}C)A+ (1\text{-}C)(1\text{-}A)(1\text{-}G)] + (1\text{-}OB)[A+ (1\text{-}A)C + (1\text{-}A)(1\text{-}C)(1\text{-}G)] \quad \text{(A14)}$$

Note that $C + (1\text{-}C)A = A + (1\text{-}A)C$, and so the two brackets within A13 are equal, and the likewise for A14, thus allowing for OB and (1-OB) to be eliminated:

$$p(\text{Correct}|\text{White \& Tool}) = (OB+(1\text{-}OB))[A + (1\text{-}A)C + (1\text{-}C)(1\text{-}A)G] \quad \text{(A15)}$$

$$= A + (1\text{-}A)C + (1\text{-}C)(1\text{-}A)G$$

$$p(\text{Correct}|\text{Black \& Gun}) = (OB+(1\text{-}OB))[A + (1\text{-}A)C + (1\text{-}C)(1\text{-}A)(1\text{-}G)] \quad \text{(A16)}$$

$$= A + (1\text{-}A)C + (1\text{-}C)(1\text{-}A)(1\text{-}G)$$

It can then be seen that Equations A15 and A16 (Figure 3) equal A5 and A8 (Figure 2) respectively.

Next, for Figure 3, consider the remaining equations, A10 and A11. OB can be eliminated from the second and fourth terms as done before:

$$p(\text{Correct}|\text{White \& Gun}) = OB\cdot C + (1\text{-}OB)(1\text{-}A)C + (OB+(1\text{-}OB))(1\text{-}C)(1\text{-}A)(1\text{-}G) \quad \text{(A17)}$$

$$= OB\cdot C + (1\text{-}OB)(1\text{-}A)C + (1\text{-}C)(1\text{-}A)(1\text{-}G)$$

$$p(\text{Correct}|\text{Black \& Tool}) = OB\cdot C + (1\text{-}OB)(1\text{-}A)C + (OB+(1\text{-}OB))(1\text{-}A)(1\text{-}C)G \quad \text{(A18)}$$

$$= OB\cdot C + (1\text{-}OB)(1\text{-}A)C + (1\text{-}C)(1\text{-}A)G$$

Note that

$$OB\cdot C + (1\text{-}OB)(1\text{-}A)C = OB\cdot C - OB\cdot C + OB\cdot A\cdot C + C - A\cdot C \quad \text{(A19)}$$

$$= OB\cdot C\cdot A + (1\text{-}A)\cdot C$$

Using Equation A19 to replace the first two terms of A17 and A18, it can be seen that Equations A17 and A18 (Figure 3) are equal to A6 and A7 (Figure 2) respectively.

Appendix B: Modeling Methods

To assure convergence on besting fitting parameters and the smallest possible G^2, multinomial models were implemented with a quasi-Newton optimization method and 100 sets of random starting parameters. This was performed using the programming language R (R Development Core Team, 2005). Though G^2 was minimized, note that similar results can be achieved using the Pearson χ^2 (c.f., Conrey et al., 2005). Alpha was set to .05. With this alpha, power to detect medium effect sizes (w = .3; Cohen, 1977) always exceeded .999 at the group level and .92 at the subject level (Faul, Erdfelder, Lang, & Buchner, 2007).

To test for a significant difference between two or more parameter estimates, the fitted model was compared to a nested model that constrained the parameters of interest to be equal. The difference in G^2 between the fitted and nested models was tested against a chi-squared distribution with one degree of freedom per parameter constraint.

Both corrections for complexity, AIC and BIC, involve adding a penalty term to G^2:

$$\text{AIC} = G^2 + 2k \tag{B1}$$

$$\text{BIC} = G^2 + k\,(\ln n) \tag{B2}$$

where k is the number of free parameters in the models and n is the sample size (see Pitt et al., 2002).

There were no empty cells in the group level data. Empty cells in the subject level data were rare, ranging from 0.6-6.9% of the cells across experiments. To allow for model fitting despite empty cells, all cell frequencies in the subject level data were increased by .5 (see Snodgrass & Corwin, 1988).

To estimate 95% confidence intervals for the OB parameter, the diagonal of the inverse of the Hessian matrix was used as an estimate of parameter variance. However, a stable solution to the inverse of the Hessian matrix could not be achieved in the Payne et al. (2002) data. Instead, for that data, a series of nested tests were performed so as to find the values of OB where p=.05, and those values were used as the confidence interval boundaries.

Appendix C: Group Parameter Estimates

Estimated parameters at the group level across different experiments and models

		Model				
Experiment (and Groups)	Parameter	Proc. Diss.	Proc. Diss. (G)	Quad-Model	Stroop (G)	Stroop
Lambert et	C_{priv}	.62	.62	.63	.63	.82
al., 2003	C_{pub}	.55	.55	.55	.56	.78
(Anticipated	$A_{priv\text{-}wh\text{-}m}$	.47	.00	.01	.01	.00
Public &	$A_{priv\text{-}wh\text{-}f}$	.46	.00	.00	.00	.00
Private)	$A_{priv\text{-}bl\text{-}m}$	.58	.10	.03	.04	.06
	$A_{priv\text{-}bl\text{-}f}$	.56	.06	.01	.01	.03
	$A_{pub\text{-}wh\text{-}m}$	.52	.10	.11	.04	.02
	$A_{pub\text{-}wh\text{-}f}$	.49	.04	.05	.02	.00
	$A_{pub\text{-}bl\text{-}m}$	.58	.11	.09	.04	.07
	$A_{pub\text{-}bl\text{-}f}$	.53	.00	.00	.00	.03
	G		.47	.46	.46	
	OB_{priv}			.00		
	OB_{pub}			1.00		
Lambert et	C_{priv}	.58	.58	.59	.59	.80
al., in prep.	C_{pub}	.64	.64	.64	.65	.83
(Actual	$A_{priv\text{-}wh\text{-}m}$	.47	.06	.04	.04	.00
Public &	$A_{priv\text{-}wh\text{-}f}$	.47	.06	.02	.03	.00
Private)	$A_{priv\text{-}bl\text{-}m}$	.60	.08	.04	.03	.08

	$A_{priv\text{-}bl\text{-}f}$	.56	.00	.00	.00	.04
	$A_{pub\text{-}wh\text{-}m}$	.44	.01	.00	.01	.00
	$A_{pub\text{-}wh\text{-}f}$	.43	.00	.00	.01	.00
	$A_{pub\text{-}bl\text{-}m}$	.63	.14	.14	.03	.07
	$A_{pub\text{-}bl\text{-}f}$	.59	.05	.06	.01	.05
	G		.43	.44	.42	
	OB_{priv}			.34		
	OB_{pub}			1.00		
Payne, 2005	C	.79	.79	.81	.81	.90
	$A_{wh\text{-}m}$	.50	.08	.02	.02	.02
	$A_{wh\text{-}f}$	.52	.11	.01	.01	.00
	$A_{bl\text{-}m}$	.60	.13	.03	.03	.04
	$A_{bl\text{-}f}$	.54	.00	.01	.01	.01
	G		.46	.47	.47	
	OB			.00		
Payne et al., 2002 (Baseline, Avoid, & Use Race Instructions)	$C_{base700}$	.90	.90	.90	.90	.95
	$C_{base450}$	.73	.73	.74	.74	.87
	$C_{base200}$	.44	.44	.46	.45	.72
	$C_{avoid700}$	.92	.92	.92	.93	.97
	$C_{avoid450}$	.72	.72	.74	.73	.87
	$C_{avoid200}$	.51	.51	.53	.52	.76
	C_{use700}	.88	.88	.90	.92	.96
	C_{use450}	.66	.66	.68	.69	.85

C_{use200}	.49	.49	.49	.51	.76
$A_{wh\text{-}base}$	.55	.06	.08	.01	.01
$A_{wh\text{-}avoid}$	.56	.09	.07	.01	.02
$A_{wh\text{-}use}$	.58	.14	.16	.04	.05
$A_{bl\text{-}base}$	.51	.05	.00	.01	.01
$A_{bl\text{-}avoid}$	.55	.13	.03	.02	.02
$A_{bl\text{-}use}$	.59	.20	.12	.05	.04
G		.52	.48	.51	
$OB_{avoid700}$			1.00		
$OB_{base700}$			1.00		
OB_{use700}			.87		
$OB_{avoid450}$			.31		
$OB_{base450}$			.79		
OB_{use450}			.83		
$OB_{avoid200}$			.00		
$OB_{base200}$			.00		
OB_{use200}			1.00		

Notes. Proc. Diss.=Process Dissociation, priv=private, pub=public, wh=white, bl=black, m=male, f=female, base=baseline; 700, 450, and 200 refer to deadlines in milliseconds.

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Footnotes

[1] For the Stroop model, Conrey et al. reported a χ^2 value of 13.25, which is very different from the G^2 value reported here. The χ^2 value appears to be a typographical error (Conrey, 2007, personal communication).

[2] For Payne et al. (2002), it could be argued that the instructional manipulation should mainly affect the Quad-Model's OB parameter, and so also allowing D and AC to be affected by instructions makes the Quad-Model unnecessarily complex. We examined simpler versions of the Quad-Model where D was assumed to be the same across instructions (i.e., $D_{base700}$=$D_{avoid700}$=D_{use700}; $D_{base450}$=$D_{avoid450}$=D_{use450}; etc.), where AC was assumed to be the same across instructions, or where both assumptions were made. However, in all versions, the Quad-Model still produced higher AIC and BIC than the Process Dissociation model.

[3] The capture model is not identifiable with the available weapon identification data because the data lack a neutral prime condition.

Table 1

Free Parameters across Different Experiments, Levels of Analysis, and Models

			Each Model's Free Parameters		
Experiment	Experiment Groups	Level of Analysis	Process Dissociation or Stroop Model	Process Dissociation/G or Stroop/G Model	Quad-Model
Lambert et al. (2003) / Lambert et al. (in prep.)	Public & Private	Group	C_{priv}, C_{pub}, $A_{priv\text{-}wh\text{-}m}$, $A_{pub\text{-}wh\text{-}m}$, $A_{priv\text{-}wh\text{-}f}$, $A_{pub\text{-}wh\text{-}f}$, $A_{priv\text{-}bl\text{-}m}$, $A_{pub\text{-}bl\text{-}m}$, $A_{priv\text{-}bl\text{-}f}$, $A_{pub\text{-}bl\text{-}f}$ (10)	C_{priv}, C_{pub}, $A_{priv\text{-}wh\text{-}m}$, $A_{pub\text{-}wh\text{-}m}$, $A_{priv\text{-}wh\text{-}f}$, $A_{pub\text{-}wh\text{-}f}$, $A_{priv\text{-}bl\text{-}m}$, $A_{pub\text{-}bl\text{-}m}$, $A_{priv\text{-}bl\text{-}f}$, $A_{pub\text{-}bl\text{-}f}$, G (11)	D_{priv}, D_{pub}, $AC_{priv\text{-}wh\text{-}m}$, $AC_{pub\text{-}wh\text{-}m}$, $AC_{priv\text{-}wh\text{-}f}$, $AC_{pub\text{-}wh\text{-}f}$, $AC_{priv\text{-}bl\text{-}m}$, $AC_{pub\text{-}bl\text{-}m}$, $AC_{priv\text{-}bl\text{-}f}$, $AC_{pub\text{-}bl\text{-}f}$, G, OB_{priv}, OB_{pub} (13)
		Subject	C, $A_{wh\text{-}m}$, $A_{wh\text{-}f}$, $A_{bl\text{-}m}$, $A_{bl\text{-}f}$ (5)	C, $A_{wh\text{-}m}$, $A_{wh\text{-}f}$, $A_{bl\text{-}m}$, $A_{bl\text{-}f}$, G (6)	D, $AC_{wh\text{-}m}$, $AC_{wh\text{-}f}$, $AC_{bl\text{-}m}$, $AC_{bl\text{-}f}$, G, OB (7)

Payne (2005)		Group	C, A_{wh-m}, A_{wh-f}, A_{bl-m}, A_{bl-f} (5)	C, A_{wh-m}, A_{wh-f}, A_{bl-m}, A_{bl-f}, G (6)	D, AC_{wh-m}, AC_{wh-f}, AC_{bl-m}, AC_{bl-f}, G, OB (7)
		Subject	C, A_{wh-m}, A_{wh-f}, A_{bl-m}, A_{bl-f} (5)	C, A_{wh-m}, A_{wh-f}, A_{bl-m}, A_{bl-f}, G (6)	D, AC_{wh-m}, AC_{wh-f}, AC_{bl-m}, AC_{bl-f}, G, OB (7)
Payne et al. (2002)	Baseline, Avoid, & Use Race Instructions	Group	$C_{base700}$,$C_{base450}$,$C_{base200}$, $C_{avoid700}$,$C_{avoid450}$,$C_{avoid200}$, C_{use700},C_{use450},C_{use200}, $A_{wh-base}$, $A_{wh-avoid}$, A_{wh-use}, $A_{bl-base}$, $A_{bl-avoid}$, A_{bl-use} (15)	$C_{base700}$,$C_{base450}$,$C_{base200}$, $C_{avoid700}$,$C_{avoid450}$,$C_{avoid200}$, C_{use700},C_{use450},C_{use200}, $A_{wh-base}$, $A_{wh-avoid}$, A_{wh-use}, $A_{bl-base}$, $A_{bl-avoid}$, A_{bl-use}, G (16)	$D_{base700}$, $D_{base450}$,$D_{base200}$, $D_{avoid700}$,$D_{avoid450}$,$D_{avoid200}$, D_{use700},D_{use450},D_{use200}, $AC_{wh-base}$, $AC_{wh-avoid}$, AC_{wh-use}, $AC_{bl-base}$, $AC_{bl-avoid}$, AC_{bl-use}, G, $OB_{base700}$,$OB_{base450}$,$OB_{base200}$, $OB_{avoid700}$,$OB_{avoid450}$,$OB_{avoid200}$, OB_{use700},OB_{use450},OB_{use200} (25)
		Subject	C_{700}, C_{450}, C_{200}, A_{wh}, A_{bl} (5)	C_{700}, C_{450}, C_{200}, A_{wh}, A_{bl}, G (6)	D_{700}, D_{450}, D_{200}, AC_{wh}, AC_{bl}, G, OB_{700}, OB_{450}, OB_{200} (9)

Notes. The parentheses below each model indicate the total number of free parameters. priv=private, pub=public, wh=white, bl=black, m=male, f=female, base=baseline; 700, 450, and 200 refer to deadlines in milliseconds.

Figure Captions

Figure 1. The Process Dissociation (top) and Stroop (bottom) multinomial models. Branches lead to correct (+) and incorrect (-) responses.

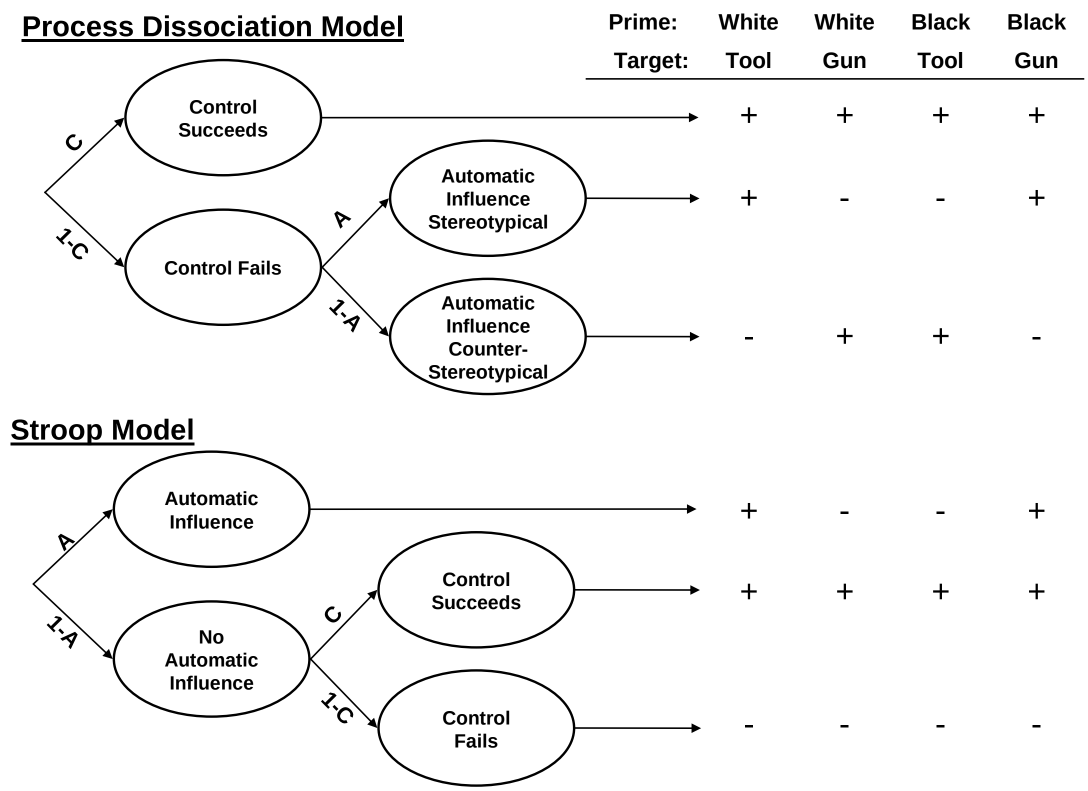
Figure 2. The original depiction of the Quad-model. Branches lead to correct (+) and incorrect (-) responses.

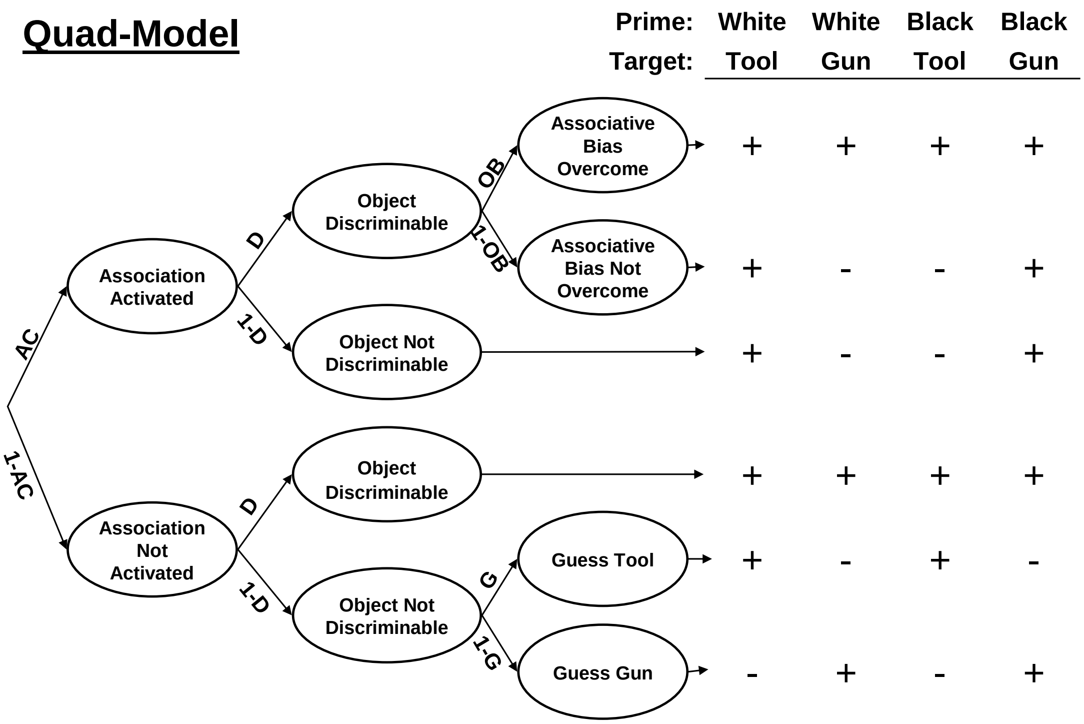
Figure 3. Algebraically equivalent version of the Quad-model that highlights its relationship to other models. D has been replaced with C, and AC has been replaced with A.

Figure 4. Estimates of the OB parameter in the Quad-Model across studies and conditions. Error bars indicate estimated 95% confidence intervals of the parameter value.

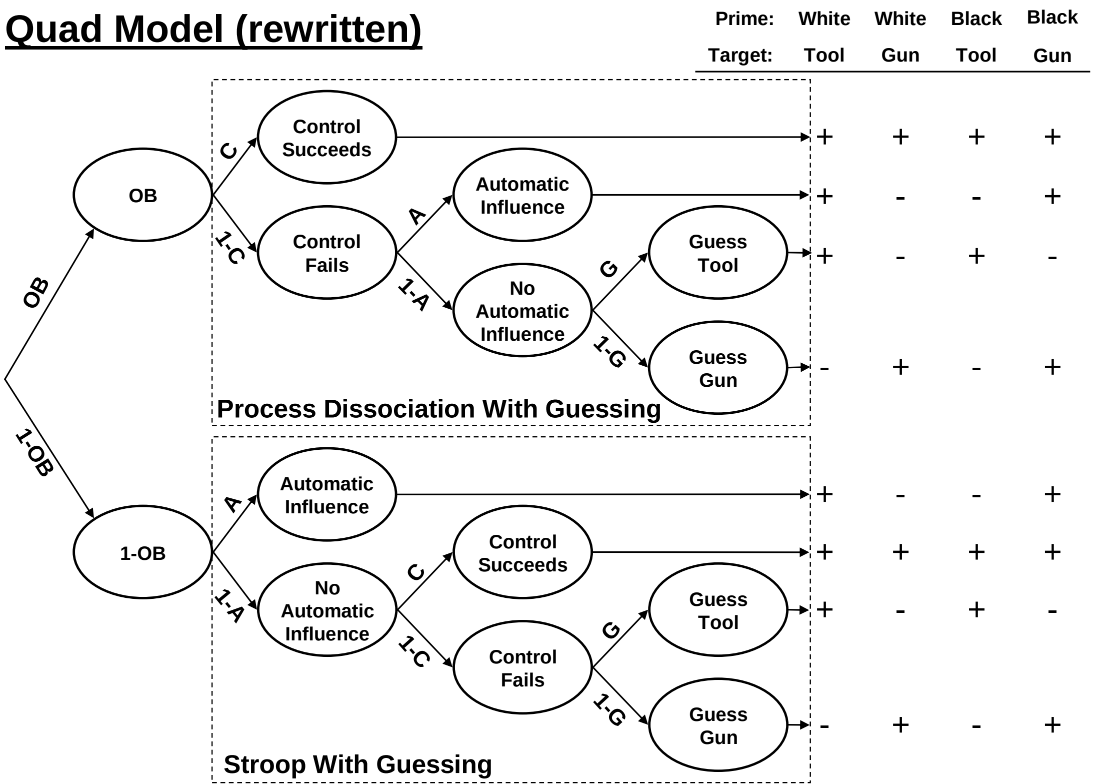
Figure 5. Model fit indices for Group level analyses. Lower values generally indicate better model performance. AIC=Akaike Information Criterion. BIC=Bayesian Information Criterion.

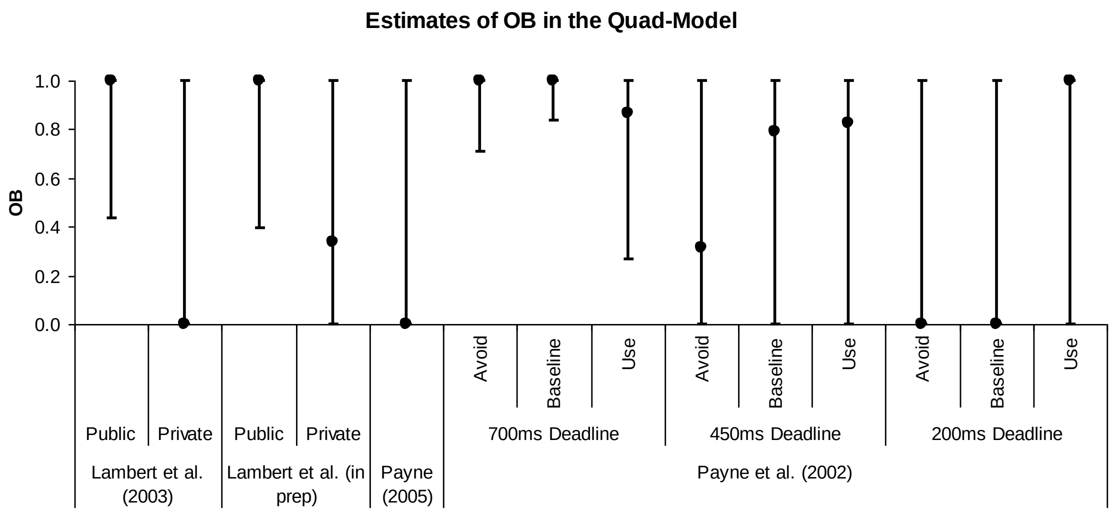
Figure 6. Model fit indices for Subject level analyses. Lower values generally indicate better model performance. Error bars indicate the 95% confidence interval of the mean. AIC=Akaike Information Criterion. BIC=Bayesian Information Criterion.

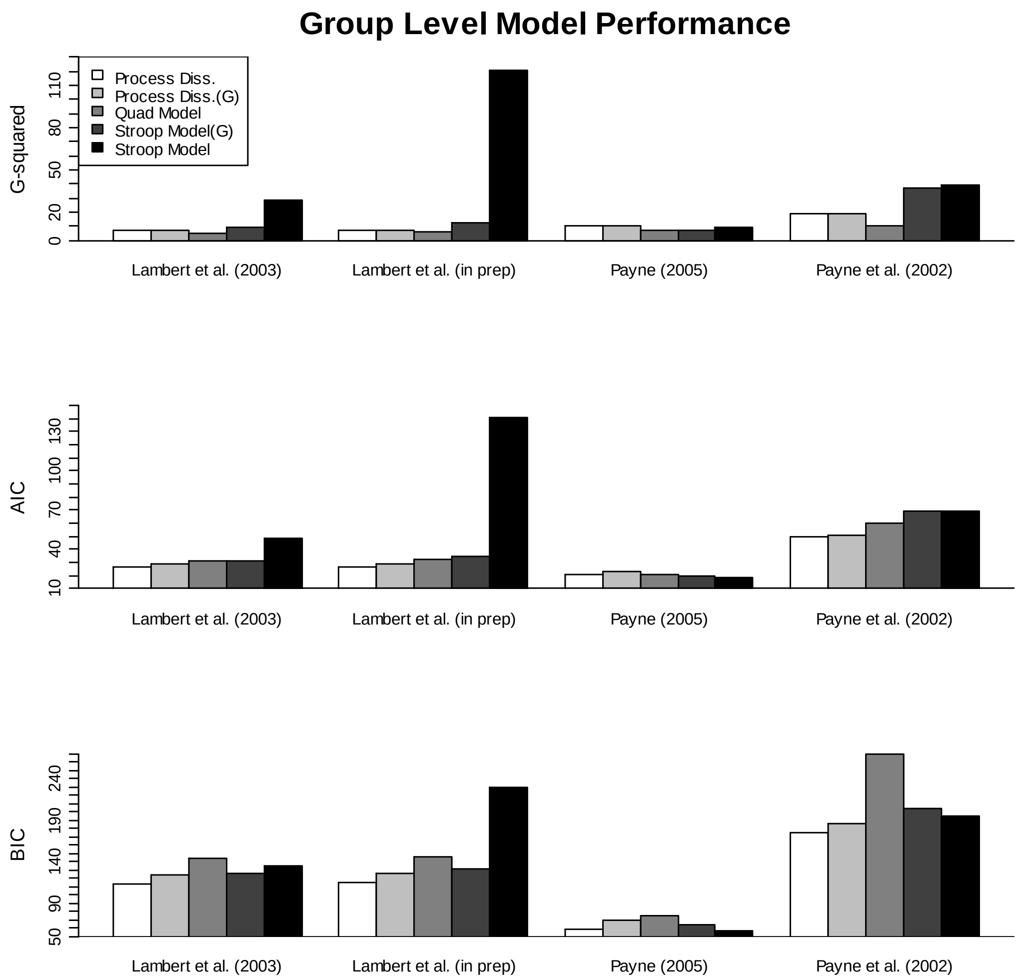

Process Dissociation Model
Prime: White White Black Black
Target: Tool Gun Tool Gun
C
1-C
Control Succeeds
+ + + +
Control Fails
A
1-A
Automatic Influence Stereotypical
+ - - +
Automatic Influence Counter-Stereotypical
- + + -
Stroop Model
A
1-A
Automatic Influence
+ - - +
No Automatic Influence
C
1-C
Control Succeeds
+ + + +
Control Fails
- - - -

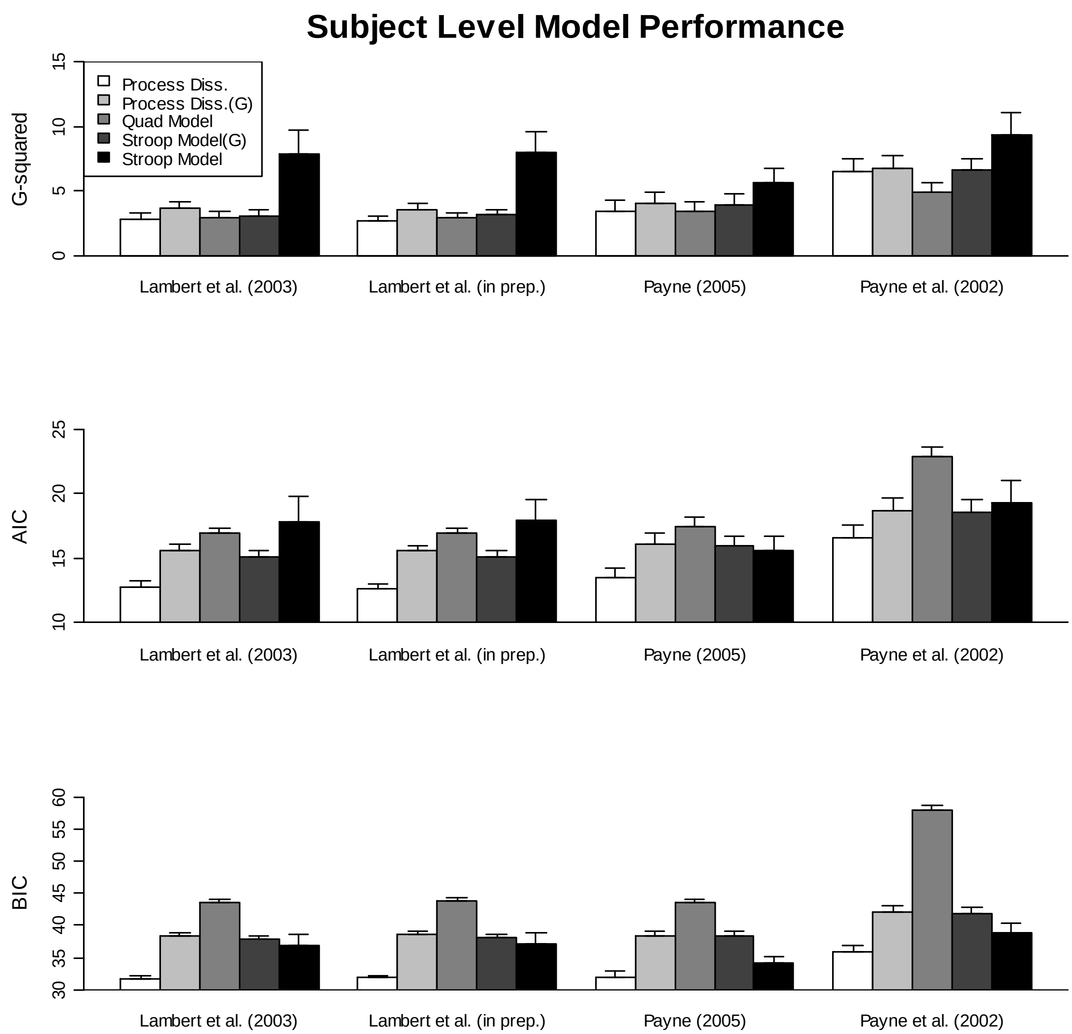

Quad-Model
Prime: White White Black Black
Target: Tool Gun Tool Gun
AC
1-AC
Association Activated
Association Not Activated
D
1-D
D
1-D
Object Discriminable
Object Not Discriminable
Object Discriminable
Object Not Discriminable
OB
1-OB
G
1-G
Associative Bias Overcome
Associative Bias Not Overcome
Guess Tool
Guess Gun
+ + + +
+ - - +
+ - - +
+ + + +
+ - + -
- + - +

Quad Model (rewritten)




Estimates of OB in the Quad-Model
OB
1.0
0.8
0.6
0.4
0.2
0.0
Avoid
Baseline
Use
Avoid
Baseline
Use
Avoid
Baseline
Use
Public
Private
Public
Private
700ms Deadline
450ms Deadline
200ms Deadline
Lambert et al. (2003)
Lambert et al. (in prep)
Payne (2005)
Payne et al. (2002)


Group Level Model Performance
Process Diss.
Process Diss.(G)
Quad Model
Stroop Model(G)
Stroop Model
G-squared
0
20
50
80
110
AIC
10
40
70
100
130
BIC
50
90
140
190
240
Lambert et al. (2003)
Lambert et al. (in prep)
Payne (2005)
Payne et al. (2002)


Subject Level Model Performance
Process Diss.
Process Diss.(G)
Quad Model
Stroop Model(G)
Stroop Model
G-squared
0
5
10
15
AIC
10
15
20
25
BIC
30
35
40
45
50
55
60
Lambert et al. (2003)
Lambert et al. (in prep.)
Payne (2005)
Payne et al. (2002)