

An Integrative Review of Process Dissociation and Related Models in Social Cognition

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Abstract

This article reviews the use of formal dual process models in social psychology, with a focus on the Process Dissociation model and related multinomial models. The utility of the models is illustrated using studies of social and affective influences on memory, judgment and decision making, and social attitudes and stereotypes. We then compare and contrast the Process Dissociation model with other approaches, including implicit and explicit tests, signal detection theory, and multinomial models. Finally, we show how several recently proposed multinomial models can be integrated into a single family of models, of which Process Dissociation is a specific instance. We describe how these process models can be used as both theoretical and measurement tools to answer questions about the role of automatic and controlled processes in social behavior.

One of the first things people want to know about behavior is whether it was intended. Did that driver intend to cut me off? Did she brush his knee by mistake or on purpose? Psychologists want to understand the differences between volitional behaviors and those that are unintended or unconscious for much the same reason. The question of how much control people have over their actions is important for fundamental questions about free will, self-control, and consciousness.

Theories about how automatic and controlled processes operate and interact have been developed in the form of dual process models in social psychology (Chaiken & Trope, 1999). Dual process models have typically been formulated as verbal descriptions of automatic and controlled processes or systems. But recently, attempts have been made to formalize these ideas into quantitative models of how automatic and controlled processes drive behavior. These formal models allow researchers to test theories about exactly how automatic and controlled processes relate to each other and how they interact. This paper reviews models rooted in the Process Dissociation Procedure (Jacoby, 1991), a model developed to separate automatic and controlled uses of memory, and which has been applied widely in recent years.

Several related models have been proposed, some of which assumes different relationships between automatic and controlled processes. By comparing how well these models account for experimental data, researchers can accomplish two simultaneous goals. First, they can test hypotheses about the nature and relationships between automatic and controlled processes. And second, the models can provide quantitative estimates of the underlying processes. The models can thus serve as both theoretical and measurement tools, allowing researchers to test quantitative hypotheses about underlying processes that are not directly observable.

In this paper, we review research in which process dissociation and related models have been applied, to survey the kinds of insights they can generate. We then examine the

assumptions of the model, and compare the process dissociation approach to the use of implicit tests and to alternative quantitative models. But first, we begin by discussing how process dissociation and related models can shed light on the relative impact of automatic and controlled processes, and their influence on behavior.

The Dominance of Automaticity?

The automatic-controlled distinction has its roots in cognitive psychology research, primarily on attention (e.g., Posner & Snyder, 1975; Shiffrin & Schneider, 1977). This research identified information processing as automatic based on several criteria. First, automatic processing is triggered passively by stimuli in the environment. Second, it cannot be interrupted once started. Third, automatic processing is efficient, in the sense that it is fast and effortless. And finally, automatic processing does not interfere with other processes, but runs in parallel with them. Controlled processes were defined as having the opposite qualities, namely being flexible, interruptible, effortful, and sequential. In a related vein, Bargh (1994) identified the “four horsemen,” the lack of intentionality, efficiency, controllability, and awareness in automatic processes. Such lists of distinguishing features of automatic and controlled processes have been applied in various degrees and combinations to many social psychology questions. As we shall see in later sections, process dissociation in some ways challenges this taxonomic approach. But even within this framework of features of automaticity, opinions differ about the relative importance of automatic and controlled influences.

Early research by Langer and colleagues suggested that ordinary behavior was “mindless” to a surprising extent (Langer, Blank, & Chanowitz, 1978). In field studies, most subjects complied with a request to let the experimenter jump in front of them in line at the copy machine, so long as the experimenter gave a reason. Any reason would do, apparently. Subjects were about as likely to let the experimenter cut in line when she gave a good reason (“May I use the Xerox machine, because I’m in a rush”) as when she gave a silly reason (“May I use the

Xerox machine, because I need to make copies”). The only case in which the experimenter did not find overwhelming compliance was when she gave no reason at all (“May I use the Xerox machine?”). Langer and colleagues interpreted these findings as evidence that in most of daily life, people respond without much thinking about what they are doing. This conclusion was a reaction to theories such as cognitive dissonance (Festinger, 1957) and attribution theory (Heider, 1958), which assumed that people normally process incoming information in a thoughtful and elaborate way.

The emphasis on the prominence of automatic processing has continued in more recent writings. Bargh (1999) described automaticity as a “cognitive monster” whose influence is too powerful to chain with conscious, deliberate thought. Bargh and colleagues have argued that most ordinary behavior is driven by automatic processes, and that the more we learn about automaticity, the less room there is for conscious control processes to explain behavior (Bargh, 1997; 2005; Bargh & Chartrand, 1999; Bargh & Ferguson, 2000). Wegner and colleagues have gone further, arguing that the experience of conscious control is an illusion and that the real causes of behavior are never conscious (Wegner, 2002).

This expansive view of automaticity has been criticized by Kihlstrom, who dubbed it the “automaticity juggernaut” (Kihlstrom, 2006; 2007). In Kihlstrom’s view, the empirical literature does not support the claims that automatic processes dominate social life. He notes that studies portraying automatic processes as ubiquitous often rely on a watered down definition of automaticity. Rather than requiring all of the features of automatic processing, they tend to establish only one or two (see also Moors & DeHouwer, 2006). And, following Bargh (1989; 1994), automaticity is treated as continuous in practice, rather than all or none. So if a process is “relatively automatic” it is hard to argue that only automatic processes are important or that controlled processes are irrelevant. Kihlstrom’s critique argues that this nearly exclusive

emphasis on automaticity amounts to ignoring the advances of the cognitive revolution in favor of a return to a thinly veiled Skinnerian behaviorism.

If Kihlstrom is right, however, we still do not have a metric to gauge exactly how much conscious control should be emphasized. There is probably no generally applicable formula for answering such a question. That is why theories dealing with the interplay between automatic and controlled processes have generally stated their claims in terms of the moderating conditions that favor one process or the other. Dual process theories have been developed to account for the automatic-controlled distinction across a wide range of topics (Chaiken & Trope, 1999). The models vary in their scope, with some aimed at explaining relatively specific phenomena, such as attitude change (Gawronski & Bodenhausen, 2006; Petty & Brinol, 2006) or prejudice (Devine, 1989; McRae & Bodenhausen, 1998). Others aim to explain the operation of automatic and controlled processing more broadly. For example, Strack and Deutsch (2004) distinguish between reflective and impulsive bases for social behavior in general. Sloman's (1996) model addresses two systems of reasoning that support all thinking and decision making. And Smith and DeCoster's (2000) model links social psychology research on automatic and controlled processing with separable memory systems that may underpin implicit and explicit forms of memory.

Although these models (and many others not reviewed here) highlight different features of mental life, they all share an emphasis on the automatic-controlled distinction. They all differentiate the conditions when automatic versus controlled processes are most likely to come into play. These conditions are tied tightly to the definitions of automatic and controlled processes. Once we understand that automatic processes are efficient and effortless, whereas controlled processes are slow and effortful, it becomes clear when each kind of process is likely to matter. When conditions allow people to think slowly and carefully, controlled processes are

likely to dictate behavior. But when they are uninclined or unable to think carefully, automatic responses will be important.

The distinctions in these models are important and useful in understanding the relative roles of automaticity and control in social life. They allow researchers to predict, for example, that when people are tired or distracted or rushed, they are more likely to respond based on automatic impulses than when they are energetic, focused, and unhurried. Such predictions have in fact been supported again and again. To name just a few examples, White American subjects are more likely to mistake a harmless object for a weapon when it is paired with a Black person than a White person, and this bias becomes stronger as subjects respond faster (Payne, 2001; Correll, Park, Judd, & Wittenbrink, 2002 ; Greenwald, Oakes, & Hoffman, 2002). People are more likely to choose junk food over fruit when they are distracted by mentally rehearsing a number, as compared to paying full attention (Shiv & Fedorkhin, 1999). And smokers tend to smoke more cigarettes when they are distracted than when they are not (Westling, Mann, & Ward, 2006). Dual process theories predict these findings because each reflects a conflict between automatic inclinations and controlled efforts to regulate responses. The contribution of automatic influences, relative to controlled influences, increases in each case when cognitive resources are taxed.

The fact that many dual process theories predict these results is both a strength and a weakness for the theories. On the one hand, predictive power is vital for a theory's value. On the other hand, these findings might be just as easily predicted by one dual process theory as another. Whether the phenomena are explained in terms of two systems of reasoning (Sloman, 1996), fast-learning and slow-learning memory systems (Smith & DeCoster, 2000), or reflective and impulsive systems (Strack & Deutsch, 2004), the predictions are often the same. So now that we know about some of the conditions that encourage automatic and controlled responding, we are still left with many unanswered questions.

One question is about the dominance of automaticity versus control, as debated in the writings of Bargh, Wegner, Langer, and Kihlstrom. If relative influence of automatic processing increases when cognitive resources are depleted, it does not follow that automatic influences are dominating controlled influences, or the other way around. We can only observe relative differences in impact across experimental conditions, but we cannot examine either kind of process in isolation. So, the questions about which processes dominate, and under what conditions, are left unanswered.

More generally, dual process models do not usually specify exactly how automatic and controlled processes relate to each other. But in understanding conflicts between automatic and controlled influences, it is often essential to know how they are related. For example, when choosing snacks do subjects select sweets by default, and only reconsider their choice if their impulses are suppressed? Or do their automatic impulses only drive their choices when controlled efforts fall apart? Or do automatic and controlled influences have equal and opposite effects, with each kind of process contributing additive force in a tug-of-war for control of action?

Most dual process theories do not distinguish between such process accounts at this level of detail. Moreover, it would be difficult to test them because increases in one process cannot usually be disentangled from decreases in the other. For instance, when subjects smoke more under cognitive load, is it because controlled self-restraint processes are reduced, leaving automatic impulses untouched? Or when self-restraint declines, do automatic impulses flare up in their absence?

To answer these questions, we need to pose a more formal model that makes assumptions about the relations between processes, and then test those assumptions. A benefit of this approach is that it can provide quantitative estimates of automatic and controlled influences separately. With these in hand, researchers are in a much better position to explain

the chain of mechanisms leading from external conditions (e.g., a distracting environment) through cognitive processes (e.g., automatic impulses and controlled restraint) to behavior (e.g., smoking). The process dissociation procedure provides a means for doing so.

The Process Dissociation Procedure

The process dissociation procedure is a family of models for estimating controlled and automatic contributions to behavior. Jacoby (1991) developed the procedure as a means of separating controlled and automatic influences of memory, particularly in regards to the distinction between intended and unintended influences. But before reviewing how the procedure is applied in memory research, we will first illustrate it using everyday behavior. Suppose that a half-hearted dieter has decided to enjoy sweets on weekends but not on weekdays. So each weekday morning he resolves to eat no sweets. On some weekdays he succeeds, and on others he does not. We can assume that there is an automatic attraction to sweets on both weekdays and weekends. But on weekdays that attraction is opposed by the intention to diet, whereas on weekends it is complimented by the intention to indulge.

We can gauge the dieter's self-control by comparing how much junk food he eats on weekends (when both automatic impulse and intent favor eating) versus weekdays (when impulse favors eating but self-control opposes it). If, for example, he eats sweets on weekends with a probability of .90, but he also eats sweets on weekdays with probability .20, then his probability of exerting self-control is .70.

Once we have an estimate of self-control, we need to make an assumption about how automatic and controlled influences are related. One plausible relationship is that automatic impulses drive behavior whenever self-control fails. (We will examine alternative relationships later). On this assumption, we can estimate the strength of the dieter's attraction to sweets. We do so by taking the likelihood that he eats despite an intention to the contrary (i.e., the .20 probability of indulging on weekdays), which represents not only the strength of the impulse but

also failures of control (impulse * self-control failure). Because we know the likelihood of control failures ($1 - .70 = .30$) we can disentangle the two by dividing by the rate of self-control failure ($.20 / .30 = .67$). We find, then, that our dieter's behaviors are driven by self-control with a probability of .70, and by automatic impulse with a probability of .67.

With this model in hand, we can examine how behavior changes as a function of various factors, and draw specific conclusions about the contributions of automatic and controlled mechanisms. In the study described above by Shiv & Fedorkhin (1999), for instance, subjects were more likely to eat sweets when they were distracted than when they were not. If we examined our dieter's behavior when he is distracted and when he is not, we could estimate the effect of distraction on automatic and controlled processes separately. We might find, for instance, that he eats more when distracted because self-control is reduced under distraction, leaving automatic appetites unaffected. Alternatively, we might find that he eats more when distracted because the distraction directly increases automatic appetites (for example, if the distraction involves food related information).

The dieting case provides an intuitive example of how the procedure can be applied, but we can state it more precisely using its formal application in a memory experiment. Research on implicit memory has shown that past experience sometimes influences later performance even in the absence of conscious memory for the experience. Implicit memory has often been tested by comparing direct tests of memory – such as recall or recognition tasks – with indirect tests of memory. Indirect tests do not ask subjects to refer back to a past experience, but instead they measure facilitation in task performance resulting from prior experience. A commonly used example of an implicit memory test is word fragment completion (Tulving, Schacter, & Stark, 1982). Subjects might be more likely to complete the fragment *Fre _ d* with Freud, as opposed to Freed, if they have recently read the psychoanalyst's name. This could happen even in the absence of conscious memory for reading it.

Indirect and direct memory tests are often affected differently by the same variables. For example, delay strongly affects direct tests, but affects indirect tests much less severely (Tulving, Schacter, & Stark, 1982). Such dissociations between indirect and direct tests have been used to argue for a theoretical distinction between implicit memory and explicit memory, based on either different anatomical systems (Schacter, 1987) or different cognitive operations (Roediger, 1990).

Jacoby (1991) noted, however, that these important theoretical distinctions relied on an unspoken assumption that indirect tests reflected only automatic or unconscious processes, whereas direct tests reflected only consciously controlled processes. This “process pure” assumption is generally not justified, because conscious memory can affect implicit test performance, and automatic influences can affect explicit memory tests. For example, when asked to complete a word fragment with the first word that comes to mind, subjects might think back to the study phase of an experiment to help generate a response. And when asked to respond with a word they remember studying, subjects might use the first item that comes to mind, a strategy influenced by implicit memory.

If implicit memory processes affect explicit memory tests, and explicit memory processes affect implicit tests, then relying on these tests can be misleading. Jacoby’s (1991) solution was to compare conditions in which implicit and explicit processes worked in concert to conditions in which they worked in opposition. For instance, in one experiment, subjects studied a list of words while either paying full attention or dividing their attention between studying the words and a distracting auditory task (Jacoby, Toth, & Yonelinas, 1993). This distracting task was used to interfere with explicit memory for the words, but it was not expected to interfere with automatic influences of memory.

At test, subjects completed word stems under two sets of conditions. In the *inclusion* condition, they were instructed to complete the stems with studied words. If they could not

recall studying an item, they were told to complete the stem with the first word that came to mind. In this condition automatic and consciously controlled uses of memory work in concert. Responding based on conscious memory for a studied word, or responding based on items that came automatically to mind would lead to the same response. In the *exclusion* condition, subjects were told to complete the stem with a word that was *not* presented earlier in the experiment. This condition placed automatic and controlled uses of memory in opposition. If subjects remembered studying a word, they could successfully exclude it. But if it came automatically to mind and they did not remember studying the word, they could be expected to complete the stem with it.

The process dissociation procedure formalizes these relationships by positing that in the in-concert condition, subjects could complete the stem with a studied word either because they consciously remembered it (with probability C) or because it came automatically to mind (with probability A) in the absence of consciously controlled memory (1-C):

$$P(\text{Studied item} \mid \text{Inclusion}) = C + A(1-C). \quad (1)$$

In the exclusion condition, subjects can be expected to use a studied item despite instructions to the contrary whenever the item comes automatically to mind but consciously controlled memory for the item fails:

$$P(\text{Studied item} \mid \text{Exclusion}) = A(1-C). \quad (2)$$

Because the experiment provides the empirical probabilities of responses in the inclusion and exclusion conditions, estimates of C and A processes can be solved. Conscious memory is estimated as the difference between performance on inclusion and exclusions conditions:

$$C = P(\text{Studied item} \mid \text{Inclusion}) - P(\text{Studied item} \mid \text{Exclusion}). \quad (3)$$

Having estimated C, the automatic memory influence can also be derived by dividing performance in the exclusion condition by the rate of control failures:

$$A = P(\text{Studied item} \mid \text{Exclusion}) / (1-C). \quad (4)$$

Jacoby and colleagues (1993) found that the divided attention task reduced the rate of responses with studied words in the inclusion condition, but increased the use of studied words in the exclusion condition. By applying these equations above, they found that this effect was due solely to the C parameter. Divided attention reduced C estimates from .25 to .00, but left A estimates unchanged (.47 and .46 in full-attention and divided attention conditions).

This approach has been used to separate conscious recollection and automatic memory in many memory studies. But the basic logic can be applied to understand automatic and controlled contributions in any number of contexts. The critical aspect of the procedure is that researchers arrange an experiment such that automatic and controlled processes are placed in opposition in some conditions, and in concert in other conditions. If this is done, then a straightforward set of equations such as the ones above can be used to estimate automatic and controlled contributions. In the following section we review the diversity of topics that have been studied using process dissociation or closely related models to illustrate the kinds of insights that they provide. This review will not cover studies that are purely aimed at memory processes, as these have been reviewed elsewhere (Kelley & Jacoby, 2000; Yonelinas, 2002). Instead this review focuses on three topics in social psychology where the procedure has been applied most commonly. These include 1) social and affective influences on memory, 2) judgment and decision making, and 3) inter-group attitudes.

Social and Affective Influences on Memory

Memory shapes social life in countless ways. Perhaps most fundamentally, memory processes determine how we mentally represent ourselves and other people. The psychology literature is full of evidence that we do not represent people objectively. Instead our representations are slanted with bias and filtered through selective attention. Biased memory representations are important to social interaction because they suggest a means by which biases are perpetuated. Each time a person revisits a biased memory, that bias is reinforced.

What are the mechanisms that drive this cycle? Dual process theories stress that many social factors could influence behavior either through automatic or controlled routes. But it is often difficult to localize such automatic or controlled pathways. Process dissociation has been useful in distinguishing these pathways in several studies of social and affective influences on memory.

Hense, Penner, & Nelson (1995) conducted one of the earliest studies using process dissociation to test the influence of social stereotypes on memory. They asked subjects to study lists of traits related to stereotypes of the old and the young. The lists were said to describe a particular set of old and young individuals. After studying the traits, participants were asked to recall the traits that described the older and younger persons under two sets of instructions. In the inclusion condition, participants were asked to respond with the trait they had studied or, if they could not remember the trait, to respond with the first word that came to mind. In the exclusion condition, participants were asked to respond with a new trait that was not studied.

Results suggested that stereotypical traits had a selective influence on the automatic use of memory without affecting controlled recollection. Stereotype-consistent traits such as *slow* and *frail* came to mind automatically when thinking about an older target person. Controlled memory was reduced by a divided attention task, but this was independent of the stereotyping effect. Importantly, the bias in automatic memory was greater for subjects who held negative attitudes toward the elderly.

Subsequent studies have generally supported these conclusions. In one study, stereotype-based expectancies were found to lead to automatic memory biases most strongly when cognitive resources were limited by a distracting task (Sherman, Groom, Ehrenberg, & Klauer, 2003). Distraction also reduced controlled memory, resulting in a double threat to memory accuracy. The biases subjects brought with them into these studies led to biases in their memory of their experience. After leaving the study, those biased memories might continue to

maintain subjects' attitudes. After all, the subjects could then easily recall many instances that confirmed the stereotype.

The fact that these biases were perpetuated via automatic processes suggests that they may be particularly deceptive when trying to sort out which memories are true and which are false. In support of this notion, one study asked subjects to describe the phenomenology of their memories as either "remembered," "known," or "guessed." Stereotype-consistent memory errors were described by subjects primarily as "known" whereas accurate memories were mainly described as "remembered" (Macrae, Schloerscheidt, Bodenhausen, & Milne, 2002). The difference is that "known" memories feel true to participants, but lack vivid details such as the visual or aural experiences that accompanied them (Tulving, 1985). This difference is reasonable because in the case of stereotypical errors, subjects did not actually perceive the events at all; they inferred them based on their own expectations. Still, they did not label errors as guesses; they "just knew" them to be true.

Payne and colleagues explored this deceptive phenomenology in a study of the consequences for correcting memory biases (Payne, Jacoby, & Lambert, 2004). Subjects studied lists of names typical of White Americans or Black Americans. Each name was described by an occupation that was stereotypically associated with Whites or Blacks (e.g., politician, basketball player). Later at test, they saw the names and were asked to remember whether each person was a basketball player or a politician. Following each response, subjects rated their confidence from 50% (chance, or not at all confident) to 100% (absolute certainty). In this paradigm, automatic and controlled processes are placed in concert and in opposition, not through inclusion / exclusion instructions, but through congruence / incongruence between memory and stereotype bias. When a White name is described as a politician or a Black name as a basketball player, memory for the pairing and stereotypic biases both favor the same response. But when the

pairings are stereotype-incongruent, memory would lead to a correct answer whereas stereotype bias would lead to a stereotype-consistent error.

Replicating earlier studies, subjects showed strong stereotypical memory distortions. Process dissociation analyses showed that the bias was entirely mediated through automatic influences rather than controlled memory. Subjective experiences of confidence were not, however, attuned to that automatic bias. As shown in Figure 1, automatic memory bias was equally prevalent when subjects expressed 100% certainty as when they felt no confidence at all. Confidence was not completely uncalibrated, however. It was strongly related to estimates of controlled memory recollection.

Putting these findings together, we see that subjects had a good sense of when they were responding based on controlled memory, and when controlled memory was poor. But when controlled memory failed, they had no sense of when they were being biased by stereotypes. It has long been known that people do not necessarily have introspective access to the processes driving their behavior (Nisbett & Wilson, 1977). But these findings suggest that they have better awareness of some processes than others. This implies that when subjects try to avoid memory errors, they will succeed and fail in specific, predictable ways.

In a second study, some subjects were given the opportunity to “pass” by not responding whenever they did not know the answer (Payne, Jacoby, & Lambert, 2004). Other subjects were required to answer every item even if they had to guess. This arrangement allows subjects to control their own accuracy rates based on their subjective feelings (Koriat & Goldsmith, 1996). As predicted on the basis of the confidence findings, subjects in the “pass” condition made fewer errors because they adaptively refrained from responding when they were unsure. However, when they made errors, they were just as likely to be stereotypically biased as subjects in the control condition. Even when subjects were deliberately trying to avoid errors, they failed to filter out stereotypical biases because they did not feel like biases.

The studies just reviewed suggest that information consistent with stereotypic expectations comes to mind automatically to bias memory. But in some cases, information that violates expectations can have a greater impact on memory (Stangor & McMillan, 1992). According to much prior research and theory, the key difference is whether the inconsistent information violates expectancies strongly enough to attract attention and elicit effortful thought processes aimed at resolving the inconsistencies (Srull & Wyer, 1980; Stangor & McMillan, 1992). Because elaborate processing tends to benefit conscious recollection, we might expect expectancy-violating information to result in higher estimates of controlled memory.

A study of group favoritism supports the link between social expectancy violation and consciously controlled memory (Gaunt, Leyens, & Demoulin, 2002). People tend to perceive members of other social groups as well as their own social groups to experience “primary” emotions such as fear, anger, and surprise. These emotions are even perceived to be expressed by non-human animals. But people attribute more “secondary” emotions – those considered uniquely human, such as hope, sympathy, or guilt – more to in-group members than to out-group members (Leyens et al., 2001). Gaunt and colleagues (2002) used the process dissociation procedure to examine memory for primary and secondary emotions attributed to in-group and out-group members. During a study phase, participants solved anagrams that paired the in-group (Belgians) or out-group (Arabs) with primary and secondary emotion words (e.g., *Belgians-sympathy*). Following the anagram task, participants listened to an auditory list of similar group-emotion word pairs. At test, participants were presented with studied and new word pairs. They were asked to recognize studied items under exclusion instructions (accept only the word pairs from the anagrams) or inclusion pairs (accept pairs from either the anagram task or the auditory list). Based on Jacoby’s (1991) prior work it was assumed that consciously controlled memory is necessary to distinguish between items from different sources.

Consistent with the notion that subjects expected out-group members to have fewer uniquely human emotions and that violations of this expectation elicit effortful thought processes, estimates of controlled memory were higher for secondary emotions attributed to out-group members compared to in-group members. There was no group difference in memory for primary emotions, suggesting that “uniquely human” emotions attributed to out-group members were especially expectancy-violating.

Summary of social memory research. These studies show how social groups can influence memory either through automatic or controlled processes. The process dissociation procedure was used in these studies to empirically separate those distinct routes. Although process dissociation was developed specifically to separate automatic and controlled contributions to memory, it has been broadened recently to investigate other phenomena, such as judgment and decision making.

Judgment and Decision Making

Extensions to decision making are very recent, but they offer an exciting way to reveal the processes underlying decisions. In one study, Fitzsimons & Williams (2000) used a modification of the process dissociation procedure to investigate the *mere measurement effect*. The mere measurement effect is the finding that simply asking a person about how likely they are to perform a behavior in the future actually increases the likelihood that they will perform that behavior (Morwitz, Johnson, & Schmittlein, 1993; Sherman, 1980). Fitzsimons & Williams (2000, study 1) asked one group of participants how likely they would be to choose a new brand of candy bar, whereas the control group was not asked about the candy bar. The mere measurement effect suggests that the group who was asked would be more likely to choose the candy bar than the control group. In addition, participants were told that they were either more or less likely to actually receive the candy bar if they chose it. This manipulation was meant to

manipulate the self-interest of participants. A rational (in the sense of self-interested) analysis would suggest that participants should be more likely to choose the candy bar when informed that they are likely to get the candy bar. By crossing the mere measurement with the self-interest information, this study created conditions in which the mere measurement effect was congruent with self-interest, and conditions in which it was incongruent with self-interest.

This study showed that, indeed, participants asked about their likely choice more often chose the candy bar. Using a modified model based on the logic of process dissociation, these researchers separated two components of the effect. One component reflected how strongly the intent question influenced choice regardless of self-interest (akin to the automatic component in the other studies discussed here). The other component reflected the extent to which choices were guided by the self-interest. This is related to the controlled component we have discussed, but because the procedure pitted self-interest against the mere measurement effect, this component reflected self-interested decision-making. The mere measurement question influenced choices largely irrespective of whether it was consistent with self-interest or not, an effect driven by the automatic component (see also Kramer & Block, 2008, for evidence that superstitious beliefs influence consumer choices via automatic, but not controlled processes). Furthermore, results suggested that the controlled, self-interested process determined behavior to a larger extent in a full attention condition than a divided attention condition.

Another interesting research effort has forged a connection between classic research on heuristics and biases (e.g., Tversky & Kahneman, 1974) with dual process theories of judgment using the process dissociation procedure. Several dual process theories have been proposed to account for the fact that people sometimes make decisions that appear rationally calculated, whereas other times they make decisions that are irrational, impulsive, biased, or based on simple heuristics (Kahneman & Frederick, 2002; Sloman, 1996; Stanovich & West, 2000). Ferreira and colleagues applied the process dissociation procedure to separate rule-based

reasoning from heuristic reasoning (Ferreira, Garcia-Marques, Sherman, & Sherman, 2006). To do this, they arranged decision problems in which the two types of reasoning could be placed in concert and in opposition.

For example, consider a problem posed by Ferreira and colleagues (2006) . Imagine that there are two sets of envelopes, and some envelopes contain prizes. In the first set, there are 10 envelopes, 2 of which contain a prize. In the second set, there are 100 envelopes, 19 of which contain a prize. Which set of envelopes would you choose from? Although it is simple to calculate that there is a 20% chance for the first set and a 19% chance for the second set, many people feel compelled to choose from the second set because it has a larger absolute number of chances to win. This problem places rule-based reasoning (e.g., calculating the probabilities) and heuristic reasoning (e.g., preferring the larger absolute number) in opposition. Judgment research demonstrating heuristics or biases almost always relies on this kind of conflict, which in the process dissociation framework can be considered an opposition (or exclusion) condition. Ferreira and colleagues completed the conceptual possibilities by adding conditions in which rule-based and heuristic reasoning were also in concert. For example, consider the same problem described above except that the second set of envelopes now has 21 (instead of 19) chances to win out of 100. In this case, both rule-based reasoning and heuristic reasoning suggest choosing the second set, because the second set has both a larger probability of winning and a larger absolute number of chances to win. Using the combination of inclusion and exclusion conditions, Ferreira and colleagues examined several types of judgmental biases. First, ratio bias (as in the envelope problem) leads people to weight absolute numbers more heavily than proportional values (Kirkpatrick & Epstein, 1992). Second, in base-rate problems people tend to neglect base rates and form judgments based on salient but non-diagnostic information. Third, in conjunction problems people often mistakenly judge that the likelihood of a salient event is greater than the likelihood of a larger class of events that includes the event. For

example, in the well-known Linda problem subjects think that a bright, outspoken woman who is deeply concerned with social justice is more likely to be a feminist bank teller than to be a bank teller (Tversky & Kahneman, 1983).

By placing rule-based and heuristic reasoning in concert and in opposition, Ferreira and colleagues (2006) were able to separately measure these two reasoning components. They found that the two components were affected by different experimental manipulations, consistent with dual-process theories of reasoning. For example, instructions to complete the problems in a reflective, rational way as opposed to an intuitive way increased the rule-based reasoning parameter but did not affect heuristic reasoning parameter. In contrast, performing a distracting cognitive task while completing the problems reduced rule-based reasoning but did not affect heuristic reasoning. Finally, when subjects were primed to respond heuristically by completing several practice problems in which heuristic responses led to the correct answers, estimates of heuristic reasoning increased.

A variation of the process dissociation procedure has been used to estimate processes involved in a classic judgmental bias, the anchoring effect. In typical anchoring experiments (e.g., Tversky & Kahneman, 1974), an initial question about a number influences a later number judgment. For example, a participant might be asked if there are more or less than 80 bowling lanes in the U.S. (a low anchor), and then asked to estimate the exact number of bowling lanes in the country. Participants' estimates tend to be biased toward the anchor.

Several authors have suggested that anchoring effects may be the result of an accessibility bias (Chapman & Johnson, 1994, 1999; Strack & Mussweiler, 1997). Specifically, participants mentally test the anchor value in the initial question, and in doing so, anchor-consistent information becomes more accessible. This heightened accessibility of anchor-consistent information contaminates the pool of accessible information used to later answer the number estimation question. Bishara (2005) expanded on this accessibility bias account with a

dual-process model. In that model, anchoring effects result from automatic accessibility biases, but only to the extent that more controlled processes fail. To examine controlled processes, participants were allowed to study the correct answers to some numerical questions in a separate study phase at the beginning of the experiment (e.g., studied “There are 130,000 bowling lanes in the U.S.”). This knowledge would allow for the possibility of controlled recollection of the correct answer later on. Though participants intended to use this knowledge, to the extent that recollection failed, number judgments may be unintentionally biased by whether the anchor was high or low. Modeling results confirmed the predictions of the dual-process account. The initial presentation of the answer did indeed selectively influence the controlled recollection parameter but not the accessibility parameter. In contrast, the direction of the anchor selectively influenced the accessibility parameter, but not the controlled recollection parameter.

As a baseline comparison condition, some trials included an anchor unrelated to the number estimation question that followed. For example, prior to estimating the number of bowling lanes, a participant would answer a more/less question about the number of Coast Guard personnel in the country. Such unrelated anchors did not produce a significant anchoring effect (see Brewer & Chapman, 2002). Only related anchors led to significant changes in participants’ number judgments.

Interestingly, whereas number judgments were strongly affected by the presence of a related anchor, participants’ confidence in those judgments was not increased. Confidence was affected only by whether an item had been earlier studied or not. This pattern suggest that participants were able to accurately monitor the source of their number estimations; when they were estimating on the basis of recollection, their confidence was high, but when they were forced to rely on whatever most easily came to mind, their confidence was low. So, even though

the anchoring effect was large in terms of number estimations, the anchoring effect was not a subjectively compelling illusion.

In a second experiment on the anchoring effect, participants were forced to make number estimations in one condition, and were free to pass in another condition. To the extent that participants are able to monitor the failure of controlled processing, and thereby strategically withhold their responses, the option to pass should reduce the anchoring effect. In fact, not only did the option to pass reduce the anchoring effect, the anchoring effect was reduced to nonsignificance. Further analyses suggested that participants were not passing at random; rather, participants strategically passed only when more controlled processing failed.

Overall, confidence and passing were related to anchoring biases (Bishara, 2005) in some of the same ways that they were related to stereotypical biases in memory (Payne et al., 2004). Just like stereotypical memory biases were unrelated to confidence, so was accessibility bias in the anchoring studies. Importantly, both studies (Bishara, 2005; Payne et al., 2004) highlight how the process dissociation approach can be used in conjunction with confidence and passing responses so as to better understand the level of awareness of psychological biases.

Summary of judgment and decision research. Studies applying process dissociation models to judgment and decision making research have advanced thinking on several fronts. First, they have produced more direct evidence than previously available that decision making relies on both deliberative and heuristic processes. These distinct influences had been theoretically predicted on the basis of dual process models, but experiments had provided only indirect evidence for the underlying processes. Second, these studies are the first to provide estimates of both deliberative and heuristic processes individually. Based on previous studies, only the relative contribution of both processes could be inferred. But if some variable (i.e., cognitive load) increased reliance of heuristics, it was impossible to tell whether that variable had its effects by increasing heuristic reasoning, decreasing rule-based reasoning, or some

combination of both. Process dissociation estimates provided a means of resolving that ambiguity.

Social Attitudes and Stereotyping

The study of heuristics and biases has been motivated by concern that they will reduce the quality of decisions and threaten the rationality of human decision makers. Stereotypes and group prejudices are often considered a type of heuristic thinking that not only reduces the quality of judgments for the decision maker, but also have unfair consequences for the person being judged. In this research, the focus has been on separating automatically activated attitudes and stereotypes from consciously controlled responding. The distinction is important in studies of prejudice and stereotyping because consciously reported attitudes are often distorted by social desirability, self-presentation concerns, and other biases. And so it is vital to study automatic responses, which may differ from these strategic responses.

We have studied automatic and controlled components of prejudice and stereotyping by examining the influence of race in decisions about threat. For example, a study reported in Payne (2001) was conducted soon after the highly publicized death of Amadou Diallo, who was mistakenly shot by New York City police officers who mistook the wallet in his hand for a gun. Because Diallo was unarmed and Black, some critics alleged that the officers' use of force was biased by race. The question in our study was whether systematically mistaking a harmless object for a weapon can reveal unintended influences of racial attitudes and stereotypes.

Subjects in the study attempted to distinguish between guns and harmless hand tools that were flashed briefly on a computer screen. Immediately preceding each gun or tool was a Black or White male face that served as a prime. This 2 x 2 design creates conditions in which intentional responding to the target items and automatic influences of racial stereotypes are in concert (analogous to an inclusion condition), and in opposition (analogous to an exclusion condition). For example, when the prime was Black and the target was a gun, subjects could

correctly respond “gun” either by intentionally controlled (C) detection of the gun, or by an automatic stereotypical response (A) when control failed ($1 - C$): $C + A(1 - C)$. In contrast, when the prime was Black and the target was a tool, subjects would incorrectly respond “gun” when controlled detection failed, but automatic stereotyping favored the gun response: $A(1 - C)$. The degree of intentional control can be solved by taking the difference between “gun” responses in the inclusion and exclusion conditions. Given that estimate, the degree of automatic bias can be solved by dividing stereotypical false “gun” responses by failures of control ($1 - C$).

This experiment controlled subjects’ intentions via the task requirements to distinguish guns from tools. For that reason, the Control estimate measures how well subjects carried out their intentions by distinguishing between target objects. In contrast, subjects do not intend to be influenced by the racial primes. The Automatic estimate measures how much their responses were biased by these unintended influences.

The results of the study showed that subjects were indeed biased by the race primes, as subjects were more likely to mistake a tool for a gun when it was primed with a Black face than a White face. This bias appears to be robust and widespread, as it has been demonstrated using several experimental paradigms and several subject populations, including college students, police officers, and civilian adult populations (Correll et al., 2002; 2007; Greenwald, Oakes, & Hoffman, 2002; Plant & Peruche, 2005). But more importantly for present concerns, the process dissociation estimates successfully separated automatic and controlled components of responses. Requiring subjects to respond quickly sharply reduced the controlled component, a well-established characteristic of controlled processing. But the controlled component was unaffected by the race primes. In contrast, the race primes affected the automatic component, but response speed did not.

A key implication of the process dissociation model is that automatic biases drive responses whenever controlled processes fail. Control can fail for many reasons beyond making

speedy judgments. For example, much research has shown that self-control can be seen as a limited capacity resource. When self-control is exerted in one setting, it can be temporarily depleted, leaving a person less likely to exert self-control in another setting (Muraven & Baumeister, 2000). Govorun & Payne (2006) tested whether the sort of controlled processing estimated in the weapons task is sensitive to this type of self-control depletion. Subjects in one group completed hundreds of trials of an attention-demanding cognitive task (the Stroop color naming task) whereas subjects in the other group completed only a few trials. All subjects then completed the weapons task to test whether exerting control in the initial task reduced subsequent control over responses. As expected, expending cognitive control in the initial task reduced the controlled component in the weapon bias, but not the automatic component (Govorun & Payne, 2006).

Although speeded responses and self-control depletion can enflame racial bias by reducing control, other factors can so increase racial bias by increasing automatic stereotyping. For instance, in one study, Payne, Jacoby, & Lambert (2002) warned some subjects that their responses could be biased by the race of the faces flashed before the objects. One group was given this warning and urged to avoid letting race bias their judgments. Another group was given the warning, but they were encouraged to use race to help them identify weapons, as if they were police engaged in racial profiling. Finally, a third group that served as a control were not warned about the impact of race at all.

Intuitively, we might expect warned subjects to gain control over their responses. This is the idea behind insight-oriented therapies and educational efforts aimed at consciousness-raising. Knowledge about a bias ought to confer a sort of power over it, according to this line of thinking. Yet research suggests that in many cases, efforts at mental control have ironic consequences (Wegner, 1994). Trying not to think about race might leave people unable to think about anything but race, and trying not to make judgments based on stereotypes might leave

those judgments hopelessly affected by stereotypes. This is precisely the pattern we observed. The group encouraged to use race stereotypes indeed showed greater bias than the control group in which race was not made salient. However, the group warned to avoid race stereotypes also showed heightened bias. In fact, they assumed that objects associated with Blacks were guns at rates indistinguishable from the group who intentionally used stereotypes. This pattern is striking because the group encouraged to use stereotypes and the group urged to avoid stereotyping had exactly opposing intentions, but their behaviors were the same. As expected, this difference was mediated by the automatic component in process dissociation analyses. Automatic influences of stereotypes were higher in both warned groups than in the control group.

The automatic and controlled influences estimated in the crucible of the weapons task have been linked to other meaningful behaviors. For instance, in one study, after completing the weapons task, subjects formed an impression of a new Black person from a vignette about a typical day in this person's life (Payne, 2005; see Higgins, Rholes, & Jones, 1977, Srull & Wyer, 1980). Although the facts and behaviors in the vignette were identical for all subjects, the kinds of impressions they formed varied widely, and they depended on the kinds of automatic and controlled processes each subject displayed in the weapons task. Subjects who showed the most stereotypical automatic biases in the weapons task liked the Black character less. This correlation is consistent with dozens of studies showing that automatic racial attitudes and stereotypes can color social perception.

But the process dissociation analyses also revealed another pattern that is more striking. The impact of automatic bias depended on how much control subjects exerted over their behaviors. Subjects who were good at controlling their responses in the weapons task were also good at controlling the influence of automatic stereotyping in their social perceptions. For these subjects, automatic stereotyping was not associated with more negative impressions. But for

subjects who were poor at controlling their responses in the weapons task, the correlation between automatic bias and social impression was much stronger.

This pattern, in which the amount of intentional control determines whether automatic biases translate into overt behaviors, is consistent with verbally described dual process theories. One example is Strack & Deutsch's (2004) model which distinguishes between reflective and impulsive determinants of behavior. Consistent with such models, several studies have shown that individual differences in cognitive control are important in moderating the relationship between implicit attitudes and behavior. For example, Hofmann and colleagues (2008) examined behaviors that can be jointly driven by automatic impulses and self-control efforts, including eating sweets. They measured cognitive control using tests of working memory – the ability to mentally maintain and manipulate multiple pieces of information at the same time. Individuals with greater working memory are believed to have greater cognitive capacity to engage in controlled processing. Hofmann and colleagues measured automatic impulses toward sweets using the Implicit Association Test (Greenwald et al., 1998), and they measured explicit attitudes and beliefs about sweets using self-report measures. As predicted by dual process models, consciously reported attitudes and beliefs were better predictors of behavior among subjects with high working memory. In contrast, automatic impulses were better predictors among subjects with low working memory (see also Hofmann, Friese, & Roefs, 2009). The same pattern was replicated for other tempting behaviors, including responding with anger to a provocation, and time spent viewing erotic pictures. This relationship is similar to the pattern assumed by process dissociation: deliberate intentions drive behavior when control is high, but automatic impulses drive behavior when control is low.

These studies provide converging evidence, across several topics and several measures, for the systematic relationship between conscious intentions/beliefs, automatic impulses, and cognitive control abilities. Some of these studies relied on three different tests to measure

intentions, automatic impulses, and control processes. But the process dissociation procedure provides an advantage by capturing all of these processes within the same task. Rather than equating automatic and controlled processes with different tasks, the components can then be modeled as they contribute to the same behavior.

This ability to model different components within the same task provides the opportunity to study processes underlying varieties of prejudice well beyond the weapon bias. For example, many studies have shown that older adults tend to display greater prejudice than younger adults. There are competing explanations for why this happens. A common assumption is that older adults are more prejudiced because they grew up in an era where prejudice was more widespread and more acceptable. By this account, older adults simply have more prejudiced thought patterns that have stayed with them over the years. In contrast, older adults might display more prejudice because they are poorer at exerting control over their responses. By this account, older and younger adults may have similar levels of prejudice in their automatic responses, but younger adults are better able to control its expression (von Hippel, Silver, & Lynch, 2000).

Stewart, von Hippel, & Radvansky (2009) measured the racial attitudes of older and younger adults using the IAT and replicated the finding that older adults showed greater bias than their younger counterparts. Although the IAT is often considered a measure of solely implicit processes (i.e., the process-pure assumption) the process dissociation approach assumes instead that behavior in any task reflect the joint operation of both automatic and controlled processes. The IAT includes “compatible” trials (e.g., *white-good, black-bad*) where automatic stereotypes and the correct task-appropriate response share a response key and “incompatible” trials (e.g., *white-bad, black-good*) where automatic stereotypes and the correct response are in conflict. Although response time is typically used to score the IAT, errors and correct responses can also be used, because respondents make more errors in incompatible

conditions than compatible conditions. These compatible and incompatible trials are analogous to “inclusion” and “exclusion” conditions or “in concert” and “in opposition” conditions of the process dissociation procedure. Stewart and von Hippel thus applied the process dissociation procedure to examine whether the difference was driven by automatic or controlled aspects of responses. Consistent with the control-deficit hypothesis, older adults showed lower control estimates than younger adults, but the groups did not differ in their automatic biases.

Another common observation is that white Americans display greater anti-black prejudice than black Americans. This difference, too, could be explained by differences in either automatic responses or control over responses. Black Americans might be more favorable to blacks in their automatic responses for the same reasons that most any other group shows in-group preferences (Hewstone, Rubin, & Willis, 2002). On the other hand, some theorists argue that blacks internalize the prejudices and stereotypes that are dominant in society, and therefore they may have the same automatic associations as whites do. If so, then blacks may have to work harder to exert control over their responses. Stewart, von Hippel, & Radvansky (2009) also compared process dissociation components of IAT performance between white and black respondents. Only the automatic component of responses distinguished the racial groups. So, both race and age influenced the amount of bias displayed on the IAT, but they did so through different processes. White Americans showed more bias because they had more biased automatic impulses. Older adults showed more bias because they lacked control.

Many of the studies just described used process dissociation to understand how intentions fail, where goals break down, and why people act with more prejudice than they would like. To be sure, these are important aspects of contemporary prejudice, in which people often struggle to regulate automatic biases according to egalitarian ideals. Although trying not to be biased may be difficult in many contexts, there may be ways to proactively exert control over automatic responses before they influence behavior. Stewart & Payne (2008) found that

automatic race bias can be effectively reduced by committing to specific plans that activate counterstereotypical thoughts. Implementation intentions are plans that link a behavioral opportunity to a specific response. They take the form of “if, then” guidelines that use cues in a person’s environment to dictate specific goal-directed behavior (Gollwitzer, 1999). In Stewart and Payne’s study, subjects completed the weapon identification task. In the critical condition, they were instructed that every time they saw a Black face, they should immediately think “safe” in order to counteract threat-related stereotypes. Participants in two control conditions were told to think either “quick” or “accurate” whenever a Black face appeared on the screen. These were used as “dummy” intentions because the task already required subjects to respond quickly and accurately.

Results of the study are illustrated in Figure 2. Replicating previous findings, participants in the ‘think quick’ and ‘think accurate’ conditions showed race bias. But participants in the ‘think safe’ condition did not. Critically, process dissociation analyses showed that this improvement was driven by reductions in the automatic component of responses. Even under conditions of fast and demanding responses, implementation intentions provided an effective means of reducing automatic bias.

Summary of attitudes and stereotyping research. Stereotypes and prejudice often have their effects automatically, leading many researchers to adopt implicit measurement strategies. Measures such as priming tasks (including the weapon identification task) and the IAT have been developed as methods of capturing automatic responses and avoiding intentional response strategies that might bias self-reports. But as the studies described here show, these tasks do not purely measure automatic processes. Instead, they reflect a mix of automatic responses and attempts to control responses. The process dissociation procedure reveals that prejudice in behavior can be influenced by both automatic and controlled components of responses, and it

provides a means for disentangling these. It also raises new questions about how automatic and controlled processes should be defined and measured, as we discuss next.

Defining Automaticity

The studies reviewed here illustrate that the automatic and controlled components estimated by process dissociation have different meanings when applied to different tasks or different contexts. Unlike approaches that define automaticity using lists of inherent features (such as intentionality, efficiency, controllability, and awareness), process dissociation requires that the researcher specify what it means to exert control in any given task. Automaticity is then defined as those influences that drive responses when control fails. As an example, in the weapons task, control is defined by respondents' task-relevant intentions to discriminate between guns and tools. This intention is what defines experimental conditions as "inclusion" or "exclusion." That is, whether putative automatic influences such as stereotyping are congruent or incongruent with intended responses. To the extent that subjects successfully carry out their task goal, they are considered to be controlling over their responses. But to the extent that stereotypical reactions to Black faces influence responses independent of that goal, those stereotypes are driving behavior automatically. It then becomes an empirical question how control and automatic influences, defined in terms of intent, relate to features such as efficiency, controllability, and awareness.

As the studies reviewed illustrate, there has been a good deal of convergence between process dissociation analyses and feature-based definitions of automatic and controlled processes. In the weapons task, C estimates were reduced under speeded responding (Payne, 2001) and self-control depletion (Govorun & Payne, 2006), providing evidence that controlled processes estimated by C were resource demanding. In contrast, A estimates were unaffected by these variables, suggesting efficiency.

Yet, the two approaches will not always converge. Consider for example the study by Stewart & Payne (2008) in which implementation intentions to think counter-stereotypic thoughts reduced automatic bias, and did so under speeded responding. This effect has qualities of both automatic and controlled processes. Implementation intentions altered the (automatic) influence of racial stereotypes, but did so intentionally. An advantage of defining automatic and controlled influences in terms of specific task requirements or goals is that this approach can naturally accommodate cases that seem puzzling from a feature-based perspective. For instance, when an initially unconscious process becomes conscious through introspection, it gains some features of controlled processing (awareness) but may lack others (e.g., efficiency, controllability). And when an initially controlled process becomes automatized through practice, it gains some “automatic” features such as efficiency, but may retain features such as intentionality and controllability. As in the case of implementation intentions, the process dissociation framework handles these cases by defining control and automaticity based on one set of criteria, and considering the others as empirical questions rather than defining assumptions.

In tasks such as the weapons task or the IAT, the criterion that defines control and automaticity is intent. Respondents intend to respond according to task instructions despite the presence of interfering information that may unintentionally influence responses. But in other tasks different criteria may be used. For example, in Jacoby’s (1991; Jacoby, Toth, & Yonelinas, 1993) early memory studies it was conscious memory (recollection) that allowed participants to respond in a controlled way. To respond correctly in the exclusion condition respondents had to remember not simply that a word was familiar but also the context in which they experienced the word. Thus the C estimate can be used to measure conscious memory for the studied item, and the A estimate can measure unconscious memory – influences of past experience despite being unable to consciously recollect the experience.

In each case, the researcher must think carefully about what control means in a given task or a given behavior. Once the researcher has defined the criteria for control, automatic influences can be defined relative to those criteria. To do so, the process dissociation procedure makes some assumptions about the relationships between processes and performance. Violating these assumptions can distort process estimates, so it is important to consider whether the assumptions are warranted in a given research context. The next section discusses these assumptions and places them in the context of the assumptions made by alternative approaches.

Assumptions of Process Dissociation and Alternative Models

Mathematical models must make assumptions to relate actual data to formal equations. When applying the process dissociation procedure in a new context, it is important to be clear about those assumptions. One assumption of process dissociation is that the controlled and automatic processes at work exert similar influences in inclusion and exclusion conditions. In other words, the two processes should exert as much influence together in the inclusion condition as they exert against each other in the exclusion condition.

The second assumption, which has been discussed more widely, is that automatic and controlled processes are independent of each other (for discussions of the independence assumption in memory research, see Curran & Hintzman, 1995; 1997; Jacoby & ShROUT, 1997; Jacoby, Begg, & Toth, 1997; Rouder, Lu, Morey, Sun, & Speckman, 2008). Whether this assumption is met depends on the experimental paradigm that is being used. In some cases, automatic and controlled processes could be positively or negatively correlated with each other, which would violate the independence assumption. Because we cannot directly observe the processes, we must indirectly test whether the processes are likely to be independent or dependent. One way to do this is to look for dissociations, or selective effects on one or both estimates. If automatic and controlled processes are independent, then it would be relatively easy to find variables that affect one but not the other. If the independence assumption is badly

violated, then automatic and controlled processes would strongly covary with each other. As a result, it would be difficult to find variables that affect one process without affecting the other¹.

Much of the work reviewed here has been focused on examining selective effects on automatic and controlled components in the weapon identification procedure. For example, Payne (2001) found a double dissociation between the two processes. Prime pictures of Black and White faces affected the automatic component but not the controlled component. In contrast, speeded responding affected the controlled component but not the automatic component. These dissociations would not be expected if the independence assumption were violated in the weapon identification task.

However, for some tasks, or under some conditions, it is always possible to violate the assumptions. Readers may be most familiar with these considerations in the context of common statistical tests. It is widely understood that different statistical tests make different assumptions. For example, analysis of variance (ANOVA) assumes 1) a dependent variable that is at least an interval scale, 2) a normally distributed dependent variable, and, 3) homogeneity of variance across different conditions, among other things. If an assumption is violated slightly (e.g. a slightly skewed distribution) the resulting biases are usually small. If an assumption is violated badly (for example, distributions are heavily skewed) it is often a good idea to choose a different test that does not depend on the problematic assumption. Just as the failure of an assumption in a particular study does not invalidate the ANOVA technique in general, studies showing that an assumption of process dissociation has been violated do not invalidate the general method. Instead, other methods may be more appropriate in a particular context.

Consider some of the other methods that are sometimes used as alternatives to process dissociation. These include the task dissociation method (comparing explicit and implicit measures), signal detection theory, and multinomial models. Although they may not be explicitly stated, each of these approaches makes its assumptions which may be violated.

Consider first task dissociations. Although this is method does not use a mathematical model, it still makes assumptions. By using an implicit task to measure automatic processes, and an explicit task to measure controlled or conscious processes, the task dissociation approach makes the tacit assumption that each measure is process-pure. That is, one assumes that the measures differ only on the dimension of interest to the researcher. If the two tasks differ in ways other than the explicit / implicit dimension, then any different results on explicit versus implicit tasks could be because of those other confounded features. The psychological processes behind implicit tasks (such as reaction times to classify words) and those behind explicit tasks (such as endorsing complex propositional statements) are very different. As a result, the assumption that implicit and explicit tasks differ only on the dimension of interest is not likely to be commonly met (Payne, Burkley, & Stokes, 2008).

Many of the studies reviewed here show empirically that the process-pure assumption is easily falsified. For example, studies demonstrating the role of controlled processing in implicit tests show that these tests do not purely measure automatic processes (e.g., Payne, 2001; Plant & Peruche, 2005; Stewart & von Hippel, 2009). And other studies have demonstrated the importance of automatic processing in “explicit” judgment tasks (Ferreira et al., 2006). Both process dissociation and task dissociation methods make assumptions to relate observed data to unobserved theoretical ideas. In the case of process dissociation, those assumptions are made explicit, whereas in the task dissociation method they often remain unstated.

A second alternative approach is signal detection theory (SDT). Signal detection theory assumes that perceivers are natural statisticians, who make decisions about events in the world the way that researchers decide whether to reject a null hypothesis (Tanner & Swets, 1954). A decision about what one is perceiving or how to respond is treated as a problem of detecting a signal in a noisy environment. Perceivers have a certain amount of evidence, and they select a criterion (similar to the conventional use of $p < .05$ in psychology research) that marks off how

strong the evidence has to be before they will accept that a signal is present. Given a pattern of correct responses and errors, signal detection theory can separate sensitivity, the ability to discriminate when a signal is actually present or absent, from bias, a tendency to respond as if a signal is present whether it is or not. Signal detection theory is mute on issues of automatic versus intentionally controlled behavior, and its development predated the current interest in automaticity.

Signal detection theory makes some of the same assumptions as process dissociation, and some that are different. For instance, SDT also makes an independence assumption. It assumes that sensitivity and bias are independent in the same way that process dissociation assumes that controlled and automatic components are independent (for discussion, see Rouder et al., 2007, 2008). In typical applications, signal detection also assumes normal distributions of evidence strength, and equal variances. Beyond statistical assumptions, signal detection makes substantive assumptions about the way that humans process information. For instance, it assumes that decisions are made on the basis of a single continuum of evidence. Even if there are qualitatively different bases of information, signal detection models typically compress this information onto a single decision dimension. Process dissociation, in contrast, treats intentional control and automatic biases as qualitatively different bases for responding.

Finally, process dissociation can be considered to be a particular example of a multinomial model. A multinomial model posits a branching tree of unobserved cognitive processes, leading eventually to behavioral responses (Riefer & Batchelder, 1988). Process dissociation and various multinomial models can be seen as specific cases of a general family of models (although multinomial models do not necessarily have any connection to automatic and controlled processing; see Riefer, Hu, & Batchelder [1994] for a multinomial model of source memory that does not invoke the automatic/controlled distinction, and Klauer & Wegener [1998] for an application of a similar model to social memory). Process dissociation and

multinomial models make similar assumptions. Both are aimed at separating unobservable psychological processes that give rise to observed behavior. The relatedness of the models can be seen in the fact that the process dissociation model can be represented and estimated as a multinomial model with two process parameters (automatic and controlled components; Jacoby, 1998; Payne, Jacoby, & Lambert, 2005). In the next section we consider the relationship between process dissociation and related multinomial models that have been proposed.

Integration of Process Dissociation and other Multinomial Process Models

Several multinomial models have been developed as a means of separating automatic and controlled processing. These include the quadruple process model (Conrey et al., 2005) which has been applied to several implicit tasks, and the ABC model (Stahl & Degner, 2007) which was developed to model performance on the Extrinsic Affective Simon Task (EAST; De Houwer, 2003). Comparing the Process Dissociation model to these may seem like comparing apples to oranges. However, we will show that many multinomial models of social cognition can be considered part of the same general family.

In order to understand how these various models relate to one another, it is important to consider which processes dominate in each model. In some dual-process models, controlled processes play a dominant role. Controlled processes determine responses and choices, and only if controlled processes fail do automatic processes have influence. In other models, though, automatic processes are more dominant and trump controlled processes. In yet other models, the relationship between control and automaticity is probabilistic. That is, one process dominates the other with a probability represented by a free parameter in the model (for discussion, see Bishara & Payne, 2009; Conrey et al., 2005; Jacoby, Kelley, & McElree, 1999).

The question of which processes dominate others is important for dual process theories. Different answers to the question of dominance would suggest different practical approaches to reducing automatic bias. For example, race biases in weapon identification could be reduced

either by increasing the success of controlled processes or by decreasing automatic influences (or both). However, the relative usefulness of these two strategies will depend on which process dominates. If automaticity dominates responding, reducing automatic racial biases should be the most potent way of reducing the error. Thus, to reduce weapon identification errors, police officers might be trained to detect and correct race-biased thoughts. In contrast, if controlled processing dominates responding and stereotypes only have their effects when control fails, then preventing failures of control may be a more effective means of reducing the stereotypical error. As an example of an approach aimed at increasing controlled processing, criminologist James Fyfe (1988) has described interesting tactics that can prevent officers from having to make split-second decisions unless absolutely necessary, allowing officers to better focus their decision-making on critical aspects of the situation (i.e., those cues that make up the appropriate criterion for a decision, such as whether an object is actually a gun or not). Thus, understanding the dominance of processes may help guide research and practice toward methods of reducing bias.

The model that we have referred to throughout this article as the Process Dissociation model is a control dominating model, shown at the top of Figure 3. In this model, successful controlled processing (with probability C) leads to correct responses (+) in all conditions. Only when controlled processing fails ($1-C$) do automatic influences hold sway. In those cases, stereotypical responses are given with probability A , and counter-stereotypical responses are given with probability $1-A$. To illustrate, consider how this model explains response patterns in the weapon-identification task. When controlled processing succeeds, the tool or gun is correctly identified in all conditions. When controlled processing fails but automatic stereotypical associations drive responses, correct responses are only given in the congruent conditions, that is, conditions where the prime is associatively related to the target (e.g., black-

gun). When controlled processing fails but automatic counter-stereotypical associations drive responses, correct responses are only given in the incongruent conditions (e.g., black-tool).

The bottom of Figure 3 shows the multinomial tree for an automaticity-dominating model. This model was originally developed for use in the Color/Word Stroop task, a task where the automatic influence of word-reading appears to dominate the controlled process of color-naming (Lindsay & Jacoby, 1994). In this model, automatic processes dominate performance; controlled processes only matter to the extent that automatic processes fail.

Figure 4 shows Conrey and colleagues' (2005) Quad-model, which includes four parameters. These include automatically activated bias (AC) and two controlled processes. One controlled parameter is discrimination (D), described in Conrey et al. (2005) as the likelihood that the correct response can be determined. The second controlled process is the overcoming of bias (OB), described as resolving conflicts between AC and D by inhibition (Conrey et al., 2005). If both AC and D are active, then OB determines which process drives the response. Finally, a guessing parameter (G) reflects general guessing tendencies when none of the other processes drive responses.

Figure 5 shows a model with a probabilistic relationship between controlled and automatic processes. One process dominates the other with a certain probability rather than all the time. It turns out that Figure 5 is algebraically equivalent to Conrey and colleagues' Quad-Model, but with D relabeled as C, and AC relabeled as A (for proof, see Bishara & Payne, 2009). As revealed by Figure 5, the Quad-Model acts like a control-dominating model with probability OB, and an automaticity-dominating model with probability 1-OB. As OB approaches 1, the Quad-Model reduces to a version of the control-dominating model, with a parameter (G) at the final branch to account for general guessing biases for one target over another. We label this the C-dominant/G model (Buchner, Erdfelder, & Vaterrodt-Plünnecke, 1995).² As OB approaches 0, the Quad-Model reduces to a version of the automaticity-dominating model that also has a

guessing parameter (A-dominant/G). In other words, variants of the C-dominant and A-dominant models are nested within the Quad-Model. Table 1 summarizes the characteristics of the five models.

Theoretical Comparison of Models

The integration of models shown in Figure 5 suggests new constraints on how model parameters can be interpreted. For example, in discussions of the original Quad-Model, strong claims have been about how the C parameter (originally labeled D) means detecting the correct response, whereas OB means implementing control operations to resolve the conflict (see Sherman et al., 2008). However, the integrated model in Figure 5 shows that a more general interpretation of parameters can be applied to all models. The C parameter can be interpreted simply as responding based on criterial information (e.g., the intended target objects), and the A parameter as responding based on primed or associative information.

The fact that the graphical order of parameters can be re-arranged in mathematically equivalent ways (compare Figures 4 and 5) highlights the fact that multinomial models do not imply a temporal order. The lack of temporal order also poses important constraints on how the parameters can be interpreted. For example, the automatic component in the C-dominant model has been described as operating “in the wake of failed control,” (Sherman et al., 2008, p. 328); it has also been argued that A operates “only when control has failed, and the model is not mathematically equipped to estimate early automatic processes” (p. 329). But the graphical “order” of the models only depicts which process is dominant when they conflict. (For examples of dual-process models that do specify temporal order, see Klauer & Voss, 2008).

Our integration of models reveals similarities between Process Dissociation and Quad models that have not been appreciated before. Past research has sometimes empirically compared how well C-dominant and A-dominant models account for empirical results by testing the fit of each model individually (e.g., Ferreira et al., 2006; Payne, Jacoby, & Lambert, 2005).

Considering the integrated model shows how examining this overall model is functionally similar to comparing the simpler models nested within it. Rather than generating a goodness-of-fit statistic for each nested model, the OB parameter provides a probabilistic estimate of the likelihood that the C-dominant versus the A-dominant model best describes the data. At the extremes, when $OB = 1$, the model reduces to the C-dominant model. When $OB = 0$, it reduces to the A-dominant model. Testing whether the OB parameter is significantly different from 0 and from 1, then, provides information about whether each of the simpler nested models can be rejected.

Empirical Comparison of Models

The integration of models not only suggests other theoretical interpretations; the integration also allows empirical comparisons among models. In comparing models, it is important to take into account the complexity of different models. Complex models (e.g., those with a large number of free parameters) can capitalize on chance, producing spuriously impressive fit statistics (see Pitt, Myung, & Zhang, 2002 for illustration). For example, the Quad-Model will tend to produce smaller (i.e., better) G^2 values relative to the G^2 values of simpler models. Even if data were generated by the C-dominant /G or A-dominant /G Model, the Quad-Model would still produce at least as small of a G^2 as the correct model would, thus giving the illusion that the Quad-Model was well supported by the data. As a solution to complexity problems such as this, adjusted fit statistics are typically used, statistics such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC; see Burnham & Anderson, 2004; Kuha, 2004).

Using AIC and BIC, Bishara & Payne (2009) empirically compared multinomial process models of weapon identification data. Specifically, the C-dominant, C-dominant /G, A-dominant, A-dominant /G, and the Quad-Model were compared. Across AIC and BIC, the C-dominant model accounted for the data better than any other model tested. Furthermore, the

results were generally consistent across four different datasets and analyses of both group data and individual subject data. In the Quad-Model, the OB parameter was often significantly higher than 0, suggesting that automaticity-dominating models did not account for the data well. However, in no case was the OB parameter significantly lower than 1. In other words, even using parameter estimates of the Quad-Model, the data were consistent with a control-dominating interpretation of weapon-identification performance.

Others have compared control-dominating and automaticity-dominating models in different tasks. Ferreira and colleagues (2006) compared the C-dominant and A-dominant models in terms of their ability to account for performance across a variety of judgment and decision-making tasks. While both models provided an adequate fit to the data in most experiments, only the C-dominant model's parameters were influenced in predictable ways. For example, in the C-dominant model, cognitive load selectively reduced the controlled parameter, as would be expected. In contrast, in the A-dominant model, cognitive load had no significant effect on either the controlled or automatic parameter (although the manipulation did affect behavioral responses). Thus, the C-dominant model seemed consistent with performance on the judgment and decision-making tasks.

Sherman and colleagues (2008) briefly summarized a large-scale comparison between the C-dominant model and the Quad-Model using the fit statistics AIC and BIC. They found that the C-dominant model tended to fit better for priming tasks (e.g., weapon identification), but that the Quad-Model tended to fit better for the IAT. However, in datasets where the Quad-Model fit better than the C-dominant model, what was the reason? One possibility is that all the parameters of the Quad-Model are needed to fit such data. However, it is also possible that simpler, untested models would also fit in some cases. It is possible that the Guessing parameter was the only necessary feature. Furthermore, it is unclear whether the OB parameter was significantly different from both 0 and 1. If the OB parameter was not significantly different

from 1, then the simpler C-dominant /G model may account for the data well. Likewise, if the OB parameter was not significantly different from 0, then the simpler A-dominant /G model may account for the data well. In fact, many Quad-Model analyses of the IAT often reveal at least one condition where OB is not significantly different from 0 (see Conrey et al., 2005). This pattern suggests that the A-dominant or A-dominant /G model may be viable in some circumstances, and it is worth investigating why.

Control and Automaticity Dominance in other Models

The family of multinomial models shown in Figures 3-5 are not only useful for contrasting models, but also for showing how models have unforeseen commonalities, even when models were designed for very different tasks. For example, Stahl & Degner (2007) developed a multinomial model for the Extrinsic Affective Simon Task (EAST). The EAST is a compatibility-based measure of implicit associations related to the IAT, but unlike the IAT it does not depend on relative evaluations of two items. In a multinomial model for the EAST, subjects respond on the basis of automatically activated valence with probability A. In the absence of this influence (1-A) subjects respond on the basis of controlled processing of the target information (C). If controlled processing fails (1-C) subjects respond with a guessing bias (B) favoring one arbitrarily defined response key over the other. Stahl & Degner (2007) named this the ABC model after its parameter names.

The ABC model may seem familiar by now: the model is algebraically equivalent to the A-dominant /G model depicted at the bottom of Figure 5. This equivalency has at least two consequences. First, it highlights the fact that ABC is an automaticity- dominating model. The evidence garnered in favor of the ABC model of the EAST can be considered as evidence that automatic processes dominate in that task. Second, the equivalency shows that the ABC model has precise relationships to other models. For example, the ABC model is nested within the Quad-Model. In particular, when OB is constrained to 0, the Quad-Model becomes the ABC

model. Likewise, data that is well-fit by the Quad-Model may be well-fit by the ABC (i.e., A-dominant /G) model so long as OB is not significantly different from o.

Summary and Future Directions for Model Comparisons

Multinomial models highlight what different theories have in common, such as controlled processes, automatic processes, and guessing biases. Multinomial models also highlight what is distinctive about each theory. One key distinction among different dual-process theories is whether controlled or automatic processes dominate responding when they conflict. Model comparisons suggest that control-dominating models make good sense out of data from weapon-bias experiments and decision-making tasks. However, automaticity-dominating models seem supported in other tasks, such as the EAST. Thus, there may not be any one “correct” dual-process multinomial model, but rather, different models may be more appropriate for different tasks and situations. Future research is needed to identify the task and situation features that encourage different processing routes.

Another avenue of future research has to do with temporal instantiations of models. Multinomial models in and of themselves are agnostic about the temporal order in which processes occur, and so they make no predictions about reaction time data. Building on the original Process Dissociation model, Klauer & Voss (2008) developed 4 time-based models. Each model made unique predictions about the qualitative pattern of results not only for errors (as do multinomial models), but also for reaction times. Results were consistent with a “default-interventionist” version of Process Dissociation, whereby controlled processing intervenes after automatic processes. For this reason, successful controlled processing is often associated with slower responses. Thus, results such as these suggest that Process Dissociation and related models can be refined and specified to address richer patterns of data, including temporal ordering of processes. More generally, the models reviewed here show that dual-process models are powerful tools for testing, elaborating, and unifying social cognitive theories.

Conclusion

Dual process theories acknowledge the importance of both automatic and controlled influences, but drawing conclusions is difficult without a means to quantify and compare their relative influence. Process Dissociation provides a solution to this problem by allowing researchers to disentangle automatic and controlled components and compare them. When cast in the form of multinomial process models, Process Dissociation allows tests of the relationships between processes, helping to answer questions about which process dominates the other. When Process Dissociation is considered in the context of other models such as the Quad model or the ABC model, a striking set of inter-relationships appears. Although these models were originally proposed as distinct models aimed at different purposes, they turn out to have a precise nested relationship. These models can therefore be seen as specific instances of a general family of models, varying in the relative dominance of automatic and controlled components. Empirical model fitting procedures can test whether an automaticity-dominating or control-dominating model best explains a given set of data.

We end by returning to the question of whether social life is dominated by an “automaticity-juggernaut” that leaves little room for consciously controlled action. Phrased this broadly, the question was probably always more of a philosophical than an empirical one. A virtue of formal models is that they force researchers to become more specific about their assumptions and their definitions, thereby rendering abstract questions more testable. An exciting contribution of the process dissociation family of models is the ability to test the dominance of automatic and controlled processes. But these process models encourage researchers to formulate the question more specifically. Rather than asking whether automatic or controlled influences are more powerful in general, researchers can empirically test the relative dominance of automatic and controlled influence on particular kinds of behavior, particular tasks, for particular persons, or in particular situations. The question then becomes,

for what kinds of behaviors, what kinds of people, and in what kinds of situations do automatic or controlled processes dominate behavior? The models integrated here set the stage for answering this next generation of questions.

References

- Bargh, J. A. (1994). The four horsemen of automaticity: Awareness, intention, efficiency, and control in social cognition. In R. S. Wyer & T. K. Srull (Eds.), *Handbook of social cognition* (pp. 1-40). Hillsdale, N.J.: Erlbaum.
- Bargh, J. A. (1997). The automaticity of everyday life. In R. S. Wyer (Ed.), *Advances in social cognition* (Vol. 10, pp. 1-61). Mahwah, N.J.: Erlbaum.
- Bargh, J. A. (2005). Bypassing the will: Toward demystifying the nonconscious control of social behavior. In R. R. Hassin, J. S. Uleman & J. A. Bargh (Eds.), *The new unconscious* (pp. 37-58). New York: Oxford University Press.
- Bargh, J. A., & Chartrand, T. L. (1999). The unbearable automaticity of being. *American Psychologist*, *54*, 462-479.
- Bargh, J. A., & Ferguson, M. J. (2000). Beyond behaviorism: On the automaticity of higher mental processes. *Psychological Bulletin*, *126*, 925-945.
- Bargh, J. A., & Uleman, J. S. (1989). Introduction. In J. S. Uleman & J. A. Bargh (Eds.), *Unintended thought: Causes and consequences for judgment, emotion, and behavior* (pp. 3-51). (pp. xiii-xxvi). New York: Guilford.
- Bishara, A. J. (2005). *Control and accessibility bias in single and multiple anchoring effects*. Unpublished doctoral dissertation, Washington University.
- Bishara, A. J., & Payne, B. K. (2009). Multinomial process tree models of control and automaticity in weapon misidentification. *Journal of Experimental Social Psychology*, *45*, 524-534.
- Bodenhausen, G., & Macrae, C. (1998). Stereotype activation and inhibition. Stereotype activation and inhibition. *Advances in Social Cognition*, *11*, 1-52. Mahwah, NJ: Lawrence Erlbaum Associates.

- Brewer, N., & Chapman, G. (2002). The fragile basic anchoring effect. *Journal of Behavioral Decision Making, 15*, 65-77.
- Buchner, A., Erdfelder, E., & Vaterrodt-Plünnecke, B. (1995). Toward unbiased measurement of conscious and unconscious memory processes within the process dissociation framework. *Journal of Experimental Psychology: General, 124*, 137-160.
- Burnham, K., & Anderson, D. (2004). Multimodel Inference: Understanding AIC and BIC in Model Selection. *Sociological Methods & Research, 33*, 261-304.
- Chaiken, S., & Trope, Y. (Eds.). (1999). *Dual-process theories in social psychology*. New York: Guilford.
- Chapman, G., & Johnson, E. (1994). The limits of anchoring. *Journal of Behavioral Decision Making, 7*, 223-242.
- Chapman, G., & Johnson, E. (1999). Anchoring, activation, and the construction of values. *Organizational Behavior and Human Decision Processes, 79*, 115-153.
- Conrey, F. R., Sherman, J. W., Gawronski, B., Hugenberg, K., & Groom, C. (2005). Separating multiple processes in implicit social cognition: The Quad model of implicit task performance. *Journal of Personality and Social Psychology, 89*, 469-487.
- Correll, J., Park, B., Judd, C. M., & Wittenbrink, B. (2002). The police officer's dilemma: Using ethnicity to disambiguate potentially threatening individuals. *Journal of Personality and Social Psychology, 83*, 1314-1329.
- Correll, J., Park, B., Judd, C., & Wittenbrink, B. (2007). The influence of stereotypes on decisions to shoot. *European Journal of Social Psychology, 37*, 1102-1117.
- Curran, T., & Hintzman, D. L. (1995). Violations of the independence assumption in process dissociation. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*, 531-547.

- Curran, T., & Hintzman, D. L. (1997). Causes and consequences of correlations in process dissociation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 23, 496-504.
- De Houwer, J. (2003). The extrinsic affective Simon task. *Experimental Psychology*, 50, 77-85.
- Devine, P. G. (1989). Stereotypes and prejudice: Their automatic and controlled components. *Journal of Personality and Social Psychology*, 56, 5-18.
- Ferreira, M. B., Garcia-Marques, L., Sherman, S. J., & Sherman, J. W. (2006). Automatic and controlled components of judgment and decision making. *Journal of Personality and Social Psychology*, 91, 797 – 813.
- Festinger, L. (1957). *A theory of cognitive dissonance*. Evanston, IL: Row, Peterson.
- Fitzsimons, G., & Williams, P. (2000). Asking questions can change choice behavior: Does it do so automatically or effortfully? *Journal of Experimental Psychology: Applied*, 6, 195-206.
- Fyfe, J. (1988). Police use of deadly force: Research and reform. *Justice Quarterly*, 5, 165-205.
- Gaunt, R., Leyens, J., & Demoulin, S. (2002). Intergroup relations and the attribution of emotions: Control over memory for secondary emotions associated with the ingroup and outgroup. *Journal of Experimental Social Psychology*, 38, 508-514.
- Gawronski, B., & Bodenhausen, G. V. (2006). Associative and propositional processes in evaluation: An integrative review of implicit and explicit attitude change. *Psychological Bulletin*, 132, 692–731.
- Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist*, 54, 493-503.
- Govorun, O., & Payne, B. (2006). Ego-depletion and prejudice: Separating automatic and controlled components. *Social Cognition*, 24, 111-136.

- Greenwald, A., McGhee, D., & Schwartz, J. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology*, *74*, 1464-1480.
- Greenwald, A. G., Oakes, M. A., & Hoffman, H. G. (2002). Targets of discrimination: Effects of race on responses to weapon holders. *Journal of Experimental Social Psychology*, *39*, 399-405.
- Heider, F. (1958). *The psychology of interpersonal relations*. New York: Wiley.
- Hense, R. L., Penner, L. A., & Nelson, D. L. (1995). Implicit memory for age stereotypes. *Social Cognition*, *13*, 399-415.
- Hewstone, M., Rubin, M., & Willis, H. (2002). Intergroup bias. *Annual Review of Psychology*, *53*, 575-604.
- Higgins, E. T., Rholes, W. S., & Jones, C. R. (1977). Category accessibility and impression formation. *Journal of Experimental Social Psychology*, *13*, 141-154.
- Hofmann, W., Friese, M., & Roefs, A. (2009). Three ways to resist temptation: The independent contributions of executive attention, inhibitory control, and affect regulation to the impulse control of eating behavior. *Journal of Experimental Social Psychology*, *45*, 431-435.
- Hofmann, W., Gschwendner, T., Friese, M., Wiers, R. W., & Schmitt, M. (2008). Working memory capacity and self-regulatory behavior: Towards an individual differences perspective on behavior determination by automatic versus controlled processes. *Journal of Personality and Social Psychology*, *95*, 962-977.
- Jacoby, L. L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory and Language*, *30*, 513-541.

- Jacoby, L. L. (1998). Invariance in automatic influences of memory: Toward a user's guide for the process-dissociation procedure. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*, 3-26.
- Jacoby, L. L., Begg, I. M., & Toth, J. P. (1997). In defense of functional independence: Violations of assumptions underlying the process-dissociation procedure? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *23*, 484-495.
- Jacoby, L., Kelley, C., & McElree, B. (1999). The role of cognitive control: Early selection versus late correction. *Dual-process theories in social psychology* (pp. 383-400). New York, NY US: Guilford Press.
- Jacoby, L. L., & ShROUT, P. E. (1997). Toward a psychometric analysis of violations of the independence assumption in process dissociation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *23*, 505-510.
- Jacoby, L., Toth, J., & Yonelinas, A. (1993). Separating conscious and unconscious influences of memory: Measuring recollection. *Journal of Experimental Psychology: General*, *122*, 139-154.
- Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), *Heuristics and biases: The psychology of intuitive judgment* (pp. 49–81). New York: Cambridge University Press.
- Kelley, C. M., & Jacoby, L. L. (2000). Recollection and familiarity: Process-dissociation. In E. E. Tulving, E. Ferguson, & I. M. Craik (Eds.), *The Oxford handbook of memory* (pp. 215–228). New York, NY: Oxford Univ. Press.
- Kihlstrom, J. F. (2006). The automaticity juggernaut. In J. Baer, J. C. Kaufman & R. F. Baumeister (Eds.), *Psychology and free will*. New York: Oxford University Press.

- Kihlstrom, J.F. (2007). The psychological unconscious. To appear in O. John, R. Robins, & L. Pervin (Eds.), *Handbook of Personality: Theory and Research, 3rd Ed.* New York: Guilford.
- Kirkpatrick, L. A., & Epstein, S. (1992). Cognitive-experiential self theory and subjective probability: Further evidence for two conceptual systems. *Journal of Personality and Social Psychology, 63*, 534-544.
- Klauer, K., & Voss, A. (2008). Effects of race on responses and response latencies in the weapon identification task: A test of six models. *Personality and Social Psychology Bulletin, 34*, 1124-1140.
- Klauer, K. C. & Wegener, I. (1998). Unraveling social categorization in the "Who said what?" paradigm. *Journal of Personality and Social Psychology, 75*, 1155-1178.
- Koriat, A., & Goldsmith, M. (1996). Monitoring and control processes in the strategic regulation of memory accuracy. *Psychological Review, 103*, 490-517.
- Kramer, T., Block, L. (2008). Conscious and nonconscious components of superstitious beliefs in judgment and decision making. *Journal of Consumer Research, 34*, 783-793.
- Kuha, J. (2004). AIC and BIC: Comparisons of Assumptions and Performance. *Sociological Methods & Research, 33*, 188-229.
- Langer, E., Blank, A., & Chanowitz, B. (1978). The mindlessness of ostensibly thoughtful action: The role of "placebic" information in interpersonal interaction. *Journal of Personality and Social Psychology, 36*, 635-642.
- Leyens, J. P., Rodriguez, A. P., Rodriguez, R. T., Gaunt, R., Paladino, P. M., Vaes, J., & Demoulin, S. (2001). Psychological essentialism and the differential attribution of uniquely human emotions to ingroups and outgroups. *European Journal of Social Psychology, 31*, 395-411.

- Lindsay, D., & Jacoby, L. (1994). Stroop process dissociations: The relationship between facilitation and interference. *Journal of Experimental Psychology: Human Perception and Performance*, *20*, 219-234.
- MacRae, C., Schloerscheidt, A., Bodenhausen, G., & Milne, A. (2002). Creating memory illusions: Expectancy-based processing and the generation of false memories. *Memory*, *10*, 63-80.
- Moors, A., & DeHouwer, J. (2006). Automaticity: A Theoretical and Conceptual Analysis. *Psychological Bulletin*, *132*, 297-326.
- Morwitz, V., Johnson, E., & Schmittlein, D. (1993). Does measuring intent change behavior?. *Journal of Consumer Research*, *20*, 46-61.
- Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin*, *126*, 247-259.
- Nisbett, R., & Wilson, T. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review*, *84*, 231-259.
- Payne, B. K. (2001). Prejudice and perception: The role of automatic and controlled processes in misperceiving a weapon. *Journal of Personality and Social Psychology*, *81*, 181-192.
- Payne, B. K. (2005). Conceptualizing Control in Social Cognition: How executive control modulates the expression of automatic stereotyping. *Journal of Personality and Social Psychology*, *89*, 488- 503.
- Payne, B. K., Burkley, M., & Stokes, M. B. (2008). Why do implicit and explicit attitude tests diverge? The role of structural fit. *Journal of Personality and Social Psychology*, *94*, 16-31.
- Payne, B. K., Jacoby, L. L., & Lambert, A. J. (2004). Memory monitoring and the control of stereotype distortion. *Journal of Experimental Social Psychology*, *40*, 52-64.
- Payne, B. K., Jacoby, L. L., & Lambert, A. J. (2005). Attitudes as accessibility bias:

- Dissociating automatic and controlled components. In R. Hassin, J. Bargh, J. & Uleman, (Eds.), *The New Unconscious*. Oxford.
- Payne, B., Lambert, A., & Jacoby, L. (2002). Best laid plans: Effects of goals on accessibility bias and cognitive control in race-based misperceptions of weapons. *Journal of Experimental Social Psychology*, *38*, 384-396.
- Petty, R., & Briñol, P. (2006). Understanding social judgment: Multiple systems and processes. *Psychological Inquiry*, *17*, 217-223.
- Pitt, M., Myung, I., & Zhang, S. (2002). Toward a method of selecting among computational models of cognition. *Psychological Review*, *109*, 472-491.
- Plant, E. A., & Peruche, B. M. (2005). The consequences of race for police officers' responses to criminal suspects. *Psychological Science*, *16*, 180-183.
- Posner, M. I., & Snyder, C. R. R. (1975). Attention and cognitive control. In R. L. Solso (Ed.), *Information processing and cognition: The Loyola Symposium* (pp. 55-85). New York: Wiley.
- Riefer, D. M., & Batchelder, W. H. (1988). Multinomial modeling and the measurement of cognitive processes. *Psychological Review*, *95*, 318-339.
- Riefer, D. M., Hu, X., & Batchelder, W. H. (1994). Response strategies in source monitoring. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *20*, 680-693.
- Roediger, H. L. (1990). Implicit memory: Retention without remembering. *American Psychologist*, *45*, 1043-1056.
- Rouder, J., Lu, J., Morey, R., Sun, D., & Speckman, P. (2008). A hierarchical process-dissociation model. *Journal of Experimental Psychology: General*, *137*, 370-389.
- Rouder, J. N., Lu, J., Sun, D., Speckman, P. L., Morey, R. D., & Naveh-Benjamin, M. (2007). Signal detection models with random participant and item effects. *Psychometrika*, *72*, 583-600.

- Schacter, D. L. (1987). Implicit memory: History and current status. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *13*, 501–518.
- Sherman, J., Gawronski, B., Gonsalkorale, K., Hugenberg, K., Allen, T., & Groom, C. (2008). The self-regulation of automatic associations and behavioral impulses. *Psychological Review*, *115*, 314-335.
- Sherman, J., Groom, C., Ehrenberg, K., & Klauer, K. (2003). Bearing false witness under pressure: Implicit and explicit components of stereotype-driven memory distortions. *Social Cognition*, *21*, 213-246.
- Sherman, S. J. (1980). On the self-erasing nature of errors of prediction. *Journal of Personality and Social Psychology*, *39*, 211–221.
- Shiffrin, R. M., & Schneider, W. (1977). Controlled and automatic human information processing: II. Perceptual learning, automatic attending and a general theory. *Psychological Review*, *84*, 127-190.
- Shiv, B., & Fedorikhin, A. (1999). Heart and Mind in Conflict: The Interplay of Affect and Cognition in Consumer Decision Making. *The Journal of Consumer Research*, *26*, 278-292.
- Slooman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin*, *119*, 3-22.
- Smith, E. R., & DeCoster, J. (2000). Dual-process models in social and cognitive psychology: Conceptual integration and links to underlying memory systems. *Personality and Social Psychology Review*, *4*, 108-131.
- Srull, T. K., & Wyer, R. S. (1980). Category accessibility and social perception: Some implications for the study of person memory and interpersonal judgments. *Journal of Personality and Social Psychology*, *38*, 841–856.

- Stahl, C., & Degner, J. (2007). Assessing automatic activation of valence: A multinomial model of EAST performance. *Experimental Psychology*, *54*, 99-112.
- Stangor, C., & McMillan, D. (1992). Memory for expectancy-congruent and expectancy-incongruent information: A review of the social and social developmental literatures. *Psychological Bulletin*, *111*, 42-61.
- Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate. *Behavioral and Brain Sciences*, *23*, 645–665.
- Stewart, B., & Payne, B. (2008). Bringing automatic stereotyping under control: Implementation intentions as efficient means of thought control. *Personality and Social Psychology Bulletin*, *34*, 1332-1345.
- Stewart, B., von Hippel, W., & Radvansky, G. (2009). Age, race, and implicit prejudice: Using process dissociation to separate the underlying components. *Psychological Science*, *20*, 164-188.
- Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review*, *8*, 220-247.
- Strack F, Mussweiler T. (1997). Explaining the enigmatic anchoring effect: Mechanisms of selective accessibility. *Journal of Personality and Social Psychology*, *73*, 437-446.
- Tanner, W., & Swets, J. (1954). A decision-making theory of visual detection. *Psychological Review*, *61*, 401-409.
- Tulving, E. (1985). Memory and consciousness. *Canadian Psychology*, *26*, 1-12.
- Tulving, E., Schacter, D. L., & Stark, H. A. (1982). Priming effects in word-fragment completion are independent of recognition memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *8*, 336–342.
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*, 1124–1131.

Tversky, A. and Kahneman, D. (1983). Extension versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review*, 90, 293–315.

von Hippel, W., Silver, L. A., & Lynch, M. E. (2000). Stereotyping against your will: The role of inhibitory ability in stereotyping and prejudice among the elderly. *Personality and Social Psychology Bulletin*, 26, 523 - 532.

Wegner, D. M. (2002). *The illusion of conscious will*. Cambridge, Ma.: MIT Press.

Wegner, D. M. (1994). Ironic processes of mental control. *Psychological Review*, 101, 34-52.

Westling, E., Mann, T., & Ward, A. (2006). Self-Control of Smoking: When Does Narrowed Attention Help? *Journal of Applied Social Psychology*, 36, 2115-2133.

Yonelinas. A.P. (2002). The nature of recollection and familiarity: A review of 30 years of research. *Journal of Memory and Language*, 46, 441-517.

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Footnotes

1. We use “independence” in the strong, stochastic definition of the word. That is, the independence assumption of interest is that control and automaticity are largely uncorrelated across subjects and trials. This assumption is difficult to test directly because most analyses require aggregation across subjects or trials. This stronger definition is not to be confused with weaker, theoretical independence, which refers merely to the fact that the theory allows parameters to vary on separate dimensions rather than forcing them onto a one-dimensional continuum.
2. Although the original Process Dissociation model lacks a guessing parameter, guessing biases are sometimes accommodated by the A parameter in that model.

Table 1

Multinomial Processing Tree Models in the Process Dissociation Family

Model	Figure	Dominating Process	Parameters	Guessing Parameter?	Notes
C-dominant	3 (Top)	Controlled	2	No	Has accounted for Weapon-Identification and judgment/decision-making task data.
A-dominant	3 (Bottom)	Automatic	2	No	
Quad-Model	4 and 5	Probabilistic	4	Yes	OB parameter determines the probability of control processes dominating; Has accounted for IAT data.
C-dominant /G	5 (Top)	Controlled	3	Yes	Equivalent to Quad-Model with OB=1
A-dominant /G	5 (Bottom)	Automatic	3	Yes	Equivalent to Quad-Model with OB=0; Equivalent to ABC model; Has accounted for EAST data.

Notes. OB=Overcoming Bias parameter, IAT=Implicit Association Test; EAST=Extrinsic Affect Simon Task.

Figure Captions

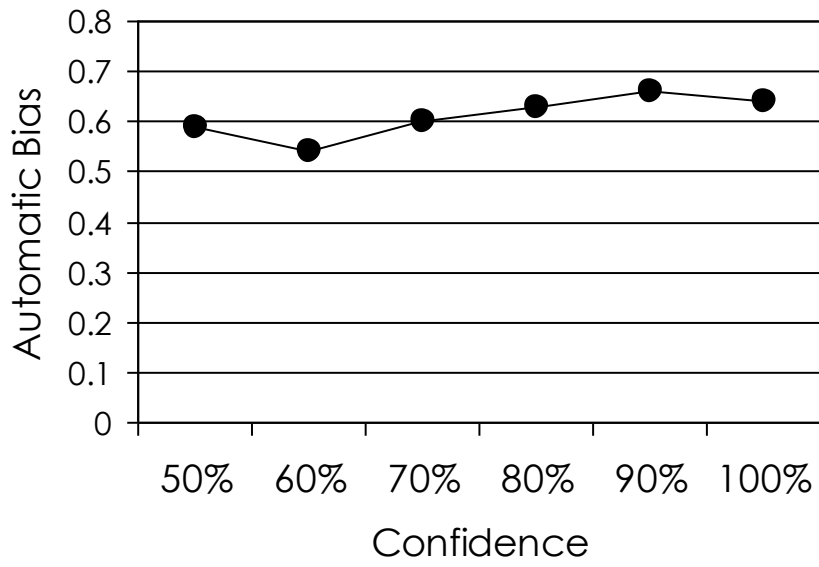
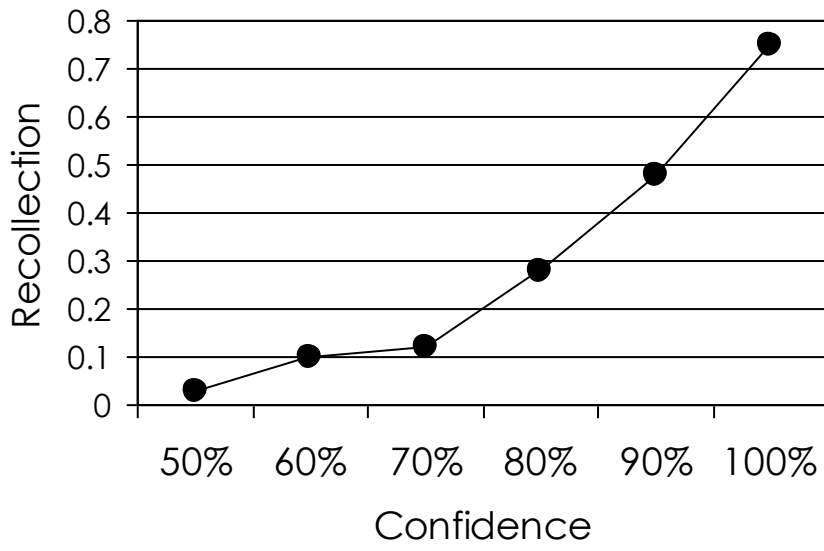
Figure 1. Relationships between subjective confidence and Recollection (top panel) and Automatic Bias (bottom panel). Confidence ranged from 50%, (i.e., responding at chance) to 100% (i.e., complete confidence). Adapted from Payne, Jacoby, & Lambert (2004).

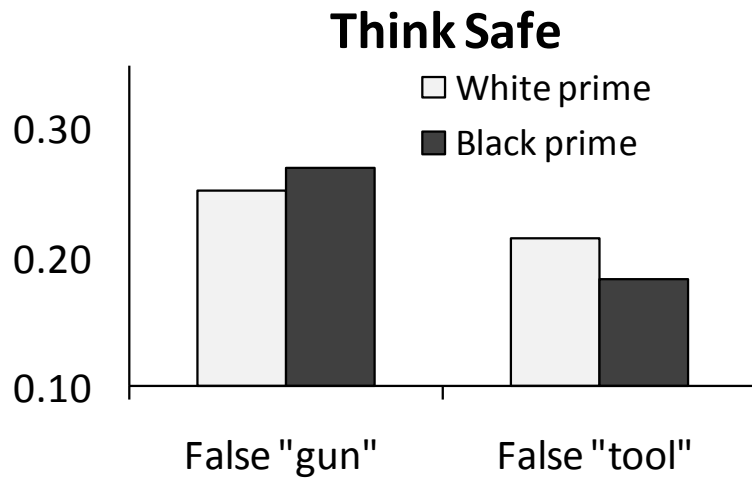
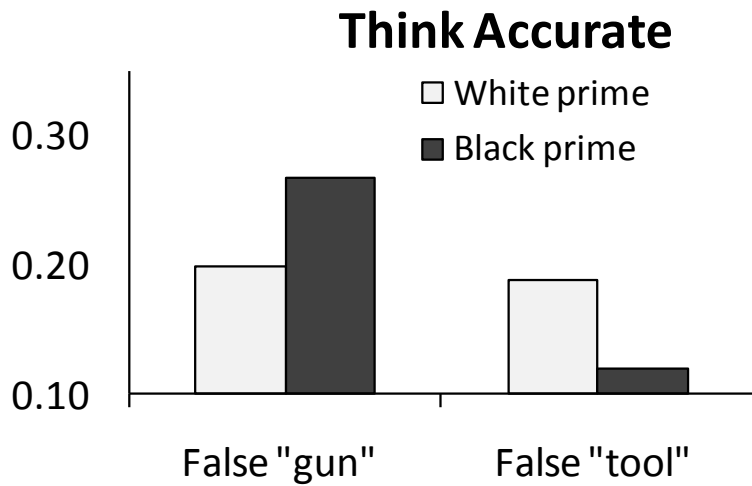
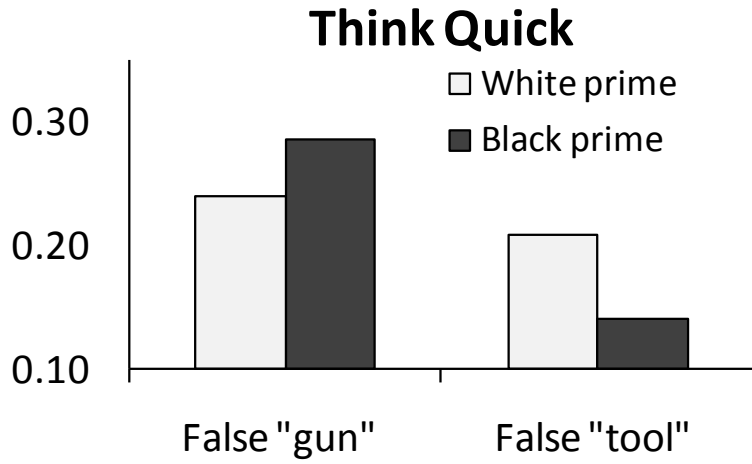
Figure 2. Patterns of bias in weapons task as a function of three implementation intentions. The y-axis represents the proportion of errors of each type. False gun errors refer to tools falsely called tools; false tool errors refer to tools falsely called guns. Adapted from Stewart & Payne (2008).

Figure 3. Multinomial processing trees for the C-dominant (Top) and A-dominant (Bottom) Models. Branches lead to correct (+) and incorrect (-) responses.

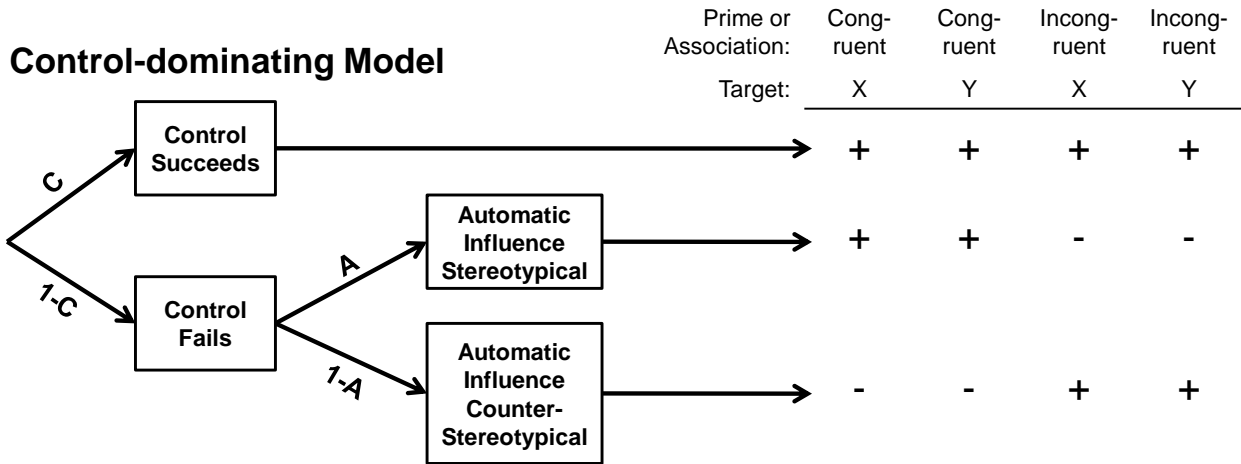
Figure 4. Original Quad-Model multinomial processing tree. Branches lead to correct (+) and incorrect (-) responses.

Figure 5. Algebraically equivalent version of the Quad-Model. D has been relabeled as C, and AC has been relabeled as A. The organization has been rearranged so as to highlight the Quad-Model's relationship to other models. Branches lead to correct (+) and incorrect (-) responses. Adapted from Bishara & Payne (2009).

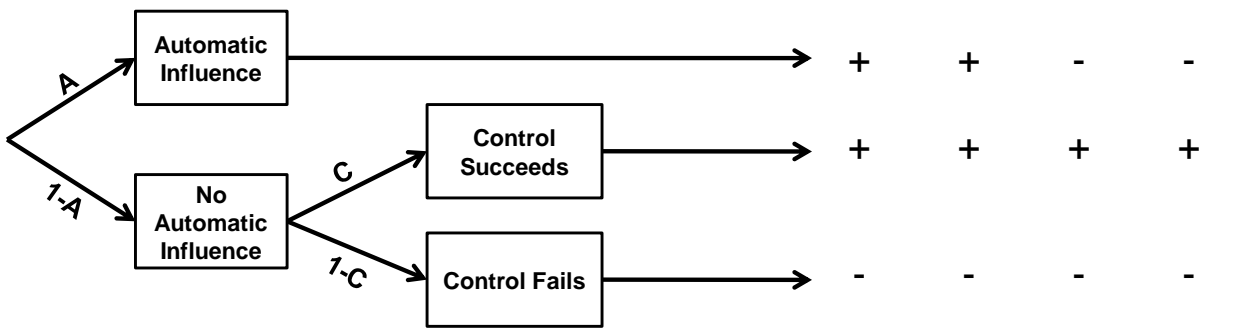




Control-dominating Model



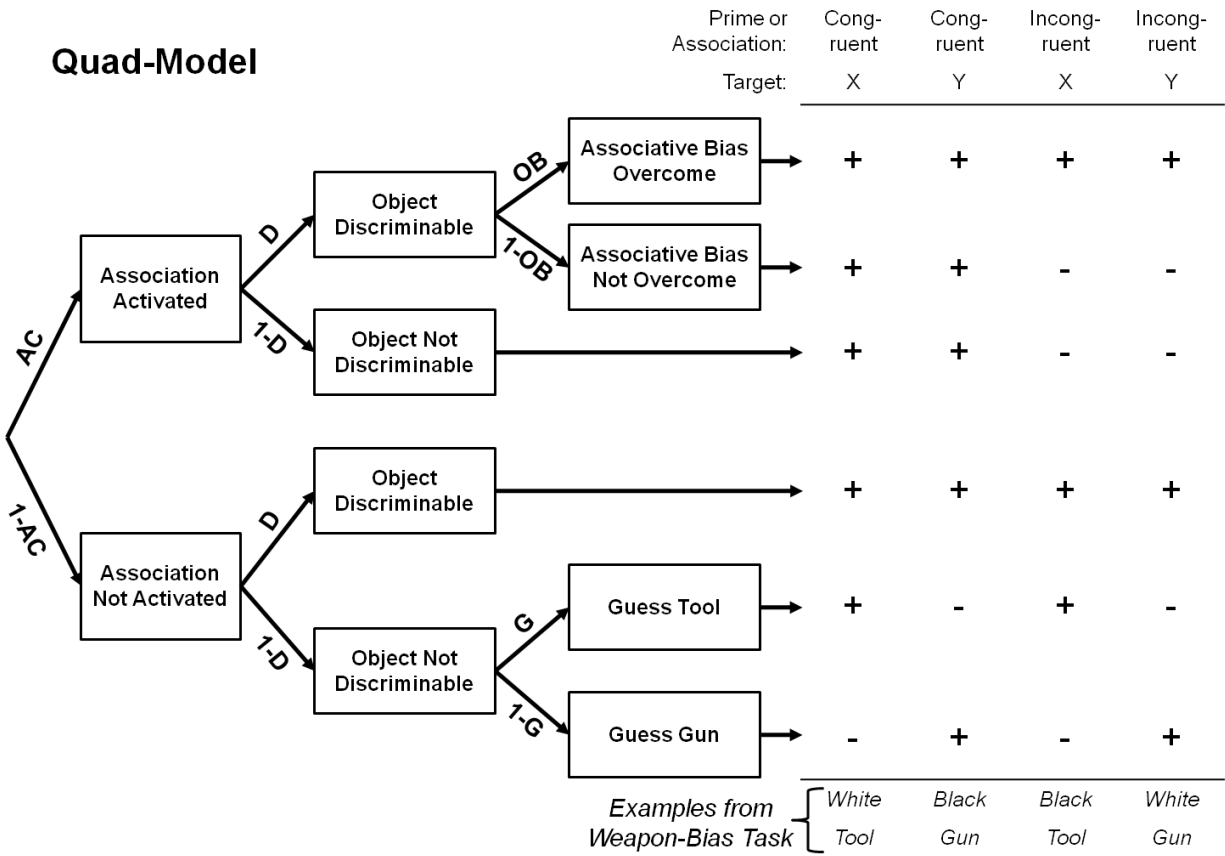
Automaticity-dominating Model



Examples from
Weapon-Bias Task

White	Black	Black	White
Tool	Gun	Tool	Gun

Quad-Model



**Quad-Model
(Algebraically Equivalent Version)**

