CHAPTER TWO

Multinomial processing trees as theoretical bridges between cognitive and social psychology

Jimmy Calanchini[a,*], Andrew M. Rivers[b], Karl Christoph Klauer[a], Jeffrey W. Sherman[b]

[a]Department of Social Psychology and Methodology, University of Freiburg, Freiburg im Breisgau, Germany
[b]University of California, Davis, Davis, CA, United States
*Corresponding author: e-mail address: jimmy.calanchini@ucr.edu

Contents

1. The problem with process-purity 42
2. Multinomial processing trees 43
   2.1 The process dissociation model and its relatives 45
3. Multinomial processing trees and the future of cognitive and social psychology 50
   3.1 Building bridges 51
   3.2 Advances to date 51
   3.3 Advances to come 53
   3.4 Operating principles versus conditions 55
   3.5 Choosing a model 56
   3.6 Limitations of multinomial processing trees 57
   3.7 Alternatives to multinomial processing trees 58
   3.8 Recommended readings 59
Acknowledgments 59
References 59

Abstract

Cognitive and social psychologists have long investigated dual-process theories of automaticity and control. These theories seek to explain and predict the conditions under which people can intentionally control their judgments and behavior in the face of impulses produced by biasing and distracting incidental stimuli. Based on this dual-process perspective, cognitive and social psychologists have developed tasks that create conditions under which impulses act in parallel or in opposition to control-oriented processes—commonly referred to as response conflict tasks. Though the response conflict tasks used by cognitive and social psychologists are often structurally similar, researchers from the two disciplines often interpret performance on such tasks in very different ways: Cognitive psychologists tend to focus on the contributions of control-oriented processes, whereas social psychologists generally focus on the contributions of

Psychology of Learning and Motivation, Volume 69
ISSN 0079-7421
https://doi.org/10.1016/bs.plm.2018.09.002

activated mental associations. Both of these interpretations rest on assumptions of process purity: that a response conflict task reflects either control-oriented processes or mental associations. However, this assumption is untenable. Both types of mental processes jointly influence behavioral responses on most response conflict tasks. Multinomial processing tree models are well suited to assess the contributions of multiple cognitive processes to response conflict tasks commonly used in cognitive and social psychology. In this chapter, we review the applications of multinomial processing trees to response conflict tasks, and highlight their utility in bridging interpretive divides that separate cognitive and social psychologists.

When are judgments and behaviors driven by impulses, and under what conditions can these impulses be controlled? In the decades since Schneider and Shiffrin first proposed the two-process theory of human information processing (Schneider & Shiffrin, 1977), the distinction between automatically-activated impulses and control-oriented processes that override impulses has been central to the fields of cognitive and social psychology. To investigate questions of automaticity and control, researchers have developed methods and measures that create conditions under which automatically-activated impulses act in concert with or in opposition to control-oriented processes. Such measures are broadly referred to as response conflict (or response interference) tasks and are widely-used in both cognitive and social psychology.

Though cognitive and social psychologists often use response conflict tasks that are structurally similar, they interpret performance on these tasks in very different ways. For example, consider the Go/No-Go Task (Donders, 1969) and the Go/No-Go Association Task (Nosek & Banaji, 2001). In both tasks, participants view a continuous sequence of target stimuli and must produce behavioral (i.e., "Go") responses to some targets and withhold behavioral responses (i.e., "No-Go") to others. The frequency with which participants fail to withhold responses on no-go trials is generally interpreted by cognitive psychologists as an index of (lack of) inhibitory control, but is interpreted by social psychologists as an index of the strength of behavioral impulses activated by the stimuli. Hence, two tasks that are procedurally identical are interpreted to reflect fundamentally different mental processes.

As another example of structurally-similar tasks interpreted differently across disciplines, consider the Stroop (1935) task and the Implicit Association Test (IAT: Greenwald, McGhee, & Schwartz, 1998), two of the most commonly used measures in cognitive and social psychology, respectively. On the Stroop task, the names of colors are presented in a variety of colors (e.g., RED printed in green), and participants respond to the color in which the word is printed rather than the semantic meaning of the word. On the IAT, stimuli are presented representing two concepts (e.g., the ingroup and the outgroup) and two attributes (e.g., good and bad), and participants categorize them into one of the four categories. Both the Stroop and IAT tasks consist of so-called *compatible* trials and *incompatible* trials. On compatible trials of the Stroop (e.g., RED printed in red), both the well-learned impulse to read the word and the task-appropriate response to name the color in which the word is presented produce the same response. However, on incompatible trials (e.g., RED printed in blue), word-reading conflicts with color-naming. Similarly, on compatible trials of the IAT (e.g., good words and pictures of the ingroup share a response key), response impulses based on both well-learned associations (e.g., regarding one's ingroup) and the task-appropriate response produce the same outcome. However, on incompatible trials (e.g., bad words and pictures of the ingroup share a response key) the response impulse produced by activated associations conflicts with the contextually task-appropriate response. On both the Stroop and the IAT, response latencies are typically faster and accuracy is higher on compatible than incompatible trials. Yet, despite structural similarities between the two tasks, differences in responding to compatible and incompatible trials on the Stroop are generally interpreted as a measure of inhibitory control, whereas differences in responding to compatible and incompatible trials on the IAT are generally interpreted as a measure of the strength of mental associations activated by the stimuli.

One possibility for these interpretive differences is that one (or both) research tradition has mischaracterized the psychological processes that determine performance on response conflict tasks. We argue for a different possibility: Rather than reflecting pure measures of any cognitive process, response conflict tasks reflect the joint contributions of impulse activation and control-oriented processes. Guided by this perspective, we propose that multinomial processing trees can be powerful tools to identify and disentangle the joint contributions of multiple cognitive processes to response conflict tasks. [a]In this chapter, we review multinomial processing trees within cognitive and social psychology, highlighting their applications and major theoretical and methodological contributions. Additionally, we emphasize

[a] A third possibility for the disparate ways in which cognitive and social psychologists interpret performance on response conflict tasks is that different stimuli (e.g., color-related words versus pictures of outgroup members) activate qualitatively distinct mental processes. However, we argue that the dual-process perspective is more parsimonious: Rather than activating qualitatively distinct processes, different stimuli activate the same cognitive processes to differing degrees.

their utility in bridging interpretive divides that separate cognitive and social psychologists, and offer suggestions for how multinomial processing trees can further aid in theory development.

1. The problem with process-purity

Consider a case of a literate adult and a pre-literate child performing a Stroop task. The adult and the child may perform equally well at naming the color in which a word is presented on incongruent trials (e.g., RED printed in green), but for very different reasons. The adult has a strong impulse to respond to the semantic meaning of the word formed through a lifetime of reading experience, but she also has a fully-developed frontal cortex and is, thus, able to inhibit her well-practiced impulse of reading in order to successfully name the color. Conversely, due to her young age, the child can identify colors but has not yet learned to read, so there is no impulse to read the word for her (still-developing) frontal cortex to inhibit in order for her to successfully name the color. Taken together, two different combinations of processes—the adult's strong word-reading impulse and strong inhibition ability, and the child's weak word-reading impulse and weak inhibition ability—produce the same observable outcome. Differences in Stroop performance are typically interpreted as reflecting differences in inhibition, but this example and others (e.g., native versus non-native speakers) illustrate the limitations of such process-pure perspectives. Aggregated task performance in itself cannot distinguish between differences resulting from variation in behavioral impulses and differences resulting from variation in inhibition. As such, assumptions of task purity can obscure meaningful differences at the process level.

We certainly are not the first to address the issue of process purity in experimental tasks. Jacoby (1991) brought this insight to bear nearly 30 years ago to the study of recognition memory. Previously, different types of memory were frequently measured using distinct tasks. For example, recollection was measured using direct recall tasks, whereas familiarity was measured using word fragment completion tasks. Jacoby argued that this approach was inherently flawed because it equated a particular cognitive process with a particular task when, in reality, performance on most tasks is likely driven by multiple processes. To address this issue, he developed a procedure to estimate the contributions of multiple memory processes to responses on a single task. The first part of the procedure was a task in which recollection and familiarity produced concordant responses in one condition, but produced conflicting responses in another condition (i.e., a response conflict task). The second part of the procedure was a mathematical model that formally specified the interplay of recollection and familiarity to produce responses in each condition. Ultimately, Jacoby's process dissociation procedure demonstrated that both recollection and familiarity influence recognition judgments.

Jacoby (1991) conceptualized recollection as a relatively intentional process, and familiarity as a relatively unintentional process which, in turn, maps onto the dual-process framework of automatic and controlled mental processes that is common across many fields of psychology. In the following decades, many other researchers also interested in questions of automaticity and control have recognized the utility and generalizability of this procedure and have spread Jacoby's methodological and theoretical innovations far beyond the study of memory. The majority of the rest of this chapter focuses upon many of the ways in which the process dissociation procedure and related techniques have advanced, and can further advance, cognitive and social psychology. First, however, we must introduce the class of analytic methods to which the process dissociation procedure belongs: multinomial processing trees.

2. Multinomial processing trees

Multinomial processing trees (MPT: Batchelder & Riefer, 1999; Riefer & Batchelder, 1988) are a class of formal mathematical models. At the most basic level, a formal model is simply a theory that is specified mathematically. By articulating a theory mathematically rather than verbally, the purpose of a formal model is to not only identify but also quantify the processes that account for outcomes on measures of behavior (e.g., judgments, error rates, reaction times). Consequently, formal models precisely describe (i.e., in mathematical equations) how multiple processes interact to produce specific performance outcomes.

An MPT begins with a set of parameters and a set of equations that establish relationships among the parameters. The parameters in the equations represent the hypothesized component processes that result in distinct categorical responses on the measure of interest (e.g., correct/incorrect, old/new, low/mid/high confidence) and the equations define the manner in which the processes interact to produce those responses.[b] MPTs can

[b] Accuracy is often very high, and sometimes near ceiling, on many response conflict tasks routinely used by cognitive and social psychologists. Consequently, reasonable questions arise regarding the validity of insight offered by a relatively infrequent response (i.e., an error). We return to this point later in the chapter, and discuss various ways in which it has been addressed.

accommodate data from individual participants as well as aggregate data and, thus, can generate parameter estimates at the individual and group levels. Entering participants' or groups' actual responses as outcomes in the equations yields estimates of the extents of the processes hypothesized to produce those outcomes. Some MPTs can be solved algebraically (e.g., Jacoby, 1991). However, other MPTs (e.g., Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005) require other estimation techniques (e.g., maximum likelihood; MCMC sampling) to generate parameter values that create as close a match as possible between the observed response frequencies and those predicted by the model. The degree to which the outcomes predicted by the model correspond to observed responses can be quantified and assessed through goodness-of-fit statistics.

Providing sufficient fit to data is only one step in demonstrating the validity of an MPT. The construct validity of each parameter in the model—that is, the relationship between a parameter and the psychological process it is assumed to reflect—must be established through a series of selective-influence studies. Such demonstrations rely on experimental manipulations that are known, based on prior research and theorizing, to influence only one cognitive process. Convergent validity is demonstrated if an experimental manipulation influences the intended parameter, and discriminant validity is demonstrated if the manipulation does not influence other, unrelated parameters. Moreover, the external validity of the model is demonstrated if parameters predict theoretically-relevant external outcomes, such as judgments and behaviors. Taken together, an MPT can be considered to be valid if it provides sufficient fit to data, its parameters are sensitive to selective influence, and it predicts relevant outcomes.

Returning to Jacoby (1991) as an example, the process dissociation model is instantiated as an MPT in which recollection (R) and familiarity (F) both influence recognition memory (see Fig. 1). In the original implementation of the process dissociation procedure, participants first studied one list of words and then studied a second list of words. In a subsequent recognition test, they were asked to identify words under two different conditions: *inclusion* and *exclusion*. In the inclusion condition, participants were asked to respond "old" to words that had appeared on either of the lists they had studied and to respond "new" to words that had not appeared on either list. During this inclusion test phase, both recollection and familiarity produce the same response: Participants can correctly identify studied words either through recollection (with probability R) or, if recollection fails, through familiarity ($F^{*}(1-R)$). Thus, the equation for correctly identifying

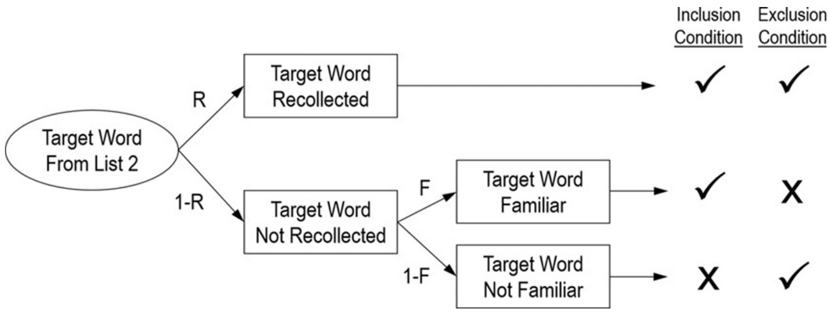

Fig. 1 A portion of Jacoby's (1991) familiarity/recollection model. Oval represents a test stimulus and rectangles represent latent cognitive processes hypothesized to influence responses to the stimulus. Parameters with lines leading to them are conditional upon preceding parameters. The table on the right side of the figure depicts correct (✓) and incorrect (X) responses as a function of process pattern and trial type.

words in the inclusion condition is $R+F(1-R)$. In the exclusion condition, participants were asked to respond "old" to words from the second list and to respond "new" to words that had either appeared on the first list or were on neither of the studied lists. During this exclusion test phase, recollection and familiarity produce divergent responses: Recollection will produce a correct response but, if recollection fails $(1-R)$, familiarity (F) will produce an incorrect response. Thus, the equation for correctly identifying words in the exclusion condition is $F^*(1-R)$. Algebraically solving these equations will yield estimates of the extent to which both recollection and familiarity processes influence responses on this task.

2.1 The process dissociation model and its relatives

Jacoby's process dissociation model is one of the most widely-applied MPTs within both cognitive and social psychology. The initial version of the model that Jacoby (1991) proposed is a control-dominant, or "early selection," model, in which the relatively more unintentional process influences responses only when the relatively more intentional process fails. For example, on a recognition memory task, recollection is a relatively more intentional process than familiarity. This control-dominant version of the model specifies that when the two processes would produce different responses (e.g., recollecting that a word was not presented before, even though it seems familiar), recollection will drive the response if both processes are activated, and familiarity can only drive a response when recollection fails. Lindsay and Jacoby (1994) proposed an alternate automatic-dominant, or "late correction," version of the PD model. In this version of the model, the relatively more intentional process only influences responses when the relatively more unintentional process fails. For example, on a Stroop task, color naming is a relatively more intentional process than word reading. This version of the model specifies that when the two processes would produce different responses (e.g., RED printed in green), word reading will drive the response if both processes are activated, and color naming can only drive a response when word reading fails (see also Jacoby, 1998 for a synthesis of these approaches).

Within cognitive psychology, a number of variations of Jacoby's (1991) process dissociation model have been proposed. For example, Buchner, Erdfelder, and Vaterrodt-Plunnecke (1995) added a parameter representing guessing or response biases that determines behavior when neither the intentional or unintentional memory process drives responses. By separately accounting for response biases, this extended model provides relatively more pure estimates of both types of memory. Hütter, Sweldens, Stahl, Unkelbach, and Klauer (2012) and Hütter and Sweldens (2013) used a similar approach to examine the extent to which evaluative conditioning depends on contingency awareness. They operationalized memory for stimulus pairings as the relatively more intentional process, the conditioned attitude resulting from stimulus pairings as the relatively less intentional process, and accounted for response biases in the absence of either of these influences. In doing so, they demonstrated that evaluative conditioning can create attitudes even when participants are not aware of stimulus contingencies.

Though Jacoby and colleagues' process dissociation models were developed within the domain of cognitive psychology, and have primarily been applied to the study of memory, the process dissociation procedure has also been successfully applied to a variety of topics within social psychology. For example, social psychologists often distinguish between attitudes that are measured explicitly versus implicitly: Explicit attitudes are assessed directly, through self-report measures, whereas implicit attitudes are inferred indirectly, often from the speed or accuracy of responses rather than the contents of responses, *per se*. Moreover, implicit measures often obscure what is being measured to a greater degree than do explicit measures, and responses on implicit measures are more difficult to strategically feign than are responses on explicit measures. Consequently, implicit attitude measures were initially assumed to assess qualitatively distinct processes than were assessed by explicit attitude measures (Greenwald & Banaji, 1995; Wilson, Lindsey, & Schooler, 2000). Implicit measures were thought to assess automatic or unconscious attitudes, whereas explicit measures were thought to assess conscious or deliberately controlled attitudes. In retrospect, this assumption clearly mirrors the conflation of task with process in recognition memory that Jacoby (1991) addressed. Subsequent social psychological research using the process dissociation procedure had similar results, demonstrating that responses on implicit measures are influenced by both relatively automatic (e.g., stimulus-driven behavioral impulses) and controlled (e.g., intentional responding) processes.

Within social psychology, Jacoby's (1991) control-dominant model has been applied to a wide variety of implicit measures of stereotyping and prejudice in order to reveal the joint contributions of multiple processes, including the weapons identification task (Conrey et al., 2005; Payne, 2001), the shooter task (Plant & Peruche, 2005), and the IAT (Payne & Bishara, 2009). Additionally, the process dissociation procedure has been used by social psychologists to identify and measure different processes in a variety of domains, such as moral reasoning (Conway & Gawronski, 2013; Gawronski, Armstrong, Conway, Friesdorf, & Hütter, 2017), processing fluency (Fazio, Brashier, Payne, & Marsh, 2015; Unkelbach & Stahl, 2009) and judgment and decision making (Damian & Sherman, 2013; Ferreira, Garcia-Marques, Sherman, & Sherman, 2006). For example, Ferreira et al. (2006) tested the assumption that logical reasoning and heuristic decision making are opposite poles on a processing continuum, such that increasing the use of one form of processing necessarily decreases the use of the other (e.g., Petty & Cacioppo, 1986). To do so, they created a series of decisions in which logical and heuristic processing would produce the same judgment in some cases, but produce conflicting judgments in other cases. They also varied the instructions given to participants in ways that should be expected to increase reliance on either logical (e.g., behave like a scientist) or heuristic (e.g., use your intuition) reasoning. By applying the process dissociation model to participants' responses across a series of conditions, Ferreira et al. (2006) demonstrated that logical and heuristic reasoning make independent and dissociable contributions to judgments. As such, the process dissociation procedure provided a more nuanced understanding of the relationship between two processes already assumed to drive responses in a given domain, and provided a means to measure those processes separately (but see Klauer, Dittrich, Scholtes, & Voss, 2015).

Additional processes have been incorporated into conceptual extensions of Jacoby's (1991) model, which, in turn, have expanded process-level understanding of a variety of behaviors. For example, Sherman and colleagues' quadruple process model (Quad model: Conrey et al., 2005; Sherman et al., 2008) builds upon the basic assumption that a relatively unintentional process (i.e., activated mental associations) and a relatively intentional process (i.e., detection of appropriate responses) jointly drive responses on implicit measures. Additionally, the Quad model accounts for guessing or response bias (e.g., Buchner et al., 1995), and includes a process that intervenes to overcome the behavioral responses activated by mental associations when they conflict with the detected correct response.

The structure of the Quad model is depicted as a processing tree in Fig. 2. Using as an example an IAT that presents stimuli representing the ingroup and outgroup along with positive and negative words, a stimulus representing the outgroup might activate negative mental associations (AC), which produce an incorrect response tendency in the incompatible condition (i.e., when "outgroup" and "good" share a response key). In contrast, accuracy-oriented detection (D) always produces a correct response tendency (i.e., to press the task-appropriate button). To the extent that biasing associations are overcome (OB), detection will drive a correct response. Thus, the likelihood of one path toward a correct response on this trial type (an outgroup stimulus in the incompatible condition) can be represented by an equation reflecting the activation of these three processes: $AC \times D \times OB$. However, to the extent that the overcoming bias process fails ($1 - OB$), activated negative associations

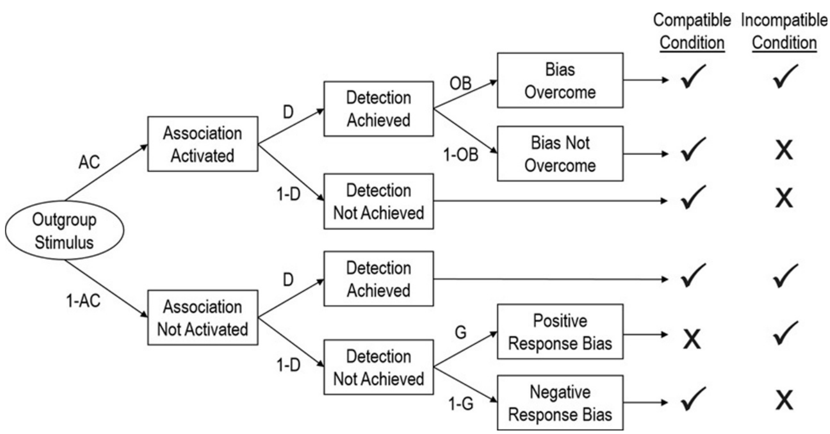

Fig. 2 A portion of Conrey et al.'s (2005) quadruple process (Quad) model. Oval represents a test stimulus and rectangles represent latent cognitive processes hypothesized to influence responses to the stimulus. Parameters with lines leading to them are conditional upon all preceding parameters. The table on the right side of the figure depicts correct (✓) and incorrect (X) responses as a function of process pattern and trial type.

will drive an incorrect response on this trial type, which can be represented by the equation: $AC \times D \times (1 - OB)$. Importantly, these are not the only possible combinations of processes through which responses can be made on a task like the IAT; instead, the Quad model posits that multiple combinations of processes can drive responses. For example, a correct response to an outgroup stimulus on an incompatible trial can also result from no associations activated and detection succeeding, $(1 - AC) \times D$, or from no associations activated, detection failing, and a positivity bias driving the response, $(1 - AC) \times (1 - D) \times G$. Similarly, an incorrect response to this trial type can also result from activated associations and detection failing, $AC \times (1 - D)$, or from no associations activated, detection failing, and a negativity bias driving the response, $(1 - AC) \times (1 - D) \times (1 - G)$. Taken together, the likelihood of making a correct response to an outgroup stimulus on an incompatible trial can be represented by the sum of these three pathways: $[AC \times D \times OB] + [(1 - AC) \times D] + [(1 - AC) \times (1 - D) \times G]$; and the likelihood of making an incorrect response can be represented by the sum of these three pathways: $[AC \times D \times (1 - OB)] + [AC \times (1 - D)] + [(1 - AC) \times (1 - D) \times (1 - G)]$.

The Quad model has been successfully applied to a variety of implicit measures, including the IAT, priming tasks (Conrey et al., 2005), and the Go/No-Go association task (Gonsalkorale, von Hippel, Sherman, & Klauer, 2009; Ramos et al., 2015). One way in which the Quad model has been instrumental is by expanding understanding of implicit attitude variability and malleability. A process-pure interpretation of implicit measures can only attribute variations in implicit attitudes to variations in mental associations. In contrast to this perspective, research using the Quad model has demonstrated a number of cases in which other non-associative processes contribute to implicit attitude variability. For example, older people demonstrate greater implicit racial bias than younger people, but biased mental associations do not vary with age. Instead, the ability to inhibit the influence of associations decreases with age, and can account for age differences in IAT performance (Gonsalkorale, Sherman, & Klauer, 2009, 2014). Thus, research using the Quad model has provided a more nuanced understanding of the combinations of processes that contribute to variations in implicit task performance.

This section of the chapter is not meant to provide a complete list of MPTs that have been applied to response conflict tasks, or even a comprehensive discussion of the MPTs described here. MPTs have been used to investigate a wide variety of topics within cognitive and social psychology, such as source monitoring (Batchelder & Riefer, 1990; Batchelder, Riefer, & Hu, 1994; Bayen, Murnane, & Erdfelder, 1996; Klauer & Ehrenberg, 2005; Klauer & Meiser, 2000), social categorization (Klauer & Wegener, 1998), illusory truth (Begg, Anas, & Farinacci, 1992), hindsight bias (Erdfelder & Buchner, 1998), gender bias (Buchner & Wippich, 1996), age-related false memory (Jacoby, Bishara, Hessels, & Toth, 2005), stereotype formation (Meiser & Hewstone, 2004), and propositional reasoning (Klauer & Oberauer, 1995; Oberauer, 2006), among many others. Additionally, a number of MPTs have also been applied to various implicit measures, such as the extrinsic affective Simon task (Stahl & Degner, 2007), affect misattribution procedure (Payne, Hall, Cameron, & Bishara, 2010), stereotype misperception task (Krieglmeyer & Sherman, 2012), and the IAT (Meissner & Rothermund, 2013).[c] In the following sections, we highlight how MPTs have been used—and can be further used—to build bridges between cognitive and social psychology.

3. Multinomial processing trees and the future of cognitive and social psychology

MPTs have made many important contributions to cognitive and social psychology. In contrast to verbal models that can be subjectively interpreted to the point of unfalsifiability, MPTs represent precise specifications of theory that can be evaluated quantitatively. Moreover, because they resolve the confound inherent in equating tasks with processes, MPTs have advanced process-level understanding of many tasks that are used widely both within and beyond the domains of cognitive and social psychology.

Despite these advances, process-pure interpretations of response conflict tasks remain dominant across both cognitive and social psychology (e.g., Bluemke et al., 2017; Snyder, Miyake, & Hankin, 2015). The persistence of the process-pure perspective will ultimately limit scientific progress because it not only obscures the influence of many important processes but also, in many cases, simply misrepresents reality. One of our goals in writing this chapter is to highlight some of the many issues that have been resolved using MPTs in order to inspire researchers to apply MPTs to new questions. We outline some of these issues below, but there are certainly more.

[c] The extent to which any of the experimental paradigms cited here fit cleanly within our definition of response conflict tasks can be debated. However, rather than focusing on methodological nuance, we err on the side of providing the interested reader more rather than less information.

3.1 Building bridges

MPTs can be helpful in building bridges between cognitive and social psychology. Jacoby's (1991) process dissociation procedure is an excellent example of a flexible model that has been profitably applied across content domains. As we have discussed above, the process dissociation procedure and its variants have been used to investigate diverse research topics such as memory, executive functioning, evaluative conditioning, judgment and decision-making, moral reasoning, and implicit attitudes. Though the meaning of the intentional and unintentional processes may vary across topics, Jacoby's (1991) model provides a common framework that spans content (Payne, 2005). For example, Sherman, Groom, Ehrenberg, and Klauer (2003) investigated a question at the intersection of cognitive and social psychology by applying a modified version of Jacoby's (1991) model to a task designed to assess false memory for stereotype-related information. In doing so, they demonstrated that the availability of cognitive resources had no influence on the extents of familiarity or recollection for stereotype-inconsistent information. In contrast, when cognitive resources were impaired, memory for stereotype-consistent information was influenced to a greater extent by familiarity and to a lesser extent by recollection.

3.2 Advances to date

In addition to building bridges between disciplines, MPTs also have been used to establish relationships among different types of cognitive processes. For example, in the anti-saccade task (Hallett, 1978), participants must overcome the reflexive impulse to look at a visual target appearing in their peripheral vision and, instead, attend to a target that has appeared in the opposite direction. This task is widely used among cognitive psychologists to measure inhibition. In contrast, social psychologists have routinely employed sequential priming-type tasks in order measure associations while minimizing the influence of control-oriented processes, such as inhibition. However, Payne (2005) found that process-dissociation estimates of intentional responding from two sequential priming variants—the weapons identification task (Payne, 2001) and an evaluative priming task (Fazio, Jackson, Dunton, & Williams, 1995)—were related to performance on the anti-saccade task, which suggests that a common process (e.g., inhibition) underlies responses on all three of these tasks. Similarly, Buchner, Erdfelder, Steffens, and Martensen (1997) applied an MPT to a recognition memory task and a source monitoring task and demonstrated that both tasks share an underlying process. Neither of these examples is intended to suggest that any one of these tasks is a pure measure of any given process, but rather to draw connections between tasks by highlighting common underlying processes.

Other research has used MPTs to sharpen the conclusions drawn from neuropsychological work. Specifically, the ability of MPTs to isolate cognitive processes allows for those processes to be localized in brain regions with greater precision than aggregate task performance can provide. For example, Beer et al. (2008) found that Quad model estimates of stimulus detection from an IAT are related to brain areas associated with conflict monitoring, and estimates of White-pleasant and Black-unpleasant associations are related to activity in brain areas associated with processing of positive and negative information. Importantly, these brain areas also correlated with aggregate task performance on the IAT, but Quad modeling provided more nuanced understanding by connecting specific processes with specific brain regions. Similarly, Amodio, Devine, and Harmon-Jones (2008) and Amodio et al. (2004) found that process-dissociation estimates of intentional responding from a weapons identification task are related to activity in brain areas associated with conflict monitoring.

MPTs are also well-suited to advance both theory and methodology by resolving discrepancies among measures. Different measures that assess the same construct or attitude object sometimes correlate strongly (e.g., Cunningham, Preacher, & Banaji, 2001), but sometimes do not (e.g., Bar-Anan & Nosek, 2014; Bosson, Swann, & Pennebaker, 2000; Nosek & Banaji, 2001). Nosek and Banaji (2001) argued that the lack of correspondence between the IAT and Go/No-Go Association Task (and among implicit measures more generally) may be due to low reliability. To be sure, implicit measures are generally less reliable than explicit measures (e.g., Gawronski, Morrison, Phills, & Galdi, 2017), but this may be only part of the issue. Different measures also have different response demands. For instance, the Go/No-Go Association Task requires that some responses be withheld, but the IAT has no such requirement. Procedural demands necessarily determine which processes influence task performance (Payne, Burkley, & Stokes, 2008). MPTs can help to isolate processes of interest from other (e.g., method-specific) processes and, in doing so, may increase correspondence across measures. Indeed, Payne (2005) demonstrated that aggregate task performance (i.e., response accuracy) on a weapons identification task was unrelated to response accuracy on an evaluative priming task, even though both tasks are assumed to reflect the same construct (i.e., race-related mental associations). However, process-dissociation estimates of controlled responding generated from the weapons identification task were related to estimates of controlled responding generated from the priming task. Similarly, process-dissociation estimates of mental associations generated from the weapons identification task were related to estimates of associations generated from the priming task. Thus, MPTs helped to establish relationships between conceptually-similar measures that were otherwise obscured by aggregate task performance. Such an approach could be useful for establishing both similarities and differences among tasks, which, in turn, could ultimately help to develop a taxonomy of implicit measures similar to the executive function framework that exists within cognitive psychology (e.g., Miyake et al., 2000). Using the processes described by the Quad model (Conrey et al., 2005) as an example of what such a taxonomy could look like, one category might consist of implicit measures that rely more heavily on the detection of appropriate responses, whereas another category might consist of implicit measures that rely more heavily on the inhibition of mental associations that conflict with appropriate responses. This will be a fruitful direction for future research.

In addition to helping to resolve discrepancies among measures, the framework formalized in the MPT approach has initiated the development of new methodologies. For example, when Jacoby (1991) initially proposed the process dissociation procedure, he elaborated on an existing recognition memory task in order to create conditions under which recollection and familiarity sometimes produce the same response but sometimes produce conflicting responses. In contrast, Krieglmeyer and Sherman (2012) designed the Stereotype Misperception Task and its accompanying MPT to specifically test their theoretical assumptions about the interplay between stereotype activation and application. Of course, theory and method are often developed synergistically: Theories can enable the development of new methods, and methods can generate previously-inconceivable data, which, in turn, inspire new theories (Greenwald, 2012). Because MPTs require the precise mathematical specification of the theorized relationships among processes, they can be thought of as the methodological embodiment of theory. Thus, they are especially well-suited to advance both method and theory.

3.3 Advances to come

MPTs have been used extensively within cognitive psychology to study memory but, perhaps surprisingly, they are not used as often to study other mental phenomena. MPTs are readily applied to response conflict tasks, and cognitive psychologists have for decades been using a wide variety of response conflict tasks to measure executive functions such as inhibiting, shifting, and updating (e.g., Miyake et al., 2000). However, to date, MPTs have been used only sparsely to investigate executive functions. For example, the Stroop (1935) task is generally interpreted as a measure of inhibition, and Lindsay and Jacoby (1994) applied a version of the procession dissociation model to it to disentangle the contributions of relatively more and less intentional processes. As another example, Oberauer, Weidenfeld, and Hörnig (2006) developed an MPT to reveal the contributions of multiple processes to working memory capacity. This paucity of MPT research in the domain of executive function may in part reflect cognitive psychologists' focus on response latency to the relative exclusion of response accuracy. The validity of latency versus accuracy is debatable; both aspects of responses likely provide insight into mental contents (Klauer & Voss, 2008). However, latency-based scoring methods typically depend on assumptions of process purity—the limitations of which are well known. In contrast, analyzing response accuracy in an MPT framework would require no modification to existing executive function experimental paradigms, and could easily be done in parallel with latency-based scoring methods. The low cost and high potential benefit of applying MPTs to the study of executive function suggest that this could be a worthwhile direction for future research.

In addition to the examples described above, it is easy to conceptualize other contexts and conditions in which MPTs can fruitfully disentangle the contributions of multiple processes to responses on measures of executive functions. One possible candidate is the flanker task (Eriksen & Eriksen, 1974), which requires participants to respond to a target character (e.g., H) that is presented either surrounded by response-compatible characters (e.g., HHHHH) or by response-incompatible characters (e.g., KKHKK). The difference in how quickly or accurately participants can respond to response-compatible versus -incompatible trials is generally interpreted as an index of inhibition. Unfortunately, the flanker task often demonstrates poor retest reliability (Wöstmann et al., 2013). One possible explanation for the low reliability of the flanker task is that the cognitive ability of inhibition is highly variable (e.g., because of depletion, circadian rhythms, etc.). However, tasks that measure inhibiting necessarily require the inhibition of *something* (Friedman & Miyake, 2004). Thus, another possible explanation for the low reliability of the flanker task is that inhibition is relatively stable but the impulses activated by flanker stimuli are highly variable (e.g., because of individual differences, saliency of information, etc.). MPTs are well-suited to test competing hypotheses such as these in the context of the flanker task and others.

In contrast to the extensive use of MPTs by cognitive psychologists dedicated primarily to study memory, social psychologists have applied MPTs to a relatively wider variety of topics. Jacoby's (1991) process dissociation procedure, in particular, has arguably had an outsized influence among MPTs on the field of social psychology. Since Payne (2001) adapted Jacoby's memory model to investigate implicit stereotyping, social cognitive researchers have applied MPTs to such diverse topics as prejudice (Conrey et al., 2005), moral reasoning (Conway & Gawronski, 2013), processing fluency (Fazio et al., 2015) and judgment and decision making (Damian & Sherman, 2013). Because MPTs map easily onto the dual-process framework of automaticity and control, they are readily applied to the many topics in social psychology that are rooted in this dual-process framework. That said, there are many more dual-process theories within social psychology that have not yet been formalized as MPTs, spanning a wide variety of domains, including persuasion (e.g., Chaiken, 1987; Petty & Cacioppo, 1986), attitude–behavior relations (e.g., Fazio, 1990), and impression formation (e.g., Brewer, 1988; Fiske & Neuberg, 1990; Gilbert, 1991; Trope, 1986), among others. These and other dual-process theories are fertile ground for future researchers to formalize the contributions of multiple processes quantitatively rather than verbally. In doing so, MPTs are poised to advance social psychological theory. For example, MPTs can be especially useful in selecting the best among competing theories. In contrast to traditional theory-selection approaches, which often involves an escalating war of experiments between research camps purported to provide the "critical test" of one theory over another (e.g., the long-running battle between dissonance and self-perception theories: Fazio, Zanna, & Cooper, 1977), competing theories instantiated as MPTs can be applied to the same data and the victor determined quantitatively through model-selection indices such as Akaike or Bayesian Information Criterion (AIC, BIC, respectively).

3.4 Operating principles versus conditions

MPTs already have helped to advance theory in several important ways. For example, many models were initially inspired by and based on dual-process frameworks of automaticity and control (e.g., Jacoby, 1991; Payne, 2001).

This distinction was based on the assumption that automatic processes are initiated unintentionally, operate efficiently, cannot be terminated once started, and operate outside of conscious awareness, whereas controlled processes are initiated intentionally, depend on cognitive resources, can be stopped voluntarily, and operate within conscious awareness (e.g., Bargh, 1999). Based on this distinction, the term "automatic" has largely become a synonym for associative processes, and the term "control" a synonym for executive function-type processes. However, a large body of research using MPTs has made it clear that mapping processes onto the framework of automaticity and control confounds the critical distinction between operating principles and operating conditions (Gawronski & Bodenhausen, 2009; Sherman, 2006), particularly when separate tasks are used to measure automatic versus control processes (e.g., free recall versus stem-completion memory tasks; implicit versus explicit measures). Operating principles refer to the qualitative nature of the cognitive processes that translate inputs into outputs. That is, operating principles describe what the process does (e.g., inhibition). In contrast, operating conditions refer to the conditions under which a given process operates (e.g., when motivation and processing capacity are high; Moors & De Houwer, 2006). The overcoming bias parameter of the Quad model (Conrey et al., 2005) provides an illustrative example of the importance of separately considering operating principles and operating conditions. The primary operating principle of overcoming bias is that it inhibits the influence of mental associations on behavioral responses. One operating condition of overcoming bias is that it influences responses within relatively short response latencies (reflecting the task demands of the IAT), so it may be categorized as relatively efficient. Consequently, from the perspective of the traditional framework of automaticity and control, overcoming bias would be classified as a controlled process based on its operating principles (i.e., it inhibits associations) but would be classified as an automatic process based on its operating conditions (i.e., it is efficient; Rivers, Calanchini, & Sherman, 2016). Such findings call into question the utility of making categorical distinctions between automatic and controlled processes and, as such, emphasize instead the qualitative, or algorithmic, nature of cognitive processes (Sherman, Krieglmeyer, & Calanchini, 2014).

3.5 Choosing a model

Given the variety of MPTs in use across cognitive and social psychology, researchers may wonder: Which one is best? The answer to this question is, in part, theoretical and, in part, analytical. For example, researchers interested in the influence of inhibitory processes will find an MPT that includes inhibition (e.g., Conrey et al., 2005; Jacoby et al., 2005) to be more useful than one that does not. That said, MPTs can be compared quantitatively to evaluate which provides best fit to a given data set. For example, Bishara and Payne (2009) applied five different MPTs to data from a weapons identification task and calculated AIC and BIC as model-selection indices to determine which MPT best describes data from this task. In this way, MPTs can help to advance both theory (i.e., validating or falsifying the assumptions articulated by the model) and methodology (i.e., which model provides best fit to data from a given task) by providing rigorous quantitative standards for both model fit and selection.

3.6 Limitations of multinomial processing trees

Despite the many benefits of MPTs we have extolled in this chapter, they are by no means a panacea. One limitation of MPTs is that they are based on categorical response data and often analyzed as a function of accuracy (e.g., Conrey et al., 2005). However, when mental resources are unconstrained by procedural demands, such as time pressure or cognitive load, people generally make relatively few mistakes on response conflict tasks. As such, models based on individual-level data are necessarily limited in terms of reliability and statistical power. These problems can be overcome in a number of ways. Implementing a response deadline can increase the relative proportion of errors, and increasing the number of trials can increase the absolute number of errors (see Meissner & Rothermund, 2013 for an implementation of both of these strategies). However, such solutions come with costs: Shorter response deadlines minimize the influence of some processes and perhaps differentially constrain the influence of some forms of control (Fazio, Sanbonmatsu, Powell, & Kardes, 1986; Nadarevic & Erdfelder, 2011). Similarly, increased trials may lead to depletion (Govorun & Payne, 2006), which in turn may differentially impact resource-dependent cognitive processes relative to more efficient cognitive processes. Thus, though both of these solutions can increase the statistical reliability of MPT estimates, they can also contaminate estimates of the processes that are involved under different operating conditions and, therefore, may not be ideal for all research applications. Alternately, data from multiple individuals can be aggregated to increase reliability, but this strategy is only useful for group-level or between-groups analyses. Another solution is to embed the model within a hierarchical framework, which retains the reliability benefits of group-level analyses while accommodating individual-level heterogeneity (Klauer, 2006, 2010; also see Burke, 2015).

A more philosophical limitation of models based on accuracy data is that, due to the relative infrequency of errors on most response-conflict tasks, errors may arguably provide less insight into psychological processes than do other aspects of responses (e.g., latencies). This point is debatable, of course. However, whether or not they provide less insight, error data likely provide insight into different psychological processes than do latency data. For example, for research questions related to judgment errors (e.g., police officers' decisions to shoot or not shoot suspects), response accuracy likely provides relevant information. In contrast, for research questions related to judgment speed (e.g., how quickly officers can discern whether the object a suspect is holding is a weapon), response latency may be more relevant. Thus, both accuracy and latency reflect important psychological processes (e.g., Pleskac, Cesario, & Johnson, 2018).

Very recently, Klauer and Kellen (2018) and Heck and Erdfelder (2016) introduced methods to incorporate response latencies into MPTs. Such RT-MPTs resolve the need to choose between response accuracy and latency. Moreover, as an added bonus, RT-MPTs by definition rely on more data than do traditional MPTs, so they tend to generate more precise parameter estimates. Thus, RT-MPTs are very well positioned to make important contributions to both the cognitive and social psychological literatures.

3.7 Alternatives to multinomial processing trees

In this chapter we have focused on MPTs as they apply to response conflict tasks in cognitive and social psychology. However, MPTs are not the only analytic option available to researchers interested in formally quantifying the contributions of multiple cognitive processes. In addition to MPTs, several other classes of formal models have been profitably applied to response conflict tasks within cognitive and social psychology, including signal detection (e.g., Correll, Park, Judd, & Wittenbrink, 2002; Nosek & Banaji, 2001; Yonelinas, Dobbins, Szymanski, Dhaliwal, & King, 1996), diffusion models (e.g., Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007; Ratcliff, Thapar, Gomez, & McKoon, 2004; Ulrich, Schröter, Leuthold, & Birngruber, 2015; White, Ratcliff, & Starns, 2011), and computational models (e.g., Cohen, Dunbar, & McClelland, 1990; Gilbert & Shallice, 2002; Logan & Cowan, 1984).

3.8 Recommended readings

The purpose of this chapter is to review the origins and applications of MPTs to response conflict tasks by cognitive and social psychologists, and highlight their utility for cross-disciplinary theoretical and methodological advancement. However, due to constraints of space and scope, this chapter is not meant to offer an exhaustive discussion of all relevant models. Interested readers should seek out the primary research articles cited here for more details. In addition to the original articles that have been cited throughout this chapter, a number of thorough reviews exist. Riefer and Batchelder (1988) is the seminal paper on MPTs in psychology. Batchelder and Riefer (1999) and Erdfelder et al. (2009) both provide excellent reviews of multinomial model theory and their applications within cognitive psychology. Payne and Bishara (2009), Sherman, Klauer, and Allen (2010), Klauer, Stahl, and Voss (2012), and Hütter and Klauer (2016) provide a variety of perspectives on process dissociation and multinomial models in social psychology. For researchers interested in applying MPTs to their own data, Stahl and Klauer (2007) and Moshagen (2010) offer stand-alone software packages, and Singmann and Kellen (2013) and Heck, Arnold, and Arnold (2018) offer R packages for this purpose.

Acknowledgments

Preparation of this manuscript was partially supported by a University of California, Davis Dissertation-Year Fellowship and a postdoctoral research fellowship from the Alexander von Humboldt Fellowship to J.C., and by an Anneliese Maier Research Award from the Alexander von Humboldt Foundation to J.W.S. The funders had no role in the preparation of the manuscript.

References

Amodio, D. M., Devine, P. G., & Harmon-Jones, E. (2008). Individual differences in the regulation of intergroup bias: The role of conflict monitoring and neural signals for control. *Journal of Personality and Social Psychology*, *94*, 60–74.

Amodio, D. M., Harmon-Jones, E., Devine, P. G., Curtin, J. J., Hartley, S. L., & Covert, A. E. (2004). Neural signals for the detection of unintentional race bias. *Psychological Science*, *15*, 88–93.

Bar-Anan, Y., & Nosek, B. A. (2014). A comparative investigation of seven indirect attitude measures. *Behavior Research Methods*, *46*(3), 668–688.

Bargh, J. A. (1999). The cognitive monster: The case against the controllability of automatic stereotype effects. In S. Chaiken & Y. Trope (Eds.), *Dual-process theories in social psychology* (pp. 361–382). New York: Guilford Press.

Batchelder, W. H., & Riefer, D. M. (1990). Multinomial processing models of source monitoring. *Psychological Review*, *97*, 548–564.

Batchelder, W. H., & Riefer, D. M. (1999). Theoretical and empirical review of multinomial process tree modeling. *Psychonomic Bulletin & Review*, *6*(1), 57–86.

Batchelder, W. H., Riefer, D. M., & Hu, X. (1994). Measuring memory factors in source monitoring. *Psychological Review*, *101*, 172–176.

Bayen, U. J., Murnane, K., & Erdfelder, E. (1996). Source discrimination, item detection, and multinomial models of source monitoring. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*, 197–215.

Beer, J. S., Stallen, M., Lombardo, M. V., Gonsalkorale, K., Cunningham, W. A., & Sherman, J. W. (2008). The quadruple process model approach to examining the neural underpinnings of prejudice. *NeuroImage*, *43*(4), 775–783.

Begg, I. M., Anas, A., & Farinacci, S. (1992). Dissociation of processes in belief: Source recollection, statement familiarity, and the illusion of truth. *Journal of Experimental Psychology: General*, *121*(4), 446–458.

Bishara, A. J., & Payne, B. K. (2009). Multinomial process tree models of control and automaticity in weapon misidentification. *Journal of Experimental Social Psychology*, *45*(3), 524–534.

Bluemke, M., Crombach, A., Hecker, T., Schalinski, I., Elbert, T., & Weierstall, R. (2017). Is the implicit association test for aggressive attitudes a measure for attraction to violence or traumatization? *Zeitschrift für Psychologie*, *225*(1), 54–63.

Bosson, J. K., Swann, W. B., Jr., & Pennebaker, J. W. (2000). Stalking the perfect measure of implicit self-esteem: The blind men and the elephant revisited? *Journal of Personality and Social Psychology*, *79*(4), 631.

Brewer, M. B. (1988). A dual process model of impression formation. In T. K. Srull & R. S. Wyer (Eds.), *Advances in social cognition: Vol. 1* (pp. 1–36). Hillsdale, NJ: Erlbaum.

Buchner, A., Erdfelder, E., Steffens, M. C., & Martensen, H. (1997). The nature of memory processes underlying recognition judgments in the process dissociation procedure. *Memory & Cognition*, *25*, 508–517.

Buchner, A., Erdfelder, E., & Vaterrodt-Plunnecke, B. (1995). Toward unbiased measurement of conscious and unconscious memory processes within the process dissociation framework. *Journal of Experimental Psychology: General*, *124*, 137–160.

Buchner, A., & Wippich, W. (1996). Unconscious gender bias in fame judgments? *Consciousness and Cognition*, *5*(1–2), 197–220.

Burke, C. T. (2015). Process dissociation models in racial bias research: Updating the analytic method and integrating with signal detection approaches. *Group Processes & Intergroup Relations*, *18*(3), 402–434.

Chaiken, S. (1987). The heuristic model of persuasion. In M. P. Zanna, J. M. Olson, & C. P. Herman (Eds.), *Social influence: The Ontario symposium: Vol. 5* (pp. 3–39). Hillsdale, NJ: Erlbaum.

Cohen, J. D., Dunbar, K., & McClelland, J. L. (1990). On the control of automatic processes: A parallel distributed processing account of the Stroop effect. *Psychological Review*, *97*(3), 332–361.

Conrey, F. R., Sherman, J. W., Gawronski, B., Hugenberg, K., & Groom, C. J. (2005). Separating multiple processes in implicit social cognition: The quad model of implicit task performance. *Journal of Personality and Social Psychology*, *89*(4), 469–487.

Conway, P., & Gawronski, B. (2013). Deontological and utilitarian inclinations in moral decision making: A process dissociation approach. *Journal of Personality and Social Psychology*, *104*(2), 216.

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*(6), 1314–1329.

Cunningham, W. A., Preacher, K. J., & Banaji, M. R. (2001). Implicit attitude measures: Consistency, stability, and convergent validity. *Psychological Science*, *12*(2), 163–170.

Damian, R. I., & Sherman, J. W. (2013). A process-dissociation examination of the cognitive processes underlying unconscious thought. *Journal of Experimental Social Psychology*, *49*, 228–237.

Donders, F. C. (1969). On the speed of mental processes. *Acta Psychologica*, *30*, 412–431.
Erdfelder, E., Auer, T. S., Hilbig, B. E., Assfalg, A., Moshagen, M., & Nadarevic, L. (2009). Multinomial processing tree models. A review of the literature. *Journal of Psychology*, *217*, 108–124.
Erdfelder, E., & Buchner, A. (1998). Decomposing the hindsight bias: A multinomial processing tree model for separating recollection and reconstruction in hindsight. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*(2), 387–414.
Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics*, *16*(1), 143–149.
Fazio, R. H. (1990). Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework. *Advances in Experimental Social Psychology*, *23*, 75–109.
Fazio, L. K., Brashier, N. M., Payne, B. K., & Marsh, E. J. (2015). Knowledge does not protect against illusory truth. *Journal of Experimental Psychology: General*, *144*(5), 993–1002.
Fazio, R. H., Jackson, J. R., Dunton, B. C., & Williams, C. J. (1995). Variability in automatic activation as an unobtrusive measure of racial attitudes: A bona fide pipeline? *Journal of Personality and Social Psychology*, *69*(6), 1013–1027.
Fazio, R. H., Sanbonmatsu, D. M., Powell, M. C., & Kardes, F. R. (1986). On the automatic activation of attitudes. *Journal of Personality and Social Psychology*, *50*(2), 229–238.
Fazio, R. H., Zanna, M. P., & Cooper, J. (1977). Dissonance and self-perception: An integrative view of each theory's proper domain of application. *Journal of Experimental Social Psychology*, *13*(5), 464–479.
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*(5), 797–813.
Fiske, S. T., & Neuberg, S. L. (1990). A continuum of impression formation, from category-based to individuating processes: Influences of information and motivation on attention and interpretation. *Advances in Experimental Social Psychology*, *23*, 1–74.
Friedman, N. P., & Miyake, A. (2004). The relations among inhibition and interference control functions: A latent-variable analysis. *Journal of Experimental Psychology: General*, *133*(1), 101–135.
Gawronski, B., Armstrong, J., Conway, P., Friesdorf, R., & Hütter, M. (2017). Consequences, norms, and generalized inaction in moral dilemmas: The CNI model of moral decision-making. *Journal of Personality and Social Psychology*, *113*(3), 343–376.
Gawronski, B., & Bodenhausen, G. V. (2009). Operating principles versus operating conditions in the distinction between associative and propositional processes. *Behavioral and Brain Sciences*, *32*(2), 207–208.
Gawronski, B., Morrison, M., Phills, C. E., & Galdi, S. (2017). Temporal stability of implicit and explicit measures: A longitudinal analysis. *Personality and Social Psychology Bulletin*, *43*(3), 300–312.
Gilbert, D. T. (1991). How mental systems believe. *American Psychologist*, *46*, 107–119.
Gilbert, S. J., & Shallice, T. (2002). Task switching: A PDP model. *Cognitive Psychology*, *44*(3), 297–337.
Gonsalkorale, K., Sherman, J. W., & Klauer, K. C. (2009). Aging and prejudice: Diminished regulation of automatic race bias among older adults. *Journal of Experimental Social Psychology*, *45*(2), 410–414.
Gonsalkorale, K., Sherman, J. W., & Klauer, K. C. (2014). Measures of implicit attitudes may conceal differences in implicit associations: The case of antiaging bias. *Social Psychological and Personality Science*, *5*(3), 271–278.
Gonsalkorale, K., von Hippel, W., Sherman, J. W., & Klauer, K. C. (2009). Bias and regulation of bias in intergroup interactions: Implicit attitudes toward Muslims and interaction quality. *Journal of Experimental Social Psychology*, *45*(1), 161–166.

Govorun, O., & Payne, B. K. (2006). Ego-depletion and prejudice: Separating automatic and controlled components. *Social Cognition*, *24*(2), 111–136.
Greenwald, A. G. (2012). There is nothing so theoretical as a good method. *Perspectives on Psychological Science*, 7(2), 99–108.
Greenwald, A. G., & Banaji, M. R. (1995). Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, *102*(1), 4–27.
Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology*, *74*(6), 1464–1480.
Hallett, P. (1978). Primary and secondary saccades to goals defined by instructions. *Vision Research*, *18*, 1279–1296.
Heck, D. W., Arnold, N. R., & Arnold, D. (2018). TreeBUGS: An R package for hierarchical multinomial-processing-tree modeling. *Behavior Research Methods*, (1), 1–21.
Heck, D. W., & Erdfelder, E. (2016). Extending multinomial processing tree models to measure the relative speed of cognitive processes. *Psychonomic Bulletin & Review*, *23*(5), 1440–1465.
Hütter, M., & Klauer, K. C. (2016). Applying processing trees in social psychology. *European Review of Social Psychology*, *27*(1), 116–159.
Hütter, M., & Sweldens, S. (2013). Implicit misattribution of evaluative responses: Contingency-unaware evaluative conditioning requires simultaneous stimulus presentations. *Journal of Experimental Psychology: General*, *142*(3), 638.
Hütter, M., Sweldens, S., Stahl, C., Unkelbach, C., & Klauer, K. C. (2012). Dissociating contingency awareness and conditioned attitudes: Evidence of contingency-unaware evaluative conditioning. *Journal of Experimental Psychology: General*, *141*(3), 539.
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*(1), 3.
Jacoby, L. L., Bishara, A. J., Hessels, S., & Toth, J. P. (2005). Aging, subjective experience, and cognitive control: Dramatic false remembering by older adults. *Journal of Experimental Psychology: General*, *134*(2), 131–148.
Klauer, K. C. (2006). Hierarchical multinomial processing tree models: A latent-class approach. *Psychometrika*, *71*(1), 7–31.
Klauer, K. C. (2010). Hierarchical multinomial processing tree models: A latent-trait approach. *Psychometrika*, *75*(1), 70–98.
Klauer, K. C., Dittrich, K., Scholtes, C., & Voss, A. (2015). The invariance assumption in process-dissociation models: An evaluation across three domains. *Journal of Experimental Psychology: General*, *144*(1), 198–221.
Klauer, K. C., & Ehrenberg, K. (2005). Social categorization and fit detection under cognitive load: Efficient or effortful? *European Journal of Social Psychology*, *35*(4), 493–516.
Klauer, K. C., & Kellen, D. (2018). RT-MPTs: Process models for response-time distributions based on multinomial processing trees with applications to recognition memory. *Journal of Mathematical Psychology*, *82*, 111–130.
Klauer, K. C., & Meiser, T. (2000). A source-monitoring analysis of illusory correlations. *Personality and Social Psychology Bulletin*, *26*(9), 1074–1093.
Klauer, K. C., & Oberauer, K. (1995). Testing the mental model theory of propositional reasoning. *The Quarterly Journal of Experimental Psychology*, *48*(3), 671–687.
Klauer, K. C., Stahl, C., & Voss, A. (2012). Multinomial models and diffusion models. In K. C. Klauer, A. Voss, & C. Stahl (Eds.), *Cognitive methods in social psychology* (pp. 331–354). New York: Guilford Press.

Klauer, K. C., & 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*(8), 1124–1140.

Klauer, K. C., Voss, A., Schmitz, F., & Teige-Mocigemba, S. (2007). Process components of the implicit association test: A diffusion-model analysis. *Journal of Personality and Social Psychology*, *93*(3), 353–368.

Klauer, K. C., & Wegener, I. (1998). Unraveling social categorization in the "who said what?" paradigm. *Journal of Personality and Social Psychology*, *75*(5), 1155–1178.

Krieglmeyer, R., & Sherman, J. W. (2012). Disentangling stereotype activation and stereotype application in the stereotype misperception task. *Journal of Personality and Social Psychology*, *103*(2), 205–224.

Lindsay, D. S., & Jacoby, L. L. (1994). Stroop process dissociation: The relationship between facilitation and interference. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(2), 219–234.

Logan, G. D., & Cowan, W. B. (1984). On the ability to inhibit thought and action: A theory of an act of control. *Psychological Review*, *91*(3), 295–327.

Meiser, T., & Hewstone, M. (2004). Cognitive processes in stereotype formation: The role of correct contingency learning for biased group judgments. *Journal of Personality and Social Psychology*, *87*(5), 599–614.

Meissner, F., & Rothermund, K. (2013). Estimating the contributions of associations and recoding in the implicit association test: The ReAL model for the IAT. *Journal of Personality and Social Psychology*, *104*(1), 45–69.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and disunity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*, 49–100.

Moors, A., & De Houwer, J. (2006). Automaticity: A theoretical and conceptual analysis. *Psychological Bulletin*, *132*(2), 297–326.

Moshagen, M. (2010). multiTree: A computer program for the analysis of multinomial processing tree models. *Behavior Research Methods*, *42*(1), 42–54.

Nadarevic, L., & Erdfelder, E. (2011). Cognitive processes in implicit attitude tasks: An experimental validation of the TRIP model. *European Journal of Social Psychology*, *41*(2), 254–268.

Nosek, B. A., & Banaji, M. R. (2001). The go/no-go association task. *Social Cognition*, *19*(6), 625–664.

Oberauer, K. (2006). Reasoning with conditionals: A test of formal models of four theories. *Cognitive Psychology*, *53*(3), 238–283.

Oberauer, K., Weidenfeld, A., & Hörnig, R. (2006). Working memory capacity and the construction of spatial mental models in comprehension and deductive reasoning. *Quarterly Journal of Experimental Psychology*, *59*(2), 426–447.

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*(2), 181–192.

Payne, B. K. (2005). Conceptualizing control in social cognition: How executive functioning modulates the expression of automatic stereotyping. *Journal of Personality and Social Psychology*, *89*(4), 488–503.

Payne, B. K., & Bishara, A. (2009). An integrative review of process dissociation models in social cognition. *European Review of Social Psychology*, *20*, 272–314.

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., Hall, D. L., Cameron, C. D., & Bishara, A. J. (2010). A process model of affect misattribution. *Personality and Social Psychology Bulletin*, *36*, 1397–1408.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, *19*, 123–205.
Plant, E. A., & Peruche, B. M. (2005). The consequences of race for police officers' responses to criminal suspects. *Psychological Science*, *16*(3), 180–183.
Pleskac, T. J., Cesario, J., & Johnson, D. J. (2018). How race affects evidence accumulation during the decision to shoot. *Psychonomic Bulletin & Review*, *25*(4), 1301–1330.
Ramos, M. R., Baretto, M., Ellemers, N., Moya, M., Ferreira, L., & Calanchini, J. (2015). Exposure to sexism can decrease implicit gender stereotype bias. *European Journal of Social Psychology*, *46*(4), 455–466.
Ratcliff, R., Thapar, A., Gomez, P., & McKoon, G. (2004). A diffusion model analysis of the effects of aging in the lexical-decision task. *Psychology and Aging*, *19*(2), 278–289.
Riefer, D. M., & Batchelder, W. H. (1988). Multinomial modeling and the measurement of cognitive processes. *Psychological Review*, *95*, 318–339.
Rivers, A. M., Calanchini, J., & Sherman, J. W. (2016). The self-regulation of implicit social cognition. In K. D. Vohs & R. F. Baumeister (Eds.), *Handbook of self-regulation: Research, theory and applications* (3rd ed.). New York: Guilford Press.
Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, *84*(1), 1–66.
Sherman, J. W. (2006). On building a better process model: It's not only how many but which ones and by which means? *Psychological Inquiry*, *17*(3), 173–184.
Sherman, J. W., Gawronski, B., Gonsalkorale, K., Hugenberg, K., Allen, T. J., & Groom, C. J. (2008). The self-regulation of automatic associations and behavioral impulses. *Psychological Review*, *115*(2), 314–335.
Sherman, J. W., Groom, C. J., Ehrenberg, K., & Klauer, K. C. (2003). Bearing false witness under pressure: Implicit and explicit components of stereotype-driven memory distortions. *Social Cognition*, *21*(3), 213–246.
Sherman, J. W., Klauer, K. C., & Allen, T. (2010). Mathematical modeling in social cognition: The machine in the ghost. In B. Gawronski & B. K. Payne (Eds.), *Handbook of implicit social cognition: Measurement, theory, and applications* (pp. 156–175). New York: Guilford Press.
Sherman, J. W., Krieglmeyer, R., & Calanchini, J. (2014). Process models require process measures. In J. W. Sherman, B. Gawronski, & Y. Trope (Eds.), *Dual-process theories of the social mind* (pp. 121–138). New York: Guilford Press.
Singmann, H., & Kellen, D. (2013). MPTinR: Analysis of multinomial processing tree models in R. *Behavior Research Methods*, *45*(2), 560–575.
Snyder, H. R., Miyake, A., & Hankin, B. L. (2015). Advancing understanding of executive function impairments and psychopathology: Gridging the gap between clinical and cognitive approaches. *Frontiers in Psychology*, *6*, 1–24.
Stahl, C., & Degner, J. (2007). Assessing automatic activation of valence: A multinomial model of EAST performance. *Experimental Psychology*, *54*(2), 99–112.
Stahl, C., & Klauer, K. C. (2007). HMMTree: A computer program for latent-class hierarchical multinomial processing tree models. *Behavior Research Methods*, *39*(2), 267–273.
Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, *18*, 643–662.
Trope, Y. (1986). Identification and inferential processes in dispositional attribution. *Psychological Review*, *93*, 239–257.
Ulrich, R., Schröter, H., Leuthold, H., & Birngruber, T. (2015). Automatic and controlled stimulus processing in conflict tasks: Superimposed diffusion processes and delta functions. *Cognitive Psychology*, *78*, 148–174.
Unkelbach, C., & Stahl, C. (2009). A multinomial modeling approach to dissociate different components of the truth effect. *Consciousness and Cognition*, *18*(1), 22–38.

White, C. N., Ratcliff, R., & Starns, J. J. (2011). Diffusion models of the flanker task: Discrete versus gradual attentional selection. *Cognitive Psychology*, *63*(4), 210–238.

Wilson, T. D., Lindsey, S., & Schooler, T. Y. (2000). A model of dual attitudes. *Psychological Review*, *107*(1), 101–126.

Wöstmann, N. M., Aichert, D. S., Costa, A., Rubia, K., Möller, H. J., & Ettinger, U. (2013). Reliability and plasticity of response inhibition and interference control. *Brain and Cognition*, *81*(1), 82–94.

Yonelinas, A. P., Dobbins, I., Szymanski, M. D., Dhaliwal, H. S., & King, L. (1996). Signal-detection, threshold, and dual-process models of recognition memory: ROCs and conscious recollection. *Consciousness and Cognition*, *5*(4), 418–441.