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CHAPTER 9



Process Models Require Process Measures

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The goal of dual-process models (DPMs) is to describe the contributions of two distinct classes of cognitive processes to judgments and behavior. One of the major challenges to achieving this goal is the need for a comprehensive measurement strategy that provides clear indicators of the dual processes, the conditions under which they operate, and the manner in which they interact to transform input into behavior. In this chapter, we review the most common measurement strategies applied to DPMs and some of the difficulties associated with those strategies. Many problems for DPMs result from the confounding of the qualitative nature of the dual processes in the models with the distinction between automaticity and control. Other problems arise from the use of behavioral measure outcomes as proxies for unmeasured cognitive processes and their operating conditions. We detail the advantages of a formal modeling approach and highlight some of the uses to which this approach has been applied in our own research with the Quadruple Process (Quad) model (Sherman et al., 2008). Finally, we describe theoretical insights related to DPMs that have been gleaned from this research.

MEASUREMENT CHALLENGES IN DPMs

Operating Principles versus Operating Conditions

Common measurement strategies developed for DPMs and some of their attendant problems can be traced to the historical origins of DPMs. Specifically, many DPMs arose in the wake of the long-standing dispute between two competing views of human information processing. The naive scientist view proposes that people try to understand their world much as scientists try to understand their topic of study—via careful, rational attempts to discover the true state of the world (e.g., Heider, 1958; Kelley, 1967). In contrast, the cognitive miser view holds that people have limited processing capacity and, as a result, rely on cognitively efficient mental shortcuts and heuristics that provide sufficiently accurate information for little effort (e.g., March & Simon, 1958; Tversky & Kahneman, 1974). Throughout the 1970s and 1980s, it became apparent that the distinction between effortful, optimizing processes and effortless, satisficing processes was not an either–or proposition. Rather,

it is clear that people engage in both kinds of processes, depending on their motivation to think carefully about a problem and the availability of the cognitive resources required to do so (e.g., Fiske & Taylor, 1984).

Broadly speaking, DPMs represent the field's attempts to characterize the moderators of when people behave like a naive scientist or a cognitive miser, and the processing mechanisms that guide these actions. In pursuit of this goal, the operations of the two types of processes proposed in many DPMs were mapped onto the distinction between automatic and controlled processes (e.g., Bargh, 1994; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). Whereas a process is considered to be *automatic* if it is initiated unintentionally, operates efficiently, cannot be terminated once started, and operates outside of conscious awareness, a process is considered to be *controlled* if it is initiated intentionally, dependent on cognitive resources, can be stopped voluntarily, and operates within conscious awareness. The processes coinciding with "miserly" processing were presumed to be relatively more automatic and less controlled than the processes coinciding with "scientific" processing.

Though of great heuristic use, the mapping of DPM processes onto the automatic-controlled distinction introduces a number of measurement problems. Most basically, this mapping confounds the critical distinction between operating principles and operating conditions (Gawronski & Bodenhausen, 2009; Gawronski, Sherman, & Trope, Chapter 1, this volume; Sherman, 2006). Operating *principles* refer to the qualitative nature of the cognitive processes that translate inputs into outputs. That is, they describe what the process does (e.g., activation of associations, information integration, inhibition, propositional reasoning). 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).

Importantly, demonstrating the conditions under which a process operates does not necessarily reveal anything about the qualitative nature of the process. For example, because inhibition processes may proceed in

a relatively automatic or controlled fashion (Calanchini & Sherman, 2013; Moskowitz, Chapter 27, this volume), identifying a process of interest as operating automatically (an operating condition) does not necessarily reveal anything about whether the process is inhibitory in nature (an operating principle). Rather, positive identification of the inhibitory nature of the process requires research that directly examines indications of inhibition. Likewise, demonstrating the operating principles of a process does not necessarily reveal anything about the operating conditions of that process. Thus, knowing that a process is inhibitory in nature does not necessarily reveal anything about whether the process operates in a relatively automatic or controlled fashion. Rather, positive identification of the operating conditions of the process requires research that directly examines indications of the features of automaticity (intentionality, efficiency, awareness, susceptibility to inhibition).

Nevertheless, research on DPMs has frequently identified operating principles from operating conditions and vice versa, rather than by directly measuring each. In terms of the former, operating principles have been inferred from markers of automaticity and control, including use of different types of judgment content (e.g., category cues vs. individuating information) that are presumed to be used more or less automatically and different types of measures (e.g., implicit versus explicit) that are presumed to reflect more or less automatic processing. The identification of a process as relatively automatic or controlled (its operating conditions) is then used to infer its operating principles (e.g., activation of associations, information integration, inhibition, propositional reasoning), not because the operating principles have been directly measured, but because evidence of automaticity or control is consistent with the assumed operating conditions of the process in question. For example, the fact that behavioral responses on implicit measures seem to reflect features of automatic processing has been taken as evidence that those responses must be driven by a process that is assumed to operate automatically, such as the activation of associations. In a similar fashion, DPMs often attempt to identify operating conditions via indications of the operating principles of the

process in question, rather than by directly testing the operating conditions. For example, evidence that a process involves recourse to propositional beliefs is typically used to infer that the process cannot be automatic in nature, an inference that may be misplaced (e.g., De Houwer, Chapter 35, this volume).

DPMs are fundamentally concerned with identifying the operating principles of the cognitive processes that transform inputs into outputs. Most DPMs also are interested in identifying the operating conditions of those processes, so that they may be distinguished as reflecting “scientific” versus “miserly” modes of processing. However, operating principles and operating conditions should not be used to infer one another. Rather, both principles and conditions must be independently established.

Behavioral Effects as Proxies for Operating Principles

Additional measurement problems for DPMs derive from the use of behavioral proxy measures to identify both operating principles and operating conditions. As far as operating principles are concerned, one fundamental challenge for DPMs (and, indeed, for all of cognitive and social cognitive psychology) is that many of the mental processes described in the models are not directly observable. Rather, the operation of these processes must be inferred from people’s responses on behavioral measures. Two different methods have been widely used to accomplish such inferences.

Content Proxies

Many DPMs have attempted to measure distinct processes, their operating principles, and the extent of their use by examining the influence of different types of information in various judgment tasks. In this method, the use of different types of information is assumed to reflect the operation of distinct cognitive processes. For example, prominent DPMs of persuasion (Chaiken, 1980; Petty & Cacioppo, 1986), impression formation (Brewer, 1988; Fiske & Neuberg, 1990), and dispositional attribution (Gilbert, Pelham, & Krull, 1988) are based on this approach. In these models, the use of one kind of information (e.g., peripheral cues, category-based

information, dispositional cues) is thought to reflect one dual process (e.g., peripheral processing, categorization, trait inference) and the use of another kind of information (e.g., argument strength, individuating information, situational cues) is thought to reflect the other dual process (e.g., central route processing, individuation, situational correction).

A problem with this approach is that it infers the operation of specific processes from the relationships among inputs (e.g., categorical and individuating information) and outputs (e.g., judgment stereotypicality) without directly measuring the processes of interest (e.g., categorization; individuation). To the extent that the input–output relationship is influenced by alternative or additional processes, the measurement outcome will be a poor proxy for the unmeasured processes of interest (e.g., De Houwer, 2011; De Houwer, Gawronski, & Barnes-Holmes, in press). For example, stereotype application and inhibition processes also influence trait judgments. This problem is exacerbated when multiple processes are inferred from a single behavioral outcome (e.g., judgment stereotypicality), as it may be impossible to assess the extent to which that outcome is due to more of one process (categorization), less of the other process (individuation), or a combination of both.

Task Proxies

A second strategy for inferring the operating principles of cognitive processes in DPMs has been to use separate measures as proxies for the two processes. For example, research on stereotyping sometimes uses implicit measures to assess the activation of associations in memory and explicit measures to assess the inhibition of stereotypic responses (e.g., Devine, 1989). As another example, research on attitudinal processes may use implicit measures to assess associative processing and explicit measures to assess propositional processing (e.g., Strack & Deutsch, 2004).

However, in relying on different tasks to infer different processes, there is always the risk that observed differences are due not to the hypothesized differences in the nature of the underlying processes but, instead, to other processes that may con-

tribute to performance on the tasks. To the extent that task performance is influenced by alternative or additional processes, task performance will be a poor proxy for the unmeasured processes of interest (e.g., De Houwer, 2011; De Houwer et al., in press). For example, responses on many implicit measures are determined not only by activated associations but also by processes that determine the correct task response, processes that override the activated associations, and so forth (e.g., Sherman et al., 2008). Responses on explicit measures are influenced by a wide range of different processes, including associative processes. The nature of this problem is well illustrated by the example of research on implicit and explicit memory systems, in which task dissociations supporting the implicit–explicit distinction were reinterpreted as reflecting the operation of perceptual versus conceptual processing (e.g., Roediger, 1990). In the same way, observed differences on implicit and explicit measures of evaluation may reflect features of the tasks that are not directly related to the distinction of interest (e.g., between associative and propositional processing; Payne, Burkley, & Stokes, 2008; Sherman et al., 2008).

Behavioral Effects as Proxies for Operating Conditions

DPMs also have used behavioral outcomes as proxies for operating conditions, with similar complications. Both content and task dissociations have been used to infer the operating conditions of the processes in question.

Content Proxies

Many DPMs have attempted to assess operating conditions by examining the influence of different types of information in various judgment tasks. In this method, the use of different types of information is assumed to reflect relatively automatic versus controlled processes. For example, the aforementioned DPMs of persuasion (Chaiken, 1980; Petty & Cacioppo, 1986), impression formation (Brewer, 1988; Fiske & Neuberg, 1990), and dispositional attribution (Gilbert et al., 1988) assume that the use of one kind of information (e.g., peripheral cues, categories, dis-

positional cues) reflects relatively automatic (unintentional, efficient, unaware, or lack of susceptibility to inhibition) processes, whereas the use of another kind of information (e.g., argument strength, individuating information, situational cues) reflects relatively controlled processes.

A major problem for this approach is that although some kinds of information (e.g., category identity) may often be accessed and applied more easily than other kinds of information (e.g., individuating information), it also is possible to reverse the situation (e.g., Erb et al., 2003; Krull & Dill, 1996; Kunda & Thagard, 1996; Trope & Gaunt, 2000). Which kind of information is more easily accessed and applied often depends on the design of the task, the specific configuration of the information, the context, or perceivers' goals. Thus, it is inherently problematic to equate different types of content with the distinction between automatic and controlled operating conditions. Content is not a strong proxy for operating conditions.

In order to solve this problem, more recent versions of these models typically dissociate content and operating conditions (Brewer & Feinstein, 1999; Fiske, Lin, & Neuberg, 1999; Petty & Wegener, 1999), proposing that all kinds of information (peripheral cues, categories, argument strength, individuating information) may be processed in either an automatic or a controlled manner. However, though this resolves the theoretical problem, a measurement problem remains. In these types of models, in any given experiment, the use of different content remains the only way to indicate the operation of two different processes that vary in features of automaticity–control. As such, proxy assumptions about content and operating conditions remain necessary.

It is possible to manipulate directly which kind of information (e.g., categorical vs. individuating information; disposition vs. situational information; source cues vs. message strength) is relatively accessible and easy to use. However, manipulating one type of information to be easier to use, then showing that it is, in fact, easier to use does not reflect on the operating conditions of the underlying processes of interest (categorization vs. individuation; trait inference vs. situational correction; peripheral vs. central route processing). Rather, because specific

content is used to instantiate the underlying processes, this does not tell us about those processes per se, only about those processes when they are instantiated in a way that makes one or the other relatively easy to accomplish.

Task Proxies

A second strategy for inferring the operating conditions of cognitive processes in DPMs has been to use separate measures as proxies for automatic and controlled processing. For example, researchers often assume that responses on implicit measures reflect processes that operate automatically, whereas responses on explicit measures reflect processes that operate in a controlled fashion (e.g., Devine, 1989; Fazio, Jackson, Dunton, & Williams, 1995; Greenwald, McGhee, & Schwartz, 1998). However, although implicit measures are certainly less susceptible to control than are explicit measures, responses on both types of measures reflect the influence of both relatively automatic and controlled processes (Calanchini & Sherman, 2013; Sherman et al., 2008). In fact, observed differences on implicit and explicit measures may not reflect differences in the extent of automatic versus controlled processing at all, as is almost unanimously assumed. Rather, such differences may reflect the influence of automatic processes, controlled processes, or both (Calanchini & Sherman, 2013; Sherman et al., 2008).

Summary

Attempts to test DPMs have been fraught with a variety of measurement problems. When operating principles and operating conditions are confounded and each is used to infer the other, neither may be measured with precision. The use of content and task dissociation proxies to measure operating principles and operating conditions also is problematic. To the extent that the content-tasks reflect operating principles and conditions beyond those of interest, then the content-tasks will be poor proxies for the operating principles and conditions they are meant to represent. Thus, when the processes in process models are not measured directly, significant problems with testing the models may arise.

CONCEPTUALIZING AND QUANTIFYING INTERACTIONS AMONG PROCESSES

Another challenge for DPMs is how to characterize and measure the joint and interactive influences of multiple processes. There are many ways to conceptualize the manner in which the dual processes in a DPM interact to produce behavior (e.g., Gilbert, 1999; Klauer & Voss, 2008). The most basic type of model is one in which the two processes are represented as distinct alternatives that do not co-occur. A number of early content proxy dissociation models took this form (e.g., Brewer, 1988; Chaiken, 1980; Petty & Cacioppo, 1986). In these models, which of the two processes guides behavior is determined by moderators having to do with the actor's motivation and ability to think carefully about the issue at hand. Obviously, these kinds of models are not well suited for considering the simultaneous, independent, and interactive contributions of the processes.

Other models propose that behavior is driven by a combination of the two processes. One variant of this approach suggests that dual processes represent two ends of a continuum (e.g., Fiske et al., 1999; Fiske & Neuberg, 1990). This sort of model imposes a hydraulic relationship between the two processes: As one increases, the other must decrease. As a result, the two processes are not independent, and it is difficult to determine the contribution of each. Movement along the continuum may reflect increased or decreased use of one process, the other process, or both. This type of model is particularly problematic when considering the distinction between automatic and controlled processes, as it requires that automatic processes are enhanced when controlled processes are diminished, and vice versa. However, it is clear that automatic and controlled processing are frequently independent of one another (e.g., Jacoby, Toth, & Yonelinas, 1993) or even positively correlated (e.g., increases in automatic processing are accompanied by increases in controlled processing; Jacoby, Begg, & Toth, 1997).

Other variants of combinatorial models permit simultaneous and distinct contributions of each process to behavior. For example, the newer versions of content proxy models that theoretically dissociate

content and operating conditions also have incorporated the idea that dual processes may simultaneously influence behavior (e.g., Brewer & Feinstein, 1999; Petty & Wegener, 1999). The two processes (e.g., heuristic and systematic processes) may contribute in an additive or interactive fashion (e.g., Chen & Chaiken, 1999). Interactive processes may take a variety of forms. One process (e.g., heuristic processing) may bias the manner in which the other process (e.g., systematic processing) operates. Alternatively, one process may constrain the influence of the other one. The most common variant of this type of model is one in which the more controlled process constrains the more automatic one when the actor possesses sufficient motivation and ability (e.g., Devine, 1989; Gilbert et al., 1988).

Conceptually, in contrast to either-or models or continuum models, joint influence models permit the independent assessment of each of the dual processes. However, in practice, the previously described measurement problems complicate these efforts. In the content proxy measurement strategy, inferences about the interactions between the two processes still depend on assumptions about which type of content reflects which type of process. Likewise, inferences about how these interactions are moderated by operating conditions may be based on proxy assumptions about the relative ease of using different pieces of information. Absent an independent means of establishing the operating conditions of the two processes, researchers run the risk of circular reasoning (e.g., whichever content is more influential under cognitive load is assumed to represent the more automatic process, thereby supporting a constraint model). Moreover, the extent of the influence of each of the processes often is inferred from a single behavioral outcome (e.g., judgment stereotypicality, extent of persuasion), rather than from distinct measures of the contributions of the two processes to the outcome. As is the case with continuum models, this restricts the ability to infer whether the single outcome is due to more of one process (e.g., category use, association activation), less of the other process (e.g., individuation, overcoming biased associations), or both (Sherman et al., 2008).

Finally, in the task proxy measurement strategy, there simply is no means to assess the simultaneous contributions of the dual processes, because they are each measured with a different dependent variable. This severely limits the ability to articulate the nature of the dual processes and the ways in which they interact to produce behavior.

FORMAL PROCESS MODELS

One increasingly common solution to these problems is the use of formalized mathematical process models of behavior (for an overview, see Sherman, Klauer, & Allen, 2010). These models seek to identify and quantify the processes that account for outcomes on measures of behavior (e.g., judgments, error rates, reaction times) via a set of variables (or parameters) and a set of equations that establish relationships among the variables. The variables in the equations represent the hypothesized component processes (operating principles; e.g., activation of associations, information integration, inhibition) that result in distinct responses on the measure of interest. The equations define the manner in which the processes interact to produce those responses. Solving the equations yields estimates of the extents of the processes.

Of most importance to the concerns raised in this chapter, an inherent feature of formal models is that the outcomes of measures are not assumed to act as proxies for the cognitive operations that produced those outcomes. Instead, the proposed underlying processes are directly linked to observed input-output relations via mathematical formulations that estimate the extents of the different processes. In this way, formal models provide a method for identifying and estimating operating principles without recourse to either content-based or task-based measurement proxies. Moreover, formal models demand a specification of the manner in which underlying processes interact to produce behavior, and provide a proxy-free means of testing those specifications. Before delving into these issues, we feel that it would be helpful to provide a concrete example of a formal model that may be used to illustrate these points.

A Brief Example

A wide variety of process models have been proposed to account for performance on a number of social cognitive measurement tasks in recent years (e.g., Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007; Krieglmeier & Sherman, 2012; Meissner & Rothermund, 2013; Mierke & Klauer, 2003; Nadarevic & Erdfelder, 2011; Payne, 2001; Payne, Hall, Cameron, & Bishara, 2010; Rothermund, Wentura, & De Houwer, 2005; Stahl & Degner, 2007). Here, we briefly introduce the Quad model (Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005; Sherman et al., 2008) to illustrate the application of a formal model. The Quad model proposes that four qualitatively distinct processes contribute to performance on implicit measures of evaluation and knowledge: (1) activation of biased associations (AC), (2) detection of correct responses (D), (3) overcoming biased associations when they conflict with correct responses (OB), and (4) guessing (G) when there is no other basis for responding. The model is depicted as a processing tree in Figure 9.1. Each path

represents a likelihood, and processing parameters with lines leading to them are conditional upon all preceding parameters. For instance, OB is conditional upon both AC and D. Similarly, G is conditional upon the lack of AC ($1 - AC$) and the lack of D ($1 - D$). Note that these conditional relationships do not imply a serial or temporal order in the onset and conclusion of the different processes. Rather, these relationships are mathematical descriptions of the manner in which the parameters interact and constrain one another to produce behavior. Thus, AC, D, and OB may occur simultaneously. However, in determining a response, the status of OB determines whether AC or D drives responses when they are in conflict.

The conditional relationships described by the model form a system of equations that predicts the number of correct and incorrect responses in the compatible (e.g., pairing black faces and negative words on an Implicit Association Test [IAT]) and incompatible trials (e.g., pairing black faces and positive words on an IAT) of an implicit measure. The model's predictions are then compared with the actual data to determine

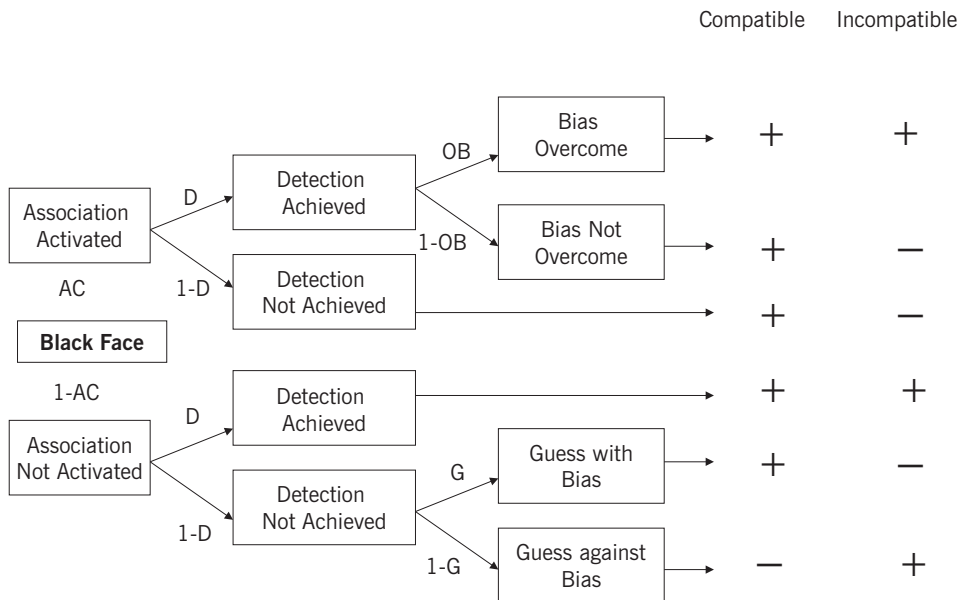


FIGURE 9.1. The Quadruple Process model. Each path represents a likelihood. Parameters with lines leading to them are conditional upon all preceding parameters. The columns on the right side of the figure depict correct (+) and incorrect (–) responses as a function of process pattern.

the model's ability to account for the data. A chi-square estimate is computed for the difference between the predicted and observed errors. To best approximate the model to the data, the four parameter values are changed through maximum likelihood estimation until they produce a minimum possible value of the chi-square. The final parameter values that result from this process are interpreted as relative levels of the four processes. We describe applications of the Quad model in more detail below.

Advantages of Formal Models

Formal modeling offers a number of important advantages over traditional DPM approaches. First, conceptually, formal models presume that the behavioral outcomes of measures are not isomorphic with the processes that are hypothesized to produce those outcomes. Thus, although behavioral outcomes provide the raw material from which process estimates are derived, the distinction between output and process is clear. Pragmatically, the extents of the processes are not inferred based on raw outcomes alone, but rather are estimated via mathematical formulations that directly tie the processes to input-output relations in the measurement task.

Second, by estimating the extents of different processes that contribute to performance on a single task that presents the same content in all conditions, formal models avoid the problem of relying on content or task proxies that may be poor indicators of the processes.

Third, formal models permit the independent and simultaneous measure of multiple distinct processes. Because the role of each process in producing an outcome is mathematically specified, the processes can be assessed independently of one another. This contrasts with process inferences made from judgment tasks, in which it is often impossible to know whether the outcome was based on more of one process (categorization), less of another process (individuation), or a combination of both.

Fourth, the act of formalizing a theory into a mathematical model demands a level of theoretical specificity that typically is not observed in verbally formulated models. In particular, the interactive and determina-

tive relationships among the processes must be defined explicitly and transformed into a set of mathematical propositions that are hypothesized to lead to specific outcomes. The theory must commit itself to a mathematical instantiation that can be directly tested against the data.

A fifth and related point is that the extent to which the assumptions of a formal model can account for behavior can be directly evaluated via model-fitting procedures. DPMs are notorious for their ability to assimilate a wide variety of findings, sometimes including data that would seem to violate the predictions of the models. This has led to concerns that DPMs may be unfalsifiable (e.g., Gawronski, 2013; Gawronski et al., Chapter 1, this volume; Keren & Schul, 2009). By contrast, model-fitting procedures (e.g., goodness-of-fit indices) provide a way in which to demonstrate clearly that formal models may be unable to account for relevant data. Moreover, competing formal models may be directly compared in their ability to account for a set of findings, yielding the possibility of incrementally improving process theories.

Finally, formalized theories permit more precise measures of processes than do traditional DPMs. This is because formal models link the proposed processes to mathematical equations that are solved to yield specific numerical estimates of the extent of each process. This approach may be contrasted with the standard measurement approach for verbally formulated theories, in which content or task outcome proxies are used to infer the relative extents (more vs. less) to which different processes occurred but cannot provide point estimates of the extents of those processes.

Operating Principles Must Be Independently Validated

It is important to note that applying and/or fitting a model provides estimates of the process parameters but, in itself, cannot validate the psychological meanings of those parameters. That is, whether the parameters reflect their intended processes must be established independently via construct validation studies that build a nomological network linking theoretical propositions about the processes, known operationalizations of

the proposed construct, and empirical data (Cronbach & Meehl, 1955). For example, if a parameter is meant to represent the extent of activation of associations (AC), then that parameter should be responsive to the extent to which a novel target has been associated with specific attributes during learning (e.g., Sherman et al., 2008). This parameter also should vary with stimulus manipulations designed to increase the likelihood of associations being activated (e.g., the category prototypicality of different targets; Krieglmeyer & Sherman, 2012). If a parameter is meant to reflect a stimulus detection process (D), then that parameter should respond to manipulations of the perceptual clarity of stimuli (Krieglmeyer & Sherman, 2012). If a parameter is meant to represent an inhibition process (e.g., OB), then this might be supported by showing that general inhibition training or instructions that encourage inhibition increase the extent of the process (e.g., Krieglmeyer & Sherman, 2012), by correlating the parameter with known group differences (e.g., alcohol and aging are known to interfere with inhibition; Gonsalkorale, Sherman, & Klauer, 2009; Gonsalkorale, Sherman, & Klauer, in press; Sherman et al., 2008), by showing that the parameter correlates with other known measures of inhibition, or by showing that it predicts inhibition-relevant behavior (e.g., Gonsalkorale, von Hippel, Sherman, & Klauer, 2009). As with all psychological constructs, careful work is required to establish convergent validity, divergent validity, predictive validity, and so forth.

Operating Conditions Must Be Independently Validated

Likewise, the conditions under which the different processes operate cannot be assumed from the design of a formal model, and must be established through independent research. In terms of DPMs, this issue is most relevant in considering the extent to which a given process operates automatically or requires control, because this is the operating process distinction around which DPMs have been built. As such, the extent to which a given process meets the various criteria of automaticity–control (intentionality, efficiency, awareness, susceptibility to inhibition) must be demonstrated with inde-

pendent empirical evidence. For example, if a parameter is meant to reflect an efficient process, this might be demonstrated by showing that the parameter is unaffected by a cognitive load or a short response deadline.

THE RELATIONSHIP BETWEEN THE QUAD MODEL AND DUAL-PROCESS THEORIES

In the remainder of this chapter, we describe in some detail the ways in which the Quad model has been used to elucidate empirical and theoretical issues in the dual-processes literature. Beyond describing the specific contributions of the Quad model, this discussion is meant to illustrate more broadly the manner in which formal models may be strategically applied to advance our understanding of the processes that contribute to cognition and behavior (see also Klauer, Chapter 10, and Payne & Cameron, Chapter 8, this volume). Before doing this, it is useful to consider in general terms the relationship between the Quad model and DPMs.

Quad Model Processes Correspond to Prevalent DPM Processes

The Quad model was not developed for the purpose of addressing DPMs. Rather, the model was developed with the more pragmatic goal of identifying the processes that contribute to performance on the IAT (Greenwald et al., 1998). It was only during the early stages of validating the model that we recognized that the processes specified in the Quad model corresponded closely to the operating principles of the processes that are very commonly included in DPMs. Specifically, AC corresponds closely to the conception of simple associations or habitual responses that are triggered by stimuli in most DPMs of attitudes (e.g., Fazio, 1990; Wilson, Lindsey, & Schooler, 2000), persuasion (e.g., Chaiken, 1980; Petty & Cacioppo, 1986), stereotyping (e.g., Brewer, 1988; Devine, 1989; Fiske & Neuberg, 1990), prejudice (e.g., Fazio et al., 1995; Greenwald et al., 1998), and judgment (e.g., Epstein, 1994; Sloman, 1996). D corresponds closely to stimulus detection processes that serve to provide an accurate representation of the

environment in DPMs of persuasion (e.g., Chaiken, 1980; Petty & Cacioppo, 1986), person perception (e.g., Brewer, 1988; Fiske & Neuberg, 1990), and memory (e.g., Jacoby, 1991). Finally, OB corresponds to self-regulatory processes that attempt to inhibit unwanted or inappropriate responses in DPMs, such as Devine's (1989) model of stereotyping or Wegner's (1994) model of thought suppression.¹

A Mea Culpa about Operating Conditions

Recognition of the similarities between the Quad model parameters and DPM processes influenced the manner in which we described the model and its purposes, and not always in a positive way. Though we are now vigilant in distinguishing between operating principles and operating conditions, this has not always been the case. On some occasions, we made the distinction clear (Sherman, 2006). However, in adopting the DPM framework for describing the Quad model parameters, we also frequently adopted the confound between operating principles and operating conditions often found in the DPM literature. As such, our descriptions of the processes measured by the Quad model were frequently presented as a contrast between automatic (activation of associations) and controlled (detection; overcoming bias) processes. Our empirical work with the model was frequently described as examining the contributions of automatic and controlled processing to the measure of interest.

Nevertheless, rather than assume that the Quad model parameters corresponded to automatic and controlled processes, in a number of studies we attempted to verify independently the operating conditions of the parameters. For instance, time pressure was shown to decrease detection and overcoming bias, but not activation of associations (Conrey et al., 2005), suggesting that AC is a more efficient process than D or OB. Neuroimaging also linked detection with activation in both the dorsal anterior cingulate cortex and the dorsolateral prefrontal cortex, areas of the brain associated with implementing control (Beer et al., 2008). Other research showed that overcoming bias is impaired by alcohol consumption (Sherman et al., 2008) and decreases with

age (Gonsalkorale, Sherman, et al., 2009; Gonsalkorale et al., in press), attesting to its status as a controlled, inhibitory process. Though these data support some of our initial assumptions about the extent to which the Quad model processes possess features of automaticity and control, we no longer frame our research in terms of operating conditions, focusing instead on the more central question of operating principles. The extent to which cognitive processes can be described as definitively automatic or controlled, including those measured by the Quad model, is a complicated matter, to which we return later.

How Many Processes Should a Process Model Have?

The Quad model has often been portrayed as a competitor to DPMs because it proposes four rather than two processes. However, in our view, the number of processes described by the model is a rather insignificant factor in comparing our approach with those of DPMs (Sherman, 2006). Instead, it is the means by which the proposed processes are measured and the specification of how those processes interactively influence behavior that most significantly differentiate the Quad model from most DPMs. Thus, despite the different numbers of processes described by the two models, the Process Dissociation (PD) model (Payne, 2001) and the Quad model share much in common, whereas the PD model is quite different from other DPMs despite the fact that they all propose two processes.

The fundamental problem with a debate about the appropriate number of processes to consider is that there are a practically limitless number of candidate processes one might identify. Broadly described processes, such as *encoding*, may be divided into many subprocesses (e.g., selection, attention, construal, attribution, representation), which may be further divided (e.g., attention capture, attention maintenance, attention switching), and so on. Any process can be described at many different levels of breadth. Thus, it is futile to argue about the "real" number of processes that contribute to any behavior. Rather, researchers should identify the processes of interest based on theoretical considerations (i.e., which pro-

cesses are most relevant to the goals of the research). Much more important than the number of processes to be considered is that those processes and their operation be adequately described and measured.

A Brief Survey of Quad Model Applications of Relevance to DPMs

The most natural application of the Quad model has been to address the problem of task confounds and the multicomponent nature of responses on implicit measures of evaluation. Implicit measures were devised to overcome the “willing” and “able” problems associated with self-report (or explicit) measures—that respondents may conceal their true evaluations due to self-presentational concerns or be unable to report accurately evaluations that are inaccessible to introspection. Implicit measures minimize these problems by assessing evaluations without directly requesting that respondents report them, for example, by structuring the task in a manner that conceals what is being measured (e.g., evaluative priming; Fazio et al., 1995) or by making responses difficult to control (e.g., IAT; Greenwald et al., 1998). These features of implicit measures have led to the widely held belief that responses on the measures reflect only the respondent’s automatically activated mental associations (e.g., Fazio & Towles-Schwen, 1999; Greenwald et al., 1998). In turn, this has led to the development of a whole family of DPMs based on the distinction between implicit and explicit processes, representations, or systems that correspond to the distinction between automatic and controlled operating conditions (e.g., Fazio et al., 1995; Greenwald et al., 1998; Lieberman, Gaunt, Gilbert, & Trope, 2002; Rydell & McConnell, 2006; Strack & Deutsch, 2004; Wilson et al., 2000). However, as we argued earlier, there are a number of problems with interpreting dissociations between implicit and explicit task performance as reflecting only the distinction between automatic and controlled processes. First, this approach promotes a confound between operating principles (e.g., associative vs. propositional processes) and their supposed operating conditions (automaticity vs. control). Second, there is the problem that observed differences on implicit and explicit

measures may be due not to the hypothesized differences in operating principles or operating conditions but, instead, to some other feature that differs between the tasks. This is because measures are not process-pure indicators of single operating principles (e.g., activation of associations) or operating conditions (e.g., automaticity). As such, the different measures may be poor proxies for operating principles and conditions. Finally, because each process must be measured with a separate implicit or explicit task, it is impossible to assess the independent and joint contributions of the dual processes to a single response. Thus, for example, it is impossible to distinguish between a person who has strongly activated, biased associations but can overcome them and a person who has weakly activated associations but cannot overcome them. Application of the Quad model and other formal models avoids all of these problems.

Multiple Processes Contribute to Implicit Task Performance

The first and most basic question we asked in our research on the Quad model is whether it provides a good account of implicit task performance. At this point, we have fitted the model to scores of datasets and have consistently found that it accounts well for performance on both the IAT and various priming tasks (Sherman et al., 2008). Because it is necessary to show that the model’s parameters are measuring the processes we claim they are measuring, we aimed other early research at establishing the construct validity of the parameters. For example, the facts that OB is negatively correlated with reaction time bias on implicit measures and is diminished among older adults and the inebriated is consistent with our claim that the parameter measures a self-regulatory process that inhibits the influence of biased associations. As described earlier, we also sought to investigate empirically the operating conditions of the model parameters, showing that AC is less dependent on processing resources than D or OB, for example. A more extensive summary of this work, which is beyond the scope of this chapter, may be found elsewhere (e.g., Sherman et al., 2008, 2010).

Having validated the model in a number of ways, most of our subsequent research

has turned to elucidating the processes that account for important implicit evaluation effects. We have been particularly interested in identifying the processes that account for the malleability of implicit evaluations, variability in implicit evaluations among different respondents, and the ability of implicit evaluations to predict behavior. As described earlier, responses on implicit measures of evaluation are commonly thought to reflect only the associations that are automatically activated in performing the task, and implicit measure outcomes are most often described as reflecting solely the extent of biased associations. This understanding of implicit measures constrains interpretations of implicit evaluation malleability, variability, and behavioral prediction. If the measures only reflect underlying associations, then any change, variability, or predictiveness of the measures must, by definition, be due only to associations in memory (e.g., the same stimuli activate different associations, the same associations are activated to a different extent, or the associations themselves are altered; Blair, 2002; Gawronski & Sritharan, 2010). In contrast, the Quad model provides a means of directly assessing the influence of four distinct processes on these outcomes. We have now accumulated a substantial body of evidence indicating that these important effects are not due solely to associations that are activated in performing the tasks. What follows is a very brief description of some of this work. Expanded treatments may be found in Sherman et al. (2008; 2010).

Implicit Evaluation Malleability

One important class of implicit evaluation effects is the demonstration that implicit evaluations can be altered by a variety of interventions (e.g., Blair, 2002). Consistent with the common view, we have shown that some of these effects, such as increases in implicit bias following ego threat (Allen & Sherman, 2011) and decreases in bias upon exposure to favorable outgroup exemplars (Gonsalkorale, Allen, Sherman, & Klauer, 2010), or racially diverse contexts (Soderberg & Sherman, 2013), are related only to changes in the AC parameter. However, other interventions that reduce bias, such as counterprejudicial training, are associated

with both reductions in AC and enhanced D (Calanchini, Gonsalkorale, Sherman, & Klauer, 2013). In still other cases, malleability effects do not appear to be related at all to activated associations. For example, the finding that placing outgroup members in positive social contexts reduces implicit bias was shown to be related only to enhanced OB instigated by the context (Allen, Sherman, & Klauer, 2010).

Implicit Evaluation Variability

Another important class of implicit evaluation effects is the observation of individual differences in implicit evaluations among different groups of respondents. Here, too, we observed that some group differences, such as those between black and white participants, are related only to differences in the AC parameter. However, other group differences, such as those between people who are internally but not externally motivated to control prejudice (high Internal Motivation to Respond without Prejudice Scale [IMS]–low External Motivation to Respond without Prejudice Scale [EMS]) and other people, are related to differences in both AC and D (in this case, lower AC and higher D among high IMS–low EMS respondents; Gonsalkorale, Sherman, Allen, Klauer, & Amodio, 2011). In still other cases, associations appear to have nothing to do with group differences in implicit evaluations. We have found that the tendency for older people to demonstrate higher levels of implicit prejudice than younger people is related only to reduced OB among older respondents (Gonsalkorale, Sherman, et al., 2009; Gonsalkorale et al., in press).

Implicit Evaluations Predicting Behavior

In other research, implicit evaluations are used to predict a variety of important behaviors. Here, too, we find evidence for the influence of multiple processes. For example, Gonsalkorale, von Hippel, et al. (2009) found that the quality of interactions between white non-Muslims and a Muslim confederate was predicted by an interaction between AC and OB. Specifically, when participants had low AC estimates of negative associations with Muslims, their level of OB was unrelated to how much they were liked

by the confederate. In contrast, participants with high AC estimates of negative associations with Muslims were liked to the extent that they had high OB estimates. Thus, the ability to overcome negative associations predicted the quality of the interaction only when those associations were strong.

THEORETICAL IMPLICATIONS FOR THE DUAL-PROCESS APPROACH

This research on the Quad model has a number of important implications for the theoretical status of operating principles and operating conditions within the dual-process approach, particularly DPMs based on the distinction between implicit and explicit processes (e.g., Fazio et al., 1995; Greenwald et al., 1998; Lieberman et al., 2002; Rydell & McConnell, 2006; Strack & Deutsch, 2004; Wilson et al., 2000). The following discussion focuses primarily on task dissociation DPMs.

Operating Principles

A fundamental underpinning of many of these DPMs is that implicit and explicit measures reflect the operation of qualitatively distinct processes that reflect distinct operations. Though a wide variety of processes are recognized to contribute to responses on explicit measures across these models, they all share the assumption that implicit measures primarily (or only) reflect the activation of associations in memory. Implicit measures are used as proxies for measuring underlying associations, and responses on implicit measures are considered to be isomorphic with the associations that give rise to those responses.

Research on the Quad model raises serious objections to this assumption. The AC parameter of the model measures the extent to which the activation of evaluative associations influences responses on implicit measures. However, D represents an accuracy-oriented process that cannot be achieved solely through the passive activation of associations in memory. OB represents a self-regulatory process that overcomes the activated associations when necessary. As such, D and OB (and sometimes G) appear to be nonassociative processes (Calanchini &

Sherman, 2013). Nevertheless, our research has clearly demonstrated the critical role played by these processes in implicit evaluation effects. In some cases, implicit evaluation malleability, variability, and behavior prediction are related to both associative and nonassociative processes. In other cases, associative processes appear to have nothing to do with these outcomes, and are based entirely on nonassociative components of task performance.

One of the primary goals of DPMs is to describe the operating principles by which stimulus inputs are translated into behavioral outputs. Based on research with the Quad model and other formal models of implicit task performance that include non-associative processes (Klauer et al., 2007; Krieglmeier & Sherman, 2012; Meissner & Rothermund, 2013; Mierke & Klauer, 2003; Nadarevic & Erdfelder, 2011; Payne, 2001; Payne et al., 2010; Rothermund et al., 2005; Stahl & Degner, 2007), it is now abundantly clear that the practice of using implicit measures as proxies for associative processing obstructs the accurate identification of operating principles. To specify and test more effectively the operating principle components of DPMs, we strongly advocate that they be uncoupled from the use of specific types of proxy content and proxy measures. The use of formal models, which allow researchers to quantify the contributions of multiple distinct processes to a given behavioral outcome, is one useful way to measure processes without relying on such proxies.

Operating Conditions

Just as DPMs based on the distinction between implicit and explicit processes assume that implicit measures reflect associative processes, so, too, do they assume that these measures reflect automatic processes. Because implicit measures either conceal what is being measured or hinder respondents' ability to control outcomes on the measures intentionally, many researchers assume that responses reflect only automatic processes that are initiated unintentionally, operate efficiently, cannot be inhibited, and operate outside of conscious awareness. We certainly do not question that implicit measures permit less control than explicit measures. Nevertheless, work with the Quad

model clearly shows that the D and OB components of implicit task performance possess some features of controlled processing. For example, the fact that both of these processes are curtailed by a response deadline, that D is linked to activation in both the dorsal anterior cingulate cortex and the dorsolateral prefrontal cortex, and that OB is impaired by old age and alcohol consumption all reveal signatures of controlled processing. Yet, at the same time, these processes are sufficiently efficient to influence behavior within the constraints of measures that are very difficult to control (for a review, see Calanchini & Sherman, 2013). These results fit comfortably within a growing body of research indicating that, like any other cognitive process, processes that work to achieve control over automatically activated associations, habits, or impulses may themselves become automatized in certain ways (e.g., Glaser & Knowles, 2008; Monteith, Lybarger, & Woodcock, 2009; Moskowitz, Chapter 27, this volume).

Following the lead of Jacoby (1991) and others, we have argued since the advent of our work on the Quad model that performance on any task must reflect both automatic and controlled processes. At this point, it also is apparent that many specific processes possess features of both automaticity and control, even those that occur within the course of completing an implicit measure. In general terms, this is not a particularly novel insight. Bargh (1994) urged researchers to think about the four “horsemen” of automaticity as dissociable, and noted that few processes would be likely to possess all four of the features of automaticity (unintentional; efficient; unaware; cannot be inhibited). Unfortunately, few researchers (ourselves included) have consistently taken this advice to heart. However, this complication raises particularly difficult challenges for DPMs that are based on the distinction between automatic and controlled processing (Gawronski et al., Chapter 1, and Moors, Chapter 2, this volume). If particular processes cannot be clearly identified as automatic or controlled, then how can they be placed into categories of processes, mental representations, or systems that are defined in terms of the distinction between automaticity (or implicit) and control (or explicit)? This problem threatens

the ontological status of the distinction that these DPMs wish to make.

SUMMARY

In this chapter, we have argued that the absence of sound measurement methods has hindered the development and utility of DPMs. At the core of many of the problems is the commonplace confounding of operating principles and operating conditions. We believe it is time for the dual-process approach to be divorced from the distinction between automatic and controlled processes, representations, or systems. Questions pertaining to automaticity and control should be viewed as empirical in nature but not as definitional features of the processes of interest or as the primary basis for categorizing qualitatively distinct processes together in DPMs (Moors & De Houwer, 2006). It is increasingly apparent that the operating principles of qualitatively distinct processes are not tightly associated with the automatic–controlled distinction. Many processes can operate in more or less automatic fashion, and all processes possess features of both automaticity and control. Progress in developing and testing DPMs also has been hindered by the use of content and task proxies for inferring operating principles and conditions. We advocate formal modeling as a proxy-free means to identify the nature of and estimate the extent of underlying cognitive processes by mathematically linking those processes to relations between stimulus inputs and behavioral outputs, specifying not only the qualitative nature of the processes but also the manner in which those processes interact to produce behavior.

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NOTE

1. In many previous descriptions of the Quad model, we also drew links between the G

parameter and response biases that influence behavior only when D fails (e.g., Jacoby, 1991). However, this effort was misguided. Whether a bias influences responses independently of D or only when D fails is not logically tied to the qualitative nature (operating principles) of the process. For example, in Payne's (2001) work, the A parameter represents the activation of biased associations (much like AC in the Quad model). However, these associations influence behavior only when Detection (the C parameter in Payne's work) fails. In contrast, associations may influence behavior independently of Detection in the Quad model. Thus, although the conditions of influence of association activation differ in the models in terms of independence from detection, the operating principles that define the nature of the processes are highly similar in the two models.

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