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CHAPTER 4

Self-Regulation of Implicit Social Cognition

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Implicit measures of social cognition have grown increasingly popular over the past two decades. Not only have they become ubiquitous within social psychology, but they are also now commonly applied in a broad array of domains beyond social psychology, ranging from brand evaluations (e.g., Perkins & Forehand, 2010) to phobias (e.g., Teachman, Gregg, & Woody, 2001) to addiction (e.g., Wiers, Houben, & de Kraker, 2007). Their widespread use is largely due to the assumption that implicit measures provide a more clear view into hidden cognitive processes than do explicit (i.e., self-report) measures. However, there is debate about which cognitive processes implicit measures primarily reflect. Tasks such as the Implicit Association Test (IAT; Greenwald, McGhee, & Schwarz, 1998) were initially designed to measure behavioral impulses induced by mental association between concepts (e.g., the outgroup) and attributes (e.g., negative). Explicit measures often do a poor job of assessing such impulses, especially socially undesirable ones, because explicit measures allow ample opportunity for initial impulses to be replaced by more socially desirable responses. In contrast, implicit measures minimize opportunity and motivation for responses to be deliberately altered. As such, implicit measures are commonly assumed primarily to reflect the influence of behavioral impulses activated by mental associations, free of self-regulatory processes that would constrain the expression of those impulses (e.g., Gawronski & Bodenhausen, 2007).

Self-regulation plays an important role in inhibiting undesirable impulses from influencing behavior in many situations encountered in everyday life (Hofmann, Vohs, & Baumeister, 2012; Vohs, Baumeister, & Ciarocco, 2005). However, self-regulation is typically conceptualized to be relatively slow, intentional, and resource-intensive. As such, self-regulatory processes require sufficient motivation and opportunity in order to influence behavior (Fazio, 1990). Implicit measures require behavioral responses, such as key presses and eye movements, which are not only behaviors in and of themselves, but they also predict other "everyday" behaviors (e.g., Gonsalkorale, von Hippel, Sherman,

& Klauer, 2009). Moreover, implicit measures were designed specifically to minimize motivation and opportunity for self-regulation to influence behavioral responses, for example, by requiring fast responses or by presenting stimuli outside of conscious awareness. However, a growing body of research suggests that some forms of self-regulation can operate quickly, efficiently, and/or unintentionally enough to influence responses on implicit measures. In this chapter, we review current research on such self-regulatory processes. We begin by discussing theoretical and definitional issues that have previously obscured the role of self-regulation on implicit measures. We then present evidence for several self-regulatory processes that contribute to performance on implicit measures. Finally, we introduce a tool to study self-regulatory processes—multinomial models—and review theoretical contributions produced by this tool.

CONCEPTUAL ISSUES AROUND SELF-REGULATION

Defining Automaticity versus Control

Implicit measures were initially developed to assess behavioral impulses (e.g., approach vs. avoidance) induced by different categories of stimuli (e.g., pictures of ingroup or outgroup members). These impulses, in turn, were assumed to reflect associations (e.g., between the ingroup and positive concepts, or between the outgroup and negative concepts) activated automatically upon exposure to the stimuli. In the context of cognitive processes, *automaticity* refers to a process that is activated quickly and unintentionally, does not depend on cognitive resources, operates outside of conscious awareness, and cannot be stopped once initiated. In contrast, *controlled* processes are ones that operate slowly and intentionally, depend on cognitive resources, operate within conscious awareness, and can be stopped once initiated (Bargh, 1999; De Houwer & Moors, 2012).

Early research showed that responses on implicit measures are indeed less controllable and their content is less consciously reportable than responses on explicit measures (Bargh, 1999). Over the years, this has led to various assumptions about the processes that drive responses on implicit measures: that they cannot be controlled (Rydell & McConnell, 2006); that they operate outside of conscious awareness (Wittenbrink, 2007); that they provide a "bona fide pipeline" to people's true attitudes (Fazio, Jackson, Dunton, & Williams, 1995); and that these "true" attitudes are "cognitive monsters" that drive behavior, despite any attempt to control them (Bargh, 1999).

Operating Principles versus Operating Conditions

Because *automaticity* and *control* are defined in opposition to one another, and because implicit measures were designed to assess automatic processes, by definition, *controlled processes* of self-regulation could not possibly influence responses on implicit measures. However, this assumed relationship between *implicit measures* and *self-regulation* is problematic because these definitions describe both the qualitative nature of self-regulation (e.g., it inhibits behavioral impulses) and simultaneously sets boundaries on when it can operate (e.g., self-regulation can only happen when it is intentionally engaged). In reality, however, the principles describing the nature of a process are orthogonal to the principles describing the conditions under which that process operates (Gawronski, Sherman, & Trope, 2014; Sherman, Krieglmeyer, & Calanchini, 2014); that is, any specific process (e.g., attention, recollection, self-regulation) may occur in a relatively automatic or controlled fashion. As such, initial definitions of self-regulation that confounded operating principles (what does the process do?) with operating conditions (when may the process operate?) precluded any possibility of self-regulation in implicit social cognition.

Broadly speaking, *operating principles* describe what a given process does, whereas *operating conditions* refer to the conditions under which a given process operates (Gawronski et al., 2014; Sherman et al., 2014). Because operating principles are orthogonal to operating conditions, it is important to define them independently from one another. To illustrate this point, consider experimental work by Allen, Sherman, and Klauer (2010) investigating the influence of context cues on implicit racial bias. Typically, people's responses on implicit measures are biased in such a way that suggests that they have more positive attitudes toward white people than toward black people. However, when pictures of black people are presented in positive contexts, such as a church setting, responses become less biased (e.g., Wittenbrink, Judd, & Park, 2001). If self-regulation is defined in terms of the conditions under which it operates (i.e., requiring sufficient time, cognitive resources, and intent), then, by definition, self-regulation cannot account for Wittenbrink and colleagues' (2001) results. Instead, from that perspective, the reduction in bias observed by Wittenbrink and colleagues can only be attributed to different behavioral impulses induced by positive contexts. Alternatively, if self-regulation is defined in terms of what it does (i.e., constrains behavioral impulses and replaces them with more appropriate responses), rather than when it operates, it is conceivable that self-regulation is involved in the observed bias reduction.

Allen and colleagues (2010) tested two competing explanations: that positive contexts reduced implicit bias by influencing the activation of biased racial associations that, in turn, influenced behavioral impulses; or that positive contexts cue self-regulatory processes that, in turn, result in reduced implicit bias (see Monteith, Ashburn-Nardo, Voils, & Czopp, 2002). Allen and colleagues (2010) found support for the latter hypothesis: Positive contexts did not influence the activation of biased racial associations but, rather, induced stronger self-regulation relative to negative contexts. These findings are incompatible with the common assumption that self-regulation is a fundamentally nonautomatic process that cannot influence responses on implicit measures (e.g., Bargh, 1999; Wittenbrink, 2007). Indeed, researchers have identified several varieties of self-regulatory processes that influence responses on implicit measures.

Examples of Self-Regulation on Implicit Measures

Goal-Driven Inhibition of Biased Associations

Goal-driven processes can regulate behavioral responses on implicit measures by inhibiting the activation of biased mental associations. For example, Moskowitz, Gollwitzer, Wasel, and Schaal (1999) argued that repetitive pursuit of egalitarian goals can inhibit the activation of racial stereotypes. Results from several experiments showed that people with chronically salient egalitarian goals showed less bias on an implicit measure than did people for whom egalitarianism was not chronically salient. Importantly, chronic egalitarians and nonegalitarians reported equivalent knowledge of racial stereotypes, which suggests that differences in implicit bias were due to self-regulatory processes activated by chronic egalitarian goals.

Expanding on these findings, Moskowitz and Li (2008) primed individuals with egalitarian or tradition goals rather than relying on individual differences in egalitarian motivations. Replicating the previous pattern of results, people primed with egalitarian goals demonstrated less racial bias on an implicit measure than people primed with tradition goals. Taken together, these findings demonstrate that goal-driven self-regulation can influence responses on implicit measures by inhibiting the activation of biased associations.

Reactive Correction

Glaser and Knowles (2008) proposed that a reactive form of self-regulation can influence responses on implicit measures. Specifically, they hypothesized that, for people who have practiced correcting for racial biases and are motivated to do so, these corrective actions become routinized. Consequently, such habitual corrective actions result in less implicit bias relative to people for whom these actions are not habitual. In testing this hypothesis, Glaser and Knowles found that, for people low in the motivation to avoid being prejudiced, the extent to which they associated black people with weapons predicted how quickly they "shot" armed black men relative to armed white men in a computer simulation. In contrast, for people high in the motivation to avoid being prejudiced, the extent to which they associated black people with weapons was unrelated to how quickly they "shot" armed black men relative to armed white men. In other words, people who were motivated to avoid being prejudiced were able to regulate their biased associations from influencing their behavior.

Goal Construal

Moving beyond the domains of racial stereotyping and prejudice, Fujita (2011) presents a version of self-regulation that is based on how goals are construed. Challenging the common assumption that self-regulation requires the effortful inhibition of impulses, Fujita instead proposed that self-regulation may be thought of as the heightened activation of distal goals in the face of proximal ones. As such, this alternative conceptualization of self-regulation can take both effortful and efficient forms. Effortful forms of self-regulation in pursuit of goals are related to executive functions such as working memory, inhibition and task-switching abilities (for a review, see Hofmann, Schmeichel, & Baddeley, 2012). For example, a person with a goal to eat healthy food can do so by willfully inhibiting th impulse to eat a candy bar and deliberately selecting an apple instead. Such effortful self regulatory processes can be diminished simply by engaging them, as well as by situationa constraints such as exerting self-restraint in an unrelated prior task or by concurrentl engaging in a cognitively taxing task (e.g., Sherman, Lee, Bessenoff, & Frost, 1998).

However, a more efficient form of self-regulation can be engaged by shifting focu from proximal goals to distal ones. For example, Fujita and Han (2009) demonstrate that people who were induced to focus on distal goals (e.g., being healthy) demonstrate an implicit preference for apples relative to candy. In contrast, people who were induce to focus on proximal goals (e.g., eating a tasty treat) demonstrated an implicit preferenc for candy relative to apples. In other words, focusing on distal versus proximal goal can influence responses on implicit measures by increasing the appeal of goal-congruer items and decreasing the appeal of goal-conflicting items.

As the three preceding examples demonstrate, a variety of self-regulatory processes can influence responses on implicit measures. However, this should not be interpreted as a comprehensive list of all of the forms of self-regulation that can do so. Instead, these findings demonstrate that self-regulation can operate under a broader range of conditions than initially expected and provide a more nuanced understanding of what implicit tasks measure.

Modeling Approaches to Investigating Self-Regulation on Implicit Measures

In highlighting the influence of self-regulation on implicit measures, the broad point of the research reviewed so far is to establish that implicit measures are not process-pure but instead reflect the contribution of multiple processes. To be sure, implicit measures are influenced by underlying mental associations, which is what they were initially developed to measure. However, activation of mental associations is only one of many types of cognitive processes that contribute to behavioral outcomes observed on implicit measures (Conrey, Sherman, Gawronski, Hugenberg, & Groom 2005; Sherman et al., 2008). To further illustrate this important point, consider the Stroop (1935) color-naming task, which is structurally very similar to many implicit measures. In the most common version of the Stroop task, participants respond to the color in which a word is displayed and ignore the semantic meaning of the word itself. For example, the correct response to the word *blue* displayed in red ink would be "red." A fully literate adult and a child who knows his or her colors but not words may perform equally well on the Stroop task, but for very different reasons. When the word *blue* is displayed in red ink, the adult must overcome his or her well-practiced habit of reading the word in order to name the color of the ink correctly, which adults are able to do on most trials. In contrast, the preliterate child has no reading habit to overcome, so he or she can easily respond correctly to the color of the ink. In other words, similar outcomes may result from quite different mixtures of cognitive processes.

The basic principle of different processes leading to the same outcome extends to measures of implicit social cognition as well. For example, consider the case of Strong Stan and Weak Willie, two hypothetical individuals completing an implicit measure designed to assess attitudes toward white and black people. Strong Stan has strong associations between whites and pleasant concepts, but also has a strong ability to regulate these biased associations. In contrast, Weak Willie only has weak associations between whites and pleasant concepts, but also has a weak ability to regulate these biased associations. Stan and Willie would appear equally unbiased on the implicit measure, but for different reasons. Stan can inhibit his strong biased associations from influencing his responses, whereas Willie does not have much bias to regulate in the first place.

In terms of behavioral responses, the adult and the child appear equally proficient at identifying colors, and Stan and Willie appear equally unbiased. However, as these examples illustrate, focusing on behavioral responses alone can obscure the contributions of multiple processes or combinations of processes that influence those responses. Fortunately, a tool exists that can disentangle the joint influence of multiple processes to behavioral responses: *multinomial modeling* (Batchelder & Riefer, 1999). At the most basic level, a multinomial model is simply a theory spelled out in precise mathematical terms. A multinomial model begins with a set of variables and a set of equations that establishes relationships among the variables. The variables in the equations represent the hypothesized component processes that result in different responses on the measure of interest, and the equations define the manner in which the processes interact to produce those responses. Plugging in participants' actual responses as outcomes in the equations yields estimates of the extent to which each of the processes contributed to those responses.

The Quadruple Process Model

One such multinomial model that has been extensively used to study the influence of self-regulation on implicit measures is the Quadruple Process model (Quad model; Conrey et al., 2005; Sherman et al., 2008). The Quad model specifies the contributions of four qualitatively distinct processes to performance on implicit measures of social cognition: (1) the activation of an association (Association aCtivation [AC]), (2) the ability to determine correct and incorrect responses (Detection [D]), (3) the ability to overcome activated associations when they conflict with the detected correct response (Overcoming Bias [OB]), and (4) the influence of a general response bias that guides responses in the absence of other available guides to response (Guessing [G]).

As an example of how the Quad model works, consider the earlier example of positive context reducing implicit bias against black targets (Allen et al., 2010). In this experiment, participants briefly viewed pictures of black or white males,and then judged whether a subsequent target word was positive or negative. To the extent that an image of a black male activates negative associations (AC), this predisposes participants to press the key labeled negative when judging a subsequent target word (see Figure 4.1). When the target word is negative (i.e., a *compatible* trial), the activated negative predisposition facilitates a correct response. In contrast, when the target word is positive (i.e., an *incompatible* trial), the activated negative disposition interferes with a correct response.

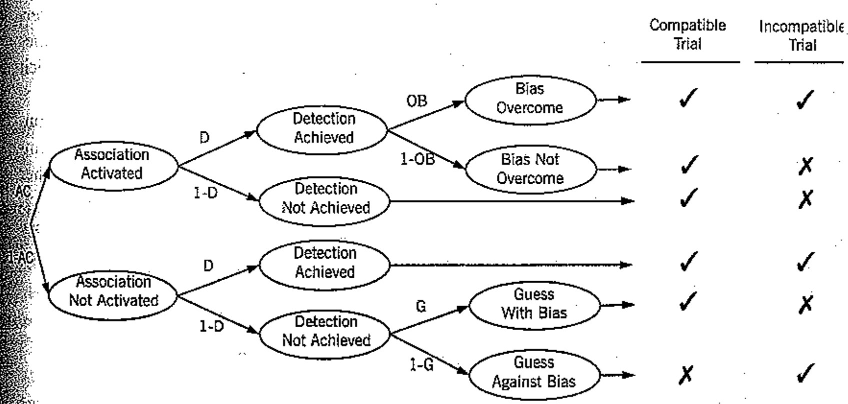

FIGURE 4.1. Quad model processing tree. ✓'s indicate correct responses; ✗'s indicate incorrect responses.

Participants can also make a correct response by accurately detecting (D) the valence of the target word. When a picture of a black male is followed by a negative word, both the activated negative association and detecting the correct response produce the same response tendency: to press the key labeled negative. However, when a picture of a black male is followed by a positive word, the response tendency activated by the negative association conflicts with the detected correct response. To the extent that participants are able to overcome their biased negative associations (OB), they will make a correct response by pressing the key labeled positive. However, if they fail to overcome their biased associations (1 – OB), these biased associations will drive an incorrect response to press the key labeled negative. Finally, when no associations are activated and the correct response is not detected, participants have to guess (G). Guessing is not necessarily random but, instead, may be quite strategic, such as a general positivity bias or a preference for stimuli on one side of the display (Conrey et al., 2005; Nisbett & Wilson, 1977).

The conditional relationships described by the model form a system of equations that predicts the numbers of correct and incorrect responses on the different trial types. For example, there are three different ways to make a correct response when a positive target word is preceded by a picture of a black male. The first way is when the picture of a black male activates negative associations (AC), the correct answer is detected (D), and the negative association is overcome in favor of the detected correct response (OB), which produces the equation $AC \times D \times OB$. The second way to make a correct response is when no biased associations are activated $(1 - AC)$ and the correct response is detected (D), which produces the equation $(1 - AC) \times D$. Finally, the third way to make a correct response is when no biased associations are activated $(1 - AC)$, the correct response is not detected $(1 - D)$, and the participant guesses correctly (G), which produces the equation $(1 - AC) \times (1 - D) \times (G)$. Taken together, the overall likelihood of making a correct response on this trial can be represented by the sum of these equations: $AC \times D \times OB + (1 - AC) \times D + (1 - AC) \times (1 - D) \times (1 - G)$. Analogous equations can be produced for the other item categories (e.g., black males, white males, positive words, negative words; in both compatible and incompatible blocks). The parameter values in these equations are changed through maximum likelihood estimation until they produce a minimum difference between the observed data and the model's predicted data, and the resulting values are interpreted as the relative contributions of each process to responses on the implicit measure.

Using the Quad model, Allen and colleagues (2010) demonstrated that positive contexts decrease implicit bias toward black targets by increasing the likelihood of overcoming biased associations without changing the activation of those associations. In other words, self-regulation alone appears to account for the observed reduction in implicit bias. Initial assumptions that implicit measures are free of the influence of regulatory processes would not only have overlooked such a possibility but also would have deemed such an outcome inconceivable, by definition.

Other Applications of the Quad Model

ANTI-AGING BIAS

This multinomial model has been used to identify the influence of self-regulation across a number of implicit bias domains. For example, Gonsalkorale, Sherman, and Klauer

(2014) applied the Quad model to study implicit age bias (Nosek, Banaji, & Greenwald, 2002) and, in doing so, illustrated an important point about how failing to account for self-regulatory processes can obscure important between-group differences. A common finding in the implicit age bias literature is that younger and older adults have implicit biases that equally favor youth over age when measured in terms of behavioral responses on implicit measures. This apparent null result has been commonly interpreted to mean that old and young people equally associate positivity with youth more strongly than with age. This interpretation assumes that implicit measures solely reflect attitudinal associations and are free of the influence of other processes. However, recognizing that self-regulation also influences responses on implicit measures suggests an alternative hypothesis. As people age, they generally show diminished executive functioning (see von Hippel & Henry, Chapter 26, this volume), and this loss of executive functioning may be especially important for inhibiting biased associations. Thus, older adults might show similar levels of implicit anti-aging bias as younger adults not because they have equally strong associations between youth and positivity, but because they have weaker associations that they are less able to inhibit (Gonsalkorale et al., 2014; von Hippel, Silver, & Lynch, 2000).

Gonsalkorale and colleagues (2014) tested these two competing hypotheses by applying the Quad model to a large sample of data ($N = 90{,}000+$) from visitors to the Project Implicit website (*implicit.harvard.edu*) who completed an age bias IAT. Younger and older people demonstrated equivalent age bias on the IAT (Nosek et al., 2002). However, applying the Quad model to these data revealed that older people had significantly weaker old-negative and young-positive associations activated than did younger people. Additionally, and importantly, older people also had weaker ability to overcome the expression of their biased associations relative to younger people. Thus, the equivalent IAT bias demonstrated by older and younger individuals both falsely suggested that older and younger people have equally negative associations with aging and obscured important group differences in the ability to self-regulate responses. These findings highlight how failing to account for self-regulation on implicit measures can bias the interpretations of such data.

AGING AND IMPLICIT RACE BIAS

Another common finding in the implicit bias literature is that older people tend to show greater implicit racial bias than do younger people (von Hippel et al., 2000). A common interpretation of this finding is that older people as a cohort have more biased racial associations than do younger people because they grew up in a time in which racism was more socially acceptable (Nosek et al., 2002). Gonsalkorale and colleagues (2009) proposed as an alternative that the ability to self-regulate responses might instead account for these observed differences in implicit racial bias. By applying the Quad model to data from more than 15,000 participants who visited Project Implicit, Gonsalkorale and colleagues (2009) found strong support for the latter hypothesis: Biased racial associations did not vary with age, but the ability to regulate biased associations decreased significantly with age. Thus, differences between older and younger people in the expression of racial bias could be entirely explained by systematic differences in the ability to self-regulate behavior.

ALCOHOL AND IMPLICIT BIAS

In another application of the Quad model, Sherman and colleagues (2008) reanalyzed data from Bartholow, Dickter, and Sestir (2006), who had found that alcohol increased stereotypical responding on an implicit measure. There are several reasons why alcohol might have influenced stereotypical responses in this manner. On one hand, alcohol might increase the accessibility of biased associations. On the other hand, alcohol might inhibit the operation of self-regulatory processes that constrain the expression of biased associations. Application of the Quad model to these data revealed that activated associations appeared unaffected by alcohol intake, whereas self-regulatory processes were diminished. This finding illustrates the need for more nuanced conceptualizations of control processes: This self-regulatory process is efficient enough to influence responses on implicit measures, yet is still constrained by factors that diminish cognitive capacity (i.e., alcohol).

SELF-REGULATION AS A DOMAIN-GENERAL PROCESS

Though work using the Quad model had demonstrated that self-regulation can influence responses on implicit measures, the extent to which such self-regulatory processes are domain-general or domain-specific has remained an open question. Put another way, is the self-regulation measured by the Quad model specific to the attitude object in question or does it reflect a general ability to self-regulate across attitude objects? To address this issue, Calanchini, Sherman, Klauer, and Lai (2014) asked people to complete multiple IAT measures that varied in conceptual overlap. For example, some completed pairs of tests with high overlap (i.e., black/white and Asian/white IATs), while others completed pairs with low overlap (i.e., flower/insect and black/white IATs). A series of experiments revealed that people's ability to regulate their responses on one IAT correlated strongly with their regulatory ability on other IATs, regardless of how much the two IATs overlapped. This suggests that, in line with previous work (see Baumeister, Vohs, & Tice, 2007), the ability to self-regulate is largely domain-general. In contrast, activated associations (AC) were relatively sensitive to conceptual overlap. Specifically, AC correlated strongly when conceptual overlap was high, but correlated much less strongly when overlap was low. Taken together, these results indicate that responses on implicit measures such as the IAT are influenced by both domain-general and domain-specific processes.

The Stereotype Misperception Task and Multinomial Model

In order to investigate a different form of self-regulation, Krieglmeyer and Sherman (2012) developed the Stereotype Misperception Task (SMT) and a multinomial model of the task to measure the joint contributions of stereotype activation and application processes. The construction and logic of the SMT is similar to that of the Affect Misattribution Procedure (Payne, Cheng, Govorun, & Stewart, 2005). In a series of trials, an association-activating prime photograph of either a black or a white male is briefly displayed. Prime photographs are quickly followed by relatively ambiguous target faces that participants rapidly judge on a given dimension (e.g., "Is this face more or less threatening than average?"). Participants are explicitly instructed to avoid letting prime photographs influence their judgments of target images. Generally, participants judge target images in ways

that are consistent with stereotypes associated with the prime stimuli. For example, afte exposure to prime photographs of black males, subsequent target images are more likel to be judged to be more threatening and more athletic than average compared agains identical target stimuli following prime photographs of white males. Krieglmeyer an Sherman (2012) tested and validated a multinomial model for disentangling processes o stereotype activation and application in the task.

The SMT model begins with a parameter representing the likelihood that stereotypical associations are activated by the prime stimuli (SAC; see Figure 4.2). When stereotypical associations are not activated (1 – SAC), a detection parameter (D) represents th likelihood of discerning the correct response based on the characteristics of the targe stimulus (which actually vary on the dimension of interest; e.g., threat, athleticism). Whe stereotypical associations are activated (SAC), they can either be applied to a judgmen (SAP) or can be corrected against (1 – SAP). As such, the stereotype application (SAF parameter represents an alternate conceptualization of self-regulation than is represente by the overcoming bias (OB) parameter in the Quad model. Functionally, both SAP an OB represent processes that constrain activated associations from influencing behaviora responses. However, in the Quad model participants must detect (D) the correct tas response in order to overcome their biased associations. In contrast, SAP exerts influenc in the SMT model in the absence of a detected correct response. Whereas overcomin bias (OB) in the Quad model maps onto the concept of inhibition, regulating the expres sion of stereotypical associations (1 – SAP) in the SMT model is a form of self-regulatio that maps onto the psychological concepts of contrasting or theory-based overcorrectio (Krieglmeyer & Sherman, 2012). Finally, when associations are not activated (1 – SAC and detection of a correct response fails (1 – D), a guessing parameter (G) represents th tendency to choose from the available response options (e.g., more threatening).

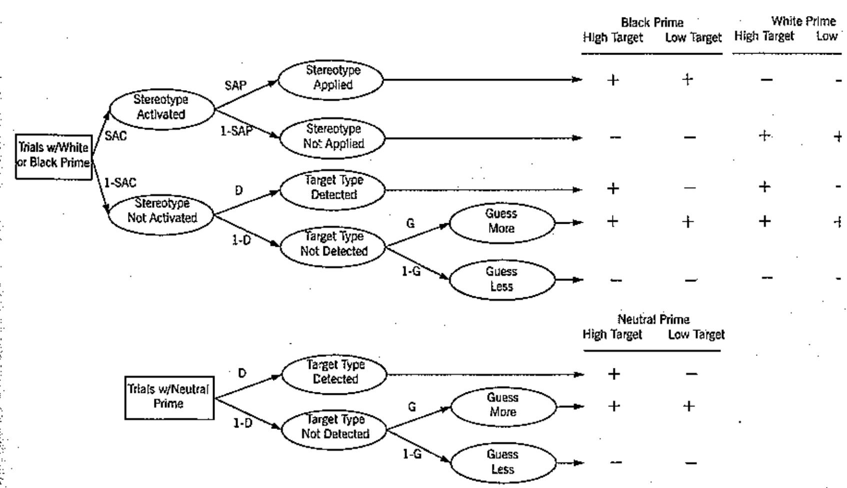

FIGURE 4.2. SMT model processing tree. Plus (+) symbols indicate "more threatening" jud ments; minus (–) symbols indicate "less threatening" judgments.

Normative Strategies for Self-Regulation on Implicit Measures

Very recent work from our laboratory seeks to understand the mechanisms underlying people's ability to self-regulate on implicit measures of stereotyping. In three experiments, we manipulated the time separating the onset of stereotype-activating images of black and white males, and ambiguous target images in a modified SMT (Rivers, Sherman, Reichardt, & Klauer, 2015). As the time separating the prime and target images increased, people's judgments became less biased. Results from the SMT multinomial model indicated that in all three experiments, stereotype activation increased as time separation increased. However, in all three experiments, people also became less likely to apply activated stereotypes to their judgments with increasing time. Without the modeling approach, we would likely have assumed that the decrease in biased judgments at longer delays was necessarily due to decreased activation of stereotypes. This counterintuitive but seemingly robust finding warrants further research and underscores the importance of understanding self-regulation on implicit measures: People can self-regulate behavior even when stereotypical associations are highly active, and diminished stereotyping may occur even in the face of increased activation.

SUMMARY

In the last 25 years, research use of implicit measures of social cognition has converged on several important points. Implicit measures provide a window into an otherwise obscured cognitive landscape. They offer new perspectives on fundamental psychological concepts such as attitudes, stereotypes, and behavioral tendencies. Additionally, implicit measures have helped to generate new hypotheses about the conditions under which cognitive processes operate and influence behavior.

Historical definitional confounds between operating principles (what the process does) and operating conditions (when the process operates) have led to the assumption that responses on these measures are automatic and uncontrollable. It is certainly true that responses on implicit measures are less controllable than their explicit counterparts. However, there is now considerable evidence that people do self-regulate their responses on implicit measures (e.g., Payne, 2001; Sherman et al., 2008).

To whatever extent behavioral responses on implicit measures (e.g., button presses) predict more complex behaviors outside of the laboratory (e.g., behavior during a social interaction), then it follows that the processes that contribute to implicit task performance also may contribute to more complex behavior. Thus, if self-regulatory processes are important contributors to the button presses that reveal implicit attitudes, and if implicit attitudes predict complex intergroup behavior, then it is likely that the same self-regulatory processes that influence implicit task performance also influence broader behavior (e.g., Gonsalkorale et al., 2009).

This chapter highlights one powerful technique for dissociating the contributions of multiple processes to responses on implicit measures: multinomial models. This technique permits researchers independently and simultaneously to measure the contributions of multiple distinct processes to implicit task performance. These models also specify mathematically the manner in which these processes interact and constrain one another in producing that performance. Thus, by formally articulating the ways in which the

theorized processes interact, the theory itself can be evaluated quantitatively using mod fit indices (e.g., chi-square). Because multinomial models make no assumptions about th operating conditions of the defined processes, they also provide a framework from whic these boundary conditions can be empirically tested. When the operating principles c self-regulatory processes are defined independently of the conditions under which the operate, it becomes clear that implicit measures reflect the joint influence of multiple cog nitive processes, including important contributions from self-regulation.

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REFERENCES

Allen, T. J., Sherman, J. W., & Klauer, K. C. (2010). Social context and the self-regulation implicit bias. *Group Processes and Intergroup Relations, 13*(2), 137–149.

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

Bartholow, B. D., Dickter, C. L., & Sestir, M. A. (2006). Stereotype activation and control of ra bias: Cognitive control of inhibition and its impairment by alcohol. *Journal of Personali and Social Psychology, 90*, 272–287.

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

Baumeister, R. F., Vohs, K. D., & Tice, D. M. (2007). The strength model of self-control. *Curre Directions in Psychological Science, 16*(6), 351–355.

Calanchini, J., Sherman, J. W., Klauer, K. C., & Lai, C. K. (2014). Attitudinal and non-attitudin components of IAT performance. *Personality and Social Psychology Bulletin, 40*(10), 128 1296.

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

De Houwer, J., & Moors, A. (2012). How to define and examine implicit processes? In R. Proct & E. J. Capaldi (Eds.), *Psychology of science: Implicit and explicit processes* (pp. 183–19 Oxford, UK: Oxford University Press.

Fazio, R. H. (1990). Multiple processes by which attitudes guide behavior: The MODE model an integrative framework. *Advances in Experimental Psychology, 23*, 75–109.

Fazio, R. H., Jackson, J. R., Dunton, B. C., & Williams, C. J. (1995). Variability in automa activation as an unobtrusive measure of racial attitudes: A bona fide pipeline? *Journal Personality and Social Psychology, 69*(6), 1013–1027.

Fujita, K. (2011). On conceptualizing self-control as more than the effortful inhibition of impuls *Personality and Social Psychology Review, 15*(4), 352–366.

Fujita, K., & Han, H. A. (2009). Moving beyond deliberative control of impulses: The effects construal levels on evaluative associations in self-control. *Psychological Science, 20*, 79 804.

Gawronski, G., & Bodenhausen, G. V. (2007). What do we know about implicit attitude measu and what do we have to learn? In B. Wittenbrink & N. Schwarz (Eds.), *Implicit measures attitudes* (pp. 265–286). New York: Guilford Press.

Gawronski, B., Sherman, J. W., & Trope, Y. (2014). Two of what? In J. W. Sherman, B. Gawron

& Y. Trope (Eds.), *Dual-process theories of the social mind* (pp. 3–19). New York: Guilford Press.
Glaser, J., & Knowles, E. D. (2008). Implicit motivation to control prejudice. *Journal of Experimental Psychology, 44*, 164–172.
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*, 161–166.
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.
Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit social cognition: The Implicit Association Test. *Journal of Personality and Social Psychology, 74*(6), 1464–1480.
Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences, 16*(3), 174–180.
Hofmann, W., Vohs, K. D., & Baumeister, R. F. (2012). What people desire, feel conflicted about, and try to resist in everyday life. *Psychological Science, 23*(10), 1130–1136.
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.
Monteith, M. J., Ashburn-Nardo, L., Voils, C. I., & Czopp, A. M. (2002). Putting the brakes on prejudice: On the development and operation of cues for control. *Journal of Personality and Social Psychology, 83*(5), 1029–1050.
Moskowitz, G. B., Gollwitzer, P. M., Wasel, W., & Schaal, B. (1999). Preconscious control of stereotype activation through chronic egalitarian goals. *Journal of Personality and Social Psychology, 77*(1), 167–184.
Moskowitz, G. B., & Li, P. (2008). Egalitarian goals trigger stereotype inhibition: A proactive form of stereotype control. *Journal of Experimental Social Psychology, 47*, 103–116.
Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review, 84*(3), 231–259.
Nosek, B. A., Banaji, M., & Greenwald, A. G. (2002). Harvesting implicit group attitudes and beliefs from a demonstration web site. *Group Dynamics: Theory, Research, and Practice, 6*, 101–115.
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., Cheng, C. M., Govorun, O., & Stewart, B. D. (2005). An inkblot for attitudes: Affect misattribution as implicit measurement. *Journal of Personality and Social Psychology, 89*(3), 277–293.
Perkins, A., & Forehand, M. (2010). Implicit social cognition and indirect measures in consumer behavior. In B. Gawronski & B. K. Payne (Eds.), *Handbook of implicit social cognition: Measurement, theory, and applications* (pp. 535–547). New York: Guilford Press.
Rivers, A. M., Sherman, J. W., Reichardt, R., & Klauer, K. C. (2015). *On the time course of stereotype activation and application: How stereotypes influence social judgment.* Manuscript in preparation.
Rydell, R. J., & McConnell, A. R. (2006). Understanding implicit and explicit attitude change: A systems of reasoning analysis. *Journal of Personality and Social Psychology, 91*(6), 995–1008.
Sherman, J. W., Lee, A. Y., Bessenoff, G. R., & Frost, L. A. (1998). Stereotype efficiency reconsidered: Encoding flexibility under cognitive load. *Journal of Personality and Social Psychology, 75*(3), 589–606.
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*, 314–335.

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.
Stroop, J. R. (1935). Studies on the interference in serial verbal reactions. *Journal of Experimental Psychology, 59*, 239–245.
Teachman, B. A., Gregg, A. P., & Woody, S. R. (2001). Implicit associations for fear-relevant stimuli among individuals with snake and spider fears. *Journal of Abnormal Psychology, 110*(2), 226–235.
von Hippel, W., Silver, L. A., & Lynch, M. E. (2000). Stereotyping against your will: The role of inhibitory ability in stereotyping and prejudice among the elderly. *Personality and Social Psychology Bulletin, 26*(5), 523–532.
Vohs, K. D., Baumeister, R. F., & Ciarocco, N. (2005). Self-regulation and self-presentation: Regulatory resource depletion impairs impression management and effortful self-presentation depletes regulatory resources. *Journal of Personality and Social Psychology, 8*, 632–657.
Wiers, R. W., Houben, K., & de Kraker, J. (2007). Implicit cocaine associations in active cocaine users and controls. *Addictive Behaviors, 32*, 1284–1289.
Wittenbrink, B. (2007). Measuring attitudes through priming. In B. Wittenbrink & N. Schwarz (Eds.), *Implicit measures of attitudes* (pp. 17–58). New York: Guilford Press.
Wittenbrink, B., Judd, C. M., & Park, B. (2001). Spontaneous prejudice in context: Variability in automatically activated attitudes. *Journal of Personality and Social Psychology, 81*(5), 815–827.