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The Relations Among Inhibition and Interference Control Functions: A Latent-Variable Analysis

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This study used data from 220 adults to examine the relations among 3 inhibition-related functions. Confirmatory factor analysis suggested that Prepotent Response Inhibition and Resistance to Distractor Interference were closely related, but both were unrelated to Resistance to Proactive Interference. Structural equation modeling, which combined Prepotent Response Inhibition and Resistance to Distractor Interference into a single latent variable, indicated that 1 aspect of random number generation performance, task-switching ability, and everyday cognitive failures were related to Response–Distractor Inhibition, whereas reading span recall and unwanted intrusive thoughts were related to Resistance to Proactive Interference. These results suggest that the term *inhibition* has been overextended and that researchers need to be more specific when discussing and measuring inhibition-related functions.

> The ability to suppress irrelevant or interfering stimuli or impulses is a fundamental executive function essential for normal thinking processes and, ultimately, for successful living. (Garavan, Ross, & Stein, 1999, p. 8301)

The notions of *inhibition* and *interference control* have existed for over 100 years (for reviews, see Dempster, 1995; MacLeod, Dodd, Sheard, Wilson, & Bibi, 2003). For example, inhibition has long played an important explanatory role in theories of psychopathology (e.g., Freud's [1910] notion of repression). Early theories of verbal learning (McGeoch, 1932; Underwood, 1957) attempted to specify the conditions mediating retroactive and proactive interference. Interest in these phenomena wavered, however, with the advent of the computer metaphor for the mind (Bjork, 1989). The information-processing perspective focused on the concept of so-called cognitive resources (e.g., memory capacity and processing efficiency) to explain cognition (Kahneman, 1973; Norman & Bobrow, 1975), and the notions of inhibition and interference control faded into the background. Within the past 20 years, however, the brain metaphor of the mind has become an important alternative to the information-processing perspective. This paradigm shift has been accompanied by a resurrection and broadening of interest in the concepts of inhibition and interference for understanding everyday cognition, as evidenced in the statement by Garavan et al. (1999) quoted above.

Now, the concepts of inhibition and interference control (hereinafter called *inhibition-related functions*) have become central players in numerous research domains within psychology (Dagenbach & Carr, 1994; Dempster & Brainerd, 1995; Sarason, Pierce, & Sarason, 1996). For example, deficient inhibition-related processes have been postulated in disorders such as attention-deficit/hyperactivity disorder (ADHD; Barkley, 1997; Nigg, 2001), schizophrenia (Nestor & O'Donnell, 1998), autism (Ciesielski & Harris, 1997), and obsessive–compulsive disorder (Enright & Beech, 1993). Changes in inhibition-related functions have also been used to explain the development of cognitive abilities (Diamond & Gilbert, 1989; Ridderinkhof, van der Molen, Band, & Bashore, 1997) as well as age-related declines in cognitive abilities (Hasher & Zacks, 1988; McDowd, Oseas-Kreger, & Filion, 1995). In addition, individual differences in inhibition-related functions in normal adults have been proposed as underlying variation in memory failures (M. C. Anderson, 2001), working memory (WM) span and reading comprehension (De Beni, Palladino, Pazzaglia, & Cornoldi, 1998; Gernsbacher, 1993), problem solving (Passolunghi, Cornoldi, & De Liberto, 1999), and general cognitive ability (Dempster & Corkill, 1999a). Inhibition-related functions have even been offered as a unifying theme for life span development (Dempster, 1992), educational psychology (Dempster & Corkill, 1999b), and psychology and neuroscience (Clark, 1996).

Recently, several theorists have proposed that inhibition-related processes are a family of functions rather than a single unitary construct (Dempster, 1993; Harnishfeger, 1995; Nigg, 2000). At this point, however, there is little empirical evidence for or against such proposals. The main goal of the current study was to examine the relations among three potentially separable inhibition-related functions—Prepotent Response Inhibition, Resistance to Distractor Interference, and Resistance to Proactive Interference (PI)—

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from an individual-differences perspective and to begin to explore how these functions are involved in complex cognition.

PREVIOUS RESEARCH ON INHIBITION-RELATED FUNCTIONS

The meanings of the terms *inhibition* and *interference control* are often broad and inconsistent across authors. For example, Clark (1996) defined inhibition as "any mechanism that reduces or dampens neuronal, mental, or behavioral activity" (p. 128). The concept of resistance to interference or interference control, which is distinguishable from but often used interchangeably with inhibition (Harnishfeger, 1995), is in some cases equally vague: It

> can refer to suppressing a stimulus that pulls for a competing response so as to carry out a primary response, to suppressing distractors that might slow the primary response, or to suppressing internal stimuli that may interfere with the current operations of working memory. (Nigg, 2000, p. 222)

Reflecting these differences in definitions, a number of tasks have been used to tap these processes (Kok, 1999; Nigg, 2001). A typical approach is to select one or more tasks thought to measure inhibition-related functions and examine the correlations between them or group differences in performance on them. Often, the results are not promising. For example, Shilling, Chetwynd, and Rabbitt (2002, Experiment 1) examined the coherence of the inhibition construct by correlating four variants of the Stroop task (Stroop, 1935) that used color words, figure–ground stimuli, numbers, and arrows. The correlations between the Stroop interference effects on these four tasks ranged from –.13 to .22 (all nonsignificant in their sample of 49 older adults). They concluded that these tasks showed no convergent validity and pointed out that any common inhibition ability was likely to be obfuscated by the idiosyncratic demands of each task.

Another example comes from a study of age-related declines in inhibition ability (Kramer, Humphrey, Larish, Logan, & Strayer, 1994). Kramer et al. administered a battery of inhibition-related tasks and found that older adults showed significant age-related impairments on some measures (Wisconsin Card Sorting Test and a stop-signal task) but not on others (negative priming, the Cognitive Failures Questionnaire [CFQ], and two measures of distractor interference). The absolute values of the correlations between these measures (partialing out age) ranged from .01 to .35, most of which were not significant in their sample of 62 participants. Kramer et al. interpreted these results as providing "only limited" evidence for age-related declines in inhibition ability and "little" evidence for the generality of inhibitory functions.

These examples represent two of the better studies of inhibition-related functions, and their results are typical. Many researchers have interpreted similar mixed results and low zero-order correlations as evidence for separable inhibition-related processes (e.g., Earles et al., 1997; Grant & Dagenbach, 2000; Tipper & Baylis, 1987). However, a lack of significant correlations or of significant group differences is difficult to interpret for several reasons (Miyake, Emerson, & Friedman, 2000).

The first problem is that the construct validities of some commonly used inhibition tasks are not well established (Rabbitt, 1997; Reitan & Wolfson, 1994). Researchers commonly use measures that they assume involve inhibitory processes, often without providing any justification for why those particular measures were selected or whether they actually involve inhibitory processes. For example, the negative priming effect is frequently used as an inhibition measure in group or individual-differences studies, but it is not universally agreed that the negative priming effect is due to inhibition (e.g., Milliken, Joordens, Merikle, & Seiffert, 1998; Neill, Valdes, Terry, & Gorfein, 1992; J. Park & Kanwisher, 1994). In fact, MacLeod et al. (2003) recently argued that many of the phenomena typically interpreted in terms of inhibitory processes (e.g., negative priming) could be explained without recourse to the notion of inhibition. Hence, low correlations among so-called inhibition tasks could arise because the measures may not be tapping the intended inhibitory processes.

The second complication arises from the fact that complex executive tasks, including tasks frequently used to tap inhibition-related functions, tend to show poor reliability (Denckla, 1996; Rabbitt, 1997). Although the sources of these low reliabilities are not clear, they are likely multifaceted. One possibility is that measures of executive functions are most valid when they are novel and impose high attentional control demands (Rabbitt, 1997). As participants gain experience with the task, it may no longer require much attentional control, particularly if they start to develop idiosyncratic strategies to cope with the task demand. These changes could lead to low reliability of the measures. Another possible source of poor reliability is that many dependent measures for putative inhibition tasks, including the ones we used in this study, take the form of difference scores (i.e., differences in accuracy or time between versions of a task that differ in inhibitory requirements), which have been known to increase measurement error (Cohen & Cohen, 1983). Regardless of its sources, low reliability puts an upper limit on the correlations. Thus, low zero-order correlations among inhibition tasks could be a result of low reliabilities, rather than of separable inhibition functions.

A third difficulty is the task impurity problem: No tasks are pure measures of inhibition. That is, inhibition is always inhibition *of something* (a response, a thought, distraction, etc.), so any putative inhibition task also involves other processes. For this reason, low scores on a task may not necessarily be due to deficient inhibition ability per se. Similarly, low correlations may not necessarily be due to separable inhibition processes, because other task demands may mask commonalities attributable to inhibition (Miyake, Friedman, et al., 2000; Shilling et al., 2002). In other words, a large proportion of the variance associated with each putative inhibition task may reflect individual variations in other idiosyncratic requirements of the task, with only a small proportion of the variance actually capturing variation in inhibitory control processes.

Shilling et al.'s (2002) approach to circumventing this task impurity problem was to make their inhibition tasks almost identical. In their Experiment 2, they used two versions of the arrow Stroop task: one with arrows pointing left and right and one with arrows pointing up and down. However, this strategy of keeping the tasks as similar as possible is problematic because the resulting common variance comes from both inhibitory demands and other demands related to the methodology. Furthermore, this strategy does not alleviate the reliability and construct validity problems.

An alternative approach for alleviating these problems is *latent-variable analysis.* This technique statistically extracts the common variance among multiple tasks chosen to tap the same underlying construct. These latent variables provide purer measures in that the variance attributable to idiosyncratic task requirements is excluded, thereby reducing the task impurity problem. Furthermore, these latent variables can be more reliable because measurement error is excluded, and, hence, the correlations between latent variables are analogous to correlations corrected for attenuation due to unreliability (Bollen, 1989). Finally, the types of latent-variable analyses used in the current study—confirmatory factor analysis (CFA) and structural equation modeling (SEM)—differ from other multivariate techniques (e.g., exploratory factor analysis) that are data-driven and a posteriori. Because CFA and SEM require a model of the underlying functions contributing to each task to be specified before analysis, they do not necessitate post hoc explanation and are less likely to capitalize on chance.

A study by Miyake, Friedman, et al. (2000) illustrated the benefits of this technique, which they used to understand the relations among three often-postulated executive functions: mental set shifting, inhibiting prepotent responses, and updating the contents of WM. On the basis of a series of CFA model comparisons, they concluded that these three functions, though moderately correlated, were separable. They then used SEM to test hypotheses as to which specific executive functions are involved in several complex executive and frontal lobe tasks. They found that random number generation (RNG) involves both updating the contents of WM and inhibiting prepotent responses (depending on the types of randomness indices used), the Wisconsin Card Sorting Test involves mental set shifting, the Tower of Hanoi puzzle involves inhibiting prepotent responses, and the operation span task (a measure of WM capacity) involves updating the contents of WM. The current study is an extension of this previous work in that it uses the same approach to further investigate inhibition-related processes.

TAXONOMIES OF INHIBITION-RELATED PROCESSES

When different definitions of inhibition are considered together, several conceptual distinctions can be made. Nigg (2000) classified inhibitory processes in psychology into four types of effortful inhibition: (a) interference control, which is suppression of interference due to resource or stimulus competition; (b) cognitive inhibition, which is suppression of irrelevant information from WM; (c) behavioral inhibition, which is suppression of prepotent responses; and (d) oculomotor inhibition, which is suppression of reflexive saccades. (Nigg also proposed that inhibition of return and covert attentional orienting reflect automatic inhibition of attention.)

Nigg’s (2000) taxonomy was based on the suggestions of Harnishfeger (1995), who proposed that inhibition processes could be classified according to three dimensions. One dimension is whether they are intentional or unintentional. Unintentional inhibition occurs prior to conscious awareness (e.g., the resolution of meaning for polysemous words and negative priming). In contrast, intentional inhibition results when a stimulus is classified as irrelevant and is then consciously suppressed (e.g., thought suppression and the control of memory intrusions). The second dimension concerns whether inhibition takes place at a behavioral or cognitive level. Behavioral inhibition controls behavior and is reflected in such processes as inhibiting motor responses and controlling impulses, whereas cognitive inhibition controls mental processes, such as attention and memory, and is reflected in suppressing unwanted or irrelevant thoughts, suppressing inappropriate meanings of ambiguous words, and gating irrelevant information from WM. Finally, Harnishfeger (who has recently published under the name Kipp) also made a distinction between inhibition and resistance to interference. According to Wilson and Kipp (1998), inhibition is an active suppression process that operates on the contents of WM, whereas resistance to interference is a gating mechanism that prevents irrelevant information or distracting stimuli from entering WM (however, Wilson & Kipp [1998] acknowledged that inhibition and resistance to interference may be related and controlled by similar neurological substrates). According to this taxonomy, Kipp would describe Nigg’s interference control as “intentional cognitive resistance to interference,” his cognitive inhibition as “intentional cognitive inhibition,” and his behavioral and oculomotor inhibitions as forms of “intentional behavioral inhibition.”

Dempster and Corkill (1999a) defined resistance to interference more broadly as “the ability to ignore or inhibit irrelevant information while executing a plan” (p. 397). Dempster (1993), however, proposed that resistance to interference is not a unitary construct, because developmental patterns in resistance to interference differ for motor, perceptual, and linguistic domains. Although this way of classifying interference control may appear different from the distinctions made by Nigg (2000) and Harnishfeger (1995), it is actually quite similar. Dempster’s control of motor interference and control of verbal–linguistic interference are analogous to Nigg’s and Harnishfeger’s behavioral and cognitive inhibitions, respectively, and the notion of perceptual interference has many similarities to Nigg’s interference control and Harnishfeger’s resistance to interference.

Note that these conceptual distinctions among different kinds of inhibition roughly correspond to different stages of information processing. Nigg’s (2000) interference control, Harnishfeger’s (1995) resistance to interference, and Dempster’s (1993) control of perceptual interference all seem to refer to an initial perceptual stage of processing, where relevant information must be selected and irrelevant information must be ignored. Nigg’s and Harnishfeger’s cognitive inhibition and Dempster’s control of verbal–linguistic interference might be considered inhibition at a more intermediate level, once information has entered WM. Finally, Nigg’s and Harnishfeger’s behavioral inhibition and Dempster’s control of motor interference seem to correspond to a later output stage of processing in which relevant responses must be selected and incorrect ones resisted.

Although different types of inhibition processes correspond to different stages of processing, such correspondence does not necessarily mean that these processes require separate inhibitory abilities. These inhibition-related functions all seem to require some degree of executive control, which is proposed to involve the frontal lobes or the anterior attentional network (Posner & Raichle, 1994). For most of the functions discussed, evidence for involvement of the frontal lobes comes from studies of patients with frontal lesions, from neuroimaging studies, or from studies of aging (because the frontal lobes deteriorate more rapidly than other brain areas with age [see Rabbitt, Lowe, & Shilling, 2001, for a review], age-related deficits in executive processes are often interpreted as evidence for frontal lobe involvement in those processes). Thus, at least one commonality among the various types of inhibition-related processes proposed is the involvement of the frontal lobes in performing the representative tasks, although few investigations have examined whether the specific frontal regions involved in these tasks overlap (but see Konishi et al., 1999; Rubia et al., 2001).

THE CURRENT STUDY

The taxonomies of inhibition-related functions proposed by Nigg (2000) and others are based primarily on conceptual distinctions. Although inhibition-related functions may be conceptually distinguishable, it is not clear the extent to which these functions reflect the same cognitive abilities. In fact, to the best of our knowledge, there is no systematic attempt to evaluate empirically the proposed taxonomies of inhibition-related functions.

The first goal of the current study was to provide an initial attempt to test the distinctions among three inhibition-related functions, using CFA. The three functions (to be described in more detail shortly) were Prepotent Response Inhibition, Resistance to Distractor Interference, and Resistance to PI. These particular functions were selected to represent the major types of inhibition-related processes discussed in the literature and conform to Nigg's (2000) recent taxonomy. Prepotent Response Inhibition is basically Nigg's behavioral inhibition combined with oculomotor inhibition (although Nigg suggested that there may be a distinction between these two types of inhibition, he also acknowledged that they are often combined), Resistance to Distractor Interference is similar to Nigg's interference control, and Resistance to PI is similar to Nigg's cognitive inhibition.[1]

The second goal of the study was to examine how these inhibition-related functions contribute to other cognitive tasks and measures that have been linked, sometimes controversially, to inhibition-related functions. Using SEM, we explicitly tested existing hypotheses about the types of inhibition-related functions implicated for each of several measures we examined. These measures included one aspect of RNG performance (related to the suppression of stereotyped sequences), negative priming, task-switching ability, recall performance on the reading span test (Daneman & Carpenter, 1980), and the occurrences of everyday cognitive failures (Broadbent, Cooper, FitzGerald, & Parkes, 1982) and of unwanted intrusive thoughts (Wegner & Zanakos, 1994). To the extent that the three target inhibition-related functions are separable, they should be differentially related to these additional measures hypothesized to implicate inhibition or interference control.

To tap the three inhibition-related functions, we chose tasks that were relatively uncontroversial in terms of their inhibition-related requirements and seemed to tap primarily one of the three target functions. Because this study was the first of its kind, we felt it wise to use well-established tasks, rather than to develop completely new tasks. We also tried to make sure that the selected tasks differed considerably in the requirements other than the hypothesized inhibition-related functions. Because latent variables capture the variance that is shared by all the indicator measures, it was essential that the tasks did not share any other idiosyncratic requirements.

Prepotent Response Inhibition

Prepotent Response Inhibition is the ability to deliberately suppress dominant, automatic, or prepotent responses. The tasks used to assess this function were modified versions of those used by Miyake, Friedman, et al. (2000):

1. Antisaccade task (Hallett, 1978)—When a cue flashes on one side of the screen, participants try to suppress the reflexive saccade toward it and instead look in the opposite direction to identify the target.

2. Stop-signal task (Logan, 1994)—Once participants have built up a prepotent response to categorize words in a particular way, they try to withhold their responses on a small proportion of trials during which they hear an auditory signal.

3. Stroop task (Stroop, 1935)—Participants name the color in which color words and neutral words are printed, ignoring the dominant tendency to read the words.[2]

Of the three inhibition-related functions examined in this study, Prepotent Response Inhibition is the most straightforwardly associated with active suppression and executive functioning. Overriding habitual responses is a primary function of the supervisory attentional system (SAS), Norman and Shallice's (1986) classic model of executive control. Findings interpreted as evidence that Prepotent Response Inhibition involves controlled, limited-capacity processes come from studies showing that performance in these tasks declines with concurrent cognitive load (e.g., Mitchell, Macrae, & Gilchrist, 2002; Roberts, Hager, & Heron, 1994) and with aging (e.g., Butler, Zacks, & Henderson, 1999). Prepotent response inhibition has also been linked to frontal lobe functioning (e.g., Everling & Fischer, 1998; Jahanshahi et al., 1998; Kiefer, Marzinzik, Weisbrod, Scherg, & Spitzer, 1998; Milham et al., 2001; Perret, 1974; Vendrell et al., 1995). Indeed, the inability to suppress habitual responses (and the tendency to perseverate) is commonly observed in patients with frontal lobe dysfunction.

Resistance to Distractor Interference

Resistance to Distractor Interference is the ability to resist or resolve interference from information in the external environment that is irrelevant to the task at hand. Following a large body of

[1] We use the term *resistance to interference* (rather than inhibition) to avoid the implication that Resistance to Distractor Interference and Resistance to PI necessarily involve an act of active suppression. As MacLeod et al. (2003) pointed out, the term *interference* describes an effect or phenomenon, whereas the term *inhibition* implies a mechanism or explanation for an effect. The common use of the term *inhibition* to denote both a phenomenon and an underlying mechanism can be misleading, given that interference effects could also reflect mechanisms other than inhibition (e.g., conflict resolution).

[2] Although the Stroop task is sometimes classified as a resistance to interference task (e.g., Nigg, 2000), it differs in that the response that must be avoided is dominant (MacLeod, 1991). Thus, the Stroop task has also been used to tap Prepotent Response Inhibition (e.g., Miyake, Friedman, et al., 2000; Vendrell et al., 1995).

research on selective attention, the current study assessed Resistance to Distractor Interference with tasks in which participants had to select targets that were presented with irrelevant distractors:

1. Eriksen flanker task (Eriksen & Eriksen, 1974)—Participants identify a target letter that is presented either alone or with response-incompatible letters flanking it.

2. Word naming (Kane, Hasher, Stoltzfus, Zacks, & Connelly, 1994)—Participants name a green target word that is presented either alone or with a red distractor word.

3. Shape matching (DeSchepper & Treisman, 1996)—Participants indicate whether a white shape matches a green shape that is presented either alone or with a red distractor shape.

Resistance to Distractor Interference has been associated with focused attention or selective enhancement for target stimuli. Several researchers have gone one step further to propose that Resistance to Distractor Interference also involves suppression of the distracting information (e.g., Eriksen & Eriksen, 1974; Tipper, 1985). As Eriksen and Eriksen (1974) put it, because distractors produce response competition, "[an] inhibitory process is required to prevent the responses from running off willy-nilly" (p. 144). Given that distractor interference effects could be caused by processes other than active suppression (MacLeod et al., 2003), this claim must be taken with a grain of salt. Nevertheless, the findings that older adults are more susceptible to distractor interference than younger adults (Earles et al., 1997) and that patients with frontal lesions show increased distractor interference effects (Stuss et al., 1999) are consistent with the view that Resistance to Distractor Interference involves executive control.

Resistance to PI

Resistance to PI is the ability to resist memory intrusions from information that was previously relevant to the task but has since become irrelevant. Although this construct and Resistance to Distractor Interference are similar in that they both involve interference control, two features conceptually distinguish them: For Resistance to PI, the interfering information is presented prior to the target information and was previously relevant to the task, whereas for Resistance to Distractor Interference, the distracting information is presented simultaneously with the target information and is not relevant. The tasks used to assess Resistance to PI were as follows:

1. Brown–Peterson variant (Kane & Engle, 2000)—Participants learn and later free recall successive lists that are composed of words drawn from the same category.

2. AB–AC–AD (Rosen & Engle, 1998)—After learning a list of cue–target word pairs to a criterion, participants learn a new list of targets that are paired with the same cues.

3. Cued recall (Tolan & Tehan, 1999)—Participants view either one or two lists of four words each and must retrieve the word on the most recent list that belongs to a cued category, ignoring any previous lists.

Although interference effects may not necessarily result from active suppression, several researchers have proposed that Resistance to PI does involve active inhibitory processes or controlled attention (e.g., M. C. Anderson & Neely, 1996; Bjork, 1989). They have supported this interpretation with findings of age differences in PI effects (Zacks & Hasher, 1994) and greater susceptibility of low WM individuals to PI (Kane & Engle, 2000; Rosen & Engle, 1998). In addition, neuroimaging studies have indicated that the frontal lobes are more strongly activated during tasks involving PI than in tasks not involving PI (Bunge, Ochsner, Desmond, Glover, & Gabrieli, 2001; Uhl, Podreka, & Deecke, 1994).

METHOD

Participants

Participants were 220 undergraduates from the University of Colorado at Boulder who received partial course credit toward an introductory psychology course for participating. This sample size permitted a participant-to-parameter ratio of at least five (as recommended by Hatcher, 1994) in all of the models. Data for 4 additional participants were not analyzed, because 2 were colorblind and 2 did not complete the second session. Participants' ages ranged from 18 to 40 years, with a mean of 19 and a standard deviation of 2. Seventy-seven were men, and 143 were women.

Materials, Design, and Procedure

Task administration was computerized (Power Macintosh 7200 computers) or paper-and-pencil. A button box with millisecond accuracy was used for the tasks requiring reaction time (RT) measures, and a voice key was attached to the button box to record RTs for verbal responses.

Tasks Proposed to Measure the Three Inhibition-Related Functions

Prepotent Response Inhibition Tasks

Antisaccade task. During each trial of the antisaccade task (adapted from Roberts et al., 1994), a fixation point appeared in the middle of the computer screen for a variable amount of time (one of nine times between 1,500 and 3,500 ms in 250-ms intervals). A visual cue (a 1/8-in. [0.3175-cm] black square) then appeared on one side of the screen for 175 ms, followed by the target stimulus (an arrow inside of an open 5/8-in. [1.5875-cm] square) on the opposite side for 150 ms. The target was then masked with gray cross-hatching, and the mask remained on the screen until the participant indicated the direction of the arrow (left, up, or right) with a button press response. Both the cues and the targets were presented 3.4 in. (8.636 cm) away from the fixation point (on opposite sides), and the participants were seated 18 in. (45.72 cm) from the computer monitor. The participants practiced on 22 trials and then received 90 target trials. The dependent measure was the proportion of errors.

Stop-signal task. The stop-signal task (Logan, 1994) consisted of five blocks of trials. On each trial in the first block of 48 trials used to build up a prepotent categorization response, participants saw 1 of 24 words (e.g., *duck, gun*; the words were balanced for both length and frequency according to Kucera & Francis, 1967) and categorized it as either an animal or a nonanimal as quickly as possible without making mistakes. Then, in the four subsequent blocks of 96 trials each, participants tried not to respond (i.e., to inhibit the categorization response) when they heard a computer-emitted signal (a tone approximately 100 ms long) on a randomly selected 25% of the trials but otherwise kept performing the same categorization task. In all trials (including 34 practice trials, 24 in the first no-signal block and 10 in the second block), the participants viewed a fixation point for 500 ms and were then allowed up to 1,500 ms to categorize the target word.

Each participant experienced signals that occurred 50 ms before his or her average RT (long stop-signal delay), 225 ms before his or her average RT (medium stop-signal delay), or 50 ms after the onset of the trial (short stop-signal delay). Each of these delays occurred equally often in each block.

As recommended by Logan (1994), the instructions emphasized that the participants should not slow down to wait for possible signals. Despite these instructions, however, many participants did show some strategic slowing from the initial no-signal block to the signal blocks (mean difference = 58 ms, *SD* = 72 ms), and the correlations of slowing with the probability of stopping were –.88 for the long stop-signal delay, –.73 for the medium stop-signal delay, and –.29 for the short stop-signal delay. For this reason, the primary dependent variable used for this task was the stop-signal RT estimated with the shortest delay. The stop-signal RT is a measure recommended by Logan and is the estimated time at which the stopping process finishes. We used the most common estimation method that assumes that the stop-signal RT is a constant.[3] Given that the estimates for the longer stop-signal delays might have been biased by strategic slowing, calculating the stop-signal RT on the basis of the data from the trials with the shortest delay seemed reasonable.

Stroop task. On each trial of the Stroop task (Stroop, 1935), adapted for computer administration, participants saw a white fixation point on a black screen for 500 ms, followed by the stimulus, which remained on the screen until the participants responded, after which the screen remained black for 1,000 ms. Participants verbally named the color of each stimulus as quickly and as accurately as possible, with RTs measured by voice key. There were three types of trials: (a) 60 trials with a string of asterisks (of variable lengths matching the lengths of the color words) printed in one of six colors (red, green, blue, orange, yellow, or purple), (b) 60 trials with a color word printed in a different color (e.g., *blue* printed in red), and (c) 60 trials with a neutral word printed in one of the six colors (the neutral words were *lot, ship, cross, advice, intent,* and *debate*; these words were selected to be the same length, number of syllables, and frequency as the color words but to start with different letters), with the different trial types nonblocked. The order of the trials was randomized such that no word or color on 1 trial was related to the word or color on the immediately preceding trial and no condition appeared more than 3 trials in a row. The trials were broken down into four subblocks. The participants also received voice-key calibration and 18 practice trials. The dependent measure for the Stroop task was the RT difference between the trials in which the word and the color were incongruent and the trials that consisted of neutral words. The use of neutral word trials (as opposed to asterisk trials) as the baseline removed the effect of distractor interference (see Milham et al., 2001, for further discussion of this logic). The results of the latent-variable analysis remained the same, however, even when asterisk trials were used as the baseline to calculate the RT difference.

Resistance to Distractor Interference Tasks

Eriksen flanker task. In this task (Eriksen & Eriksen, 1974), participants responded with a button press, as quickly as possible without sacrificing accuracy, to the identity of a centrally presented letter, ignoring any other letters that flanked the target letter. Participants pressed a button on the right when the target letter was *H* or *K,* and a button on the left when the target letter was *S* or *C.* In three conditions, the target letter was flanked by three noise letters on each side: (a) noise same as target (*HHHHHHH*), (b) noise response compatible (*KKKHKKK*), and (c) noise response incompatible (*SSSHSSS*). There was also a no-noise condition (*H*). The letters were printed in capital, 22-point, bold, Courier font (3/16-in. [0.4763-cm] square), and the spatial separation of the letters was the same as the spacing of letters in a printed word (1/16 in. [0.1588 cm]). On each trial, a 1,000-ms blank screen preceded a 500-ms fixation point. Then the stimuli, printed in black on a white background, remained on the screen until the participant responded. There were 40 trials of each type, for a total of 160 trials, and there were 32 practice trials with all conditions represented. The four trial types were intermixed in a fixed random order, with the constraint that the same condition did not occur on more than 3 successive trials and that there were no negative priming trials (i.e., trials in which the current target letter was the flanker noise letter ignored on the previous trial). The trials were broken down into four subblocks. The primary dependent measure was the difference in RT in the noise-response-incompatible condition versus the no-noise condition. This measure was selected because it was the most similar to the other Resistance to Distractor Interference measures, which were both calculated by subtracting a no-distractor condition from a response-incompatible distractor condition.

Word naming and shape matching. The word-naming and shape-matching tasks (illustrated in Figure 1) incorporated negative priming trials in addition to trials designed to assess distractor interference (negative priming was one of the inhibition-related measures examined for the second goal of the study). Distractor interference effects were calculated on the prime trials, whereas the negative priming effects were calculated on the probe trials. Hence, the measures for distractor interference and for negative priming came from entirely separate trials of the word-naming and shape-matching tasks.

The tasks were composed of 168 prime–probe pairs of trials. A third of the prime trials (56) were no-distractor primes, in which the target was presented alone. The other 112 of the prime trials were distractor primes, in which the target was accompanied by a distractor. All of the probe trials contained both targets and distractors. There were two types of probe trials that followed the distractor prime trials: (a) 56 control distractor probes, in which the target and distractor were unrelated to the target and distractor in the prime trial, and (b) 56 negative priming probes, in which the target was the same as the distractor on the preceding prime trial. The targets and distractors in the probe trials following the no-distractor prime trials (the remaining 56 probe trials) were never related to the prime targets. The order of the various types of prime–probe pairs was randomized and fixed, with the constraints that the stimuli on any given prime were unrelated to the stimuli on the preceding probe and that each condition did not occur more than 3 trials in a row. Before completing the experimental trials, participants completed 36 practice prime–probe pairs representing all of the conditions. The dependent measure for both the word-naming and shape-matching tasks was the difference in RT to the distractor primes and the no-distractor primes.

In the word-naming task (Kane et al., 1994), the stimuli were selected from eight three-letter nouns (*cat, pot, jar, tie, cup, fun, bag,* and *rod*). These words have frequencies between 10 and 50 per 1,000,000 (Kucera & Francis, 1967), do not rhyme, and do not form compound words. On each trial, the words were printed in capital letters (22-point Courier font) above and below the fixation point (the space between them was 0.125 in. [0.3175 cm]) in red and green on a black background. Targets appeared equally often in each position. The participants' task was to name aloud the target word (indicated by a green color) and ignore distracting words (indicated by a red color). Participants indicated their readiness for a trial by pressing a button (the center button in a button box) in response to a blue *READY?* cue, after which a blank screen appeared for 1,100 ms, followed by a fixation point for 500 ms. After the fixation point disappeared, the prime display appeared for 225 ms and was then immediately masked by a fine grating of colored dots for 100 ms. Following the offset of the mask, the screen became blank and remained so until the participant responded, after which the screen was blank for 100 ms, then another fixation point appeared for 500 ms, followed by the probe display for 225 ms, the mask for 100 ms, and a blank screen until the participant responded (see Figure 1A for an illustration).

[3] Specifically, the stop-signal RT for each delay was calculated as follows: The RTs for the no-signal go trials were rank ordered, and the stop-signal delay was subtracted from the *n*th RT, where *n* was the number of all the no-signal RTs multiplied by the probability of responding at that delay.

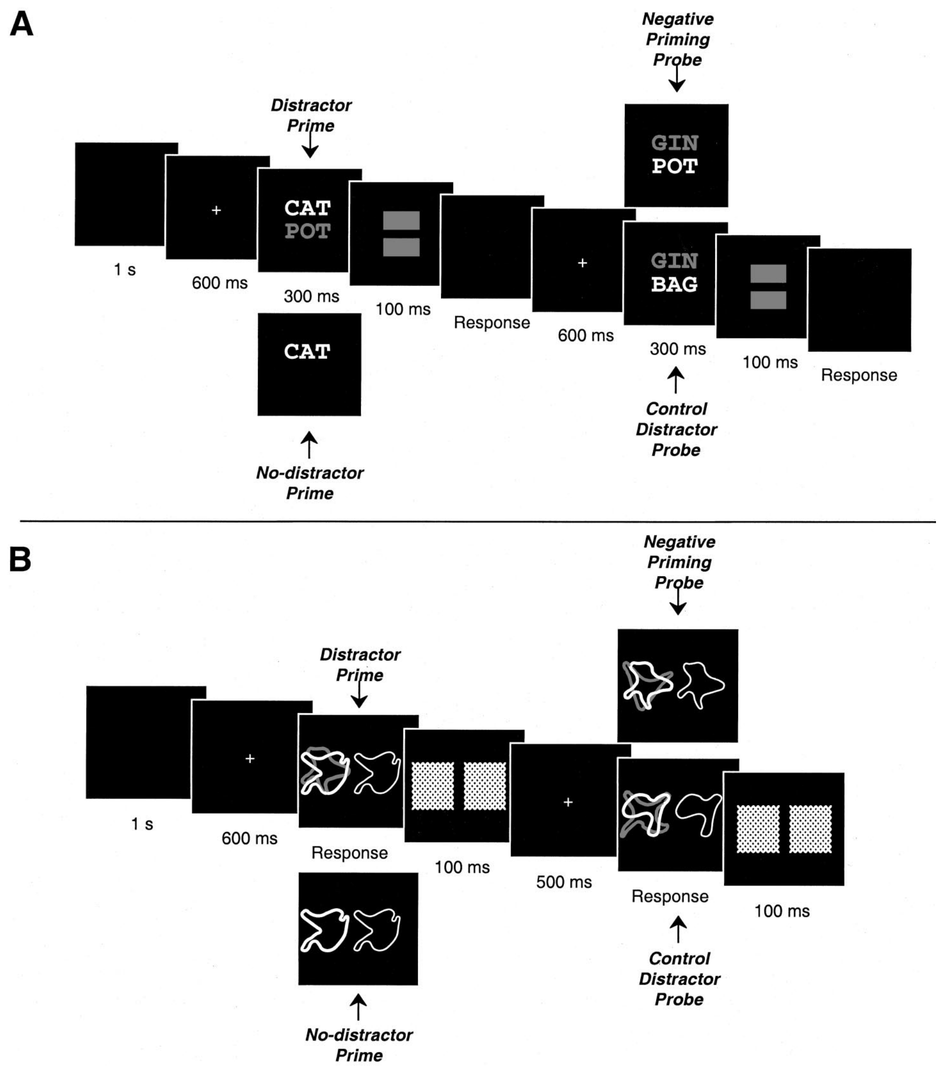

Figure 1. Example prime–probe pairs of the (A) word-naming and (B) shape-matching tasks. In each task, a fixation point was followed by a prime trial (either a distractor prime or a no-distractor prime), a mask, another fixation, a probe trial (either a negative priming probe or a control distractor probe), and then another mask. In the word-naming task, participants named the target word (illustrated in white), ignoring the distractor word (illustrated in gray) when one was present. In the shape-matching task, participants indicated whether the target shape on the left (illustrated in white) matched the white shape on the right, ignoring the distractor shape (illustrated in gray) when one was present. Interference effects were calculated as the difference in reaction times (RTs) between the distractor primes and the no-distractor primes. Negative priming effects were calculated as the difference in RTs between the negative priming probes and the control distractor probes.

The stimuli in the shape-matching task (DeSchepper & Treisman, 1996) were selected from a set of eight abstract shapes. The shapes were printed in red, green, or white on a black background. Each display contained (a) a green target shape that either was presented alone or was centered on a red distractor shape (when the two figures overlapped, the green lines always occluded the red) on the left side of the fixation point and (b) a white shape that appeared alone on the right side of the fixation point. Each shape was approximately 1.5 square inches (3.81 square centimeters) and appeared centered on a point that was 1.5 in. away from the fixation point (thus, the distance between the shapes on the left and right was 1.5 in.). Participants judged whether the green and white shapes matched and pressed the right button for a match and the left button for a mismatch. Participants indicated their readiness for a trial by pressing a button (the center button in a button box) in response to a blue *READY?* cue, after which a blank screen appeared for 1,100 ms, followed by a fixation point for 500 ms. After the prime fixation point disappeared, the prime display appeared and remained on the screen until the participant responded with a button press. After the prime response, the screen was blank for 100 ms, then another fixation point appeared for 500 ms, followed by the probe display, which remained on the screen until the participant responded (see Figure 1B for an illustration).

Resistance to PI Tasks

For the Resistance to PI tasks, we originally planned to use the difference-score measures as stated below. As we discuss shortly, however, the low reliability of these PI measures prevented us from using these difference-score measures in the final analysis. We provide more details in the RESULTS AND DISCUSSION section regarding the alternative analysis we ended up using for Resistance to PI.

Brown–Peterson variant. In each of three blocks of this task (based on Kane & Engle, 2000), participants viewed four lists of eight words each. The first three lists were taken from the same category, and the last list, which served as the "release from PI" list, was taken from a different category. Words within each category were selected from Battig and Montague's (1969) norms. All of the words were less than 10 letters long and were ranked below the 12 strongest associates to that category. Between the presentation of each list and recall, participants completed a distracting task: Upon seeing a letter paired with a two-digit number ranging from 10 to 90 (e.g., *D–36*), participants alternated between counting aloud from the letter and number for 16 s, starting with the pair provided ("D–36, E–37, F–38," etc.).

The procedure for each block was as follows: After viewing a 1,500-ms warning, *!!Get Ready!!*, in blue type, participants read aloud the list of eight words (in black type) as they were presented at a rate of one word every 2,000 ms (1,750-ms stimulus followed by a 250-ms interval); 250 ms after the last word disappeared, the letter–number pair appeared (in pink type), and participants immediately began the distracting task and continued until the letter–number pair disappeared 16 s later and a green screen signaled them to recall orally the words from the list. They had 20 s to recall as many words as possible in any order, and they were encouraged to continue attempting to recall for the entire 20 s. After the recall period, a red screen appeared for 2 s to signal them to stop recalling, and the sequence repeated. Between blocks, participants were given a 15-s rest period. In addition, participants completed a practice block with two lists from unrelated categories to familiarize themselves with the general procedure.

Consistent with the findings of other researchers using similar tasks, the most substantial interference occurred in the second list (e.g., Kane & Engle, 2000, Experiment 2; Wickens, Born, & Allen, 1963). Hence, the originally intended dependent measure was the difference in recall for the first list and the second list in each block, summed across the three blocks. Recall for the fourth release from PI lists was not included in the analyses because these lists were included primarily to allow for a release from PI before the next block.[4]

AB–AC–AD. The paired-associate list-learning procedure was modified from Rosen and Engle (1998). Participants learned three 12-item lists of the form AB–AC–AD. For the purpose of maximizing interference, each response word belonged to the same category as its cue word as well as the other response words subsequently paired with the same cue word. We constructed each set of three lists by selecting 12 quadruplets from Battig and Montague's (1969) category norms. Each quadruplet consisted of four of the top five exemplars associated to the category. The most frequent exemplar for each category was selected as the cue word, and the remaining three exemplars were randomly allocated to the three lists. For example, the cue word *CARROT* was paired with the response word *pea* in the AB list, *potato* in the AC list, and *corn* in the AD list.

For each list, the procedure was as follows: After completing a study phase in which each pair appeared on the computer screen for 2 s, participants completed the testing phase, in which they saw a fixation point on the screen, then saw a cue for 1 s, then heard a computer-emitted beep. If participants did not begin to vocalize their responses before the beep, their responses were counted wrong. After the beep, the correct pair appeared on the computer screen for 2 s to allow additional study. The experimenter then entered a code to indicate whether the response was correct. Participants continued the testing phase until they correctly responded to each cue three times. Once the criterion of three correct responses was reached for each cue, that cue was dropped from the list, but otherwise the cue–response pairs were always retested in the same order. Once all the pairs had been recalled three times, participants were given a final cued-recall test on all 12 pairs so that they had all been retrieved equally recently before the next list. They were then instructed that they would learn a new list with the same cues, and the procedure was repeated. Prior to the experimental lists, participants completed a practice list with 3 digit–letter pairs to familiarize them with the procedure. The originally intended dependent variable was the number of trials taken to reach criterion on the second (AC) list minus the number of trials to criterion on the first (AB) list (selected over a measure that incorporated performance on the AD list to make this variable more analogous to the measure for the Brown–Peterson variant).

Cued recall. In this task (Tolan & Tehan, 1999), participants saw "blocks" of four serially presented words presented at a rate of one word per second. They were instructed that at any time, they were to remember only the most recent block. In 12 trials, they saw only one block before performing a short distractor activity and then being cued to recall ("one-block" trials). In 12 trials, they saw two blocks before the distracting activity and the cue ("two-block" trials). Following Tolan and Tehan, there were also 12 two-block "lure" trials in which the first block contained a lure that fit the cued category (e.g., the first list contained *blonde* and the second list *auburn* for the cue *hair color*); however, these lure trials were not included in the primary dependent measure.[5] The trials were presented in a fixed random order; hence, participants had to pay attention to the first lists in the two-block trials, because they did not know until after the list passed (and the second list started) whether they would need to remember or forget that list.

Immediately before each block, participants also received instructions on how to read each block (*SILENT* or *ALOUD*). The two-block trials were ALOUD–SILENT trials, in which the participant was instructed to read the first block aloud and the second block silently (this procedure was implemented to maximize the interference from the first list; Tolan & Tehan, 1999). The one-block trials were all ALOUD trials. Before being cued to recall, participants completed a distracting task, which consisted of eight magnitude judgments about two-digit numbers (i.e., whether the number was greater than or less than 50). In each trial, the participant viewed a *READY* signal for 2 s, the reading instruction signal for 1 s, and then four words presented at a rate of one word per second. In the two-block trials, participants then immediately saw the reading instruction for the second block for 1 s, followed by four words in the second block. Immediately after the last word in the block, participants saw the eight two-digit numbers for 1 s each and vocalized their judgments. After the last number, the category cue appeared and participants had 5 s to recall the answer.

An example one-block trial was as follows: The participant read aloud "cattle, mint, falsetto, ocean"; then said "above" or "below" for each of eight numbers; then received the cue *herb* and had 5 s to retrieve the correct answer (*mint*). An example two-block trial was as follows: The participant read aloud "dress, couch, donkey, hockey"; then read silently *mosquito, football, cream, democracy*; then made magnitude judgments for eight

[4] Kane and Engle (2000) found that the release from PI effect was not affected by individual differences in WM capacity or by a concurrent load and used those findings to argue that release from PI reflects an automatic process. In the current study, release from PI, calculated as the difference in recall between the fourth and third lists summed across blocks, did not correlate with the Resistance to PI difference scores, rs(218) = –.08, .07, and .09 for AB–AC–AD, Brown–Peterson, and cued recall, respectively, corroborating Kane and Engle's finding.

[5] Tolan and Tehan (1999) hypothesized that the lure intrusions reflected PI, but, even on the nonlure trials, participants often vocalized high-frequency associates to the cued category. This pattern suggested that lure intrusions might be more related to Prepotent Response Inhibition. Thus, neither the lure intrusions nor recall performance on the lure trials (which was closely related to the number of lure intrusions, $r[218] = -.58$, $p < .001$) was used in calculating the dependent measure.

numbers; and then received the cue *dairy product* and had 5 s to retrieve the correct answer from the most recent list (*cream*). Participants were given one one-block trial and one two-block trial as practice trials. The originally intended dependent measure was the number of items correctly recalled in the one-block trials minus the number of items correctly recalled in the two-block trials. This measure was considered to capture the extent to which participants experienced PI from the previous list in the two-block trials (reflected in an inability to produce the correct response from the second list), controlling for baseline recall performance in the one-block trials.

Other Tasks or Constructs Hypothesized to Involve Inhibition-Related Functions

Random Number Generation

In the RNG task, participants heard computerized beeps at the rate of one beep per second and said a number from 1 to 9 for each beep such that the string of numbers was in as random an order as possible. As an illustration of the concept of randomness, the participants were given the analogy of picking a number out of a hat, reading it out loud, putting it back, and then picking another. The importance of maintaining a consistent response rhythm was emphasized during the instructions, and participants received a brief practice of 10 beeps.

The 100 valid responses generated were analyzed using Towse and Neil's (1998) RgCalc program, which produces many different "randomness" indices that seem to tap different underlying executive control processes. Following Miyake, Friedman, et al. (2000), 14 of these indices were analyzed with principal-components analysis with an oblique promax rotation. The three-component solution was suggested by the scree plot, and the three components replicated the analysis presented by Miyake, Friedman, et al. The loadings and intercomponent correlations are presented in Appendix A. The factor scores for the first two components (Prepotent Associates and Equality of Response Usage) were the dependent variables.

Negative Priming

Negative priming effects were calculated from the probe trials of the word-naming and shape-matching tasks. Each effect was calculated as the difference in RT for the negative priming probes and the control distractor probes (see Figure 1). Kane, May, Hasher, Rahhal, and Stoltzfus (1997) suggested that targets that are difficult to identify (degraded or presented very briefly) and repeated targets across prime and probe trials can lead to negative priming effects that reflect the operation of episodic retrieval rather than inhibition; hence, these conditions were avoided.

Task-Switching Ability

Three tasks were used to assess task-switching ability. In each of the three tasks, there were four blocks of 48 trials, each of which contained 24 no-switch and 24 switch trials. Each trial was preceded by a cue indicating which subtask should be performed on that trial, and the cue remained on the screen throughout the trial. In the first two blocks, the cue was presented 150 ms before the onset of the stimulus, and both the cue and the stimulus remained on the screen until the participant responded, at which point the next cue appeared after a 350-ms response-to-cue interval. In the second two blocks, everything was the same except that the cue appeared 1,500 ms before the onset of the stimulus. Throughout each task, participants were asked to use whatever time they had between the cue and the stimulus to prepare for the forthcoming subtask. They were also asked to respond as quickly as possible without making mistakes. To firmly master the cue–subtask associations and the key mappings, participants completed two practice blocks of 24 trials each before the task began. In addition, there were also 6 warm-up trials at the beginning of each block that were not analyzed. For all tasks, the order of the trials was randomized with the constraint that no more than 4 switch trials could occur in a row. Furthermore, there were no item-specific negative priming trials in which the stimulus on a switch trial was the same as that on the previous trial. The dependent variable in each task was the switch cost, calculated as the difference between the average RTs of the trials that required a switch and the average RTs of the trials in which no switch was necessary. Switch costs were computed for both the trials with the short (150-ms) cue-to-stimulus interval (regular switch cost) and for the trials with the long (1,500-ms) cue-to-stimulus interval (residual switch cost).

Number–letter task. In each trial of this task (adapted from Rogers & Monsell, 1995), a number–letter pair (e.g., *7G*) was presented in one of two squares above or below a line dividing the computer screen in half. The participants were instructed to indicate whether the number was odd or even (2, 4, 6, and 8 for even; 3, 5, 7, and 9 for odd) when the pair was in the top square and to indicate whether the letter was a consonant or a vowel (G, K, M, and R for consonant; A, E, I, and U for vowel) when the pair was in the bottom square. The cue in this task was the onset of the square. The squares were 0.875 in. (2.2222 cm) and appeared approximately 0.25 in. (0.635 cm) above or below the median line, and the number–letter pairs were printed in 36-point Courier font.

Local–global task. In each trial of this task (adapted from Miyake, Friedman, et al., 2000), a geometric figure in which the lines of the global figure (e.g., a triangle) was composed of much smaller, local figures (e.g., circles) was presented on the computer screen. Depending on the color of the background (either blue or yellow), participants pressed a key indicating the number of lines (*1* for a circle, *2* for an X, and *3* for a triangle) in the global, overall figure (blue) or the local, smaller figures (yellow). Thus, when the color of the background changed across trials (the cue was the onset of the background color), the participants had to shift from examining the local features to the global features or vice versa. Each stimulus was a 4-in. (10.16-cm) square figure composed of 28 or 29 smaller figures (each approximately 1/4-in. [0.635-cm] square) that was presented inside a 4-in. colored square (i.e., the background color) centered on a black screen.

Category-switch task. In each trial of this task (adapted from Mayr & Kliegl, 2000), participants saw a word that could be categorized in terms of (a) whether it describes a living or nonliving thing or (b) whether it describes a thing that is smaller or larger than a soccer ball. The 16 words were drawn from those used by Mayr and Kliegl: *table, bicycle, coat, cloud, pebble, knob, marble, snowflake, shark, lion, oak, alligator, mushroom, sparrow, goldfish,* and *lizard.* A symbol appearing above the word cued which categorization to use (a heart indicated living vs. nonliving, and a cross indicated large vs. small). The words were presented in the center of the screen in 22-point Courier font, and the 9/16-in. (1.4288-cm) high by 11/16-in. (1.7463-cm) wide symbols appeared 3/8 in. (0.9525 cm) above them.

Reading Span Test

In each trial of the computerized reading span test (Daneman & Carpenter, 1980), participants read a set of sentences aloud and tried to remember the last word of each sentence. At the end of the trial, red question marks signaled the participants to recall all of the sentence-final words, with the instructions stipulating that words should be recalled in order when possible, but if recalling in order was not possible, then the last word should not be recalled first. Each sentence remained on-screen until the participant finished articulating it, at which point the experimenter immediately pushed a button for the next sentence. In addition, to minimize the use of idiosyncratic strategies, the experimenter instructed participants to begin reading each sentence as soon as it appeared and reminded them of this requirement if they detected pauses (Friedman & Miyake, 2003). After practicing on two trials at Set Size 2, participants performed three target trials at each set size from 2 to 5. The trials were presented in a fixed order such that all four levels were experienced in a random order before being repeated. The total number of words in perfectly recalled sets was the primary dependent measure (i.e., participants received 2 points for each set recalled correctly at Set Size 2, 3 points for each set recalled correctly at Set Size 3, etc., but no points for partially recalled sets). Intrusion errors voiced by each participant were also tabulated.

Questionnaires

Cognitive Failures Questionnaire. The CFQ (Broadbent et al., 1982) asked participants to rate, on a scale from 0 (*never*) to 5 (*very often*), the frequencies of 25 everyday cognitive failures, such as “Do you read something and find you haven’t been thinking about it and must read it again?” “Do you say something and realize afterwards that it might be taken as insulting?” and “Do you start doing one thing at home and get distracted into doing something else (unintentionally)?” The dependent measure was the typical one used with this questionnaire: the sum of the reported frequencies across all the questions.

White Bear Suppression Inventory. The White Bear Suppression Inventory (WBSI; Wegner & Zanakos, 1994) asked participants to rate how well they agreed with 25 statements on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Blumberg (2000) factor analyzed this survey and reported that a three-factor solution provided the best fit to the data. He named the factors Unwanted Intrusive Thoughts, Thought Suppression, and Self-Distraction. Accordingly, the data from the current study were analyzed with exploratory factor analysis (principal axis factoring with a promax rotation) to obtain three sets of factor scores corresponding to these three factors. Both the scree plot and the Kaiser–Guttman rule (Kaiser, 1960) suggested a three-factor solution. These three factors explained 57% of the variance, and the factor loadings and interfactor correlations replicated the results of Blumberg (see Appendix B). The dependent measure was the factor scores for the first factor (Unwanted Intrusive Thoughts), for reasons to be discussed in the RESULTS AND DISCUSSION section.

Marlowe–Crowne Social Desirability Scale. The Marlowe–Crowne Social Desirability Scale (MCSDS; Crowne & Marlowe, 1964) consisted of 33 true–false questions designed to assess the tendency to respond in socially desirable ways. For example, one of the questions asked participants to indicate whether they are ever irritated by people asking favors of them; another question asked them to indicate whether they are always polite, even to unpleasant people. We included this questionnaire to control for individual differences in the tendency to respond in socially desirable ways on the other questionnaires. The dependent measure was the typical one used with this questionnaire, the number of “true” responses, with some of the questions reverse-coded when necessary.

General Procedure

Testing took place in two 2-hr sessions, administered individually during a 4-week period. The stimuli in each task were balanced for relevant parameters (there were equal numbers of answer types; repeated stimuli occurred in all conditions equally often; all possible combinations of stimuli were used approximately equally), and the order of the trials within each task was randomized and then fixed for all participants. The order of task administration was fixed for all participants to minimize any measurement error due to participant by order interaction. The task order for the first session was as follows: antisaccade, number–letter, CFQ, word naming, RNG, local–global, Stroop, and cued recall. The order for the second session was as follows: reading span, Eriksen flanker, Brown–Peterson, stop-signal, MCSDS, shape matching, category-switch, WBSI, and AB–AC–AD.

Statistical Procedures

Data Trimming and Outlier Analyses

Seven participants were each missing data for one task because of equipment malfunction or failures to understand task instructions (2 participants were missing AB–AC–AD scores, 4 were missing stop-signal scores, and 1 was missing shape-matching scores). To avoid eliminating these 7 participants from the analysis, we replaced these missing data with estimates obtained with multiple regression (i.e., Buck’s method of imputation; Little & Rubin, 1987); the scores for each of these observations were predicted on the basis of these participants’ scores on the other eight tasks used to measure the three inhibition-related functions. The replacement of these data points did not change the conclusions for any of the analyses. For the three questionnaires, some participants did not answer some of the questions (24 participants were missing observations for the CFQ, 18 were missing observations for the WBSI, and 6 were missing observations for the MCSDS). For the CFQ and WBSI, the answers were estimated with the means for those questions. For the MCSDS, the missing answers were entered as “false.”

For the RT-based measures, all RTs from errors (voice key or other errors) and all RTs less than 200 ms were eliminated. For the three tasks from which switch costs were obtained, RTs for trials immediately following errors were also excluded from further analysis, because the correct set might not have been achieved on the immediately preceding trials. For the word-naming task, RTs greater than 1,500 ms were also eliminated as presumed voice key errors. The percentage of the trials eliminated because of various errors was less than 10% in all of these tasks.

To prevent extreme RTs from unduly influencing the means for each participant, RT data were trimmed in the following way: First, on the basis of visual inspections of the RT distributions, upper and lower criteria were established for each task, and any values exceeding those criteria were replaced with those values.[6] Second, for each participant and each task, RTs farther than 3 *SD*s from the mean for each condition were replaced with values that were 3 *SD*s from the mean for that condition (the first stage ensured that the *SD*s calculated for this second stage were not biased by rare, extreme RTs). This two-stage process affected no more than 2.5% of the observations for any of the tasks (the data for the stop-signal task were not subjected to this trimming procedure because the dependent measure was not influenced by extreme RTs). After these two trimming stages, all of the between-participant distributions (both RT and other measures) were examined for extreme scores. For each variable used in the models, observations farther than 3 *SD*s from the group mean were replaced with values that were 3 *SD*s from the mean. This final trimming stage affected no more than 1.8% of the observations for any measure. After this multistage trimming, all of the distributions showed acceptable levels of skewness and kurtosis.

To further ensure that any extreme scores were not unduly influencing the results, we also examined the bivariate correlations for outliers using leverage, studentized t, and Cook’s D values, which assess how much influence a single observation has on the correlations (Judd & McClelland, 1989). Although some observations had extreme values (i.e., levers greater than .05, t values greater than $|3.00|$, or Cook’s D values that were much larger than those for the rest of the observations), the correlations did not change much with these observations removed. A similar result was obtained when the multivariate distributions were examined for the initial CFA model: Although Mardia’s index of multivariate kurtosis (9.27) was significant and there were several multivariate outliers (indicated by significant Mahalanobis d^2 values), the results were the same even when these outliers were removed. For these reasons, no observations were removed from the reported analyses.

[6] The criterion values were 400 ms and 2,000 ms for Stroop, 300 ms and 1,000 ms for word naming, 200 ms and 2,000 ms for shape matching, 200 ms and 1,500 ms for Eriksen flanker, 200 ms and 3,500 ms for number–letter and local–global, and 200 ms and 3,000 ms for category-switch.

Model Estimation

We used the AMOS program (Arbuckle, 1999) to perform maximum likelihood estimation based on the covariance matrix. Because there is no clear consensus as to the best fit indices for the evaluation of structural models, we followed the recommendation of Hu and Bentler (1998) to evaluate the fit of each model with multiple indices. Specifically, the chi-square statistic was supplemented with indices that have been found to be most sensitive to model misspecification without being overly sensitive to sample size: the standardized root-mean-square residual (SRMR) and Bentler's comparative fit index (CFI). In addition, we examined Akaike's information criterion (AIC).

The most commonly used fit index is the chi-square statistic, which measures the "badness of fit" of the model compared with a saturated model. Because this statistic measures the degree to which the covariances predicted by the specified model differ from the observed covariances, a small value indicates no statistically meaningful difference between the predicted and observed covariances, suggesting a satisfactory fit. AIC modifies the chi-square statistic to take model complexity into account, penalizing more complex models. Lower values of AIC indicate better fit, although there is no absolute cutoff for a good fit. The SRMR is the square root of the averaged squared residuals or differences between observed and predicted covariances. Thus, lower SRMR values indicate a closer fit, with values less than .08 indicating a fair fit to the data and values less than .05 indicating a good fit (Hu & Bentler, 1998). For CFI, higher values indicate better fit, because CFI quantifies the extent to which the model is better than a baseline model (e.g., one with all covariances set to 0). Hu and Bentler have advocated a CFI cutoff of .95 as an indication of a good fit, although .90 is also commonly used.

To examine if one model was significantly better than another, we performed chi-square difference tests on nested models. These tests entailed subtracting the chi-square for the full model from the chi-square for a nested, restricted model with fewer free parameters (degrees of freedom were calculated with an analogous subtraction). If the resulting chi-square difference was significant, then the fuller model provided a significantly better fit. All analyses used an alpha level of .05.

RESULTS AND DISCUSSION

We first examined the reliability of the measures to be used in the CFA model. As shown in Table 1, the reliability estimates for the tasks used to construct Prepotent Response Inhibition and Resistance to Distractor Interference were reasonable, mostly above .70. However, the difference-score measures of the two PI tasks for which reliability could be estimated (Brown–Peterson and cued recall) had unacceptably low estimates (.12 and .08, respectively), which likely reflects the fact that they were difference scores (Cohen & Cohen, 1983). For this reason, although we briefly discuss the results of our original model based on these difference-score measures, we present an alternative model that circumvents the low reliability problem. For clarity and simplicity, however, we decided to retain the difference scores used for the Resistance to Distractor Interference tasks and the Stroop task because they all showed reasonable reliabilities.

We also examined the zero-order correlations between the nine tasks chosen to tap the three target inhibition-related functions. As shown in Appendix C, these correlations were generally low (.23 or smaller). The magnitudes of the correlations are consistent with the results of previous studies (e.g., Kramer et al., 1994; Shilling et al., 2002) and most likely reflect the task impurity problem. Given the low correlations, it is understandable why Shilling et al. and others have questioned the construct validity of inhibition-related functions. The current study, however, goes beyond examination of these zero-order correlations. As will become clear later, despite the low correlations there was some evidence for the construct validity of the three inhibition-related functions, and these functions were also able to predict performance on other inhibition-related measures or tasks in line with a priori predictions. Hence, this correlation matrix, although attenuated, can still

Table 1
Descriptive Statistics for the Measures Used to Construct the Inhibition Latent Variables

Measure	*M*	*SD*	Range	Skewness	Kurtosis	Reliability
Prepotent Response Inhibition						
Antisaccade errors	0.13	0.09	0 to 0.40	0.86	0.34	.87[a]
Stop-signal RT (ms)	370	67	177 to 576	0.49	0.90	.72[a]
Stroop effect (ms)	147	69	33 to 357	0.66	−0.05	.80[a]
Resistance to PI: Difference scores						
Brown–Peterson difference (words)	3.68	2.97	−3 to 12	0.18	0.07	.08[b]
AB–AC–AD difference (trials)	8.32	8.18	−9 to 34	0.92	1.17	—
Cued recall difference (words)	2.14	2.51	−4 to 9	0.18	−0.02	.12[a]
Resistance to PI: Component scores						
Brown–Peterson: List 1 (words)	15.37	2.75	7 to 22	−0.49	0.38	.53[b]
Brown–Peterson: List 2 (words)	11.68	3.02	3 to 21	−0.07	0.13	.47[b]
AB–AC–AD: AB list (trials)	43.29	5.96	36 to 63	1.57	2.56	—
AB–AC–AD: AC list (trials)	51.80	11.25	37 to 87	1.19	1.00	—
Cued recall: 1-block (words)	8.37	2.09	2 to 12	−0.42	−0.02	.45[a]
Cued recall: 2-block (words)	6.23	2.31	0 to 12	0.03	−0.43	.55[a]
Resistance to Distractor Interference						
Eriksen flanker INT effect (ms)	73	41	−13 to 205	0.99	1.33	.59[a]
Word-naming INT effect (ms)	60	21	−3 to 111	0.11	−0.11	.76[a]
Shape-matching INT effect (ms)	100	53	−3 to 270	1.07	1.55	.71[a]

Note. For all tasks except Brown–Peterson recall and cued recall, higher scores indicate worse performance. Dashes indicate that reliability for the AB–AC–AD measure could not be calculated because there was only one observation for each list. RT = reaction time; PI = proactive interference; INT = interference.
[a] Reliability was calculated by adjusting split-half (odd–even) correlations with the Spearman–Brown prophecy formula. [b] Reliability was calculated using Cronbach's alpha.

reveal a good deal of information about the relations among different inhibition-related functions.

One point we should note here is that although the methods used in this study allow one to work with latent variables based on low covariances (and consequent low communalities for the latent variables), the primary cost associated with doing so is that the factor loading and path coefficient estimates may be less precise (i.e., characterized by larger standard errors) than cases in which latent variables are based on high intercorrelations. For this reason, we report standard errors for all the model parameters presented in the figures (in brackets next to the standardized estimates) so that the reader may ascertain the precision of the estimates. Of course, precise estimates are more desirable than imprecise estimates, but it is important to point out that some imprecision in parameter estimates does not pose a major problem for the conclusions we endorse later, because we are more concerned with the general patterns of the estimates than with their exact values.

How Are the Three Inhibition Functions Related?

The first goal of the study was to examine how Prepotent Response Inhibition, Resistance to Distractor Interference, and Resistance to PI are related. We performed a series of CFAs to address this question.

Initial Model of the Three Inhibition-Related Functions

We initially constructed the measurement model of the three inhibition-related functions with the Resistance to PI difference scores, as depicted in Figure 2. The numbers next to the straight, single-headed arrows are the standardized factor loadings (interpretable as standardized regression coefficients). The numbers at the ends of the smaller arrows are the error variances for each task

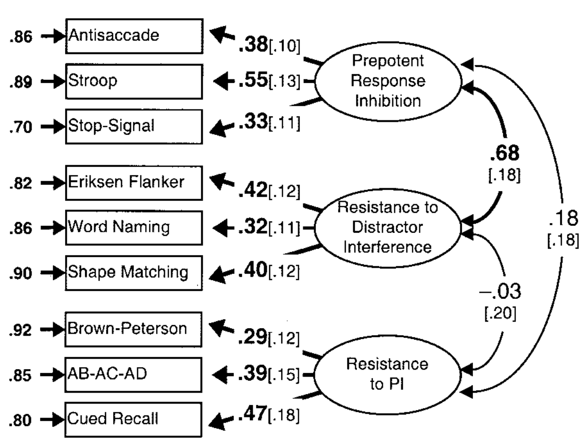

Figure 2. The initial three-factor model of the inhibition-related functions. The numbers next to the straight, single-headed arrows are the standardized factor loadings (interpretable as standardized regression coefficients). The numbers at the ends of the smaller arrows are the error variances for each task, attributable to idiosyncratic task requirements and measurement error. The numbers next to the curved, double-headed arrows are the correlations between the latent variables. For all parameters, boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors. Resistance to PI = Resistance to Proactive Interference.

and represent the variance attributable to idiosyncratic task requirements and measurement error. The numbers next to the curved double-headed arrows are the correlations between the latent variables. Bracketed numbers are the standard errors of the standardized parameter estimates. The fit of this model was reasonable, with a nonsignificant chi-square, $\chi^2(24, N = 220) = 20.68$, $p = .658$; an SRMR less than the .05 criterion for a good fit (SRMR = .039); a CFI value greater than the recommended criterion value of .95 (CFI = 1.00); and an AIC value of 62.68. In addition, all of the nine tasks loaded significantly on their respective factors, providing some support for the convergent validity of these constructs (for all tasks, higher scores indicate worse performance).

As mentioned earlier, however, the low reliability of the Resistance to PI difference-score measures raised the concern that the Resistance to PI latent variable may not be capturing what it is supposed to. This concern is important, given that the correlations between the Resistance to PI latent variable and the other two inhibition-related functions were almost zero. It is thus preferable to construct the Resistance to PI factor with more reliable measures. Donaldson (1983) suggested that structural modeling may provide an alternative to difference scores when the difference scores are unreliable. We followed his suggestion and used a structural approach to modeling this factor.

An Alternative Model of Resistance to PI

The logic behind the difference scores for the Resistance to PI tasks is that participants' performances during trials during which PI is possible (i.e., the second list of the Brown–Peterson, the AC list of the AB–AC–AD task, and the two-block trials of the cued recall task) should be influenced by at least two factors: (a) the amount of PI experienced during the list and (b) the individual's baseline performance. The latter can presumably be measured by the trials during which PI is not present or is at least less present (i.e., the first list of the Brown–Peterson, the AB list of the AB–AC–AD task, and the one-block trials of the cued recall task). Hence, the difference between performance on the trials in which PI is present and the trials in which it is absent can be interpreted as the amount of PI, controlling for baseline performance.

In our alternative model of Resistance to PI, we implemented this logic from the perspective of regression analysis (Cohen & Cohen, 1983). Specifically, we created two latent variables, as shown in Figure 3: The first tapped performance on trials in which there was little PI (List 1 Recall), and the second tapped performance on trials in which there was more PI (List 2 Recall). As Table 2 indicates, the reliabilities for these component scores were higher (around .50) than for the difference scores used in the original model. We then used List 1 Recall to predict List 2 Recall, reasoning that whatever was left over (the residual variance) should be a combination of PI and measurement error. The fit of this model was good, $\chi^2(5, N = 220) = 5.17$, $p = .395$, SRMR = .022, CFI = 1.00, AIC = 37.17. As shown in Figure 3, List 1 Recall predicted 68% of the variance in List 2 Recall; the residual variance (32%) was significantly greater than zero, $t(219) = 2.64$, $p = .009$, suggesting List 2 Recall contained enough variance not attributable to recall ability. One potential concern is that because the new Resistance to PI construct is in fact residual variance, it is possible that it is all measurement error. As we discuss later,

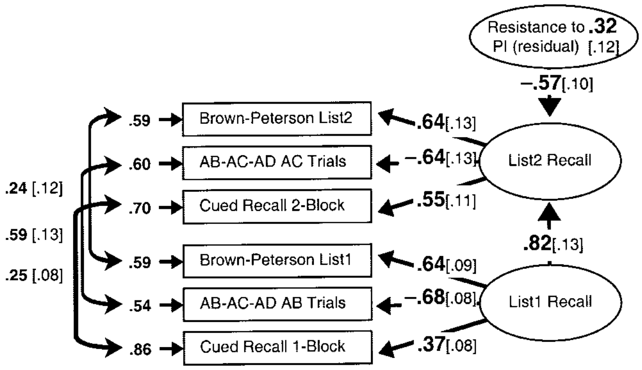

Figure 3. The alternative model of Resistance to Proactive Interference (PI). List 1 Recall is a latent variable constructed from the trials of the Resistance to PI tasks during which there was little PI. List 2 Recall is a latent variable constructed from the trials during which there was more PI. The error variances for each task were allowed to correlate because trials from the same task were presumed to share specific task variance. The Resistance to PI latent variable is the residual variance (32%) remaining after List 1 Recall is allowed to predict List 2 Recall. Boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors.

however, this variable significantly predicted performance on other tasks thought to involve PI, thus ruling out this possibility.

In constructing these latent variables, it was necessary to allow error variances that came from different components of the same task to correlate with each other (as indicated by the curved arrows between the error variances for the List 1 Recall and List 2 Recall measures). These error variances were allowed to correlate because the individual components that came from the same task may have correlated for methodological reasons not attributable to the latent variables.

Revised Model of Inhibition-Related Functions

Figure 4A depicts the three-factor model of inhibition-related functions using this alternative way of modeling Resistance to PI. Note that this model is the same as the one in Figure 2 except that the Resistance to PI construct is now modeled as the residual that is left after List 1 Recall is used to predict List 2 Recall. In addition, List 1 Recall (or baseline verbal recall ability) has been allowed to correlate with Prepotent Response Inhibition and Resistance to Distractor Interference.

As shown in Table 2, the fit of the model depicted in Figure 4A (Model 1) was reasonable, $\chi^2(45, N = 220) = 42.53$, $p = .577$, SRMR = .041, CFI = 1.00, AIC = 108.53. Table 2 also presents the fit of the so-called null model in which all the covariances among the individual tasks are hypothesized to equal zero (but the variances of the tasks are allowed to vary freely); in other words, this null model assumes that there is essentially nothing going on in the data. Given that the zero-order correlations were low, one might be tempted to conclude that there really is not much to be modeled and that the fit of any model would be adequate. As shown in Table 2, however, the fit of the null model (Model 2) was poor, $\chi^2(66, N = 220) = 452.51$, $p < .001$, SRMR = .185, CFI = 0.00, AIC = 476.51. Moreover, it provided a significantly worse fit than the three-factor model in Figure 4A, $\chi^2_{\text{diff}}(21, N = 220) = 409.98$, $p < .001$. This comparison establishes that the covariances are substantial enough to support model-fitting procedures.

The main question that motivated this study was how the three inhibition-related functions are related. To answer this question, one can examine the correlations in Figure 4A as well as the results of specific model comparisons comparing the fit of this model with

Table 2
Fit Statistics for the Confirmatory Factor Analysis Models of the Three Inhibition-Related Constructs

Model	*df*	χ^2	SRMR	CFI	AIC
1. Three inhibition factors (Figure 4A)	45	42.53	.041	1.00	108.53
2. Null model (all covariances = 0)	66	452.51*	.185	0.00	476.51
3. Three inhibition factors unrelated	48	55.30	.055	0.98	115.30
Two inhibition factors unrelated					
4. Prepotent Response Inhibition/Resistance to Distractor Interference $r = 0$	46	55.21	.055	0.98	119.21
5. Prepotent Response Inhibition/Resistance to PI $r = 0$	46	42.59	.041	1.00	106.59
6. Resistance to PI/Resistance to Distractor Interference $r = 0$	46	42.61	.041	1.00	106.61
7. Unity model (all inhibition *r*s = 1)	48	56.66	.044	0.98	116.66
Two inhibition factors the same					
8. Resistance to PI = Resistance to Distractor Interference	46	53.75	.043	0.98	117.75
9. Prepotent Response Inhibition = Resistance to PI	46	54.14	.043	0.98	118.14
10. Prepotent Response Inhibition = Resistance to Distractor Interference	46	45.10	.043	1.00	109.10
11. Final model (Figure 4B)	48	46.00	.044	1.00	106.00

Note. Chi-squares not significant at the .05 level indicate reasonable fits to the data. Lower values of standardized root-mean-square residual (SRMR) indicate better fit, with SRMR < .08 indicating a fair fit to the data and SRMR < .05 indicating a close fit to the data. Values above .95 for Bentler's comparative fit index (CFI) indicate excellent fit. Lower values of Akaike's information criterion (AIC) indicate better fit. PI = proactive interference.
*$p < .05$.

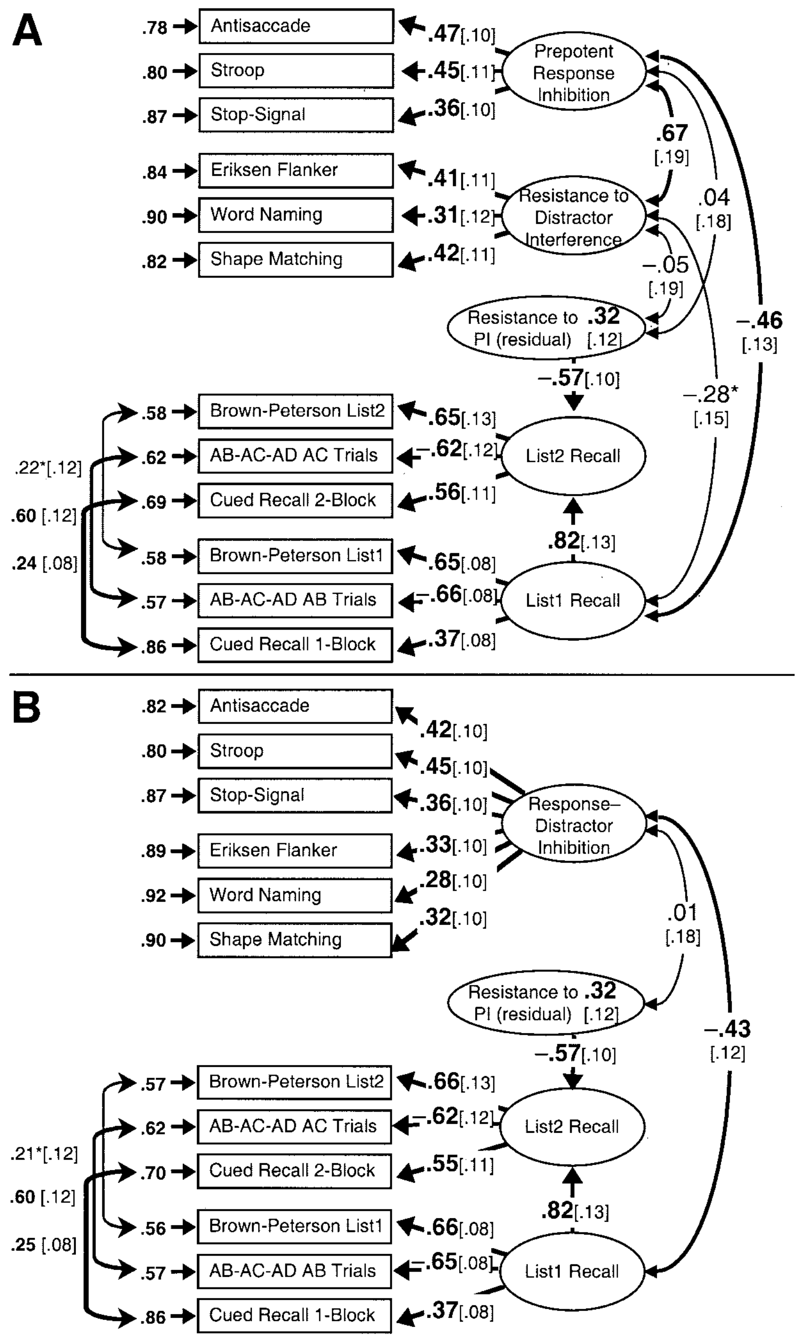

Figure 4. (A) The three-factor model and (B) the revised two-factor model of the inhibition-related functions incorporating the alternative model of Resistance to Proactive Interference (PI). These models also include correlations from List 1 Recall to the inhibition-related latent variables, except for Resistance to PI (because Resistance to PI is defined as the residual variance in List 2 Recall after List 1 Recall is removed, its correlation with List 1 Recall must be zero). Boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors. *$p < .10$.

the fits of alternative models in which these correlations are constrained to particular theoretical values. For example, one can test the hypothesis that the Prepotent Response Inhibition and Resistance to PI functions are independent (or uncorrelated) by examining (a) whether the correlation is significantly different from zero or (b) whether a model in which this correlation is constrained to zero (i.e., Model 5 in Table 2) provides a significantly worse fit than the three-factor model (Model 1). Table 2 presents the fit statistics for alternative theoretical models that we considered.

As shown in Figure 4A, the correlation between Prepotent Response Inhibition and Resistance to Distractor Interference was significant ($r = .67$), but Resistance to PI was not significantly correlated with either of them ($r = -.04$ and .05, respectively), replicating the pattern obtained for the original model (Figure 2) that used difference-score measures for the Resistance to PI variable. Furthermore, the model that constrained the correlation between Resistance to Distractor Interference and Prepotent Response Inhibition to be zero (Model 4) significantly worsened the model fit, $\chi^2_{\text{diff}}(1, N = 220) = 12.67$, $p < .001$, but the models that constrained the correlation between Resistance to PI and Prepotent Response Inhibition to be zero (Model 5) or the correlation between Resistance to PI and Resistance to Distractor Interference to be zero (Model 6) did not significantly worsen the model fit, $\chi^2_{\text{diff}}(1, N = 220) = 0.05$, $p = .818$, and $\chi^2_{\text{diff}}(1, N = 220) = 0.08$, $p = .777$, respectively. These model comparisons suggest that Prepotent Response Inhibition and Resistance to Distractor Interference are related to each other but not to Resistance to PI.

We also calculated whether each of the correlations could be constrained to unity (1.0) without harming model fit. The model that constrained the correlation between Resistance to Distractor Interference and Prepotent Response Inhibition to be 1.0 (Model 8 in Table 2) did not significantly worsen the model fit, $\chi^2_{\text{diff}}(1, N = 220) = 2.56$, $p = .109$, but the models that constrained the correlation between Resistance to PI and Prepotent Response Inhibition to be 1.0 (Model 9) or the correlation between Resistance to PI and Resistance to Distractor Interference to be 1.0 (Model 10) did significantly worsen the model fit, $\chi^2_{\text{diff}}(1, N = 220) = 11.60$, $p = .001$, and $\chi^2_{\text{diff}}(1, N = 220) = 11.22$, $p = .001$, respectively. Considering that the correlation between Prepotent Response Inhibition and Resistance to Distractor Interference was only .67, it is premature to conclude that these two functions are identical, but it seems reasonable to conclude that they are at least closely related to each other. (Prepotent Response Inhibition and Resistance to Distractor Interference were likely statistically indistinguishable in this sample because of the relatively large standard errors resulting from the low correlations.)

Given these results, a more parsimonious model was constructed. As shown in Figure 4B, this revised model collapses the Prepotent Response Inhibition and Resistance to Distractor Interference variables into a single latent variable (hereinafter called *Response–Distractor Inhibition* for short). The fit of this model (Model 11 in Table 2) was good, $\chi^2(48, N = 220) = 46.00$, $p = .555$, SRMR = .044, CFI = 1.00, and AIC = 106.00. Furthermore, the fit was not significantly worse than that of the full three-factor model depicted in Figure 4A, $\chi^2_{\text{diff}}(3, N = 220) = 3.47$, $p = .325$, and its AIC (106.00) was slightly smaller than that for the three-factor model (108.53). Accordingly, this reduced model is used in the rest of the analyses (collapsing them into a single latent variable also helps avoid potential multicollinearity problems that might occur in subsequent SEM analyses).[7]

Theoretical Implications

The results of these model comparisons have interesting theoretical implications. In particular, the finding that Resistance to PI is unrelated to Prepotent Response Inhibition and Resistance to Distractor Interference is at odds with the hypothesis that all three inhibition-related functions are measuring some common ability. Such a hypothesis has been advocated by researchers promoting the idea of a general inhibition function or a general controlled-attention ability. For example, Hasher and Zacks (1988) proposed that age-related declines in cognitive performance may be primarily explained by deficits in general inhibition abilities. The near-zero correlation between Resistance to PI and the other two constructs suggests that a general inhibition account of cognitive aging cannot be extended to explain patterns of individual differences among young adults. The separability of Resistance to PI is also inconsistent with the controlled-attention account of inhibition-related functions. According to Kane, Bleckley, Conway, and Engle (2001), controlled attention is the "ability to effectively maintain stimulus, goal, or context information in an active, easily accessible state in the face of interference, to effectively inhibit goal-irrelevant stimuli or responses, or both" (p. 180). This controlled-attention ability is proposed to be an important, domain-general component of WM capacity and is applicable to a variety of situations that require executive control, including resisting PI in verbal tasks (Kane & Engle, 2000; Rosen & Engle, 1998). This framework would predict that Resistance to PI would correlate with Prepotent Response Inhibition and Resistance to Distractor Interference, but the current data set did not support this prediction.

The finding that Resistance to PI and Resistance to Distractor Interference were uncorrelated also goes against an intuitive notion that all types of resistance to interference are mediated by a common ability, regardless of the sources of the interference. It is, however, consistent with Dempster's (1993) proposal that resistance to interference may differ depending on the nature of the interference (e.g., motor, perceptual, verbal–linguistic). There does not seem to be a common resistance to interference function that applies to interference from memory (as in Resistance to PI) as well as to interference from the environment (as in Resistance to Distractor Interference).

In contrast, Prepotent Response Inhibition and Resistance to Distractor Interference were closely related. This finding makes sense given that both inhibiting prepotent responses and resisting distractor interference require maintaining the task goal in a state of high activation in the face of more dominant but inappropriate responses or distracting stimuli present in the environment (as suggested by the above quote about controlled attention by Kane et al., 2001). Without strong guidance from goals, it may be difficult

[7] Interesting to note was the fact that List 1 Recall was significantly correlated with response–distractor inhibition even though the tasks used to construct this latter variable were not highly verbal in nature. There are at least two possible explanations for this result. First, response–distractor inhibition may involve retrieving information about the task instructions (in verbal format) when the goals are not actively maintained or are temporarily forgotten. Second, verbal recall ability may involve some response–distractor inhibition. Even when there is no PI on a list, participants may still need to resist interference from associates to the target words and from prepotent responses associated with the category or the target items. For example, in the Brown–Peterson task, a participant recalling target animal names may need to resist saying very common animal names not on the list (e.g., cat) and resist saying words that might be associated with the words that were on the list (e.g., if "puppy" is on the list, "puppy love" might come to mind).

or even impossible to avoid making an inappropriate prepotent response or to filter out task-irrelevant information. The ability to actively maintain critical goal-related information may be the key mechanism shared between Prepotent Response Inhibition and Resistance to Distractor Interference.

Do the Inhibition-Related Functions Predict Performance on Other Inhibition Measures?

The second goal of the study was to examine how the inhibition-related functions would relate to other tasks or measures proposed to require some form of inhibition. Descriptive statistics for the measures analyzed, including reliability estimates, are presented in Table 3.

For these analyses, we first developed hypotheses about which inhibition-related latent variable or variables (Response–Distractor Inhibition, Resistance to PI, or both) would significantly predict each measure on the basis of the existing literature and our task analysis. We then tested these a priori hypotheses by examining the significance of the two path coefficients in an SEM model in which that measure was predicted by the two inhibition-related latent variables as well as by List 1 Recall. This analysis is analogous to examining the significance of standardized regression coefficients in multiple regression. For each dependent measure, we also tested whether dropping particular path coefficients harmed model fit. Furthermore, we created a so-called no-paths model in which none of the latent variables depicted in Figure 4B were allowed to predict the task or tasks of interest. Comparing the fit of this no-paths model with the all-paths model provides an indication of whether the task or tasks of interest are correlated at all with the inhibition-related functions and verbal recall ability. If the all-paths model fits significantly better than the no-paths model, then at least one of the latent variables (Response–Distractor Inhibition, Resistance to PI, or List 1 Recall) is predicting the measure of interest. However, if the no-paths model fits as well as the all-paths model, then none of the latent variables are explaining the measure or measures of interest.

For all of the SEM models tested, the factor loadings and the interfactor correlations for the inhibition-related latent variables were allowed to vary, as recommended by J. C. Anderson and Gerbing (1988), so the parameters could differ from the values depicted in Figure 4B. Substantial variation in these parameters with the addition of other variables is an indication that the model is misspecified or that the factor structure is unstable. Examination of the parameters suggested that the estimates depicted in Figure 4B were stable. The factor loadings and interfactor correlations showed average absolute value changes of only .02 and .01, respectively. This stability across different SEM models further supports the factor model depicted in Figure 4B.

The following sections each begin with a brief review of the literature discussing which inhibition-related function or functions each measure may tap. Then, the results of the SEM models testing those proposals are presented. In many cases, multiple variables are simultaneously included in each model (e.g., two different RNG variables are included in the first SEM model) to examine the extent to which the three latent variables differentially predict different measures. This inclusion of multiple variables provides a more powerful test of the discriminant validity of the inhibition-related constructs, because it imposes more constraints on the models and allows for specific comparisons between path coefficients. Table 4 summarizes the fit statistics for these models, and Figures 5–9 illustrate the SEM model for each task or measure. For simplicity, the factor loadings are not shown in these SEM models, as the average change was negligible.

Random Number Generation

The first task examined was RNG, which has been the most frequently used task to examine the functioning of the so-called central executive within Baddeley's (1986) WM model. We in-

Table 3
Descriptive Statistics for the Other Tasks Proposed to Involve Inhibition Abilities

Measure	*M*	*SD*	Range	Skewness	Kurtosis	Reliability
RNG Prepotent Associates	−0.01	0.98	−1.70 to 3.00	1.07	0.95	—
RNG Response Usage	−0.03	0.90	−1.49 to 3.00	1.51	2.63	—
Word-naming NP (ms)	3	13	−38 to 43	0.10	0.87	.10[a]
Shape-matching NP (ms)	8	40	−88 to 118	0.02	0.02	.13[a]
Number–letter REG SC (ms)	423	247	−28 to 1,170	0.97	0.45	.82[a]
Local–global REG SC (ms)	497	206	−4 to 1,074	0.47	0.07	.63[a]
Category-switch REG SC (ms)	285	156	−19 to 765	0.85	0.82	.66[a]
Number–letter RES SC (ms)	176	124	−85 to 558	0.95	0.78	.63[a]
Local–global RES SC (ms)	218	159	−139 to 700	0.94	0.86	.76[a]
Category-switch RES SC (ms)	71	85	−181 to 324	0.53	0.66	.43[a]
Reading span recall (words)	7.78	4.44	0 to 21	0.69	0.12	.65[b]
Reading span intrusions (words)	2.69	2.03	0 to 10	0.95	0.92	.52[b]
CFQ	42.17	10.71	10 to 74	0.21	0.15	.86[a]
WBSI Factor 1	0.00	0.94	−2.14 to 2.17	−0.07	−0.50	.86[b]
MCSDS	15.38	4.70	3 to 27	0.07	−0.38	.79[a]

Note. Dashes indicate that reliability could not be calculated for the random number generation (RNG) task. NP = negative priming; REG SC = regular switch cost; RES SC = residual switch cost; CFQ = Cognitive Failures Questionnaire; WBSI = White Bear Suppression Inventory; MCSDS = Marlowe–Crowne Social Desirability Scale.
[a] Reliability was calculated by adjusting split-half (odd–even) correlations with the Spearman–Brown prophecy formula. [b]Reliability was calculated using Cronbach's alpha.

Table 4
Fit Indices for the Structural Equation Models Depicted in Figures 5–9

Dependent measure	*df*	χ^2	SRMR	CFI	AIC
RNG (Figure 5)					
All paths from inhibition and List 1 Recall factors	67	64.91	.044	1.00	140.91
All nonsignificant paths removed	72	73.51	.052	1.00	139.51
No paths from inhibition and List 1 Recall factors	73	83.53	.062	0.97	147.53
Negative priming (Figure 6)					
All paths from inhibition and List 1 Recall factors	69	74.10	.054	0.99	146.10
No paths from inhibition and List 1 Recall factors	72	74.93	.054	0.99	140.93
Switch costs (Figure 7B)					
All paths from inhibition and List 1 Recall factors	123	150.53*	.053	0.97	246.53
All nonsignificant paths removed	125	150.78	.054	0.97	242.78
No paths from inhibition and List 1 Recall factors	126	222.91*	.114	0.88	312.91
Reading span (Figure 8)					
All paths from inhibition and List 1 Recall factors	66	70.64	.047	0.99	148.64
All nonsignificant paths removed	70	72.43	.048	0.99	142.43
No paths from inhibition and List 1 Recall factors	72	113.13*	.081	0.90	179.13
Questionnaires (Figure 9)					
All paths from inhibition and List 1 Recall factors	75	72.71	.045	1.00	162.71
All nonsignificant paths removed	82	79.02	.050	1.00	155.02
No paths from inhibition and List 1 Recall factors	84	94.89	.054	0.98	166.89

Note. Chi-squares not significant at the .05 level indicate reasonable fits to the data. Lower values of standardized root-mean-square residual (SRMR) indicate better fit, with SRMR $< .08$ indicating a fair fit to the data and SRMR $< .05$ indicating a close fit to the data. Values above .95 for Bentler's comparative fit index (CFI) indicate excellent fit. Lower values of Akaike's information criterion (AIC) indicate better fit. RNG = random number generation.
* $p < .05$.

cluded this task to replicate previous results (Miyake, Friedman, et al., 2000) and thereby to further validate the Response–Distractor Inhibition construct.

There are many ways to measure randomness, and different indices are sensitive to different aspects of randomness (Towse & Neil, 1998). Specifically, studies of human random generation have revealed three biases or characteristic sequential dependencies (Rabinowitz, 1970): (a) Humans tend to produce stereotyped sequences, such as numbers adjacent on the number line; (b) they cycle through the numbers, using most or all of them before repeating a response; and (c) they avoid repeating responses in close succession. Miyake, Friedman, et al. (2000) found that the first two biases are related to different executive processes. Specifically, individual differences in the tendency to cycle through the number set were related to the ability to update the contents of WM, whereas individual differences in the ability to resist producing stereotyped sequences were related to the ability to inhibit prepotent responses.

Following Miyake, Friedman, et al. (2000), we extracted three components (which accounted for 63% of the variance) in a principal-components analysis of randomness indices produced by the RgCalc program (Towse & Neil, 1998). Appendix A presents the loadings and intercomponent correlations obtained with an oblique promax rotation. The indices that loaded on the first component (called *Prepotent Associates*) assessed the tendency to produce stereotyped sequences, such as counting; those that loaded on the second component (called *Equality of Response Usage*) assessed the tendency to cycle through the response set and use all responses equally often; and the measures that loaded on the third component (called *Repetition Avoidance*) assessed the tendency to avoid repeating responses at various intervals (e.g., "1, 1" or "1, 5, 1").

Based on the results of Miyake, Friedman, et al. (2000), the factor scores from the Prepotent Associates component, which were significantly related to Prepotent Response Inhibition in that study, should be primarily related to Response–Distractor Inhibition. In contrast, Miyake, Friedman, et al. found that the Equality of Response Usage component was related to WM updating ability, a construct that was not measured in the current study. Hence, the prediction for this component was that it would not be significantly related to either inhibition construct. Because we had no a priori predictions for the Repetition Avoidance component and because previous research has suggested that it may be an automatic process that does not require limited capacity resources (e.g., Baddeley, Emslie, Kolodny, & Duncan, 1998), this component was not included.

The SEM model predicting the first two RNG components is presented in Figure 5, and the fit indices are presented in Table 4. The fit of the all-paths model was good, $\chi^2(67, N = 220) = 64.91$, $p = .550$, SRMR $= .044$, CFI $= 1.00$, AIC $= 140.91$. Although the two components came from the same task, their zero-order correlation was not significant (.11), so it was not necessary to allow their errors to correlate. As shown in the figure, Response–Distractor Inhibition significantly predicted Prepotent Associates, but neither List 1 Recall nor the inhibition-related constructs significantly predicted Equality of Response Usage. Model comparisons indicated that the all-paths model was significantly better than the no-paths model, $\chi^2_{\text{diff}}(6, N = 220) = 18.62$, $p = .005$, but it was not significantly better than a model with only a single path from Response–Distractor Inhibition to RNG Prepotent Associates, $\chi^2_{\text{diff}}(5, N = 220) = 8.60$, $p = .126$.

These results replicate the finding of Miyake, Friedman, et al. (2000) that different aspects of randomness may tap different cognitive processes. In doing so, they also suggest that the

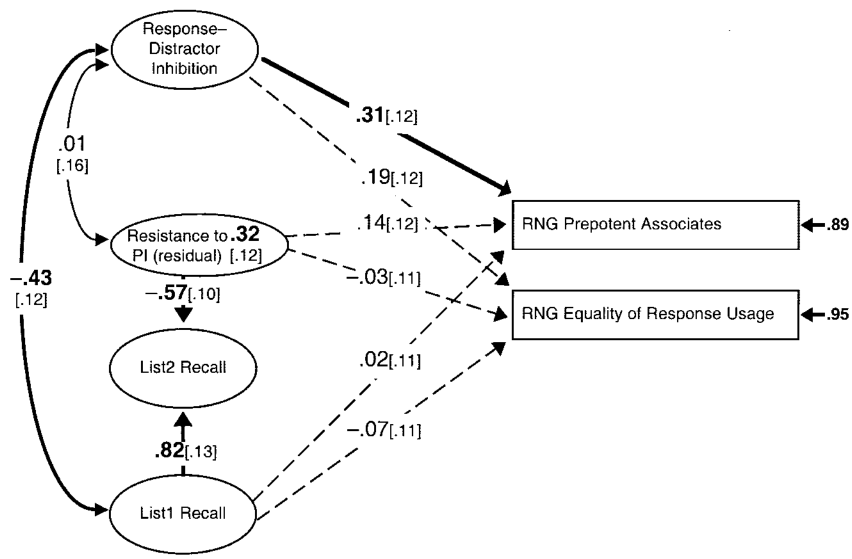

Figure 5. The structural equation model of the random number generation (RNG) Prepotent Associates and Equality of Response Usage components. Response–Distractor Inhibition predicted RNG Prepotent Associates but not Equality of Response Usage. Neither Resistance to Proactive Interference (PI) nor List 1 Recall predicted either score. Boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors.

Response–Distractor Inhibition construct measures similar cognitive abilities as those measured by the Prepotent Response Inhibition construct in Miyake, Friedman, et al.'s study.

Negative Priming

The second construct examined is one that has been closely associated with the notion of inhibition: identity negative priming. The negative priming effect is the slowdown that people show when they must respond to a target that was previously a distractor. This slowdown has frequently been interpreted as the persistence of distractor inhibition, and, hence, negative priming is often used as a measure of inhibition ability (e.g., Earles et al., 1997; Filoteo, Rilling, & Strayer, 2002; Kane et al., 1994; Kramer et al., 1994; Metzler & Parkin, 2000; Ozonoff & Strayer, 1997; Stuss et al., 1999; Tipper & Baylis, 1987). Despite its popularity as a measure of inhibition, however, there is considerable debate regarding whether this effect actually reflects active suppression (see Fox, 1995; May, Kane, & Hasher, 1995; Neill, Valdes, & Terry, 1995; and Tipper, 2001, for reviews). Alternative accounts of the effect that do not involve inhibition at all, such as an episodic retrieval account (Neill et al., 1992), a temporal discrimination account (Milliken et al., 1998), and a feature mismatch account (J. Park & Kanwisher, 1994), have been proposed. Because negative priming is so frequently used as a measure of inhibitory ability, its relation to other inhibition-related measures is an important issue.

The average negative priming effects obtained in this study were extremely small but were statistically significant: 3 ms for the word-naming task, $t(219) = 2.80$, $p = .006$, $\eta^2 = .03$, and 8 ms for the shape-matching task, $t(219) = 2.90$, $p = .004$, $\eta^2 = .04$. Negative priming effects are typically small (an 8-ms effect is not unusual; see Verhaeghen & De Meersman's [1998] meta-analysis), but the fact that even a 3-ms effect was significant (a small effect size according to Cohen's, 1977, criteria of $\eta^2 = .02$ for a small effect size, .13 for a medium effect size, and .26 for a large effect size) is probably due to the increased power of the current study compared with most studies of negative priming (which typically have sample sizes around 20 to 30 participants).

As shown in Table 3, the internal reliabilities of the negative priming effects were only .10 and .13. Despite their low reliabilities, the two negative priming effects in the current study correlated significantly, $r(218) = .15$, $p = .027$ (see Appendix C), and it was possible to construct a negative priming latent variable.[8] If negative priming reflects active suppression of distracting information, then it should be negatively related to Response–Distractor Inhibition, because greater inhibition of distractors should result in less interference from these distractors but more inhibition to overcome when those distractors become targets.

Table 4 presents the fit indices for the SEM model predicting the negative priming latent variable. As shown in the table, the fit of the all-paths model was satisfactory, $\chi^2(69, N = 220) = 74.10$, $p = .316$, SRMR = .054, CFI = 0.99, AIC = 146.10, but, as Figure 6 indicates, none of the path coefficients were significant, suggesting that negative priming is not related to Response–Distractor Inhibition, Resistance to PI, or verbal recall ability. In fact, the all-paths model was not statistically better than the no-paths model, $\chi^2_{\text{diff}}(3, N = 220) = 0.83$, $p = .842$. These results do not support the prevalent assumption that negative priming reflects active suppression of distracting information.

[8] Because the negative priming latent variable had only two indicators and did not correlate with any other variables in the model, it was necessary to constrain the factor loadings of the standardized negative priming effects for the word-naming and shape-matching tasks to be equal so that the models could be empirically identified (Bollen, 1989).

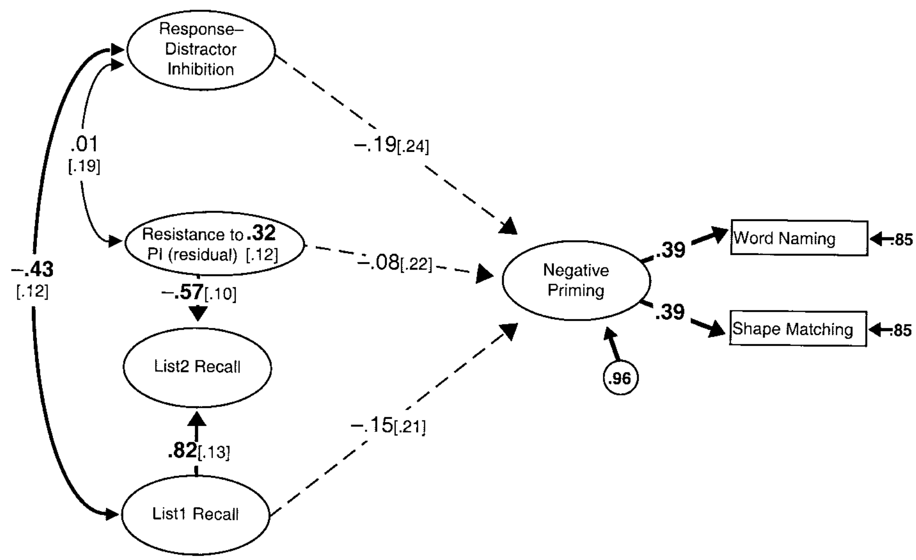

Figure 6. The structural equation model of negative priming. In this model, negative priming is measured as a latent variable constructed from two measures. Neither inhibition-related function significantly predicted negative priming effects. For all parameters, boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors. Resistance to PI = Resistance to Proactive Interference.

It is possible that this lack of relationship between negative priming and the two inhibition-related variables was due to the low reliabilities of the negative priming measures used here. These low reliabilities, however, are likely due to the nature of the negative priming effects rather than to problems with the specific tasks used to obtain these effects. Recall that the negative priming measures were obtained from the probe trials of the word-naming and shape-matching tasks, and that the prime trials of these same tasks were used to calculate interference effects for two of the Resistance to Distractor Interference measures. In both tasks, the distractor interference effects had good reliabilities (.76 and .71, respectively; see Table 1). Furthermore, these results are nearly identical to those obtained by Bestgen and Dupont (2000), who found in two experiments (*N*s = 36 and 151) that the reliability estimates of multiple negative priming effects were all close to zero, whereas the reliability of a distractor interference score calculated on one of the tasks (*N* = 151) was much higher (.74). D. C. Park et al. (1996) also found that the two measures of negative priming they obtained were not reliable, nor did they correlate with any other measures they collected.

The fact that multiple studies (Bestgen & Dupont, 2000; D. C. Park et al., 1996) have now yielded unacceptably low reliability estimates for negative priming measures suggests the importance of being cautious about using negative priming effect as an individual-differences measure of inhibition. Such caution may even extend to experimental studies of negative priming, because even though the negative priming effect may be obtained consistently across experiments, such consistency does not necessarily mean high reliability in terms of individual differences. It is entirely possible for there to be a significant negative priming effect (because more people show the effect than do not show the effect) but, at the same time, for that effect to be quite inconsistent across different parts of the task (e.g., the first vs. second half, odd vs. even trials) or on different occasions (e.g., the first vs. second session) in terms of who is showing an effect of what magnitude. Such reliability problems, combined with the finding that there was no relation between negative priming and Response–Distractor Inhibition, suggest that using negative priming as a measure of inhibition ability requires great caution.

Task-Switching Ability

The third construct examined was task-switching ability, the ability to flexibly switch back and forth between tasks or mental sets. This ability was measured by a switch cost, defined as the difference in RT for trials that required a switch and trials that did not require a switch. In the last several years, the cognitive processes associated with switching between multiple tasks have been the subject of an explosion of research (see Monsell, 2003, for a review).

Recent findings have suggested that the time it takes to switch sets reflects multiple processes (e.g., Goschke, 2000; Meiran, 2000; Rubinstein, Meyer, & Evans, 2001). First, switching involves active and intentional retrieval of task set or instantiation of the current task goal. This retrieval of task set on each trial is crucial for reducing the effects of interference from the irrelevant dimension of the task, because it involves activating the criteria for what information is currently relevant and what is currently irrelevant and should be ignored (Ahn & Miyake, 2001). Evidence for this endogenous control of task switching comes from findings that people can substantially reduce their switch costs if they are given time to prepare for the next trial (e.g., Meiran, 1996; Rogers & Monsell, 1995).

A substantial switch cost remains, however, even with plenty of time to prepare for upcoming switches. This so-called residual switch cost has been interpreted by some researchers as evidence that switching involves more than just mentally reconfiguring the task set. In particular, the residual switch cost has been interpreted as reflecting involuntary effects of PI from irrelevant stimulus dimensions and stimulus–response mappings corresponding to the previous task set (e.g., Allport & Wylie, 2000; Gilbert & Shallice, 2002). Although this interpretation has been influential, the residual switch cost is not universally attributed to involuntary (or automatic) interference effects. Rogers and Monsell (1995), for example, suggested that the residual switch cost reflects an exogenous control process of task-set reconfiguration that can be fully completed only when cued by the stimulus. In a similar vein, several researchers have also suggested that the residual switch cost may involve attentional control and may not be the result of purely involuntary PI effect from the previous task set (e.g., Hübner, Futterer, & Steinhauser, 2001).

These characterizations suggest that a large component of switch costs may be the ability to establish a task set for what information to focus on and what information to filter out, an ability that seems to be tapped by Response–Distractor Inhibition. In addition, it seems that switch costs also reflect interference from previous task sets. Some researchers (e.g., Allport & Wylie, 2000) have characterized this interference as involuntary. However, if participants do attempt to actively resolve this interference, then switch costs may also be related to Resistance to PI.

To examine these hypotheses, both regular switch costs (i.e., switch costs for trials with essentially no preparation intervals) and residual switch costs (i.e., switch costs for trials with long preparation intervals) were obtained from three tasks, and the relations of both types of switch costs to the inhibition-related latent variables were examined with SEM models. In all three tasks, participants showed significant reductions in switch costs from the short to the long preparation intervals: a 247-ms (42%) reduction in the number–letter task, $t(219) = 18.97$, $p < .001$, $\eta^2 = .63$; a 279-ms (44%) reduction in the local–global task, $t(219) = 21.08$, $p < .001$, $\eta^2 = .67$; and a 214-ms (25%) reduction in the category-switch task, $t(219) = 20.96$, $p < .001$, $\eta^2 = .67$. In addition, participants showed significant (i.e., nonzero) residual switch costs in all three tasks: 178 ms in the number–letter task, $t(219) = 21.26$, $p < .001$, $\eta^2 = .67$; 218 ms in the local–global task, $t(219) = 20.32$, $p < .001$, $\eta^2 = .65$; and 71 ms in the category-switch task, $t(219) = 12.35$, $p < .001$, $\eta^2 = .41$.

We first conducted a CFA to assess the extent to which these costs are related. As discussed earlier, a prevalent view is that regular switch costs reflect both the time needed to voluntarily instantiate the task set and involuntary effects of PI, whereas residual switch costs reflect primarily the latter. If this view is correct, then the two switch costs should be somewhat related but not identical. These hypotheses were tested with a CFA model of the two switch costs, presented in Figure 7A. Note that in this model, the error variances for each task were allowed to covary to take into account the possibility that there might be some task-specific variance shared between the regular and residual switch costs.[9] This model provided a good fit to the data, $\chi^2(5, N = 220) = 1.87$, $p = .867$, SRMR = .012, CFI = 1.00, AIC = 33.87.

The main parameter of interest in Figure 7A is the correlation between the two switch-cost latent variables, which was very high (.90), suggesting that these two types of switch costs might be tapping virtually the same ability. Supporting this conclusion, a model in which the correlation was constrained to be 1.0 did not show a significant decrease in model fit, $\chi^2_{\text{diff}}(1, N = 220) = 2.81$, $p = .094$. Hence, despite the substantial reduction from regular to residual switch costs (a reduction of 214–279 ms or 25%–44%), these two types of switch costs cannot be distinguished at the level of latent variables. This finding contradicts the prevalent view that regular and residual switch costs measure something qualitatively different despite some common elements.

Given this finding, we collapsed the regular and residual switch costs into a single latent variable (called *Switch Cost*) and examined its relation to the inhibition-related constructs with SEM. Figure 7B depicts the SEM model predicting the switch-cost latent variable with the two inhibition-related latent variables (see Table 4 for a summary of fit indices).[10] The fit of this all-paths model was satisfactory, $\chi^2(123, N = 220) = 150.53$, $p = .046$, SRMR = .053, CFI = 0.97, AIC = 246.53. Although the chi-square was significant, both the SRMR and CFI indices indicated adequate fit.

As Figure 7B indicates, Resistance to PI was not significantly related to Switch Cost, whereas Response–Distractor Inhibition was significantly related to Switch Cost. Model comparisons indicated that the all-paths model was significantly better than the no-paths model, $\chi^2_{\text{diff}}(3, N = 220) = 72.38$, $p < .001$, but was not significantly better than a model with a single path from Response–Distractor Inhibition to Switch Cost, $\chi^2_{\text{diff}}(2, N = 220) = 0.25$, $p = .882$. The standardized path coefficient from Response–Distractor Inhibition to Switch Cost (.91) was not statistically distinguishable from 1.0, $t(219) = 1.04$, $p = .299$, although this finding most likely reflects the high standard error of the path coefficients (see Figure 7B) that is a consequence of the generally low correlations among the inhibition-related tasks.

These results support the hypothesis that as far as individual differences are concerned, an important component of both regular and residual switch costs is the ability to activate the relevant task set and use this task set to filter out multiple sources of distraction (perceptual, response-mapping, etc.), regardless of how much time an individual has had to prepare for an upcoming switch. This finding agrees with the claim made by Hübner et al. (2001) that attentional control is involved in both the preparatory reconfiguration of task set and the remaining processes of switching after this preparation (i.e., residual switch cost). In addition, these results are compatible with Rogers and Monsell's (1995) suggestion that switch costs reflect a controlled process of task-set reconfiguration.

[9] As shown in Figure 7A, these error variances were significantly correlated only for the number–letter task. One explanation for this task-specific correlation is that the number–letter task differed from the other two switching tasks in that its stimuli were composed of two discrete elements that were presented in a fixed configuration (i.e., number–letter) and that the cues involved spatial locations. These differences may have caused the variance in the number–letter switch costs to contain an additional component of spatial processing or spatial attention that was not present for the other tasks, and this variance would have shown up in the error covariances.

[10] We note that the factor loading of the word-naming task dropped below significance (standardized loading = .10) in this model. However, the other loadings changed little, and the factor structure remained the same. Furthermore, the results were the same when the word-naming task was dropped from the model. Hence, it does not seem to pose a threat to the validity of the CFA models.

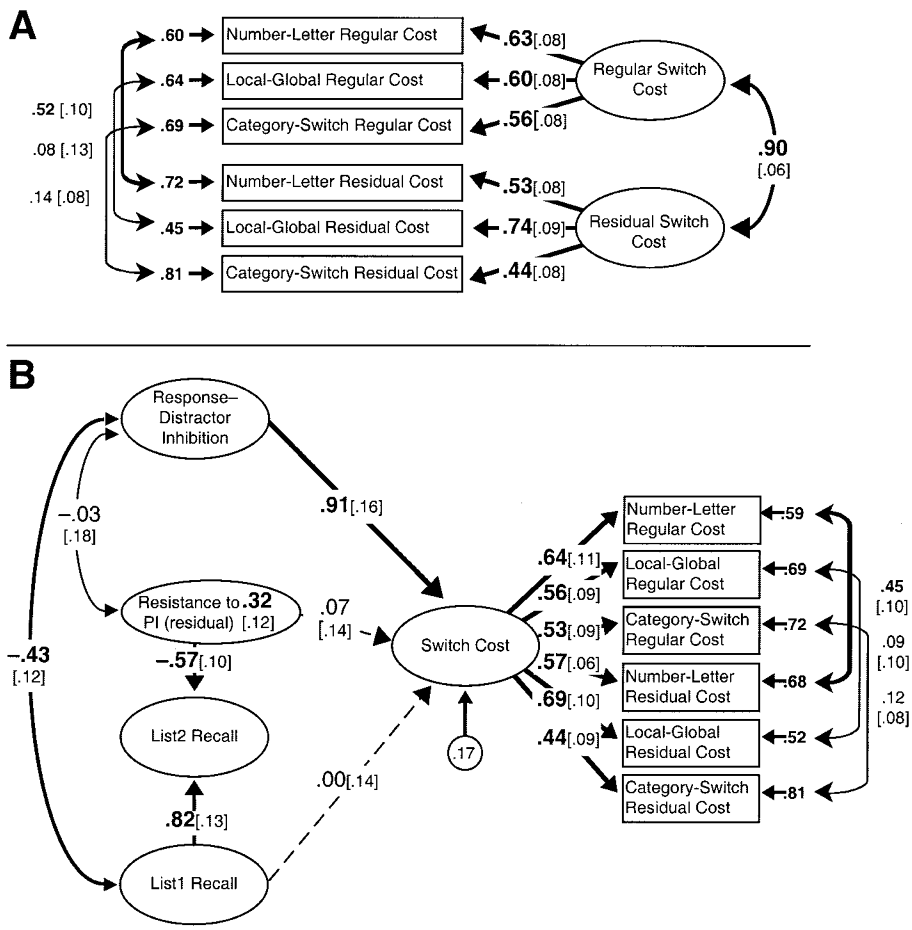

Figure 7. The confirmatory factor analysis (CFA) model used to examine the relations between regular and residual switch costs (A) and the structural equation models (SEMs) of switch costs (B). In both models, the error terms for the switch costs measures derived from each task were allowed to correlate, because the measures may have shared variance unique to that task in addition to the variance due to switching abilities. In the CFA model, the correlation between regular and residual switch costs was not significantly different from 1.0. Hence, in the SEM, these two types of switch costs were allowed to load on a single factor. Response–distractor inhibition significantly predicted switch cost, but Resistance to Proactive Interference (PI) did not. Boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors.

Reading Span

The fourth task examined was the reading span test (Daneman & Carpenter, 1980), which is a frequently used measure of WM capacity. In this task, participants read sets of sentences aloud while trying to remember the last words of the sentences until the end of each set. This task and its variants have been shown to predict performance on complex cognitive tasks (e.g., reading comprehension and inference making) reliably better than more traditional measures of short-term memory capacity, such as digit or word spans (see Daneman & Merikle, 1996, for a meta-analysis). Recently, there has been a surge of interest in specifying what this span task really measures (Miyake, 2001).

Although there are several hypotheses regarding what the reading span task is measuring, one inhibition-related hypothesis that has received a good deal of consideration is the idea that a crucial component of this task is an interference control requirement (e.g., Chiappe, Hasher, & Siegel, 2000; De Beni et al., 1998; Lustig, Hasher, & May, 2001; May, Hasher, & Kane, 1999; Passolunghi et al., 1999). Specifically, the reading span test requires reading sentences for comprehension but then eliminating the words in these sentences from memory (except for the to-be-recalled sentence-final words). The task also requires forgetting the sentence-final words from previous sets as the task progresses. These sources of interference can be seen in the intrusion errors that participants make during recall. In the current study, 61% of intrusion errors were words from the sentences, 30% were sentence-final words from previous sets, and 9% were other words. Most of these intrusions (i.e., the interference from sentence words and from to-be-recalled words from previous sets) seem to reflect failures to resist PI during recall. Recall that Resistance to PI is defined in the current study as the ability to resist intrusions from information in memory that was once relevant but has since become irrelevant. In the reading span test, both the words in the sentence and the to-be-recalled words are relevant and must enter memory at some point during the task but must be expelled from memory when they become no longer relevant. Thus, according to this hypothesis, reading span recall scores, as well as intrusion errors, should be negatively related to Resistance to PI (because higher scores on the Resistance to PI tasks indicate more interference).

The model in Figure 8 tests the hypothesis by allowing the Response–Distractor Inhibition, Resistance to PI, and List 1 Recall to predict both reading span recall and intrusion errors. Although the residuals from the recall scores and intrusion scores were allowed to correlate in this model, the correlation (–.10) was not significant. The fit of the all-paths model (Table 4) was good, $\chi^2(66, N = 220) = 70.64$, $p = .326$, SRMR = .047, CFI = 0.99, AIC = 148.64. As shown in Figure 8, both Resistance to PI and List 1 Recall significantly predicted reading span recall. Although the finding that verbal recall ability (as measured by List 1 Recall) significantly predicts reading span recall is hardly surprising, it is noteworthy that the contribution of Resistance to PI to the prediction of reading span recall goes beyond that of verbal recall ability. Model comparisons indicated that the all-paths model was reliably better than the no-paths model, $\chi^2_{\mathrm{diff}}(6, N = 220) = 42.50$, $p < .001$, but was no better than a model with two paths from Resistance to PI and List 1 Recall to reading span recall, $\chi^2_{\mathrm{diff}}(4, N = 220) = 1.80$, $p = .773$.

In contrast to the pattern of results obtained for reading span recall, none of the latent variables predicted reading span intrusions (see Figure 8 and Table 4). One possible explanation for the absence of correlations with intrusion errors is that participants' decision criteria for voicing responses influence the number of intrusions reported. Some participants report whatever words come to mind (thus yielding many intrusions), but others refrain from voicing these words unless they are absolutely sure that they were actually the sentence-final words. Thus, individual differences in the number of intrusions reported may reflect individual differences in decision criteria in addition to the PI effect, which may be masking any relation between Resistance to PI and these intrusions.

Three Questionnaires

With the questionnaires, we attempted to go beyond laboratory-based tasks and examine the contribution of inhibition-related functions (or the lack thereof) to everyday problems that people encounter: cognitive failures and unwanted thoughts. If inhibition abilities as measured by laboratory tasks are essential for successful living (as suggested by the Garavan et al., 1999, quote), then the two inhibition-related functions should predict the frequency of cognitive failures and the efficiency of suppressing unwanted thoughts. In the following sections, we first briefly describe the hypotheses for three questionnaires and then present a model that includes all three questionnaires.

Cognitive Failures

The CFQ (Broadbent et al., 1982) is a common measure of everyday cognitive failures. This questionnaire asks participants to rate how often they make mistakes, such as forgetting why they went from one part of the house to another, losing their tempers and regretting it, or saying things that might be insulting without realizing it. Scores on this scale are related to self-report measures of memory deficit, absentmindedness, and action slips (Broadbent et al., 1982).

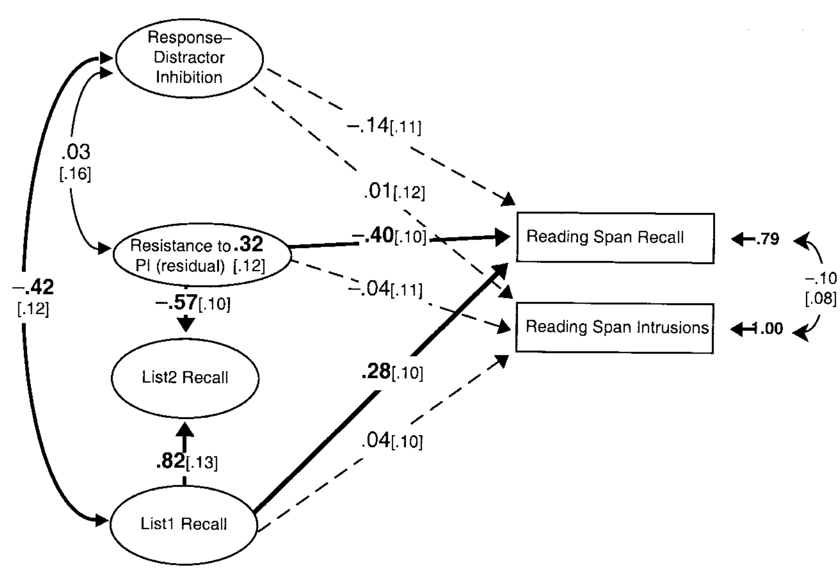

Figure 8. The structural equation models of reading span recall and intrusion errors. Both List 1 Recall and Resistance to Proactive Interference (PI) significantly predicted reading span recall scores, but no latent variables significantly predicted intrusion errors. In addition, the reading span recall and intrusion variables were not correlated, as indicated in the model. Boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors.

An examination of the items on the CFQ reveals that many of the errors about which this questionnaire asks involve becoming distracted by something that is irrelevant to the current task goal or doing something that is relatively automatic (e.g., driving or reading) without thinking about it. This intuition matches Reason's (1990) characterization of many action slips and cognitive failures:

> The greater part of the limited attentional resource is claimed either by some internal preoccupation or by some external distractor at a time when a higher-order intervention . . . is needed to set the action along the currently intended pathway. As a result, the control of action is usurped by the strongest schema leading onwards from that particular point in the sequence. (p. 68)

In other words, many cognitive failures may be the result of lapses in executive control (often due to distraction) that permit more automatic or prepotent responses to take priority. This characterization suggests that CFQ scores may be related to Response–Distractor Inhibition.

Suppression of Unwanted Thoughts

The WBSI (Wegner & Zanakos, 1994) assesses the tendency to suppress thoughts and the incidence of unwanted thoughts. Thought suppression is an important concept in understanding clinical disorders related to anxiety and depression, as overall scores of the WBSI have been found to correlate with measures of obsession and compulsion, depression, trait anxiety, and emotional reactivity in one study (Wegner & Zanakos, 1994) and neuroticism, depression, obsession and compulsion, and intrusive thinking in another (Muris, Merckelbach, & Horselenberg, 1996).

In a recent factor analysis of the WBSI, Blumberg (2000) reported that the WBSI is statistically best explained by a three-factor model with the three factors allowed to correlate. In the current study, this result was replicated (see Appendix B), and factor scores were obtained to examine which inhibition-related latent variable or variables would predict the efficiency of thought suppression. The first factor in the current study was what Blumberg called *Unwanted Intrusive Thoughts*, and it seems to measure the frequency of intrusive thoughts that the respondent "cannot stop." The second factor was what Blumberg called *Self-Distraction.* It measures the frequency with which participants attempt to distract themselves from thinking certain thoughts by doing something else or keeping busy. The third factor was what Blumberg called *Thought Suppression,* and it assesses the tendency of respondents to avoid thinking about certain things or "put them out of mind." With regard to the hypothesis that inhibition-related functions might predict the effectiveness of thought suppression, only the scores for the first factor are of interest. The other two factors, Self-Distraction and Thought Suppression, essentially measure the extent to which participants use distraction and suppression techniques, rather than measuring the effectiveness of these techniques per se.

The process of thought suppression shares many similarities with Resistance to PI: An unwanted thought occurs for some reason, and the thinker attempts to eliminate this thought from WM. This elimination of information from memory is close to the definition of Resistance to PI. This similarity suggests that individuals who have more difficulty resisting PI may also have more unwanted intrusive thoughts; that is, people who are less successful at suppressing their thoughts may have more rebounds of these thoughts intruding into memory, because the thoughts were never effectively suppressed in the first place. The primary hypothesis to be tested, then, was that Resistance to PI predicts the factor scores from the first factor of the WBSI.

Social Desirability

The MCSDS (Crowne & Marlowe, 1964) is designed to assess the extent to which participants respond in a socially desirable way to questionnaires. It was included for two reasons. First, participants' responses on the other two questionnaires might have been influenced by individual differences in their desire to portray themselves in a socially positive light. This variance due to social desirability, as well as other variance due to the self-report method, is not of theoretical interest. Hence, inclusion of the MCSDS allows us to partial out this variance when examining the CFQ and WBSI. Second, there is no reason we know of to hypothesize that the MCSDS should be associated with inhibition-related abilities. Thus, inclusion of this questionnaire in the SEM model allows us to confirm that these inhibition-related constructs do not just predict any self-reported traits; rather, we hypothesize that the inhibition-related variables will predict only specific self-reported traits related to cognitive failures and unwanted intrusive thoughts.

A Model Predicting All Three Questionnaires

Figure 9 presents a model predicting all three questionnaires. The fit of this all-paths model was good, $\chi^2(75, N = 220) = 72.71$, $p = .553$, SRMR $= .045$, CFI $= 1.00$, AIC $= 162.71$. As shown in Appendix C, the three questionnaires were all significantly correlated, probably because they all reflect method-related variance due to the fact that they are all self-report measures (including the tendency to respond in a socially desirable way). To capture this common method-related variance, the model in Figure 9 included a self-report method latent variable. As shown in the figure, the factor loadings for the three questionnaires on this latent variable were all significant.

In terms of relations to the inhibition-related latent variables, we were interested in whether the inhibition-related functions could predict individual differences on each measure once the variance due to the self-report method was removed. We thus examined the paths from the Response–Distractor Inhibition, Resistance to PI, and List 1 Recall latent variables to the residuals for each questionnaire. Specifically, we predicted that the CFQ would be related to Response–Distractor Inhibition, WBSI would be related to Resistance to PI, and MCSDS would not be related to either. As far as the relations of these questionnaires to List 1 Recall, we had no reason to believe that individual differences in these measures would have any relation to verbal recall ability.

As shown in Figure 9, these hypotheses were supported. First, neither the inhibition-related latent variables nor the List 1 Recall latent variable was related to MCSDS once the variance associated with the self-report methodology was eliminated. The CFQ was significantly related to Response–Distractor Inhibition but not Resistance to PI or List 1 Recall. As for the WBSI, neither Response–Distractor Inhibition nor List 1 Recall significantly predicted this measure, but Resistance to PI did. Model comparisons indicated that the all-paths model was significantly better than the

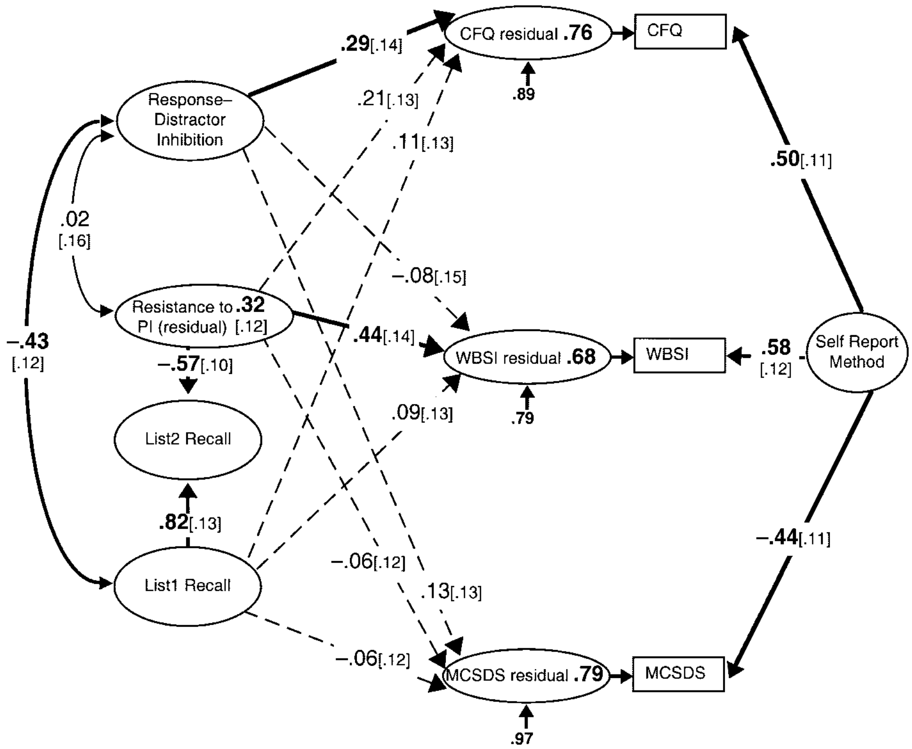

Figure 9. The structural equation models of the questionnaire data. Response–Distractor Inhibition predicted cognitive failures, but Resistance to Proactive Interference (PI) did not. In contrast, Resistance to PI predicted Unwanted Intrusive Thoughts, but Response–Distractor Inhibition did not. As expected, neither inhibition function predicted responding in a socially desirable way. Boldface type is used to indicate significance at the .05 level. Bracketed numbers are standard errors. CFQ = Cognitive Failures Questionnaire; WBSI = White Bear Suppression Inventory; MCSDS = Marlowe–Crowne Social Desirability Scale.

no-paths model, $\chi^2_{\text{diff}}(9, N = 220) = 22.18$, $p = .008$, but was not significantly better than a model with a path from Response–Distractor Inhibition to CFQ Residual and a path from Resistance to PI to WBSI Residual, $\chi^2_{\text{diff}}(7, N = 220) = 6.31$, $p = .504$.

These results suggest that latent variables constructed from laboratory-based tasks can predict everyday problems that people encounter. Moreover, avoiding everyday cognitive failures and effectively suppressing intrusive thoughts implicate different abilities, suggesting that both kinds of inhibition-related abilities are important in day-to-day functioning.

Summary of Structural Model Results

In five SEM analyses, we examined how the two inhibition-related constructs predicted other measures thought to involve inhibition. The key results were as follows: The ability to resist producing stereotyped sequences in the RNG task was related to Response–Distractor Inhibition but not to Resistance to PI. Similarly, task-switching ability (composed of both regular and residual switch costs) was predicted by Response–Distractor Inhibition but not Resistance to PI. Reading span recall, in contrast, was significantly related to Resistance to PI but not Response–Distractor Inhibition. Finally, cognitive failures were predicted by Response–Distractor Inhibition but not Resistance to PI, whereas unwanted intrusive thoughts showed the opposite pattern. Taken together, these SEM results suggest that not only are Response–Distractor Inhibition and Resistance to PI separable at the level of latent variables, but they also differentially predict performance on a variety of measures thought to involve inhibition.

To further support this claim of differential predictions, we tested, for each model, whether constraining the path coefficients from Response–Distractor Inhibition and Resistance to PI to each measure of interest to be equal significantly worsened model fit, compared with the all-paths model. These analyses allowed for formal statistical tests of whether the two inhibition-related constructs differentially predicted the measures of interest. As expected, given that neither inhibition-related construct predicted negative priming (Figure 6), constraining the paths from Response–Distractor Inhibition and Resistance to PI to the negative priming latent variable to be equal to each other did not harm model fit, $\chi^2_{\text{diff}}(1, N = 220) = 0.70$, $p = .403$. In contrast, for the task-switching model (Figure 7B), constraining the paths from Response–Distractor Inhibition and Resistance to PI to be equal to each other significantly worsened model fit, $\chi^2_{\text{diff}}(1, N = 220) = 11.51$, $p = .001$. Similarly, for the reading span model (Figure 8), constraining the two paths to equal each other also significantly worsened fit, $\chi^2_{\text{diff}}(1, N = 220) = 10.00$, $p = .002$. For the questionnaire model (Figure 9), constraining the two paths to CFQ residual to equal each other and constraining the two paths to

WBSI residual to equal each other significantly worsened fit, $\chi^2_{\text{diff}}(2, N = 220) = 9.34$, $p = .009$. The only model that did not show the expected significant differential predictions was the RNG model (Figure 5), in which constraining the paths to RNG Prepotent Associates to equal each other did not significantly worsen model fit, $\chi^2_{\text{diff}}(1, N = 220) = 1.23$, $p = .268$. These results for the most part support the claim that Response–Distractor Inhibition and Resistance to PI are separable abilities that differentially predict performance on other measures.

Alternative Explanations

Our interpretations of the CFA and SEM results critically depend on the assumption that the latent variables actually tap their respective inhibition-related abilities. If this assumption is false, these models would be essentially uninterpretable. Thus, it is crucial to rule out some alternative explanations for the results that might compromise the conclusions we present.

The first alternative explanation is that the latent variables are not really measuring anything at all, because the zero-order correlations and factor loadings (the magnitude of which depend on the zero-order correlations) were too low to conduct this type of analysis. In other words, "Garbage in, garbage out." There are three main lines of evidence that argue against this interpretation. First, despite the low zero-order correlations, the tasks all loaded significantly on their respective factors. Second, as discussed throughout the RESULTS AND DISCUSSION section, the models we endorsed showed a significantly better fit than various alternative models with fewer parameters. Specifically, the CFA model presented in Figure 4A fit the data significantly better than a null model in which all the covariances were set to zero, as well as several alternative models in which particular correlations were constrained to theoretical values. In addition, with the exception of negative priming, all the SEM models we presented were significantly better than no-path models in which the path coefficients from the inhibition-related functions and verbal recall ability were constrained to zero. If there were no systematicity in the data because of the low zero-order correlations, then none of the models should have been better than the null model, and they certainly should not have been better than models with one or two parameters changed (i.e., the no-path models). Third and most important, the inhibition-related latent variables significantly predicted other constructs or measures in ways that conformed to our a priori hypotheses. These results form a coherent pattern—one that we find difficult to describe as "garbage out."

Another alternative explanation is that the similarity of the Prepotent Response Inhibition and Resistance to Distractor Interference latent variables, as well as their separability from the Resistance to PI variable, may have been simply due to the nature of the dependent measures used to tap these constructs. Specifically, the Response–Distractor Inhibition measures were predominantly based on RTs, whereas the Resistance to PI measures were based on recall performance. According to this alternative interpretation, these functions may have differed because they reflected different aspects of performance (speed vs. recall), rather than because they tapped different inhibition-related abilities. The strongest evidence against this explanation is that the two inhibition-related latent variables predicted performance on other constructs or measures in line with a priori predictions. In particular, the two questionnaire measures (CFQ and WBSI), which do not conform to either of these categories (speed or recall), were each predicted by one of the latent variables. Hence, this alternative explanation is not compelling.

Yet another possibility is that the two inhibition-related functions (Resistance to PI and Response–Distractor Inhibition) were separable because the tasks used to measure Resistance to PI were all verbal, whereas the Prepotent Response Inhibition and Resistance to Distractor Interference tasks were both verbal and nonverbal. Although this criticism might apply to the first model that used difference scores for the Resistance to PI construct (Figure 2), it fails to account for the later models (Figures 4–9). In the latter, the Resistance to PI latent variable was uncorrelated with baseline performance (List 1 Recall), which is a good indicator of verbal recall ability (because the Resistance to PI variable is actually the residual variance left in List 2 Recall after List 1 Recall has been regressed out, it must by definition be uncorrelated with List 1 Recall). In contrast, the difference scores used to construct the Resistance to PI latent variable in the original model (Figure 2) were substantially correlated with List 1 Recall component scores, $r(218) = .44$ for Brown–Peterson, $r(218) = .23$ for AB–AC–AD, and $r(218) = .51$ for cued recall. Hence, the alternative model of Resistance to PI eliminated the confounding of Resistance to PI with verbal recall ability. Furthermore, the presence of a latent variable for verbal recall ability (List 1 Recall) also allowed us to examine how this ability relates to the other inhibition-related functions and to control for this relation when examining the predictive power of these inhibition-related latent variables. For these reasons, it is unlikely that verbal abilities are accounting for any of the effects reported above.

GENERAL DISCUSSION

With respect to the first goal of evaluating how the inhibition-related functions related to each other, the CFA results suggested that two of the functions, Prepotent Response Inhibition and Resistance to Distractor Interference, were closely related to each other, but neither was related to Resistance to PI. These results provide evidence for some common inhibition ability (i.e., between Prepotent Response Inhibition and Resistance to Distractor Interference) but also suggest that this common ability is not involved in all so-called inhibition functions.

With regard to the second goal of examining how these inhibition-related functions contribute to other cognitive measures, the SEM models indicated that the two kinds of inhibition (Response–Distractor Inhibition and Resistance to PI) were differentially involved in other cognitive measures previously linked to inhibition-related functions. Specifically, the ability to resist producing stereotyped sequences in the RNG task, task-switching ability (as measured by switch costs), and the frequency of cognitive failures were related to Response–Distractor Inhibition but not Resistance to PI, whereas reading span recall and the frequency of unwanted thoughts were related to Resistance to PI but not Response–Distractor Inhibition. These results largely conformed to predictions based on task analyses and previous proposals, and they further support the separability of the Response–Distractor Inhibition and Resistance to PI constructs.

It is important to keep in mind that the participants examined in this study were young, healthy college students; hence, these results may not fully generalize to more diverse samples, such as populations including children, older adults, or individuals with brain damage. For example, it is possible that a more diverse sample would show a closer relation between Response–Distractor Inhibition and Resistance to PI. Similarly, the nature of the relationships between the inhibition-related latent variables and the hypothesized inhibition tasks might not be identical among other populations. Although the generalizability of the results needs to be tested in a more diverse sample, the current results provide a first step toward specifying the extent to which these inhibition-related functions are related and provide a foundation upon which future studies can build.

Taxonomies of Inhibition-Related Functions Revisited

The design of the current study was motivated by previous taxonomies of inhibition-related functions that were based in large part on theoretical distinctions. In particular, the study was designed to test whether previous conceptual distinctions correspond to differences in abilities. One important finding of the study was that the Prepotent Response Inhibition and Resistance to Distractor Interference constructs were correlated at $r = .67$. Thus, despite the conceptual distinction between behavioral inhibition and resistance to interference (i.e., distractor interference) proposed by Harnishfeger (1995) and Nigg (2000), as well as the similar distinction between motor interference and perceptual interference posited by Dempster (1993), these inhibition-related abilities are highly related. As discussed earlier, one explanation for their similarity is that these two functions may share the requirement to actively maintain task goals in the face of interference, usually interference from external stimuli (e.g., the presence of a to-be-categorized word in the stop-signal task, the presence of irrelevant letters in the Eriksen flanker task).

Another important result was that these two constructs were not related to Resistance to PI. This finding provides empirical support for the conceptual distinctions between cognitive inhibition and behavioral inhibition or resistance to interference (Harnishfeger, 1995; Nigg, 2000) and between perceptual interference and verbal–linguistic interference (Dempster, 1993). At the same time, however, the separability of the Response–Distractor Inhibition and Resistance to PI constructs provides evidence against the general inhibition (e.g., Hasher & Zacks, 1988) and controlled attention (e.g., Kane et al., 2001) views that predict at least some commonality between these constructs.

An interesting question that arises is why Resistance to PI is separable from Response–Distractor Inhibition. One possible explanation is that Resistance to PI may not actually be reflecting an effortful, controlled ability; instead, the tasks used to measure Resistance to PI may tap the amount of interference that automatically accrues without any active resistance by participants. The current study cannot disprove this possibility, but neurological studies of PI have indicated that the frontal lobes, particularly the right frontal cortex, is more activated during tasks involving PI than in tasks not involving PI (Bunge et al., 2001; Uhl et al., 1994). If there were no active control process that attempted to resist this interference, one would not expect frontal activation during these tasks.

Another explanation for the separability may be that Resistance to PI involves a different source of interference. Specifically, in the Response–Distractor Inhibition tasks, the source of distraction comes from external stimuli in the environment, and if attention is captured by these distractions, the task goal is neglected or even forgotten. In contrast, PI comes from information residing in memory, which does not seem to interfere with the maintenance of the task goals. That is, the person experiencing PI knows that the task requires remembering currently relevant words but just cannot distinguish those words from previously relevant words or cannot eliminate the previously relevant words from memory. Although this explanation is speculative, it raises an interesting question of how (and where in the WM system) task goals may be actively maintained.

Finally, the finding that Resistance to PI and Response–Distractor Inhibition are unrelated raises the possibility that these functions may involve separable neural mechanisms or substrates. Although most neuropsychological studies indicate that the frontal cortex may play a role in both Resistance to PI and Response–Distractor Inhibition (e.g., Bunge et al., 2001; de Zubicaray, Andrew, Zelaya, Williams, & Dumanoir, 2000; Garavan et al., 1999; Uhl et al., 1994), it is possible that different regions of the frontal cortex are involved. In fact, there is evidence that the orbital region of the prefrontal cortex may be involved in Resistance to PI, whereas the dorsolateral prefrontal cortex may be more involved in Prepotent Response Inhibition (see West, 1996, for a discussion). It seems worthwhile to further test this hypothesis, although it would require studying multiple inhibition-related functions together, preferably with multiple tasks to tap each function (see, for example, Konishi et al., 1999; Rubia et al., 2001). This methodology could also be used to examine the hypothesis that the same brain areas are involved in Prepotent Response Inhibition and Resistance to Distractor Interference tasks.

The inhibition-related functions examined in the current study represented only the main ones discussed in the literature, but this focus should not be interpreted as a claim that these are the only inhibition-related functions. It is possible that others exist. For example, inhibition of return, which has been characterized as more automatic forms of inhibition (Nigg, 2000), may be separable from the kinds of inhibition examined in this study. It may also be possible to fractionate a particular inhibition-related construct (e.g., Resistance to PI) into multiple subcomponents. For example, the ability to resist verbal PI may not be identical to the ability to resist spatial PI. Thus, further identifying and delineating different forms of inhibition-related functions, empirically testing the relationships among them, and refining the proposed taxonomic distinctions appears to be an important future task toward a better understanding of inhibition and interference control.

Methodological Implications for Studies of Inhibition-Related Functions

In the current study, the zero-order correlations between measures proposed to tap the same underlying inhibition ability were low. Despite these low correlations, latent variables for the proposed inhibition-related functions were successfully extracted (albeit with some imprecision in the estimates), and these latent variables predicted performance on other inhibition-related measures in accordance with a priori predictions. This success was due in part to the use of the latent-variable methodology. However, in many studies of inhibition-related functions—particularly those targeting special populations, such as individuals with clinical disorders or brain damage—latent-variable designs are not practical or even feasible. Our results nonetheless have several methodological implications for future studies of inhibition-related functions, including studies with non-latent-variable designs.

First, it is important to keep in mind that inhibition is a difficult construct to measure. For whatever reason, some measures (e.g., PI tasks and negative priming) are not reliable, and even the measures that show reasonable reliability may not correlate well with other measures purported to measure the same type of inhibition ability. Although the individual tasks used in this study all significantly loaded on their respective factors, the magnitudes of these loadings were relatively low. Such measurement difficulty is not restricted to the current study or to studies involving only college students. Some carefully conducted cognitive aging studies that included a wider range of age and intellectual abilities (e.g., Kramer et al., 1994; Shilling et al., 2002) have also yielded low intercorrelations among inhibition measures. It thus appears that, for most so-called inhibition tasks, the relative proportion of the variance attributable to the hypothesized inhibition ability may be quite small in comparison with the variance attributable to other idiosyncratic requirements of the task or the error variance. In other words, the task impurity problem is severe for inhibition-related functions.

One obvious solution to this problem is to develop new tasks that are more psychometrically reliable and more sensitive to individual variation in inhibition-related processes. Although our strategy in the current study was to focus on existing measures used in the field, it is becoming increasingly clear that new measures are needed for the field to make further progress. Such measures must be relatively simple and easy to administer, demonstrate high reliability, and primarily tap one of the inhibition-related functions examined here or hypothesized in the literature. More important, such tasks must be able to tap more inhibition-related variance than has been possible with the existing measures. Of course, such a goal is easily stated but much more difficult to realize. Creation of reliable and sensitive inhibition tasks would also involve a good deal of research to validate them.

Until better measures are developed and validated, a more practical solution to the problems of low reliability and task impurity may be to use multiple measures of the inhibition-related process of interest, either in the same study or across a series of studies. This solution applies to not only correlational but also experimental investigations. Use of multiple tasks allows researchers to examine whether the results of different measures or different experimental manipulations converge on a single result, thus reducing the problem that the correlations or experimental effects may be due to non-inhibition-related variance. In addition, multiple measures can be combined into *z*-score aggregates or used in multivariate analyses (e.g., multivariate analysis of variance) to increase power.

Another methodological implication of the study is that the construct validities and reliabilities of the tasks to be used should be established before interpreting correlations (or the lack thereof) with these measures. Many tasks have been proposed to measure inhibition-related functions without validation that they reliably do so. An example is the negative priming effect. Although it is frequently used to measure individual differences in distractor inhibition, negative priming was unrelated to Response–Distractor Inhibition in the current study. In addition, the low reliability of the negative priming scores (Bestgen & Dupont, 2000; D. C. Park et al., 1996) suggests that extreme caution is necessary if negative priming is used as an index of inhibitory ability (in this regard, Resistance to PI measures also may need to be used more cautiously, particularly if difference scores are used to index the PI effect). One solution to these problems may be to always examine how the task of interest relates to other tasks proposed to tap the same process. Regularly calculating reliability estimates (not just in correlational studies but also in experimental studies) may also be important, at least in the context of inhibition-related functions.

Implications for Theories Positing a Role for Inhibition-Related Functions

As mentioned at the beginning, inhibition and interference control are used as explanatory concepts in nearly every area of psychology. The results of the current study thus have implications that extend beyond cognitive psychology. In particular, the finding that Prepotent Response Inhibition and Resistance to PI are unrelated functions may help explain some inconsistencies in the literature and enable more detailed theories to be specified.

For example, one hypothesis that has received a good deal of consideration recently is the idea that ADHD is an inhibition disorder (e.g., Barkley, 1997; Gaultney, Kipp, Weinstein, & McNeil, 1999; Nigg, 2000, 2001; Nigg, Butler, Huang-Pollock, & Henderson, 2002; Pliszka, Liotti, & Woldorff, 2000). Nigg's work and the current study's findings indicate that it is important to specify the type of inhibitory functions impaired in individuals with ADHD. Given that Response–Distractor Inhibition was separable from Resistance to PI and negative priming, ADHD may involve deficits in only one of these kinds of inhibition. Consistent with this view, the preponderance of the evidence indicates that individuals with ADHD are impaired on response inhibition tasks, whereas the few studies that have examined their performance on measures of cognitive inhibition (Resistance to PI) have found little evidence that they are impaired on these measures (Gaultney et al., 1999; see Nigg, 2001, for a discussion). Furthermore, Nigg et al. (2002) found that adults with ADHD showed deficits in Prepotent Response Inhibition but not in negative priming (Ozonoff & Strayer, 1997, reported a similar pattern for children with autism). Hence, the preliminary evidence suggests that ADHD may be a response inhibition disorder, rather than a disorder of all inhibition-related functions. At this point, it is unclear whether individuals with ADHD are also impaired on distractor interference tasks, but they should be, to the extent that Resistance to Distractor Interference and Prepotent Response Inhibition tap the same ability among ADHD individuals.

The results we reported also have implications for theories of depression and anxiety. These disorders have been linked to the tendency to suppress unwanted thoughts and to the frequency of these unwanted intrusive thoughts (Muris et al., 1996; Wegner & Zanakos, 1994), and several theories of depression and anxiety include a role for intrusive thoughts (e.g., Ellis & Ashbrook, 1988; Eysenck & Calvo, 1992; Ingram, 1984). For example, Ingram proposed that depressed individuals show performance decrements in effortful tasks because their attentional resources are consumed by distracting and task-irrelevant thoughts or depression-related thoughts. Consistent with this hypothesis, Seibert and Ellis (1991) found that depression is accompanied by a higher proportion of task-irrelevant thoughts and that the proportion of such thoughts was negatively related to task performance. Given that the efficiency of thought suppression was related to Resistance to PI but not to Response–Distractor Inhibition in the current study, the type of inhibition deficits involved in disorders related to depression and anxiety is likely different from the type of inhibition deficits involved in other disorders (e.g., ADHD). This suggestion is consistent with the finding that children with ADHD, but not anxious children, show impaired response inhibition (Oosterlaan, Logan, & Sergeant, 1998). Hence, researchers interested in the inhibitory underpinnings or consequences of depression and anxiety may need to focus on cognitive inhibition (or Resistance to PI) rather than Response–Distractor Inhibition.

More generally, the results of the current study suggest that theories positing inhibition as a unifying mechanism or theme may be overly ambitious. Although these theories do not necessarily assume that all types of inhibition are the same, they nevertheless use the term *inhibition* as if it refers to something commonly measured by different tasks. For example, Dempster (1992) argued that similar patterns of deficits on tasks such as the Stroop task, the Brown–Peterson task, and selective attention tasks in young adults, old adults, and patients with frontal lobe lesions point to a unifying role for inhibition in these areas. If not all of these kinds of inhibition are related to each other, it is unlikely that these patterns found among diverse populations can be adequately unified by a single unitary mechanism, unless one is willing to accept that empirically unrelated cognitive processes or abilities can be called the same thing. This argument is not to say that inhibition cannot provide unifying explanations of these areas—only that inhibition as it is currently defined (i.e., too broadly) cannot do so. It is possible that one kind of inhibition may provide a unifying framework, but the nature of this inhibition must be more clearly specified. This need for more specificity in the particular inhibition functions involved in various areas of psychology need not be an obstacle to unifying theories. Rather, it can be a catalyst for better, more complete theories.

Concluding Remarks

With this study, we have provided a first attempt to examine the relations between three inhibition-related functions from the perspective of individual differences. The results were promising, providing some answers to the issues we examined. This study was only meant to be a first pass, however, and we by no means see it as the final word. We hope that it stimulates further research on these issues, especially research using different methodologies and tasks. Some of the topics that seem pressing to explore are whether research using other tasks or methodologies and research using different populations will support the distinctions made here and whether there are other inhibition-related functions not explored in the current study. In a related vein, it also seems important to examine the extent to which the types of inhibition-related functions examined here are distinct from other related cognitive constructs, such as general intelligence and processing speed (e.g., Salthouse & Meinz, 1995; Salthouse, Atkinson, & Berish, 2003). Methodologically, developing new, more reliable measures that can better capture the variance attributable to the hypothesized inhibition function is also a high priority. Given the ubiquity of theories asserting the importance of inhibition-related processes in normal and pathological performances on laboratory tasks as well as in successful day-to-day living (as the quote at the beginning of this article indicates), a deeper understanding of these processes will likely have a broad impact on all areas of psychology.

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(*Appendixes follow*)

Appendix A

Factor Loadings and Interfactor Correlations for the Principal-Components Analysis of Random Number Generation

Item	Prepotent Associates	Equality of Response Usage	Repetition Avoidance
	Factor loadings		
TPI	**−.92**	.16	−.20
A	**.91**	−.10	.19
Runs	**.87**	−.10	−.08
RNG	**.78**	.25	−.14
RNG2	**.46**	**.47**	−.32
R	.01	**.90**	.02
Coupon	−.08	**.88**	.06
Mean RG	.12	**−.85**	−.26
Phi4	.07	.11	**.80**
Phi3	.09	−.14	**.75**
Phi2	.02	−.17	**.68**
Phi5	.03	.24	**.62**
Phi6	.05	.21	**.58**
Phi7	−.12	.24	**.37**
	Correlations		
Prepotent Associates	—		
Equality of Response Usage	.11	—	
Repetition Avoidance	−.13	−.10	—

Note. Loadings greater than .35 are in boldface. Factors 1, 2, and 3 accounted for 24%, 20%, and 19% of the variance, respectively. TPI = turning point index; A = total adjacency; RNG = Evan's random number generation score; RNG2 = analysis of interleaved diagrams; R = redundancy; Mean RG = mean repetition gap; Phi2–7 = phi indices.

Appendix B

Factor Loadings and Interfactor Correlations for the Exploratory Factor Analysis of the White Bear Suppression Inventory

Item	Unwanted Intrusive Thoughts	Self-Distraction	Thought Suppression
Factor loadings			
3. I have thoughts that I cannot stop.	**.84**	−.07	−.12
4. There are images that come to mind that I cannot erase.	**.77**	−.02	−.11
2. Sometimes I wonder why I have the thoughts I do.	**.69**	−.17	.12
6. I wish I could stop thinking of certain things.	**.61**	.05	.18
7. Sometimes my mind races so fast I wish I could stop it.	**.55**	.10	.01
9. There are thoughts that keep jumping into my head.	**.54**	.08	.08
5. My thoughts frequently return to one idea.	**.53**	.23	−.24
15. There are thoughts that I have that I don't tell anyone.	**.42**	−.07	.26
12. Sometimes I really wish I could stop thinking.	**.39**	.27	−.10
14. I often have thoughts that I try to avoid.	**.36**	.18	**.35**
13. I often do things to distract myself from my thoughts.	−.03	**.88**	.07
10. Sometimes I stay busy just to keep thoughts from intruding on my mind.	.02	**.80**	.01
1. There are things I prefer not to think about.	−.02	−.16	**.75**
11. There are things that I try not to think about.	.00	.12	**.62**
8. I always try to put problems out of my mind.	−.17	.17	**.49**
Correlations			
Unwanted Intrusive Thoughts	—		
Self-Distraction	.56	—	
Thought Suppression	.55	.47	—

Note. The data analyzed were ratings for each item that could range from 1 (*strongly disagree*) to 5 (*strongly agree*). Loadings greater than or equal to .35 are in boldface. Factors 1, 2, and 3 accounted for 38%, 10%, and 8% of the variance, respectively. The White Bear Suppression Inventory items are from "Chronic Thought Suppression," by D. M. Wegner and S. Zanakos, 1994, *Journal of Personality, 62,* p. 622. Copyright 1994 by Blackwell Publishing. Reprinted with permission.

(*Appendixes continue*)

Appendix C

Pearson Correlation Coefficients for All Measures Used in the Models

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Antisaccade	—												
2. Stop-signal	**.16**	—											
3. Stroop effect	**.23**	**.15**	—										
4. Brown–Peterson INT	−.01	.00	.03	—									
5. AB–AC–AD INT	.03	−.05	.13†	.11	—								
6. Cued recall INT	−.02	.03	.07	**.14**	**.17**	—							
7. Brown–Peterson List 1 recall	**−.18**	−.11	−.05	**.44**	**−.17**	−.06	—						
8. Brown–Peterson List 2 recall	**−.16**	−.10	−.07	**−.58**	**−.26**	**−.19**	**.48**	—					
9. AB–AC–AD AB trials	**.16**	.11†	.09	−.05	**.23**	.02	**−.45**	**−.36**	—				
10. AB–AC–AD AC trials	**.10**	.02	**.14**	.05	**.85**	.13†	**−.36**	**−.38**	**.69**	—			
11. Cued recall 1-block recall	**−.19**	−.04	−.06	.00	**−.13**	**.51**	**.21**	**.19**	**−.26**	**−.24**	—		
12. Cued recall 2-block recall	**−.15**	−.07	−.13†	**−.15**	**−.30**	**−.63**	**.25**	**.38**	**−.26**	**−.36**	**.35**	—	
13. Eriksen flanker INT	.04	**.15**	**.18**	.02	−.02	−.05	−.07	−.09	.06	.02	−.07	−.01	—
14. Word naming INT	.03	.06	**.18**	−.07	.05	−.05	**−.14**	−.06	.07	.07	−.08	−.02	.11
15. Shape-matching INT	**.15**	.12†	.08	−.01	−.05	.11	−.13†	−.11	−.03	−.05	.07	−.05	**.18**
16. RNG Prepotent Associates	**.17**	.08	**.16**	.12†	.10	.03	−.02	−.13†	**.14**	**.16**	−.02	−.04	−.02
17. RNG Response Usage	.09	.11	.11	.02	−.01	.03	−.03	−.05	**.14**	.07	−.09	−.11†	−.06
18. Word-naming NP	.06	−.04	.06	−.11	−.06	.02	**−.15**	−.03	.10	.01	−.04	−.06	−.06
19. Shape-matching NP	−.10	**−.14**	−.06	.07	−.07	.11	.05	−.03	−.13†	−.12†	**.15**	.01	.00
20. Number–letter regular cost	**.25**	**.23**	**.24**	.00	.12†	.06	**−.15**	**−.14**	**.21**	**.19**	−.13†	**−.18**	**.21**
21. Local–global regular cost	**.21**	**.24**	.10	−.11	.09	.07	**−.16**	−.04	**.25**	**.20**	−.12†	**−.18**	.12†
22. Category-switch regular cost	**.15**	**.35**	.06	.01	−.05	.07	.02	.00	.10	.01	.03	−.04	**.15**
23. Number–letter residual cost	**.28**	**.21**	**.19**	.00	.00	−.03	−.12†	−.11	.12†	.06	**−.15**	−.11	**.27**
24. Local–global residual cost	**.25**	**.32**	.12†	−.04	.10	**.14**	**−.19**	−.13†	**.22**	**.19**	−.06	**−.21**	**.27**
25. Category-switch residual cost	**.22**	**.16**	**.19**	.09	**.14**	.01	.02	−.08	.09	**.15**	−.04	−.05	**.23**
26. RSPAN recall	−.07	−.03	**−.23**	**−.14**	**−.25**	−.07	**.20**	**.32**	**−.17**	**−.28**	**.27**	**.32**	−.09
27. RSPAN intrusions	.06	.05	−.05	.00	.00	−.10	.08	.07	.02	.03	−.07	.05	−.07
28. CFQ	.12†	.09	**.14**	.08	.05	.00	.01	−.07	−.05	.01	**−.16**	**−.14**	.06
29. WBSI Factor1	−.09	.04	−.02	.07	**.14**	**.18**	.04	−.04	−.09	.05	.06	**−.14**	−.05
30. MCSDS	.10	.01	.05	.06	−.07	−.04	−.05	−.10	.05	−.02	−.07	−.02	.12†

Note. Boldface type indicates $p < .05$. INT = interference; RNG = random number generation; NP = negative priming; RSPAN = reading span; CFQ = Cognitive Failures Questionnaire; WBSI = White Bear Suppression Inventory; MCSDS = Marlowe–Crowne Social Desirability Scale.
† $p < .10$.

14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
—																
.13	—															
.08	.11†	—														
.09	.06	.11	—													
.02	.07	.08	−.01	—												
−.06	.04	−.05	−.11	**.15**	—											
.05	**.16**	**.14**	**.16**	−.04	.00	—										
−.05	**.17**	**.14**	−.02	−.10	−.08	**.36**	—									
−.02	**.20**	**.14**	.03	−.02	−.07	**.35**	**.37**	—								
.15	**.22**	.05	.07	−.06	−.06	**.65**	**.28**	**.27**	—							
−.06	**.21**	**.20**	.04	−.01	−.01	**.43**	**.44**	**.36**	**.41**	—						
−.01	.07	**.16**	.00	−.01	−.01	**.28**	**.24**	**.33**	**.21**	**.32**	—					
−.06	−.02	−.09	−.09	.02	.01	**−.18**	−.03	.09	**−.15**	**−.15**	−.04	—				
−.02	.03	**.14**	−.01	.00	−.08	−.04	.01	−.02	−.03	**.14**	−.04	−.05	—			
−.04	.00	.05	.09	.06	.06	.09	.01	.01	.01	.05	.07	−.01	.02	—		
−.01	−.05	.02	.05	−.03	.03	.00	−.01	−.03	.05	**.15**	−.04	−.07	.02	**.34**	—	
−.03	.01	.12†	−.01	−.02	−.01	.05	.06	.06	−.02	.01	.02	−.02	.11	**−.21**	**−.29**	—

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