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# Horse-race model simulations of the stop-signal procedure

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## Abstract

In the stop-signal paradigm, subjects perform a standard two-choice reaction task in which, occasionally and unpredictably, a stop-signal is presented requiring the inhibition of the response to the choice signal. The stop-signal paradigm has been successfully applied to assess the ability to inhibit under a wide range of experimental conditions and in various populations. The current study presents a set of evidence-based guidelines for using the stop-signal paradigm. The evidence was derived from a series of simulations aimed at (a) examining the effects of experimental design features on inhibition indices, and (b) testing the assumptions of the horse-race model that underlies the stop-signal paradigm. The simulations indicate that, under most conditions, the latency, but not variability, of response inhibition can be reliably estimated. © 2002 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

Inhibitory control is an indispensable concept for explaining behavioral flexibility (for a review, see Logan & Cowan, 1984). Everyday activities such as driving and

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sports would be impossible without the ability to dynamically adjust one's actions to the changing demands of the environment. Complete suppression of a pending response is one of the best-defined varieties of inhibitory control. The stop-signal paradigm provides tools for examining this relatively simple type of control (i.e., its success, duration, and variability). The stop-signal paradigm consists of a reaction time (RT) task in which the occasional presentation of a stop signal indicates that the pending response should be cancelled. The probability of stopping can be manipulated by the timing of the stop signal vis-à-vis the reaction signal. This paradigm provides a way to test everyday requirements such as the abortion of actions (e.g., to countermand the impulse to start driving if the wrong traffic light turns green) or replacement of action (e.g., to replace the first utterance that comes to mind after hurting oneself by a more acceptable word) in an elementary form that is suited for the controlled laboratory environment (Lappin & Eriksen, 1966; Logan, 1994; Logan & Burkell, 1986; Logan & Cowan, 1984).

A quantitative interpretation of the performance on a stop-signal task is enabled by the horse-race model, which asserts that the stopping and reaction processes compete for the first finishing time (see Logan & Cowan, 1984, for an analytic approach). If stopping processes finish before the reaction processes the response is inhibited. Otherwise, the response escapes from inhibitory control. Given a small set of assumptions, it is possible to calculate the time required for stopping the response; that is, the stop-signal reaction time (SSRT). It appears that the horse-race model describes empirical data quite well (for a review Logan, 1994). Thus, the stop-signal paradigm has been successfully applied to examine inhibitory control under a variety of experimental conditions. For example, the SSRT of young adults is close to 200 ms when they try to interrupt continuous actions such as typing (Logan, 1982), over-learned responses, such as speaking (Ladefoged, Silverstein, & Papcun, 1973), or incompatible responses (Logan, 1981). The similarity of stop results has been interpreted as support for a model with one stopping mechanism that can be used to stop a variety of actions (see Logan, 1994).

An extensive review of the stopping literature is beyond the scope of the current study. Here it suffices to say that the stop-signal paradigm is used in human subjects but also in monkeys (Hanes, Patterson, & Schall, 1998). Stopping is examined in children (Band, van der Molen, Overtom, & Verbaten, 2000; Ridderinkhof, Band, & Logan, 1999; Schachar & Logan, 1990) and in older adults (Kramer, Humphrey, Larish, Logan, & Strayer, 1994; for a life-span study see Williams, Ponesse, Schachar, Logan, & Tannock, 1999). The stop-signal paradigm is used to examine deficiencies in inhibitory control in clinical groups, including ADHD children (Jennings, van der Molen, Pelham, Brock, & Hoza, 1997; Nigg, 1999; Oosterlaan & Sergeant, 1995; Schachar & Logan, 1990; Schachar, Mota, Logan, Tannock, & Klim, 2000; for reviews of ADHD studies with the stop-signal paradigm see Nigg, 2001, Oosterlaan, Logan, & Sergeant, 1998).

The stop-signal paradigm is used in pharmacological studies examining the effects of methylphenidate (Tannock, Schachar, Carr, Chajczyk, & Logan, 1989) or alcohol (Mulvihill, Skilling, & Vogel-Sprott, 1997). Finally, investigators used the stop-signal paradigm to assess inhibitory control as reflected by single cell brain activity (Hanes

et al., 1998) or brain potentials (De Jong, Coles, & Logan, 1995, 1990; van Boxtel, van der Molen, Jennings, & Brunia, 2001). Likewise, investigators examined the temporal dynamics of stopping motor responses at more peripheral levels by recording heart rate changes (Jennings, van der Molen, Brock, & Somsen, 1992) or muscle activation (McGarry & Franks, 1997). For a review of psychophysiological studies of inhibitory control using the stop-signal paradigm, the interested reader is referred to Band and van Boxtel (1999).

Logan (1994) presented a nontechnical introduction to the use of the stop-signal paradigm. Following a description of the basics of the stop-signal paradigm, he focused on a variety of important design issues, including stop-signal probability and the setting of stop-signal delays vis-à-vis the onset of the reaction signal. Most importantly, he provided procedures for obtaining various indices of stopping using the horse-race model, and a convenient test for assessing a major assumption underlying the horse race model (i.e., the assumption that go and stop processes are independent). The primary aim of the current study is to extend Logan's (1994) presentation and the guidelines that were derived from it by examining how the horse race model fares under sub-optimal conditions. This is an important issue when experimental design, for whatever reason, does not allow for great trial numbers (e.g., in clinical, developmental or pharmacological studies). A series of simulation studies were performed to examine how stopping indices are affected when the conditions for obtaining these indices are less than optimal. Thus the simulations addressed: (a) various procedures for setting stop-signal delay, (b) the distributions of stop and go latencies, (c) variability of the stop process, and (d) violations of independence assumption underlying the horse-race model. The outcomes of the simulations were used to derive a set of guidelines for the proper use of the stop-signal paradigm, including some recommendations for experimental design and economy.

## 2. The stop-signal paradigm

The stop-signal paradigm comes in many varieties (see Logan, 1994) but in all versions subjects perform on a primary reaction task requiring a speeded response and a secondary stop task requiring the inhibition of the speeded response. Usually, the primary (go) task is a visual choice RT task. On a proportion of trials, an auditory (stop) signal follows the onset of the visual reaction signal with a fixed or variable stimulus-onset asynchrony (SOA). The stop signal instructs the subject to refrain from responding to the go signal, if possible. The remaining trials are nonsignal trials, on which subjects should respond as they would on a regular RT task. A low proportion of stop signals (e.g., 25%) is usually chosen to avoid unwanted strategies such as delaying the response to the go signal in order to increase the probability of successful inhibits. For each SOA, a probability of responding is obtained given a stop signal (response rate, RR, a value between 0 and 1).

Fig. 1 illustrates how variations of SOA, the duration of go processes, and SSRT affect RR. The finishing time of stopping on trial  $k$  ( $SOA_k + SSRT_k$ ) is plotted relative to the distribution of go RTs. Note that RR (the part of the distribution to

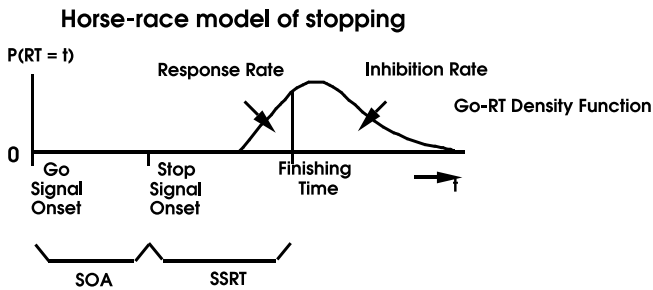


Fig. 1. An illustration of the horse-race model of response inhibition by means of the density function of the duration of go-processes. The stop-signal is presented after a SOA relative to the go-signal. The stop-processes finish after the SSRT relative to the stop-signal onset. When the SSRT is assumed to be constant, this finishing time intersects the density function of go-RT. Responses from the left part of the go-RT density function are too fast to be inhibited whereas responses from the right part are stopped correctly. Thus, the finishing time of the stop-process divides the go-RT density function into the RR and the inhibition rate. See the text for details.

the left of the finish line) increases when mean RT is shorter, or SOA and/or SSRT are longer. The stop-signal paradigm generates two important indices for evaluating inhibitory control and one criterion for evaluating the validity of the horse-race model. First, the horse-race model allows for estimating stop latency. Secondly, the slope of the function describing the relation between RR and SOA, coined the 'inhibition function', is assumed to provide an estimate of the variability of stopping. In addition, the stop-signal paradigm allows for a test of the independence assumption underlying the horse-race model. The two indices for evaluating inhibitory control and the validity criterion are detailed in the sections below.

### 2.1. Stop latency

Five methods have been proposed to estimate stop latency ( $SSRT_{in}$ ). These methods require different assumptions and different input information. The methods are summarized in Table 1 and the details of how to calculate SSRT according to each method are provided in Appendix A. The basic idea is that SSRT consists of the time between the start and finish of the stop processes (Logan, 1981). The SOA marks the start, and the finish time can be derived from the RR on signal trials and the RT distribution on nonsignal trials. Under the assumption that go processes are the same on signal and nonsignal trials, the nonsignal RT distribution can be treated as the underlying distribution of go-processes on signal trials. Fig. 1 illustrates that this distribution is dissected by the finishing time of stop processes. Go processes that finish before the stop processes lead to an overt response, so the upper limit of responses that escape inhibition equals the finishing time of stop processes. If we assume a constant  $SSRT_{in}$  (and consequently a constant finish time), this upper limit can be derived from the RR. If  $RR = x$ , at a given SOA, the stop processes must have finished at point  $x$  of the rank-ordered go RTs. For example, if stop signals at  $SOA = 220$  ms result in  $RR = 0.45$ , and the 45th percentile RT of nonsignal trials

Table 1

The acronyms of inhibition measures are identical to the ones used in the text

| Measures              | Explanations   |
|-----------------------|--|
| SSRT <sub>in</sub>    | Input SSRT or internal SSRT; the true SSRT   |
| SSRT <sub>obs</sub>   | Observed SSRT per SOA, not corrected for SOA effects on SSRT   |
| Summary SSRT          | Single SSRT measures independent of SOA that are used to correct for SOA effects on SSRT <sub>obs</sub> . These summary SSRT measures include: |
| SSRT <sub>mean</sub>  | Difference between the mean of the inhibition function and mean RT   |
| SSRT <sub>med</sub>   | Difference between the median of the inhibition function and the median RT   |
| SSRT <sub>centr</sub> | Observed SSRT for the SOA where $p(\text{Resp}) = 0.5$   |
| SSRT <sub>av</sub>    | Average of all the observed SSRTs that corresponded to $0.15 < p(\text{Resp}) < 0.85$  |
| SSRT <sub>p50</sub>   | The 50th percentile score of the SSRT distribution as estimated by the Colonius (1990) method  |
| RR                    | Response rate; the proportion of stop-signal trials on which responses are given (i.e., failed inhibits)                                       |
| RFT                   | Relative finishing time = $RT - SOA - SSRT_{av}$   |
| ZRFT                  | Z-transformed RFT = $(RT - SOA - SSRT_{av})/SD_{RT}$<br>The ZRFT score replaces SOA in a corrected inhibition function                         |
| Observed RT           | Mean of stop-signal response RT  |
| Predicted RT          | Mean of the fastest responses in the nonsignal RT distributions that should correspond to the observed RT                                      |
| Population SD         | Standard deviation of a score (RT or SSRT <sub>in</sub> ) in a virtual population  |

See Appendix A for details of how SSRT measures were calculated.

is 410 ms, then the observed SSRT (SSRT<sub>obs</sub>) is  $410 - 220 = 190$  ms for this particular SOA.

SSRT<sub>obs</sub> usually decreases with SOA (Logan, 1981; Logan & Cowan, 1984); so one SSRT<sub>obs</sub> is insufficient information to estimate SSRT<sub>in</sub> reliably. A method for obtaining a reliable estimate of a single SSRT was introduced by Slater-Hammel (1960). It involves selecting the central SOA, which yields  $RR = 0.5$ , and thus represents the situation where the race between response and inhibition processes ends in a tie. Logan, Schachar, and Tannock (1997) demonstrated that, at the central SOA, the SSRT<sub>obs</sub> (SSRT<sub>centr</sub>) is a reliable estimate of the overall speed of inhibition. The go-RT distribution that is used for estimating SSRT<sub>centr</sub> has the highest density around the 50th percentile, and this density enhances the resolution for calculating SSRT.

Another procedure to obtain a reliable estimate of SSRT is using summary scores (see Appendices). These scores constitute single SSRT measures across SOAs, and thus overcome the SOA bias of SSRT<sub>obs</sub> (cf. Logan & Cowan, 1984). One such summary measure is the average of SSRT<sub>obs</sub> or SSRT<sub>av</sub>. Other measures consist of the difference between the mean SOA and mean RT (SSRT<sub>mean</sub>), and the difference between the median SOA and median RT (SSRT<sub>med</sub>). Finally, Colonius (1990) showed how the entire distribution of SSRT<sub>in</sub> can be estimated from stop-signal observations. The median of this distribution can be seen as another summary SSRT measure (SSRT<sub>p50</sub>) (see also De Jong et al., 1990). In addition, this method can be used to estimate the variability in SSRT<sub>in</sub> by using the inter-quartile distance; that is, the distance between the 25th and 75th percentile of the estimated SSRT distribution (SSRT<sub>p75</sub> - SSRT<sub>p25</sub>).

## 2.2. Inhibition function

*Mean:* The inhibition function (see Fig. 2A, for an example) is affected by mean RT and mean  $SSRT_{in}$  (Logan & Cowan, 1984). For example, an increase of mean RT by 40 ms implies that the inhibition function will shift 40 ms to the right, all other things being equal. For a comparison between conditions, inhibition functions can be transformed into relative finishing times (RFT) by expressing SOA as a latency relative to the finish of response and inhibition processes ( $RFT = \text{mean RT} - \text{SOA} - SSRT_{av}$ ). Different RFT-transformed inhibition functions should have the same mean on the horizontal axis, but may differ in slope.

*Slope:* The slope of the inhibition function [calculated as  $d(RR)/d(\text{SOA})$ , and therefore expressed in units 1/s] contains information about the variability of stop and go processes. The slope can be corrected for the standard deviation (SD) of go RT by a Z-transformation of the RFT ( $ZRFT = [\text{mean RT} - \text{SOA} - SSRT_{av}] / SD_{RT}$ ). The ZRFT value is expressed in unit-less numbers distributed around zero. The ZRFT slope (see Fig. 2B, for an example) can be calculated by a linear regression through the data points where the function is close to linear, such as the range of RR between 0.15 and 0.85. This slope [calculated as  $d(RR)/d(ZRFT)$ , and therefore lacking a unit] is thought to reflect trial-by-trial differences in the stop processes (Logan, Cowan, & Davis, 1984; Oosterlaan & Sergeant, 1995; Schachar & Logan, 1990; Schachar, Tannock, & Logan, 1993; Schachar, Tannock, Marriott, & Logan, 1995; Tannock et al., 1989; Tannock, Schachar, & Logan, 1995).

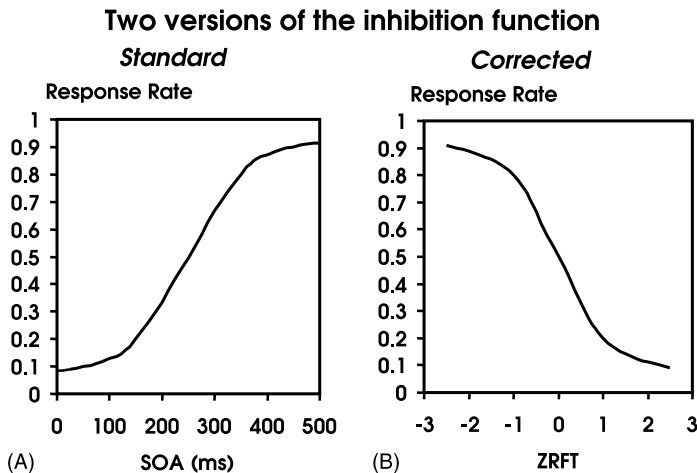


Fig. 2. Illustration of the standard (panel A) and corrected inhibition functions (panel B). Note that some inhibition functions show inhibition rate as the dependent variable, and that inhibition rate =  $(1 - RR)$ . Both inhibition rate and RR are values without units between zero and 1. The ZRFT correction is a transformation of the standard inhibition function, calculated with the values  $\text{mean RT} = 500$  ms,  $SSRT_{av}$  and  $SD_{RT} = 100$  ms. In the calculation of ZRFT, ms units are canceled out. See the text for details.

### 2.3. *Validity criterion*

The stop-signal paradigm yields RTs for trials without stop signals (nonsignal trials) and RTs for trials with stop signals (stop-signal respond trials). It is assumed that the part of the go RT distribution to the left of the finish line (see Fig. 1) corresponds to the RTs observed on signal-respond trials. It then follows that the mean of the left part of the go RT distribution (predicted RT) is equal to the mean signal-respond RT distribution (observed RT). The difference between observed RT vs. predicted RT is used to test the independence assumption of the horse-race model. In some studies small differences were found between observed RT vs. predicted RT suggesting little violation of stochastic independence between stop and go processes (cf. De Jong et al., 1990; Jennings et al., 1992; Logan & Cowan, 1984). Other studies, however, reported sizable differences challenging the independence assumption underlying the horse-race model (Van Boxtel et al., 2001; van den Wildenberg, van der Molen, & Logan, in press).

## 3. Simulations

Logan (1994) provided a cookbook for researchers using the stop-signal paradigm for evaluating inhibitory control. The cookbook's recipes were based on a review of stop-signal paradigm studies and the formal analysis of the horse-race model reported previously (Logan & Cowan, 1984). The recipes serve the experimenter well who presents the stop-signal paradigm to young adults who are willing and able to perform on many trials. They may work less well, however, for experimenters who are focusing on deficiencies in inhibitory control in atypical populations or under sub-optimal conditions. Under those circumstances there are many factors presenting a challenge to the horse-race model. Previously, De Jong et al. (1990) addressed two of those challenges (i.e., violation of the constant SSRT and independence assumptions underlying the horse-race model) by performing Monte Carlo simulations. The major goal of the current study was extending the work done by De Jong et al. (1990) by performing a series of simulation studies focusing on a variety of inhibition parameters and on different procedures for setting stop-signal delay. The simulation studies examined the dynamics of the horse-race model and the inhibition indices derived from it. Statistical and power issues were addressed also as within-subject variance and measurement error may affect the reliability of inhibition indices and the probability of detecting between-subjects differences in inhibitory ability. Before turning to the specific issues, the methods will be described that were used to run the simulations.<sup>1</sup>

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<sup>1</sup> The C source code of the simulations is available at [http://fsw.leidenuniv.nl/www/w3\\_func/band/Research/horserace/horserace.html](http://fsw.leidenuniv.nl/www/w3_func/band/Research/horserace/horserace.html).

### 3.1. Methods

Performance on the stop-signal task was simulated based on the horse-race model with randomization and regression procedures derived from Press, Flannery, Teukolsky, and Vetterling (1986). The basic principle for implementation of the horse-race model was that if  $(SOA_k + SSRT_k) < RT_k$ , the response is correctly withheld whereas a response is executed when  $(SOA_k + SSRT_k) \geq RT_k$ . Under some parameter values, the model did not conform to the horse-race model, as described by Logan and co-workers (Logan, 1994; Logan & Cowan, 1984), because violations of its assumptions were object of investigation. Furthermore, a failure of triggering inhibitory processes was implemented by letting the primary task win the race on a subset of signal trials, regardless of  $SOA_k$ ,  $SSRT_k$  and  $RT_k$ , as if stop processes were not executed at all.

$RT_k$  and  $SSRT_k$  were sampled at random from a normal (Gaussian) or an ex-Gaussian distribution. An ex-Gaussian distribution is a convolution of a Gaussian and an exponential distribution. Ex-Gaussian distributions are known to give a good fit of empirical choice-RT data (Ratcliff, 1979; Ratcliff & Murdock, 1976). Correlations between normally distributed RT and  $SSRT_{in}$  were created by combining one shared source of covariance with two unique sources of variance, for  $RT_k$  and  $SSRT_k$ . For example,  $SSRT_k = \text{mean } SSRT_{in} + \text{a unique deviation} + \text{a deviation shared with } RT_k$ , where each deviation is the product of the desired SD and a random value chosen from a Z-distribution. This procedure could not be used for establishing a correlation of SOA and  $SSRT_{in}$ , because SOA was not a random variable. As  $SOA_k$  was not randomly determined, the correlation between  $SSRT_{in}$  and SOA was established by basing  $SSRT_k$  in part on  $SOA_k - \text{mean SOA}$ .

In order to evaluate within-group heterogeneity, population deviations were introduced to modify single subject means of  $SSRT_{in}$  and of RT. For example, for a virtual subject the mean  $SSRT_{in}$  and RT could be 241 and 512 ms, while the population mean was 250 and 500 ms. Both population deviations were drawn from normal distributions.

The list of parameters of the race model is presented in Table 2 as well as the default values and the range of tested values. Default parameter values were based on the literature, and the range of parameter values was selected to cover individual and conditional differences. Simulations did not include different values of mean RT as increasing mean RT by  $x$  ms, given a set of SOAs, is similar to decreasing mean  $SSRT_{in}$  or the SOAs by the same amount. Thus evaluating the effect of changes in mean RT would therefore be redundant to the tests that are already reported here. The default and range of parameter values that were used in the simulations correspond well to the actual observations reported by Williams et al. (1999) in an extensive life-span study of stop-signal performance. Thus the default  $SD_{RT}$  of 100 ms and a range between 25 and 200 ms is consistent with the values 79–205 ms reported by Williams et al. In addition, the population SDs of RT sized 50 and 100 ms is consistent with the 63–122 ms they reported. The SSRT with a mean of 250 and population SD of 50 ms approximates the 198–274 ms and 63–76 ms that Williams et al.



Table 2

The parameters that were used in the simulations of the horse-race model

| Parameter          | Explanation                                       | Default | Minimum | Maximum |
|--------------------|---|---------|---------|---------|
| Mean RT (ms)       | Mean go process RT                                | 500     | Fixed   | Fixed   |
| $SD_{RT}$ (ms)     | Total SD RT                                       | 100     | 25      | 200     |
| $\tau_{RT}$ (ms)   | SD of the exponential contribution to RT          | 60      | 0       | 90      |
|                    | Population SD of mean RTs                         | 0       | 0       | 100     |
| $SSRT_{in}$ (ms)   | Internal stop-signal reaction time                | 250     | 210     | 300     |
| $SD_{SSRT}$ (ms)   | Total SD $SSRT_{in}$                              | 50      | 0       | 100     |
| $\tau_{SSRT}$ (ms) | SD of the exponential contribution to $SSRT_{in}$ | 20      | 0       | 40      |
|                    | Population SD of mean $SSRT_{in}$                 | 0       | 0       | 50      |
| $r_{(SOA,SSRT)}$   | Correlation SOA and $SSRT_{in}$                   | 0       | -0.8    | +0.65   |
| $r_{(RT,SSRT)}$    | Correlation RT and $SSRT_{in}$                    | 0       | -0.4    | +0.4    |
| $p(\text{Trig})$   | Proportion of trials with inhibition triggered    | 1.0     | 0.75    | 1.0     |

reported for  $SSRT_{med}$ .  $SD_{SSRT}$  cannot be derived from the literature thus the default setting was based on a typical  $SD_{RT}$  in simple tasks of 50 ms (cf. De Jong et al., 1990; Luce, 1986). Correlations of  $SSRT_{in}$  to SOA and to RT were simulated across a wide range because the true values cannot be derived from the literature. Likewise, the failure to inhibit was simulated by using a minimum of 0.75 as the triggering rate of inhibition.

There were three types of simulations using different numbers of trials and subjects. The first type of simulation was for determining the asymptotic outcome of the race. For every parameter value 500,000 nonsignal and 5 (SOA)  $\times$  250,000 signal trials were simulated, with the remaining parameters fixed at default values. Note that the proportion of signal trials does not affect the asymptotic outcome. The second type of simulations was done to calculate 95% confidence intervals =  $3.92 \times$  standard error (SE). To calculate SE values reliably as a function of the number of trials, 600 virtual subjects performed on each test with default parameter settings. These tests contained between 120 nonsignal + 5 (SOA)  $\times$  10 signal trials and 1200 nonsignal + 5  $\times$  100 signal trials; while the ratio between nonsignal and signal trials remained constant. A proportion of signal trials of 0.29, as used here, is representative for the proportions used in the literature (a range 0.25 and 0.50, with a median close to 0.25). It should be noted that a different ratio between the number of nonsignal trials and the number of signal trials per SOA marginally modifies the SE values. Furthermore, the use of less than five SOAs will affect some measures (e.g.,  $SSRT_{av}$ ) more than others (e.g.,  $SSRT_{centr}$ ). The third type of simulations was performed to estimate the number of subjects required for reaching sufficient statistical power ( $1 - \beta = 0.8$ ) for a *t*-test to detect effects of varying size (cf. Cohen, 1992). For these simulations, the default settings were used and the population SD parameters of RT and SSRT were both varied at two levels (i.e., 50 and 100 ms, and 25 and 50 ms, respectively). More detailed information is presented below, in the sections dealing with the pertinent issues addressed by the

simulations. The details of how confidence intervals and power are calculated can be found in the Appendices.

#### 4. Setting stop-signal delays

The selection of stop-signal delays, or the choice of how to manipulate SOA, is based on three considerations: the inhibition index under study, the available time for testing, and the anticipated strategy of the subjects. For a detailed discussion of the various procedures for setting stop-signal delays, the interested reader is referred to Logan (1994).

It will be shown that for assessing SSRT, it suffices to use one well-chosen SOA. For examining the slope of the inhibition function, however, it is necessary to manipulate SOA along a considerable range. It should be noted, however, that testing time is proportional to the numbers of SOA used to derive the inhibition function. To reduce time-on-task, investigators may increase stop-signal probability. The obvious danger is that, as the proportion of stop signals increases, subjects tend to delay their response to the primary signal (e.g. Logan, 1981; Logan & Burkell, 1986). Thus, Logan (1994) recommended using 25% stop-signal trials as a compromise between sufficient trial numbers and the subjects' slowing tendency. Furthermore, the occurrence of stop signals should not be predictable. If the stop signal is always presented at a fixed SOA, the subject may increase primary task RT in an attempt at increasing inhibition success (e.g., Lappin & Eriksen, 1966; Logan, 1981; Ollman, 1973).

One way to prevent unwanted strategies is to insert some early and late SOAs in addition to the target SOA. Alternatively, SOAs are adjusted based on performance on the immediately preceding trial block and experimenters continue to instruct the subject to give priority to the primary task. Finally, SOAs can be adjusted dynamically based on the mean RT of immediately preceding trials or RR. The simulation results of the former method, based on mean RT, were virtually similar to the findings obtained using a fixed SOA. Therefore, these results will not be reported here but it should be noted that in the real world, mean RT based SOAs and a fixed SOA may produce different findings due to subjects' strategies. The latter method, based on RR, will be referred to as RR tracking. Basically, SOA is lengthened following successful inhibits and shortened following failed inhibits. Different adjustment rules will yield different RRs (see Levitt, 1970). For every adjustment rule, the actual SOA values can be averaged for calculating inhibition scores.

##### 4.1. Simulations

The five SOAs that were used in the simulations with the fixed-SOA procedure are listed in Table 3. The SOAs also served as the starting values for the RR-tracking procedure. The SOAs were adjusted after every presentation with different step sizes

Table 3  
SOA settings, adjustment rules and asymptotic RRs for default parameter levels

| SOA level | Starting value<br>(ms) | Adjustment of SOA |                | Response rate |
|-----------|------------------------|-------------------|----------------|---------------|
|           |                        | Signal-respond    | Signal-inhibit |               |
| A         | 150                    | –12               | +3             | 0.20          |
| B         | 200                    | –10               | +5             | 0.33          |
| C         | 250                    | –7                | +7             | 0.50          |
| D         | 300                    | –5                | +10            | 0.67          |
| E         | 350                    | –3                | +12            | 0.80          |

Note: These SOA values were used consistently for the fixed-SOA procedure, and served as the starting values for SOAs in the RR-tracking procedure. In the RR-tracking procedure, SOAs were adjusted by the indicated amounts (in ms) following each signal-respond or signal-inhibit trial.

to obtain a range of RRs.<sup>2</sup> Mean  $SSRT_{in}$  was varied to test the effect of SOA selection. SOAs were optimal for a  $SSRT_{in}$  of 250 ms.

In Fig. 3 it can be seen that the fixed-SOA procedure yielded data from dissimilar sections of the inhibition function, with some measurements close to  $RR = 0$  or 1. In contrast, the RR-tracking procedure resulted in parallel sections of the inhibition functions, for different levels of mean  $SSRT_{in}$ . The inhibition functions of the RR-tracking procedure were only moved to left or right and the RR values were equal. This means that differences in  $SSRT_{in}$  can be reliably detected without the confounding influence of SOA on  $SSRT_{obs}$ .

#### 4.1.1. Inhibition function

The middle section of the inhibition function (e.g.,  $0.15 < RR < 0.85$ ) can be approximated by a straight line. Outside this range, the slope of the inhibition function is shallower due to ceiling and floor effects. The fact that the fixed-SOA procedure yields measurements from dissimilar sections of the inhibition function carries the risk that ceiling and floor effects affected the slope more for some levels of  $SSRT_{in}$  than for others. This problem does not apply to the RR-tracking procedure, because it yields measurements only at the specified range of RR.<sup>3</sup>

#### 4.1.2. Stop-signal reaction time

It can be seen in Fig. 3B that  $SSRT_{obs}$  decreased with SOA, in accordance with empirical findings (e.g., Logan & Burkell, 1986). The most accurate estimate of  $SSRT_{in}$  was found at the central SOA. This SOA is selected automatically by the RR-tracking

<sup>2</sup> RR tracking typically consists of adjusting SOA with a constant step size but different frequencies for correct and failed inhibits. For example, if SOA increases following every correct inhibit and decreases following every second failed inhibit, the asymptotic RR is 71% (Levitt, 1970; Osman, Kornblum, & Meyer, 1986). The current simulations used the opposite procedure; i.e., a variable step size and a change after each signal trial. This was done to obtain evenly distributed RR values within the most interesting range of the inhibition function. There is no reason to believe that constant step size vs. a variable step size will yield different outcomes.

<sup>3</sup> Tannock et al. (1989) pointed to response omissions on nonsignal trials and proposed to correct  $p(\text{inhibit})$  using the formula: Corrected  $p(\text{Inhibit}) = [\text{Observed } p(\text{Inhibit}) - p(\text{Omission})] / [1 - p(\text{Omission})]$ . This correction will alter the slope of the inhibition function.

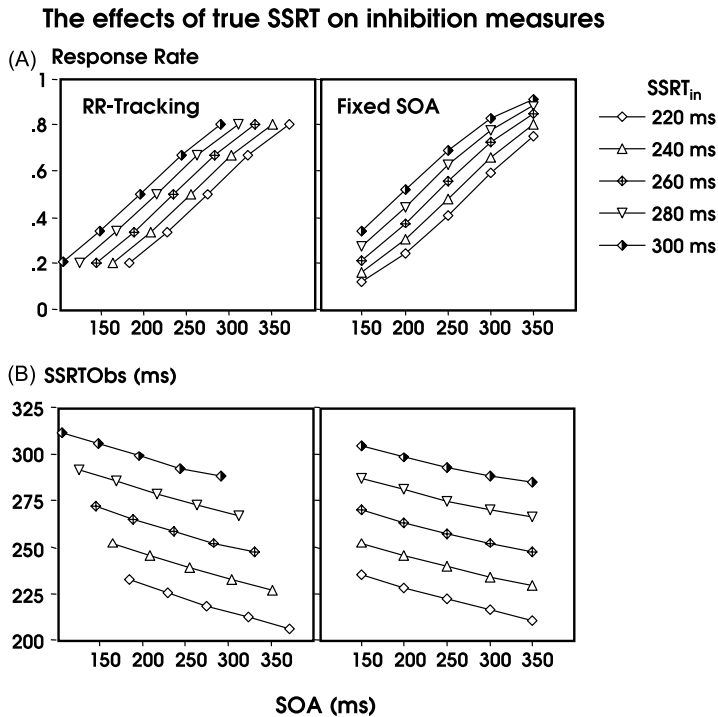


Fig. 3. The effect on inhibition measures of mean stop-signal RT, SOA, and the SOA-procedure, expressed in the inhibition function (panel A) and the  $SSRT_{obs}$  function (panel B). While the RR-tracking procedure ensures data points at the same levels of RR, the fixed-SOA procedure may yield RRs near 0 or 1, reducing the reliability of SSRT estimates.

algorithm but needs to be estimated when the fixed-SOA procedure is used. Table 4 shows summary SSRT measures.  $SSRT_{av}$  was accurate within 5 ms for all fixed-SOA conditions, and accurate within 2 ms for all RR-tracking conditions. The  $SSRT_{mean}$  was not an accurate estimate of  $SSRT_{in}$  when the fixed-SOA procedure was used.  $SSRT_{med}$  was reliable for both SOA procedures, (note that the 50th percentile  $SSRT_{in}$  was 2 ms below the mean due to the positively skewed  $SSRT_{in}$  distribution). Surprisingly,  $SSRT_{p50}$  largely underestimated  $SSRT_{in}$  for both SOA procedures.

#### 4.1.3. Observed RT – predicted RT

The observed RT of signal responses was longer than predicted for all conditions, in particular for early SOAs. For  $SOA = 250$  ms, the difference amounted to 4–11 ms. For early SOAs, the difference could be as high as 20 ms. For the fixed-SOA procedure, the difference increased if SSRT was faster than anticipated. Given that even the idealized horse-race model may yield a mismatch of observed RT and predicted RT, it seems that observed RT – predicted RT does not provide a valid criterion for testing the independence assumption of the horse-race model. Below it will be demonstrated that the mismatch between observed RT and predicted RT is caused primarily by SSRT variability.

Table 4  
Summary stop-signal RT measures as a function of input SSRT and SOA procedure

| Mean<br>SSRT <sub>in</sub> | SSRT <sub>av</sub> |     | SSRT <sub>mean</sub> |     | SSRT <sub>med</sub> |     | SSRT <sub>p50</sub> |     |
|----------------------------|--------------------|-----|----------------------|-----|---------------------|-----|---------------------|-----|
|                            | RR-T               | Fix | RR-T                 | Fix | RR-T                | Fix | RR-T                | Fix |
| 220                        | 219                | 220 | 221                  | 243 | 217                 | 218 | 207                 | 200 |
| 240                        | 239                | 240 | 240                  | 246 | 237                 | 238 | 225                 | 217 |
| 260                        | 259                | 258 | 260                  | 249 | 257                 | 257 | 248                 | 240 |
| 280                        | 279                | 278 | 280                  | 252 | 277                 | 278 | 269                 | 257 |
| 300                        | 299                | 296 | 300                  | 255 | 297                 | 297 | 286                 | 277 |

Note: RR-T: response-rate tracking procedure; Fix: fixed-SOA procedure; SSRT: stop-signal reaction time in ms (see Appendix A for details).

#### 4.1.4. Reliability

The selection of SOA depends in part on the amount of time that an experiment is allowed to last. Therefore, an important question is how many trials are required for a reliable assessment of inhibition. Thus, the number of trials required for acceptable confidence intervals were determined. It is shown in Fig. 4A, that for all single-SOA measurements of RR, a confidence interval of RR amounting 0.02–0.05 was obtained using 50–100 trials per SOA for the fixed-SOA procedure, and 30–50 trials per SOA for the RR-tracking procedure. Clearly, using the RR-tracking procedure is more efficient compared to fixed SOA settings.

The confidence interval for SSRT<sub>obs</sub> is depicted in Fig. 4B, as a function of SOA and the number of stop trials. Around the central SOA, the confidence interval of SSRT<sub>obs</sub> dropped to <20 ms with 30 trials per SOA and to <10 ms with 50 trials per SOA. However, 40–70 trials per SOA were required to attain the same reliability levels for noncentral SOAs. Thus, the SSRT<sub>obs</sub> at the central SOA was not only the most accurate but also the most reliable estimate of SSRT<sub>in</sub>. The 95% confidence interval of summary SSRTs was calculated as a function of the number of signal trials and this relationship was reduced to the following regression equations (all  $R^2$ s > 0.99). This was done for the results of RR-tracking and the fixed-SOA procedures. The difference between these two algorithms was minimal.

$${}^{10}\log(95\% \text{ confidence interval SSRT}_{av}) = 2.41 - (0.99 \times {}^{10}\log n)$$

$${}^{10}\log(95\% \text{ confidence interval SSRT}_{med}) = 2.84 - (1.19 \times {}^{10}\log n)$$

For SSRT<sub>mean</sub>, only the RR-tracking data were regressed and yielded:

$${}^{10}\log(95\% \text{ confidence interval SSRT}_{mean}) = 2.74 - (1.14 \times {}^{10}\log n)$$

It should be noted that the reliability is likely to decrease if less than five SOAs are used. These equations imply that for a confidence interval of <5 or <10 ms one needs 60 or 30 trials per SOA, respectively. With only the central SOA, the reliability changed to

$${}^{10}\log(95\% \text{ confidence interval SSRT}_{centr}) = 2.71 - (1.00 \times {}^{10}\log n)$$

**Effects of number of signal trials (n) on the 95% confidence interval of inhibition measures**

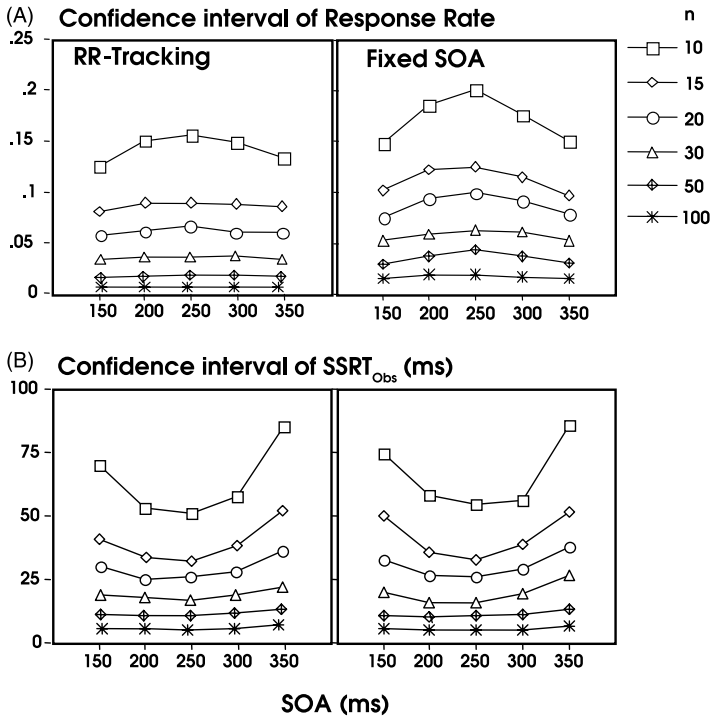


Fig. 4. The size of the 95% confidence interval of inhibition scores as a function of the number of stop-trials per SOA, SOA, and the SOA-procedure. A smaller confidence interval reflects a more reliable measurement. Confidence intervals of RR are fractions from the range between 0 and 1, which have no unit. Confidence intervals of SSRT<sub>obs</sub> are fractions from the range of SSRT<sub>obs</sub> in ms. Panel A shows that the RR-tracking procedure requires less signal trials than the fixed-SOA procedure for obtaining reliable RR estimates. Panel B shows that SSRT<sub>obs</sub> is most reliable for the central SOA.

This means that, using a single SOA, SSRT<sub>centr</sub> reached the same criterion using 100 or 50 signal trials, respectively. In contrast, SSRT<sub>p50</sub> did not reach a confidence interval <27 ms for the first 100 stop-signal trials per SOA.

Finally, the confidence interval of observed RT – predicted RT at the central SOA decreased from 50 ms at  $n = 10$  to 5 ms at  $n = 100$ .

**4.1.5. Power**

The number of subjects required to detect SSRT<sub>obs</sub> differences in a between-subjects design is presented in Table 5. The number is based on 300 nonsignal trials and 100 stop-signal trials for the closest-to-central SOA, as a function of population SDs of RT and SSRT. A large difference in SSRT (60 ms difference in SSRT<sub>centr</sub>) can be

Table 5

Required sample size per group for a power of 0.8, as a function of heterogeneity for detecting differences in observed SSRT, given 100 signal trials with the closest to central SOA ( $PSD_{RT} = 50, 100$ ;  $PSD_{SSRT} = 25, 50$ )

| Effect size (ms) | $PSD_{RT}$<br>$PSD_{SSRT}$ | RR-tracking procedure |     |     |     | Fixed SOA procedure |     |     |     |
|------------------|----------------------------|-----------------------|-----|-----|-----|---------------------|-----|-----|-----|
|                  |                            | 50                    |     | 100 |     | 50                  |     | 100 |     |
|                  |                            | 25                    | 50  | 25  | 50  | 25                  | 50  | 25  | 50  |
| 10               |                            | 190                   | 613 | 213 | 635 | 179                 | 490 | 233 | 592 |
| 20               |                            | 48                    | 153 | 53  | 159 | 45                  | 123 | 58  | 148 |
| 40               |                            | 12                    | 38  | 13  | 40  | 11                  | 31  | 15  | 37  |
| 60               |                            | 5                     | 17  | 6   | 18  | 5                   | 14  | 6   | 16  |

Note: PSD: population standard deviation (ms); SSRT: stop-signal reaction time in ms.

shown with only 18 subjects or less. In contrast, a small difference (20 ms) requires at least 50 subjects. In Table 6, it can be seen that, using more than one SOA, approximately 40 subjects are required to obtain a difference of 20 ms, even for small population SDs in RT and SSRT. Power was hardly affected by the number of stop-signal trials per SOA (e.g. 70 vs. 40 trials). It appears that  $SSRT_{mean}$  is more sensitive to RT-variability whereas  $SSRT_{av}$  and  $SSRT_{med}$  are more affected by  $SSRT_{in}$ -variability.

#### 4.1.6. Interim conclusions

RR-tracking procedure has clear advantages over the fixed-SOA procedure (cf. Logan et al., 1997). Because it equates RR, conditions are easier to compare and less stop-signal trials are needed to obtain robust findings. Using fixed SOAs, some SOAs yield RR outliers. This will reduce the slope of the inhibition function and thus lead to incorrect conclusions about the variability of SSRT. Moreover, SOAs should be distributed symmetrically around the central SOA and this is easier to accomplish using the RR-tracking procedure.

The simulations showed considerable differences between SSRT measures.  $SSRT_{obs}$  can be used as a first approximation of  $SSRT_{Av}$ , but it is not accurate as long as RR does not equal 0.5. While  $SSRT_{centr}$ ,  $SSRT_{av}$  and  $SSRT_{med}$  are accurate estimates of  $SSRT_{in}$ ,  $SSRT_{mean}$  fails when the fixed-SOA procedure is used. Finally,  $SSRT_{p50}$  is less accurate than other summary SSRT measures and it requires much more trials.

The simulations indicate that the optimal design, in terms of trial numbers and group sizes, depends on the inhibition measure of interest. If the interest is in the latency of stopping, indexed by SSRT, and not in its variability, the experimenter is advised to employ the RR-tracking procedure for obtaining  $SSRT_{centr}$  based on 300 nonsignal trials and 100 signal trials (approximately 20 min of testing time). Using fixed SOAs, a similar accuracy of  $SSRT_{av}$  can be obtained using 900 nonsignal trials and  $5 \times 60$  signal trials (approximately 60 min of testing time).

Finally, it should be noted that the range of  $SSRT_{in}$  values used here was not meant to include the values observed in every possible population. For example, a

Table 6

Required sample size per group for detecting differences (ms) in summary SSRTs with a power of 0.8, as a function of heterogeneity, SOA procedure, and given 40 or 70 signal trials per SOA ( $PSD_{RT} = 50, 100$ ;  $PSD_{SSRT} = 25, 50$ )

| Effect                     | $PSD_{RT}$<br>$PSD_{SSRT}$ | RR tracking (70) |     |     |     | Fixed SOA (70) |     |     |     | RR tracking (40) |     |     |     | Fixed SOA (40) |     |     |     |
|----------------------------|----------------------------|------------------|-----|-----|-----|----------------|-----|-----|-----|------------------|-----|-----|-----|----------------|-----|-----|-----|
|                            |                            | 50               |     | 100 |     | 50             |     | 100 |     | 50               |     | 100 |     | 50             |     | 100 |     |
|                            |                            | 25               | 50  | 25  | 50  | 25             | 50  | 25  | 50  | 25               | 50  | 25  | 50  | 25             | 50  | 25  | 50  |
| <i>SSRT<sub>av</sub></i>   |                            |                  |     |     |     |                |     |     |     |                  |     |     |     |                |     |     |     |
| 10                         |                            | 162              | 608 | 153 | 565 | 151            | 558 | 157 | 494 | 172              | 599 | 190 | 613 | 148            | 512 | 191 | 567 |
| 20                         |                            | 41               | 152 | 38  | 141 | 38             | 139 | 39  | 124 | 43               | 150 | 47  | 153 | 37             | 128 | 48  | 142 |
| 40                         |                            | 10               | 38  | 10  | 35  | 9              | 35  | 10  | 31  | 11               | 37  | 12  | 38  | 9              | 32  | 12  | 35  |
| 60                         |                            | 5                | 17  | 4   | 16  | 4              | 15  | 4   | 14  | 5                | 17  | 5   | 17  | 4              | 14  | 5   | 16  |
| <i>SSRT<sub>mean</sub></i> |                            |                  |     |     |     |                |     |     |     |                  |     |     |     |                |     |     |     |
| 10                         |                            | 156              | 394 | 317 | 556 | *              | *   | *   | *   | 190              | 321 | 594 | 737 | *              | *   | *   | *   |
| 20                         |                            | 39               | 98  | 79  | 139 | *              | *   | *   | *   | 47               | 80  | 148 | 184 | *              | *   | *   | *   |
| 40                         |                            | 10               | 25  | 20  | 35  | *              | *   | *   | *   | 12               | 20  | 37  | 46  | *              | *   | *   | *   |
| 60                         |                            | 4                | 11  | 9   | 15  | *              | *   | *   | *   | 5                | 9   | 16  | 20  | *              | *   | *   | *   |
| <i>SSRT<sub>med</sub></i>  |                            |                  |     |     |     |                |     |     |     |                  |     |     |     |                |     |     |     |
| 10                         |                            | 167              | 613 | 161 | 589 | 215            | 669 | 329 | 648 | 187              | 653 | 227 | 695 | 226            | 684 | 501 | 708 |
| 20                         |                            | 42               | 153 | 40  | 147 | 54             | 167 | 82  | 162 | 47               | 163 | 57  | 174 | 56             | 171 | 125 | 177 |
| 40                         |                            | 10               | 38  | 10  | 37  | 13             | 42  | 21  | 41  | 12               | 41  | 14  | 43  | 14             | 43  | 31  | 44  |
| 60                         |                            | 5                | 17  | 4   | 16  | 6              | 19  | 9   | 18  | 5                | 18  | 6   | 19  | 6              | 19  | 14  | 20  |

Note: PSD: population standard deviation (ms); SSRT: stop-signal reaction time in ms (see Appendix A for details); (\*) the  $SSRT_{mean}$  is not reliable for the fixed-SOA procedure. The number of stop trials per SOA is given in parentheses.



meta-analysis of Oosterlaan and Sergeant (1995) calculated that a weighted average SSRT of children with ADHD was 349 ms. The methods evaluated in Section 4 will work the same way if mean  $SSRT_{in}$  were 350 and mean RT was 600 ms. The threat to the reliability of summary SSRT measures lies not in the value of  $SSRT_{in}$ , but in how well the SOAs are distributed around the central SOA.

## 5. Variability in primary task reaction time

The horse-race model does not make assumptions about the distribution of primary RT. However, differences in RT variability between conditions may obscure measures of inhibitory control. For example, the slope of the inhibition function is sensitive to variability in go as well as stop processes (e.g., Schachar & Logan, 1990). The ZRFT correction of the inhibition function for individual task parameters is used to reveal differences in stop variability between groups of subjects (Logan, 1994; Logan & Cowan, 1984; Logan et al., 1984; Schachar & Logan, 1990) or between conditions. For example, Tannock et al. (1995) found that the slope of the ZRFT transformed inhibition functions varied between 0.28 and 0.33, depending on the dosage of methylphenidate given to ADHD children. They concluded that, due to the ZRFT correction, this difference cannot be attributed to differences in mean RT,  $SD_{RT}$  and  $SSRT_{av}$ . Instead, the differences were attributed to either  $SD_{SSRT}$  or the reliability of triggering the stop processes.

### 5.1. Simulations

The effect of variability in the go processes was simulated with  $SD_{RT} = 25, 50, 100, 150$  and 200 ms, with a fixed proportion of exponential variance = 0.36.

#### 5.1.1. Inhibition function

Table 7 shows that the slope of the inhibition function is affected considerably by  $SD_{RT}$ . Logan and Cowan (1984) argued that ZRFT transformation should remove slope differences caused by  $SD_{RT}$ . However, the simulations showed that it did not.

Table 7

The inhibition function and summary stop-signal RT (ms) as a function of variability in primary task RT (ms) and SOA procedure

| $SD_{RT}$ | ZRFT-slope |       | SOA-slope ( $s^{-1}$ ) |     | $SSRT_{av}$ |     | $SSRT_{mean}$ | $SSRT_{med}$ |     |
|-----------|------------|-------|------------------------|-----|-------------|-----|---------------|--------------|-----|
|           | RR-T       | Fix   | RR-T                   | Fix | RR-T        | Fix | RR-T          | RR-T         | Fix |
| 25        | -0.16      | -0.16 | 6.3                    | 6.3 | 249         | 249 | 248           | 248          | 248 |
| 50        | -0.25      | -0.26 | 5.0                    | 5.3 | 249         | 248 | 249           | 248          | 248 |
| 100       | -0.33      | -0.33 | 3.3                    | 3.3 | 249         | 249 | 250           | 247          | 248 |
| 150       | -0.35      | -0.37 | 2.3                    | 2.5 | 249         | 249 | 252           | 247          | 248 |
| 200       | -0.36      | -0.39 | 1.8                    | 1.9 | 247         | 248 | 254           | 245          | 244 |

Note: RR-T: response-rate tracking procedure; Fix: fixed-SOA procedure; ZRFT-slope: slope of the normalized inhibition function. This measure has no metrical unit.

5.1.2. Stop-signal reaction time

$SD_{RT}$  had a substantial effect on  $SSRT_{obs}$ , as can be seen in Fig. 5. Although  $SSRT_{obs}$  was quite consistent across SOAs when  $SD_{RT} = 100$  ms, this index decreased rapidly with SOA when  $SD_{RT} = 25$  ms. Most importantly, however,  $SSRT_{av}$  and  $SSRT_{med}$  cancel out the  $SD_{RT}$  effect on  $SSRT_{obs}$ , as can be seen in Table 7.

5.1.3. Observed RT – predicted RT

The simulations indicated that an increase of  $SD_{RT}$  reduced the difference between observed RT and predicted RT. This finding provides another challenge to the use of this criterion for testing the independence assumption of the horse-race model.

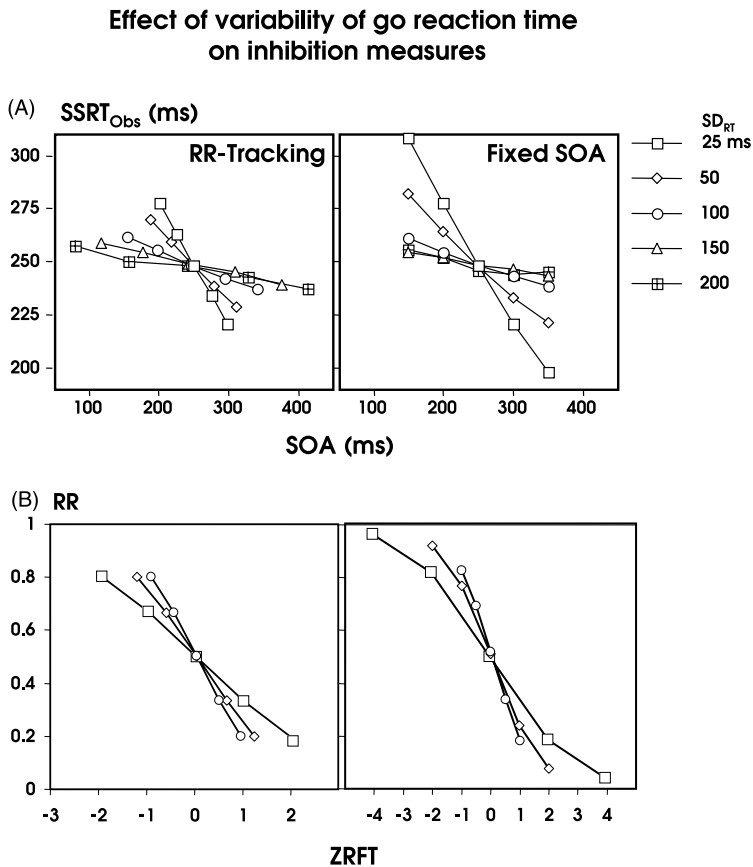


Fig. 5. The effect on observed SSRT and the ZRFT-transformed inhibition function, of variance in RT, SOA, and the SOA-procedure. Panel A shows that high variance of go-speed has limited effect on the estimation of stop-speed, but low variance reduces the reliability of SSRT estimates obtained from noncentral SOAs. Panel B shows that the slope of the inhibition function is not equalized for different levels of  $SD_{RT}$  by the ZRFT-transformation.

#### 5.1.4. Skewness of primary task reaction time

It was tested whether positive skewness of the go-RT distribution influenced inhibition measures. The effects were simulated with a fixed  $SD_{RT}$  of 100 ms, and exponential proportions of variance 0; 0.01; 0.04; 0.16; 0.36; or 0.81. Skewness had negligible effects when  $\tau_{RT}^2/SD_{RT}^2 \leq 0.36$ , but there were some effects when  $\tau_{RT}^2/SD_{RT}^2 = 0.81$ . For the fixed-SOA procedure, skewness had marginal effects on the slope of the inhibition function and  $SSRT_{obs}$ . Additionally, summary SSRTs were somewhat less accurate. When RR-tracking is used, the effects of skewness were even less. These results suggest that there are no alarming consequences of skewness for the observed measures.

#### 5.1.5. Interim conclusions

The simulations made at least two important points. First, variability in primary task RT influences the slope of the ZFRT corrected inhibition function. This observation provides a challenge to using ZFRT functions to examine between group or condition differences in stopping variability, as differences in RT variability between groups or conditions are rule rather than exception. Second, RT variability affected the difference between observed RT and predicted RT. This finding is adding to the growing skepticism about using this criterion for testing the independence assumption.

## 6. Variability in stop-signal reaction time

The horse-race model assumes that  $SSRT_{in}$  is constant but this assumption is not likely to be true. A variable SSRT affects  $SSRT_{obs}$ , but, on the other hand, it is also a meaningful characteristic of the stop mechanism. In stopping studies, differences in  $SD_{SSRT}$  are typically evaluated by examining the slope of the ZRFT function (e.g., Schachar & Logan, 1990). To date,  $SD_{SSRT}$  is quantified only in theory (Colonius, 1990) or, empirically, for only three subjects (Logan & Cowan, 1984).

### 6.1. Simulations

In these simulations,  $SD_{SSRT}$  was 0, 10, 20, 50, 70 or 100 ms, and the proportion of exponential variance  $\tau_{SSRT}^2/SD_{SSRT}^2$  was fixed at 0.16.

#### 6.1.1. Inhibition function

An increase in  $SD_{SSRT}$  reduced the slope of the inhibition and ZRFT transformation did not correct for this effect, as can be seen from Table 8. It is important to note, however, that  $SD_{RT}$  affects the ZRFT slope to a similar extent (see Section 5.1.1). Thus, it is not easy to determine whether groups or conditions differ with respect to  $SD_{SSRT}$  or by other factors.

#### 6.1.2. Stop-signal reaction time

In Fig. 6A, it is illustrated that the decrease of  $SSRT_{obs}$  with SOA was steeper as  $SD_{SSRT}$  increased. When  $SD_{SSRT} = 100$  ms,  $SSRT_{obs}$  overestimated  $SSRT_{in}$  by more

Table 8

The inhibition function and summary stop-signal RT (ms) as a function of variability in stop-signal RT and SOA procedure

| SD <sub>SSRT</sub> | ZRFT-slope |       | SOA-slope (s <sup>-1</sup> ) |     | SSRT <sub>av</sub> |     | SSRT <sub>mean</sub> | SSRT <sub>med</sub> |     | Est. SD <sub>SSRT</sub> |     |
|--------------------|------------|-------|------------------------------|-----|--------------------|-----|----------------------|---------------------|-----|-------------------------|-----|
|                    | RR-T       | Fix   | RR-T                         | Fix | RR-T               | Fix | RR-T                 | RR-T                | Fix | RR-T                    | Fix |
| 0                  | -0.37      | -0.38 | 3.7                          | 3.8 | 250                | 250 | 252                  | 249                 | 249 | 41                      | 36  |
| 10                 | -0.36      | -0.36 | 3.6                          | 3.6 | 250                | 250 | 252                  | 248                 | 248 | 46                      | 48  |
| 20                 | -0.33      | -0.33 | 3.3                          | 3.3 | 249                | 249 | 250                  | 248                 | 247 | 69                      | 69  |
| 50                 | -0.30      | -0.30 | 3.0                          | 3.0 | 248                | 248 | 249                  | 247                 | 247 | 89                      | 85  |
| 70                 | -0.26      | -0.27 | 2.6                          | 2.7 | 249                | 247 | 249                  | 247                 | 247 | 117                     | 109 |
| 100                | -0.21      | -0.22 | 2.1                          | 2.2 | 258                | 251 | 255                  | 256                 | 255 | 160                     | 147 |

Note: RR-T: response-rate tracking procedure; Fix: fixed-SOA procedure; ZRFT-slope: slope of the normalized inhibition function, this measure has no metrical unit; SSRT: stop-signal reaction time in ms (see Appendix A for details); Est. SD<sub>SSRT</sub>: the estimated SD of SSRT (ms) based on Eq. (A.4).

than 35 ms. Importantly, however, summary SSRT measures did not overestimate SSRT<sub>in</sub> more than by 8 ms, as is shown in Table 8.

### 6.1.3. Observed RT – predicted RT

Variability in SSRT<sub>in</sub> contributed considerably to the difference between observed RT and predicted RT (see Fig. 6B). A SD<sub>SSRT</sub> close to zero led to a near-perfect match of signal responses and the predictions from the race model. For greater values of SD<sub>SSRT</sub>, observed RT – predicted RT increased. Even when go and stop processes were statistically independent, greater values of SD<sub>SSRT</sub> were associated with larger mismatches between observed RT and predicted RT.

### 6.1.4. Skewness of stop-signal reaction time

The influence of skewness of the SSRT<sub>in</sub> distribution was investigated by fixing SD<sub>SSRT</sub> at 50 ms and then varying the exponential contribution to the ex-Gaussian distribution ( $\tau_{SSRT}^2/SD_{SSRT}^2$ ) between 0 and 0.64. The difference between a normal distribution and the most skewed distributions tested was only marginal compared to the effect of SD<sub>SSRT</sub>.

### 6.1.5. Reliability and power

The confidence intervals of the slopes of the ZRFT transformed and the regular inhibition function were regressed onto the number of signal trials per SOA ( $R^2$ s > 0.99, mixed across SOA procedures), yielding:

$$^{10}\log(95\% \text{ confidence interval ZRFT slope}) = 0.232 - (1.064 \times ^{10}\log n)$$

$$^{10}\log(95\% \text{ confidence interval SOA slope}) = 1.27 - (1.09 \times ^{10}\log n)$$

This result implies that a small or large effect size on the ZRFT slope (0.02 and 0.05) requires 65 and 27 trials, respectively, for each of the five SOAs. Demonstrating such differences in an experimental setting, however, would require an unusually large number of subjects. In Table 9, it can be seen that even a large effect would require approximately 25 subjects per condition performing on 70 stop-signal trials

per SOA whereas 45 subjects are needed when using 40 stop-trials. A small effect ( $<0.03$ ) can be shown using 70–140 subjects, depending on the number of stop-signal

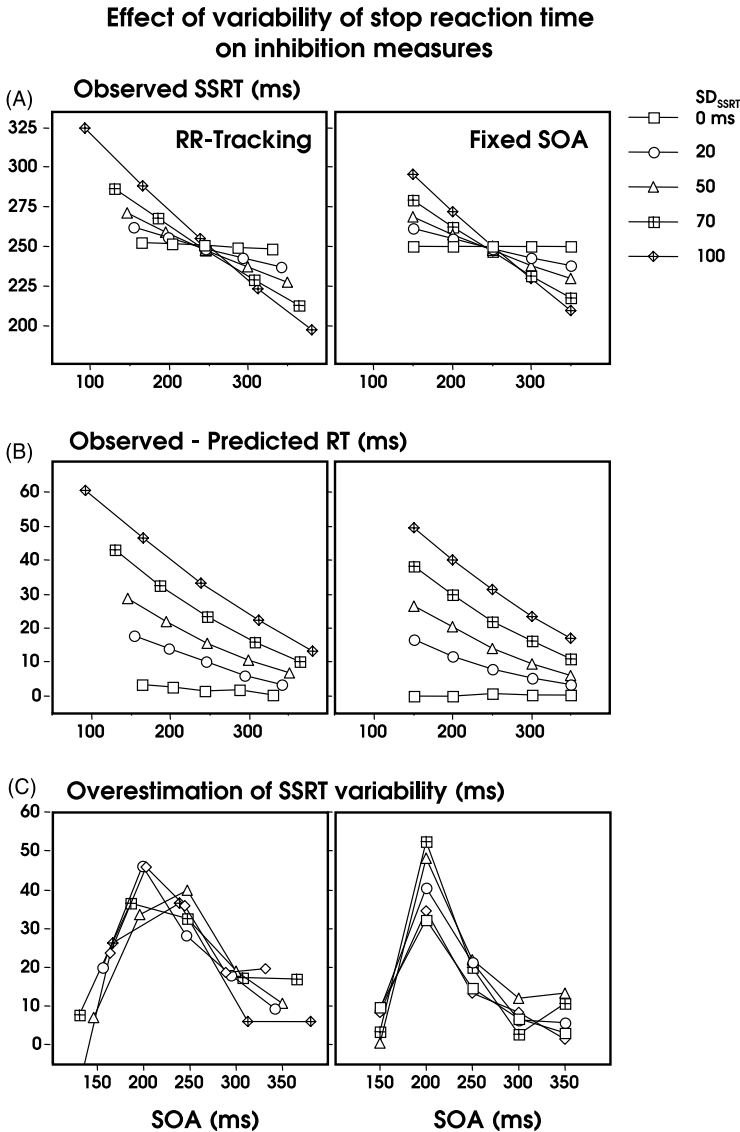


Fig. 6. The effect on inhibition measures of variance in stop-speed, SOA, and the SOA-procedure. Panel A shows that  $SSRT_{obs}$  decreases more with SOA as  $SD_{SSRT}$  increases. Panel B shows that observed–predicted signal RT is strongly influenced by  $SD_{SSRT}$  (even though the independence assumption holds). Panel C shows that the estimated interquartile distance ( $SSRT_{p75} - SSRT_{p25}$ ; see Appendix A) overestimates the true interquartile distance.

Table 9

Required sample size per group for detecting differences in the slope of the inhibition function with a power of 0.8, as a function of heterogeneity, SOA procedure, and given 40 or 70 signal trials per SOA ( $PSD_{RT} = 50, 100$ ;  $PSD_{SSRT} = 25, 50$ )

| Effect                                 | $PSD_{RT}$ | RR tracking (70) |    |     |    | Fixed SOA (70) |     |     |     | RR tracking (40) |     |     |     | Fixed SOA (40) |     |     |     |
|--|------------|------------------|----|-----|----|----------------|-----|-----|-----|------------------|-----|-----|-----|----------------|-----|-----|-----|
|  |            | 50               |    | 100 |    | 50             |     | 100 |     | 50               |     | 100 |     | 50             |     | 100 |     |
|  |            | 25               | 50 | 25  | 50 | 25             | 50  | 25  | 50  | 25               | 50  | 25  | 50  | 25             | 50  | 25  | 50  |
| <i>ZRFT-slope</i>                      |            |                  |    |     |    |                |     |     |     |                  |     |     |     |                |     |     |     |
| 0.03                                   |            | 55               | 63 | 69  | 76 | 109            | 161 | 189 | 205 | 99               | 126 | 164 | 136 | 240            | 221 | 335 | 312 |
| 0.05                                   |            | 20               | 23 | 25  | 27 | 39             | 58  | 68  | 74  | 36               | 45  | 59  | 49  | 86             | 79  | 121 | 112 |
| 0.08                                   |            | 8                | 9  | 10  | 11 | 15             | 23  | 27  | 29  | 14               | 18  | 23  | 19  | 34             | 31  | 47  | 44  |
| 0.1                                    |            | 5                | 6  | 6   | 7  | 10             | 15  | 17  | 18  | 9                | 11  | 15  | 12  | 22             | 20  | 30  | 28  |
| <i>SOA-slope (<math>s^{-1}</math>)</i> |            |                  |    |     |    |                |     |     |     |                  |     |     |     |                |     |     |     |
| 0.3                                    |            | 53               | 59 | 65  | 75 | 108            | 159 | 188 | 199 | 173              | 123 | 162 | 368 | 228            | 218 | 339 | 295 |
| 0.5                                    |            | 19               | 21 | 23  | 27 | 39             | 57  | 68  | 71  | 62               | 44  | 58  | 132 | 82             | 79  | 122 | 106 |
| 0.8                                    |            | 7                | 8  | 9   | 10 | 15             | 22  | 26  | 28  | 24               | 17  | 23  | 52  | 32             | 31  | 48  | 42  |
| 1                                      |            | 5                | 5  | 6   | 7  | 10             | 14  | 17  | 18  | 16               | 11  | 15  | 33  | 20             | 20  | 30  | 27  |

Note: PSD: population standard deviation (ms). ZRFT-slope effects are expressed as differences between slopes, which have no metrical unit. The values of stoptrials per SOA are given in parantheses.

trials. Moreover, the fixed-SOA procedure requires doubling the number of subjects for the detection of slope differences. Similar numbers are required to reveal a difference of 0.3 in the slope of the normal inhibition function.

#### 6.1.6. Estimating variability in stop-signal RT

The two methods for estimating variability in  $SSRT_{in}$  both yielded disappointing results. In Fig. 6 it can be seen that the Colonius method overestimated the inter-quartile distance of  $SSRT_{in}$  by 10–50 ms; most strongly for early SOAs. This over-estimation is considerable given a true inter-quartile distance between 0 and 190 ms. Note that estimating the  $SSRT_{in}$  distribution requires a large number of observed RTs on signal and nonsignal trials. Table 8 shows that  $SD_{SSRT}$  was also over-estimated when calculated using the inhibition function (see Eq. (A.4) in the Appendix A).

#### 6.1.7. Interim conclusions

The simulations clarified three misconceptions that can be found in the stopping literature relating to  $SD_{SSRT}$ . First, it is incorrect to assume that  $SD_{SSRT}$  does not affect  $SSRT_{obs}$ . But, as Logan and Cowan (1984) demonstrated, the effect of  $SD_{SSRT}$  on  $SSRT_{av}$ ,  $SSRT_{med}$  and  $SSRT_{centr}$  is negligible. Secondly, observed RT – predicted RT strongly increases with  $SD_{SSRT}$ . This is even true when stop and go processes are stochastically independent. Thirdly,  $SD_{SSRT}$  has a strong effect on the slope of the ZRFT transformed inhibition function but in the opposite direction of the effect exerted by  $SD_{RT}$ . It then follows that group or condition differences in the slope of the ZRFT function cannot be used to unambiguously index variability in stop-signal RT.

## 7. Stopping failures

Response inhibition requires fast stop processes but also a high reliability in triggering stop processes. Deficiencies in triggering may occur when the stop signal is not detected or not translated into an internal stop command. Schachar and Logan (1990) (see also Logan & Cowan, 1984) noted that children with ADHD may differ from normal control children in triggering rate. They observed that the slope of the ZRFT function discriminates between ADHD children and controls and concluded that this slope provides a diagnostic of triggering deficiencies. The interested reader is referred to Tannock et al. (1995) for an illustration of the use of the slope of the ZRFT function as a diagnostic. The power of the slope of the ZRFT function to detect triggering deficiencies will be examined below.

### 7.1. Simulations

Six levels of triggering rate were analyzed, from  $p(\text{Trig}) = 0.75$ –1.0 in steps of 0.05.

7.1.1. Inhibition function

In Fig. 7A, it can be seen that the inhibition function was more sensitive to a decreased triggering rate for early SOAs, resulting in an increased RR. Note that  $RR \leq 0.2$  could not be reached for  $p(\text{Trig}) \leq 0.8$ . For the RR-tracking procedure, this implies that the SOA could not reach asymptote. These results are therefore not reported here. Finally, ZRFT transformation did not correct the slope of the inhibition function. The slope was less steep as stop processes are triggered less often.

7.1.2. Stop-signal reaction time

A failure to trigger stop processes affected  $SSRT_{\text{obs}}$ , in particular at early SOAs (see Fig. 7B). Interestingly, this failure to trigger caused nonlinear relationships between  $SSRT_{\text{obs}}$  and SOA, not seen previously. The summary  $SSRT$  measures, pre-

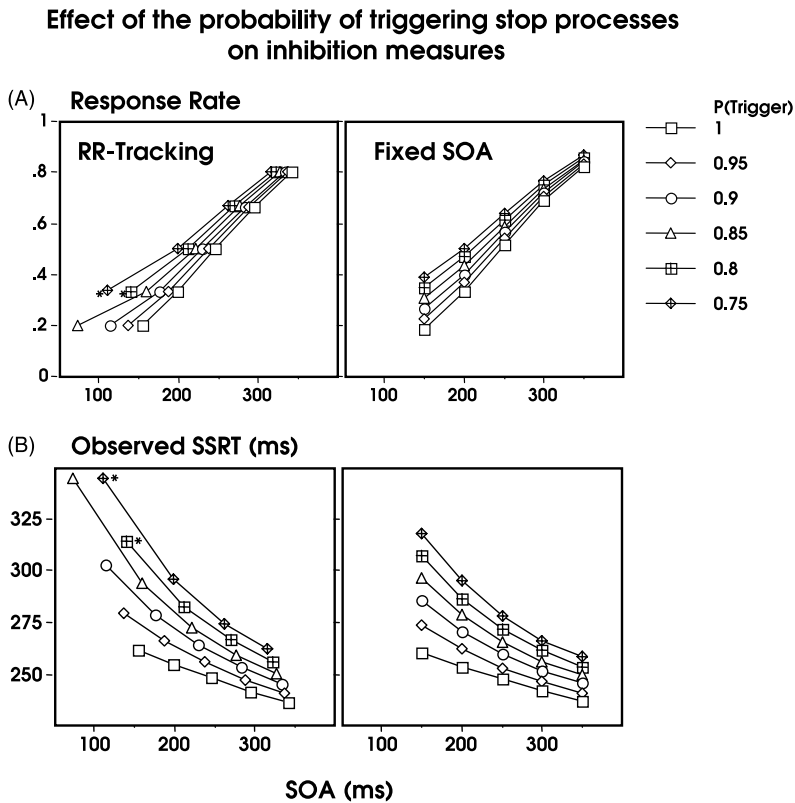


Fig. 7. The effect on inhibition measures of a decreased triggering rate of the inhibition mechanism, SOA, and the SOA-procedure. Panel A shows that the slope of the inhibition function decreases as a result of failures to trigger and that the RR-tracking procedure may cause spurious results if the tracked level of RR is lower than  $1 - P(\text{Trigger})$ . Panel B shows that  $SSRT_{\text{obs}}$ , including  $SSRT_{\text{centr}}$ , becomes inaccurate as triggering inhibition fails. Note that the RR-tracking procedure reduces SOA to meaningless values if triggering failures become more frequent than inhibition rate.



sented in Table 10, overestimated  $SSRT_{in}$  considerably for  $p < 1.0$ . It can be seen that overestimations amounted to 40 ms (fixed-SOA procedure) or more (RR-tracking procedure).

### 7.1.3. Observed RT – predicted RT

The mismatch between observed RT and predicted RT increased as stop processes are triggered less often. For  $p = 0.75$ , the difference was 18 ms at the central SOA.

### 7.1.4. Interim conclusions

A failure to engage has major effects on all inhibition measures tested. In contrast to all other parameters manipulated, the effects of trigger deficiencies were not compensated for using the RR-tracking procedure or summary SSRT measures. In accord with the stopping literature (e.g., Tannock et al., 1989), trigger failures affected the slope of the ZRFT transformed inhibition function. They did so, however, to a similar extent as the changes in slope associated with go RT and SSRT variability. Thus, it seems dangerous ground to use the slope of the ZRFT function as an index uniquely pointing to triggering deficiencies. At this point, there seems to be no tool available to identify reliably a failure in triggering the stop mechanism. At best, a triggering failure is indicated by decreasing trends in SOA when using the RR-tracking procedure.

## 8. Dependence between primary task RT and stop-signal task RT

The horse-race model assumes independence between stopping and go processes. The independence assumption takes two related forms; context independence and stochastic independence. Context independence means that the duration of primary task processes are not affected by the presence of stop processes, and vice versa. Stochastic independence means that their durations are not correlated. Together, these assumptions allow for treating the nonsignal RT distribution as the distribution of

Table 10

The slope of the inhibition function and summary stop-signal RT (ms) as a function of triggering rate of the inhibition process

| $p$  | ZRFT-slope |       | SOA-slope ( $s^{-1}$ ) |     | SSRT <sub>av</sub> |     | SSRT <sub>mean</sub> | SSRT <sub>med</sub> |     |
|------|------------|-------|------------------------|-----|--------------------|-----|----------------------|---------------------|-----|
|      | RR-T       | Fix   | RR-T                   | Fix | RR-T               | Fix | RR-T                 | RR-T                | Fix |
| 1.00 | -0.33      | -0.33 | 3.3                    | 3.3 | 249                | 248 | 250                  | 247                 | 247 |
| 0.95 | -0.31      | -0.31 | 3.1                    | 3.1 | 258                | 256 | 258                  | 257                 | 255 |
| 0.90 | -0.28      | -0.30 | 2.8                    | 3.0 | 269                | 263 | 266                  | 267                 | 264 |
| 0.85 | -0.24      | -0.28 | 2.4                    | 2.8 | 284                | 272 | 276                  | 282                 | 274 |
| 0.80 | *          | -0.27 | *                      | 2.7 | *                  | 281 | 287                  | *                   | 286 |
| 0.75 | *          | -0.25 | *                      | 2.5 | *                  | 289 | 293                  | *                   | 299 |

Note: RR-T: response-rate tracking procedure; Fix: fixed-SOA procedure; ZRFT: slope of the normalized inhibition function, this measure has no metrical unit; SSRT: stop-signal reaction time in ms (see Appendix A for details); (\*) these values cannot be computed reliably.

duration of go processes on stop trials. Violations of stochastic independence are thought to increase the difference between observed RT and predicted RT on signal trials (e.g., De Jong et al., 1990; Jennings et al., 1992; Logan & Cowan, 1984). Thus, observed RT – predicted RT is used to test whether the data fit the horse-race model (e.g., Jennings et al., 1992; Logan & Cowan, 1984).

De Jong et al. (1990) examined the effects of dependency on estimations of  $SSRT_{in}$ . They showed that  $SSRT_{obs}$  was influenced by the correlation between  $SSRT_{in}$  and RT. The effect was more pronounced for noncentral SOAs and increased with  $SD_{SSRT}$ . A positive correlation caused an increase of  $SSRT_{obs}$  with SOA, a steeper inhibition function and greater mismatch between observed RT and predicted RT. Unfortunately, De Jong et al. did not examine the effects of independence on the ZRFT slope.

### 8.1. Simulations

The effect of a correlation between RT and  $SSRT_{in}$  was tested by varying the proportion shared vs. nonshared variance. The correlations that were thus created varied from  $r = -0.4$  to  $+0.4$ , in steps of 0.1.

#### 8.1.1. Inhibition functions

A more positive correlation ( $r$ ) between RT and  $SSRT_{in}$  resulted in a steeper inhibition function and this effect did not disappear after ZRFT-transformation. The slopes of the functions were ( $R^2s > 0.91$ ; curvilinear functions provided a better fit):

$$\text{ZRFT slope} = -0.326 - 0.127 \times r$$

$$\text{SOA slope} = 3.26 + 1.27 \times r$$

These findings indicate that the correlation between SSRT and RT may increase the slope of the ZRFT function. The obvious danger is, of course, that the slope difference is erroneously interpreted in terms of SSRT variance rather than suggesting a violation of the stochastic independence.

#### 8.1.2. Stop-signal reaction time

Values of  $r > 0.2$  caused  $SSRT_{obs}$  to increase with SOA while a negative relation between go and stop processes enhanced the decrease of  $SSRT_{obs}$  with SOA. Summary measures of  $SSRT_{obs}$  were not sensitive to interdependence between go and stop processes.

#### 8.1.3. Observed RT – predicted RT

In Fig. 8, it can be seen that observed RT – predicted RT increased with  $r$ , up to 12 ms for the central SOA. Moreover, the mismatch was not reduced to zero when RT and SSRT were not correlated. Note that the dependence effect is small compared to the effects of  $SD_{RT}$  and  $SD_{SSRT}$  (see Sections 5.1.5 and 6.1.7). This pattern of results presents a serious challenge to the use of observed RT – predicted RT as a test of the independence assumption (e.g., De Jong et al., 1990; Jennings et al., 1992).

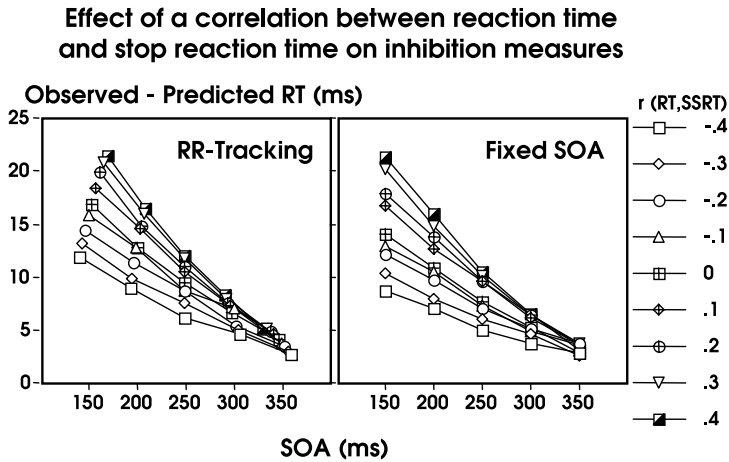


Fig. 8. The effect of correlation between RT and  $SSRT_{in}$ , SOA, and the SOA-procedure on the difference between observed and predicted signal RT. Although this measure is used as a test of independence between the two processes, dependence has a relatively small effect in comparison to  $SD_{SSRT}$  or the measurement error.

#### 8.1.4. Interim conclusions

The simulations make at least three important points. First, summary measures of  $SSRT$  are relatively robust against violations of the independence assumption underlying the horse-race model. Second, the mismatch between observed RT and predicted RT is not a valid test of the independence assumption. Third, and perhaps most importantly, violations of the independence assumption exert an effect on the slope of the ZRFT function that can be interpreted, mistakenly, in terms of  $SSRT$  variance.

## 9. Dependence between stop-signal delay and stop-signal reaction time

A decrease of  $SSRT_{obs}$  with SOA is not indicative of a negative relation between  $SSRT_{in}$  and SOA, which would be a violation of context independence. Instead, it is compatible with the horse-race model, given that  $SD_{SSRT} > 0$ . For early SOAs, even a slow  $SSRT_{in}$  may result in successful inhibition. Obviously, for longer SOAs only a fast  $SSRT_{in}$  results in correct inhibition.

There are several reasons, why SOA and  $SSRT_{in}$  do not need to be independent. For example, it is well established that primary task RTs shorten when warning intervals increase up to 1 s (e.g., Sanders, 1998). In a similar vein,  $SSRT_{in}$  can be affected by stop-signal delay. Alternatively, the shortening of  $SSRT_{in}$  associated with longer SOAs could be due to a refractory effect on short SOAs. Logan and Burkell (1986), for example, found that  $SSRT_{obs}$  decreased by 42 ms with SOA even after correcting for the effect of  $SD_{SSRT}$ , and interpreted this residual decrease as a refractory effect (see also Pashler, 1994).

9.1. Simulations

The effect of a correlation between SOA and  $SSRT_{in}$  was tested by letting part of the single-trial deviation of  $SSRT_{in}$  from the mean  $SSRT_{in}$  depend on the difference between the current SOA and the mean of SOAs. This procedure did not allow close control over the correlation levels. The resulting  $r$  varied from  $-0.80$  to  $+0.52$ .

9.1.1. Inhibition functions

The slope of the inhibition function increased with  $r$ , and the difference remained after ZRFT correction. The slopes of the functions, after combining the results obtained using different SOA procedures, were  $R^2s > 0.96$  (curvilinear functions provided a better fit):

$$ZRFT \text{ slope} = -0.342 - 0.205 \times r$$

$$SOA \text{ slope} = 3.42 + 2.05 \times r$$

This pattern indicates that the ZRFT slope is sensitive to dependencies between SSRT and SOA.

9.1.2. Stop-signal reaction time

The  $SSRT_{obs}$  decreased with SOA when  $r > 0.1$  and increased when  $r < 0.1$ , as can be seen in Fig. 9. Summary SSRT scores were robust against dependencies between SSRT and SOA.

9.1.3. Observed RT – predicted RT

The results indicated that the difference between observed RT and predicted RT was greatest when  $r = 0$  (i.e., 10 ms at the central SOA).

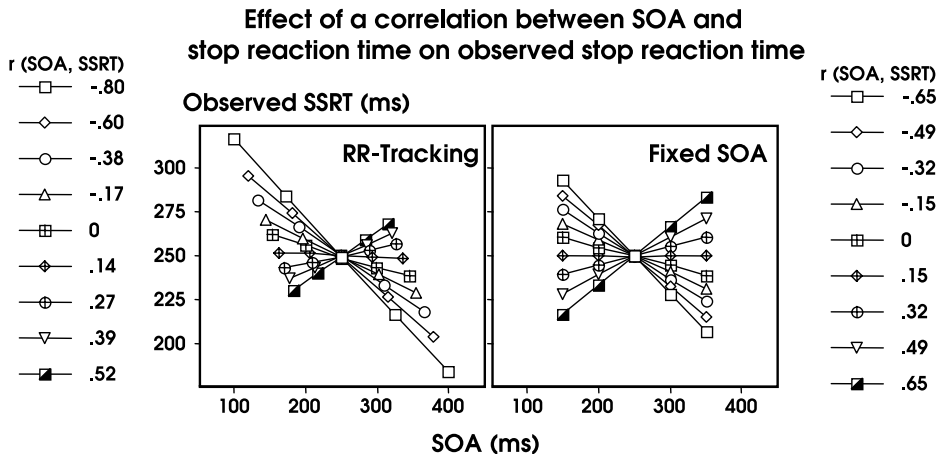


Fig. 9. The effect on  $SSRT_{obs}$  of SOA, the SOA-procedure, and correlation between SOA and  $SSRT_{in}$ . Note that correlations were not identical for the simulations of response-rate tracking and the fixed-SOA procedure.

#### 9.1.4. Interim conclusions

The simulations revealed that, in contrast to summary SSRT scores, ZFRT slope is sensitive to dependencies between SOA and SSRT. The latter finding contributes to the growing evidence against the use of ZFRT slope as an index for stop variability.

## 10. Discussion

The simulation studies based on the horse-race model had three major goals. The first goal was to determine the robustness of inhibition indices, i.e., stop-signal RT and the ZRFT function. The second goal was to examine how violations of the assumptions underlying the horse-race model, i.e., constant stop-signal RT and independence of stop-signal RT and primary task RT, may influence inhibition indices. The third goal was to obtain a set of guidelines for using the stop-signal paradigm.

### 10.1. Inhibition indices

Two inhibition indices are typically used in studies using the stop-signal paradigm. One is stop-signal RT and the other is the slope of the ZRFT function. The former is assumed to provide a sensitive index of the duration of inhibition processes, which is relevant both as an absolute measure and in comparison between conditions. The latter has little meaning as an absolute measure. It is used only to compare between conditions or groups and is assumed to provide an estimate of the trial-by-trial variability of inhibition processes (Logan, 1994).

#### 10.1.1. Stop-signal RT

Several summary measures of stop-signal RT provided accurate estimates of stopping latency under a wide range of parameter settings. However, there were a few notable exceptions. First, substantially more trials or subjects are needed to obtain reliable estimates when between-subject variability in SSRT is higher. Secondly, increased variability in stop-signal RT necessitates a judicious choice of stop-signal delay. Thirdly, and most importantly, occasional failures of triggering the stop mechanism resulted in a considerable overestimation of SSRT. Finally, it should be noted that three SSRT measures provided less accurate estimates.  $SSRT_{av}$  calculated across noncentral SOAs does not yield a reliable estimate of stop latency. In addition,  $SSRT_{mean}$  fails to reveal differences between stop latencies when SOA is determined using the fixed procedure. Furthermore, the Colonius method for estimating SSRT (e.g., Colonius, 1990) seems to underestimate stop latency and requires large trial numbers. Thus, the Colonius method is not recommended for obtaining a reliable estimate of stop latency.

#### 10.1.2. ZRFT function

The simulations yielded largely negative outcomes with regard to the slope of the ZRFT function as an index of between-group or between-conditions differences in

stopping. The use of the slope of the ZRFT function requires that primary task RT distributions between-groups or between-conditions are basically similar, sample sizes should be large and trial numbers high, and within-group or within-conditions performance should be homogeneous. It is doubtful that these ideal conditions are met in the laboratory.

The simulation results indicated that the slope of the ZRFT function is affected by SSRT variability and stop failures. In this respect, the results are consistent with the assumptions made in the literature (e.g., Logan, 1994). But the results also showed that the slope is sensitive to variability in primary task RT for which the ZRFT transformation is thought to correct. Thus, it seems impossible to attribute slope differences unequivocally to between-group and condition variance in stopping.

### *10.2. Horse-race model assumptions*

The simulations focused on two assumptions underlying the horse-race model; constant SSRT and independence of SSRT and primary task RT. For the calculation of  $SSRT_{obs}$  the horse-race model assumes that SSRT is constant but this assumption is not likely to be true. As formally derived by Logan and Cowan (1984) and demonstrated by simulations reported by De Jong et al. (1990), violation of the constant SSRT assumption does not seem to impact summary estimates of stopping duration. The current results are in accord with this literature. The summary SSRT measures provided accurate estimates of stop latency.

The independence assumption takes two varieties, stochastic independence and context independence. Violations of stochastic independence refer to situations when the durations of the go processes and stop processes are correlated. Previously, it has been shown that a positive correlation of go and stop durations caused an increase of SSRT with SOA (De Jong et al., 1990). A similar result was obtained in the current simulations. This finding contributes to the skepticism of using the slope of the ZRFT function as an index of stopping variability. Summary measures of SSRT were not significantly affected by correlated durations of go and stop processes. A similar pattern of findings was obtained for violations of context independence; that is, when SSRT was correlated with SOA.

Several investigators used the difference between observed RT and predicted RT as a criterion for testing the independence assumption (e.g., De Jong et al., 1990; Jennings et al., 1992; Logan & Cowan, 1984; Van Boxtel et al., 2001). The current simulations examined the validity of this criterion. The results were disappointing and suggested that this criterion cannot be used as a valid test of independence. The pattern of results indicated that the effect of dependence on observed RT – predicted RT was small compared to the effects of RT variability, stopping failures or early SOAs.

### *10.3. Guidelines*

The pattern of results that emerged from the current simulations can be used to formulate a set of recommendations for using the stop-signal paradigm to assess the ability to inhibit a motor response.

### 10.3.1. Setting stop-signal delay

From the perspective of experimental economy, setting stop-signal delay by tracking based on a RR on signal trials of  $p = 0.5$  seems to offer the best solution—less trials are needed for a more accurate estimate of SSRT. Recent empirical illustrations of this procedure can be found in Ridderinkhof et al. (1999), Williams et al. (1999), or Van Boxtel et al. (2001). Other considerations than experimental economy may determine the setting of stop-signal delay. Investigators may want to use the slope of the ZRFT function to examine between-group or condition differences in the variability of the stopping mechanism (but see below). In that case, the best solution is using a tracking algorithm to obtain a set of SOAs that are symmetrically distributed around the central SOA (i.e., the delay resulting in a RR on stop-signal trials of  $p = 0.5$ ). A recent illustration of this procedure for setting three stop-signal delays is provided by Band et al. (2000). Finally, investigators may want to use fixed SOAs. For example, time locking between respond and stop-signals may be required for the analysis of psychophysiological measures (e.g., event-related brain potentials or heart rate frequency) obtained during task performance. In that case, it is important to ascertain that SOAs cover the most interesting part of the inhibition function (i.e., the part relating to RRs greater than 0.15 and less than 0.85). Psychophysiological illustrations of the use of fixed SOAs are provided by De Jong et al. (1990) and Jennings et al. (1992). When more than one fixed SOA is used, several summary SSRT measures provide an accurate estimate of stopping duration (see Section 10.1.1).

*Recommendation 1:* The tracking procedure based on RR ( $p = 0.5$ ) is the most optimal strategy for setting stop-signal delay.

### 10.3.2. Stop-signal reaction time

The most results that emerged from the current simulations indicated that, using the horse-race model, accurate estimates are obtained of the duration of stopping processes. Central SSRT measures were fairly robust against variability in primary task RT or stop-signal task RT and even to violations of the dependency assumption underlying the horse-race model. Less accurate estimates of SSRT were only obtained when the triggering of the stop mechanism failed. Stopping failures have been assumed to occur when the slope of the ZRFT function discriminated between groups or conditions (e.g., Tannock et al., 1989, 1995). If true, investigators should be aware that their estimates of SSRT might be inaccurate.

*Recommendation 2:* Central SSRT measures provide the best estimate of the duration of stop processes.

### 10.3.3. ZRFT function

The simulations yielded disappointing outcomes with regard to the slope of the ZRFT function. The slope of the ZRFT function was sensitive to variability in primary-task RT and was not robust against violations of the assumptions underlying the horse-race model. The conclusion is that slope of the ZRFT function does not provide a valid index to discriminate between groups or conditions.

*Recommendation 3:* The slope of the ZRFT function should not be used to examine between-group or between-condition differences in the variability of the stopping mechanism.

#### 10.3.4. Observed RT – predicted RT

The results of the simulation studies made two important points. First, observed RT – predicted RT was strongly affected by variability in primary-task RT and stop-signal task RT. Thus, observed RT – predicted RT cannot be used as a valid criterion for testing the independence assumption underlying the horse-race model. Secondly, violations of the independence assumption did not result in inaccurate estimates of the duration of stopping processes. Thus, it seems fair to conclude that there is no need to examine whether the data violate the independence assumption.

*Recommendation 4:* Observed RT – predicted RT should not be used as a test of the independence assumption underlying the horse-race model.

#### 10.3.5. Experimental economy

The simulation studies indicated that central measures of SSRT do not only provide the most accurate estimates but are also the most reliable. In addition, central measures of SSRT are also more powerful to detect differences between groups or conditions.

*Recommendation 5:* The detection of a difference in SSRT of approximately 20 ms requires about 50 subjects performing on 300 nonsignal and 100 signal trials using RR tracking for setting stop-signal delay.

### 10.4. Conclusion

The simulations yielded some good news and some bad news. The good news is that, using proper procedures, an accurate and reliable measure can be obtained of the duration of stop processes that can be used to discriminate between groups and conditions. The estimate of stopping duration can be obtained even when the constant stopping duration and independence assumptions of the horse-race model are violated. The bad news is that the slope of the ZRFT function should not be used to discriminate between groups assumed to differ in inhibitory ability or conditions predicted to impose different demands on the stopping mechanism. The implication is that conclusions derived from studies using the slope of the ZRFT function should be taken with great caution. In particular, when considering that the current findings were obtained using idealized data sets. That is, the simulations were run with consistent parameter values, a constant shape of the stop-signal primary-task RT distributions, large numbers of trials, no measurement error, and without accounting for strategies subjects may use when performing the stop-signal task. Moreover, the simulations did not examine the effects of interactions of the factors that were examined. Thus, the possibility cannot be ruled out that the bad news concerning the slope of the ZRFT function might even be worse. But this remains to be seen in future simulations studies. At this point, it is concluded that SSRT provides a robust index of



stopping duration but researchers should stay away from using the slope of the inhibition function.

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## Appendix A. Calculation of summary SSRT measures, confidence intervals and power

### A.1. Average stop RT: $SSRT_{av}$

It is a recurrent finding that  $SSRT_{obs}$  changes with SOA. This can be due to variability in  $SSRT_{in}$  that is independent of SOA. If variability of  $SSRT_{in}$  cannot be ruled out, the speed of stopping can be expressed as a single SSRT across SOAs, that serves as a summary measure (e.g., Logan, 1994; Logan & Cowan, 1984). This summary measure ( $SSRT_{av}$ ) is obtained by averaging  $SSRT_{obs}$ 's for which  $0.15 < RR < 0.85$ .

### A.2. Stop reaction time at the mean of the inhibition function: $SSRT_{mean}$

Another summary SSRT measure, suggested by Logan and Cowan (1984), is the difference ( $SSRT_{mean}$ ) between mean RT and the mean of the inhibition function. The accuracy of the estimated mean of the inhibition function increases with the number of SOAs and symmetry of the SOAs around the midpoint of the inhibition function. To calculate the mean of the inhibition function, one step is to subtract the RR at SOA ( $n - 1$ ) from SOA ( $n$ ). This cannot be done for the first SOA. In the simulations, where five SOA levels were used, the fifth SOA was also rejected for the calculation of the  $SSRT_{mean}$ . This is because there should be an equal number of SOAs at both sides of the function's midpoint. Thus, the  $SSRT_{mean}$  was calculated on the basis of SOA 2, 3, and 4 by using the following equation:

$$\begin{aligned} SSRT_{mean} &= \text{mean RT} \\ &\quad - \frac{\{[(RR_2 - RR_1)SOA_2] + [(RR_3 - RR_2)SOA_3] + [(RR_4 - RR_3)SOA_4]\}}{(RR_4 - RR_1)} \end{aligned} \tag{A.1}$$

### A.3. Stop-signal reaction time at the median of the inhibition function: $SSRT_{med}$

The median SSRT ( $SSRT_{med}$ ) is based on the same principle as  $SSRT_{mean}$ . It is calculated as the median primary-task RT minus the median of the inhibition function. Note, that if a distribution is symmetrical, the mean equals the median. The median

is easier to calculate than the mean of the inhibition function. The median is the SOA where  $RR = 0.5$ . This point can be determined by linear regression of  $RR$  onto  $SOA$ . The median of the  $RT$  distribution minus the median of the inhibition function is interpreted as  $SSRT_{med}$ . When the tracking procedure is used, the  $SOA$  where  $RR = 0.5$  is observed directly. Under these circumstances, the  $SSRT_{med}$  can safely be used as the only  $SSRT_{obs}$ , which is also referred to as  $SSRT_{centr}$  in this report.

#### A.4. The Colonius (1990) method for calculating the $SSRT$ distribution

De Jong et al. (1990, Appendix) and Colonius (1990) proposed a method that is meant to recover the distribution of  $SSRT_{in}$  for every  $SOA$ . Here, the cumulative distribution of  $SSRT_{obs}$ 's is calculated based on the ratio between the density functions of signal and of nonsignal  $RT$  and the probability of responding on signal trials. Formally,

$$p(SSRT + SOA > t|SOA) = RR(SOA)f_s(t|SOA)/f_{ns}(t) \quad (A.2)$$

where, as a function of time  $t$ ,  $p(SSRT + SOA > t|SOA)$  is the cumulative distribution function of  $SSRT$ s, given a  $SOA$ ;  $RR(SOA)$  is the  $RR$  at  $SOA$ ; and  $f_s$  and  $f_{ns}$  are the density functions of the signal and nonsignal  $RT$  distributions, respectively. As Eq. (A.2) estimates the entire distribution of  $SSRT_{in}$ , it is possible to derive the median from that distribution ( $SSRT_{p50}$ ), and it is also possible to estimate variability of  $SSRT_{in}$  with the interquartile distance ( $SSRT_{p75} - SSRT_{p25}$ ).

This method requires smoothed and stable distributions of  $RT$  and a monotonic inhibition function. As experiments do not usually employ more than 30% signal trials, the signal  $RT$  distribution has to be based on approximately 15% of all trials, given that half of all responses are inhibited. Moreover, these signal trials are usually distributed across several  $SOA$ s, which results in even less data to obtain a distribution per  $SOA$ . It is likely that, for these reasons, this method does not seem to be in use in empirical studies.

In the present simulations, Eq. (A.2) was used to calculate the cumulative distribution of  $SSRT_{obs}$  for intervals of 10 ms between 0 and 800 ms. In order to remove spurious data points and to create a monotonically rising cumulative function, the data were smoothed by averaging nonmonotonic values across adjacent intervals. Density functions were smoothed by averaging large local probability differences with adjacent values. Smoothing continued until the function was monotonic or smooth, but there was a maximum of ten iterations, because further iterations would flatten the functions. The median  $SSRT$  was calculated using this method for each of five  $SOA$ s. Theoretically, the five measures should be equal if there is no relation between  $SOA$  and  $SSRT_{in}$ . The mean of these five values is reported as  $SSRT_{p50}$ .

For every  $SOA$ , the interquartile distance, i.e. the difference between the 25th ( $SSRT_{p25}$ ) and 75th ( $SSRT_{p75}$ ) percentile score was calculated. This measure is less sensitive than the  $SD$  to the distortion of the estimated distribution at the tails, which is said to occur using the Colonius method (Logan, 1994). In addition, it is not as

easy to extract the SD from a cumulative distribution as it is to calculate the inter-quartile distance.

#### A.5. The Logan and Cowan (1984) method for estimating $SD_{SSRT}$

An alternative method for estimating the variance of  $SSRT_{in}$  is suggested by Logan and Cowan (1984). They argued that the inhibition function can be interpreted as the cumulative distribution of a random variable  $T_d$ , and its variance can be calculated from the slope of the inhibition function at the *central* SOA (i.e. the SOA where  $RR = 0.5$ ). For example, if a normal distribution is assumed, the relation between the slope ( $B$ ) and SD is

$$B_{0.5} = 1/[SD_{T_d}(2\pi)^{-1/2}] \quad (\text{A.3})$$

The variability in the arrival of stop- and go-processes is the only source of variance contributing to the variance of the inhibition function. Furthermore, the variance in stop-signal RT and primary-task RT are assumed independent. It then follows that the variance of  $T_d$  is the sum of the variances of RT and SSRT. Therefore, the  $SD_{SSRT}$  can be calculated by

$$SD_{SSRT}^2 = \left( \frac{1}{B_{0.5}\sqrt{2\pi}} \right)^2 - SD_{RT}^2 \quad (\text{A.4})$$

#### A.6. Confidence interval

The size of the 95% confidence interval depends on the SE and was calculated as  $2 \times 1.96 \times SE$ , because the area of a normal distribution between  $z$ -scores  $-1.96$  and  $+1.96$  is 0.95.

#### A.7. Calculation of power ( $1 - \beta$ )

The power ( $1 - \beta$ ) to detect a difference between two averages depends on four factors: (a) the effect size, (b)  $\alpha$ , (c) sample size and (d) population variability. Three methods were used to calculate the number of subjects that are required in order to reach a power ( $1 - \beta$ ) of 0.8 for the detection of differences between two scores using a  $t$ -test, with an  $\alpha$  of 0.05. The calculations are based on the assumption that two groups or conditions yield the same distribution of measurements, but a different mean. The number of subjects ( $n$ ) that need to be tested to achieve a power of 0.8 was computed as follows. For two indices (a and b), with mean  $\mu$  and standard error  $\sigma$ , the probability of finding a difference at the  $\alpha = 0.05$  level is  $1 - \beta = 0.80$  when,

$$(\mu_a + \sigma_a)\Phi^{-1}(0.95) = (\mu_b + \sigma_b)\Phi^{-1}(0.80) \quad (\text{A.5})$$

where  $\Phi^{-1}$  is the inverse  $t$ -distribution.

It is assumed that the standard error of a and b are equal, and for  $n$  subjects, the standard error is

$$\sigma_a = \sigma_b = \frac{SD}{\sqrt{n}} \quad (\text{A.6})$$

Therefore,

$$\frac{\sqrt{n(\mu_a - \mu_b)}}{SD} = 2[\Phi^{-1}(0.8) + \Phi^{-1}(0.95)] \quad (\text{A.7})$$

$$n = 4[\Phi^{-1}(0.8) + \Phi^{-1}(0.95)]^2 \frac{\sigma^2}{(\mu_a - \mu_b)^2} \quad (\text{A.8})$$

$$n = 24.73(\text{SD}/\text{effect size})^2 \quad (\text{A.9})$$

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