



The location-based Simon effect: Reliability of ex-Gaussian analysis

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Abstract

Task-irrelevant stimulus location can influence the response performance to task-relevant attributes, generating the location-based Simon effect. Using a Monte Carlo study and other methods, we examined whether the ex-Gaussian distribution provides a good fit to empirical reaction time (RT) distributions in the Simon task and whether reliable Simon effects occur on the ex-Gaussian parameters: (a) the mean (μ), (b) the standard deviation (σ) of the normal distribution, and (c) the tail (τ). Results showed that the ex-Gaussian function fits well to empirical RT distributions, and that these ex-Gaussian parameters are reliable between two trial blocks at the group level. At the individual level, correlation analysis showed that the Simon effect was reliable on the μ parameter but not on σ and τ . Moreover, a partial correlation analysis, with μ s of the two blocks as controlling variables, showed that the Simon effect on τ was reliable. These results provide evidence that the ex-Gaussian function is a valuable tool for analyzing the Simon effect and can be considered as an alternative for analyzing RT distributions in Simon-type tasks.

Keywords Reliability · Simon effect · Ex-Gaussian distribution · Reaction time distribution

Introduction

Correspondence of a task-irrelevant stimulus location and response position can accelerate the response to a task-relevant non-spatial attribute of the stimulus, as illustrated by the *Simon task*, named for J. R. Simon (1990). In the typical visual Simon task, left and right key-presses are mapped to the non-spatial stimulus attributes (e.g., red and blue colors). Responses are faster and more accurate when task-irrelevant left or right stimulus location corresponds with the response position than when it does not, which is called the standard, spatial, or location-based Simon effect (see reviews by Lu & Proctor, 1995; Luo & Proctor, 2017, 2018a, 2018b; Proctor, Miles, & Baroni, 2011; Simon, 1990; Umiltà & Nicoletti, 1990). The location-based Simon effect has been attributed to responses being primed by automatic processing of the stimulus location, which interferes with responses activated by processing of the task-relevant attribute in accordance with the instructed stimulus-response (S-R) mapping (De Jong,

Liang, & Lauber, 1994; Kornblum, Hasbroucq, & Osman, 1990; Zhang, Zhang, & Kornblum, 1999).

Initial studies of the Simon effect and related correspondence effects focused on differences in mean (or median) reaction time (RT) that provide estimates of the central tendency for each condition (see Lu & Proctor, 1995), which are still the focal point of many investigations. However, only analyzing mean RT makes it difficult to characterize thoroughly how the experimental manipulation influences RT (Balota & Yap, 2011; Heathcote, Popiel, & Mewhort, 1991; Ratcliff, 1979). RT may be affected by experimental manipulations that have no obvious effect on the mean RT. For instance, Luo and Proctor (2018b) found that when a location word (*left or right*) was presented eccentrically, a word-based Simon effect did not occur on mean RT but the skew of the RT-distribution was significantly increased for trials on which the word and response did not correspond.

Alternatively, an increase of mean RT may be due to an increase of skew of the RT distribution, a shift of the RT distribution, or both (Luo & Proctor 2018a, 2018b; Spieler, Balota, & Faust, 2000). For instance, Luo and Proctor (2018a, 2018b) found that the location-based Simon effect on mean RT arose mainly from a shift of the RT distribution on non-corresponding versus corresponding trials, whereas the word-based Simon effect (faster response to the color of a centrally presented location word left or right when the meaning of left or right corresponds with the response position than when it

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does not) on mean RT arose mainly from an increase in the skew of the RT distribution. The arrow-based Simon effect (faster response to the color of a centrally presented arrow when the left or right direction in which it points corresponds with the response position than when it does not) on mean RT arose from both. The findings of various Simon effects on the RT distributions parallel the view that (a) the location-based Simon effect occurs rapidly and decays quickly, (b) the word-based Simon effect occurs slowly, and (c) the arrow-based Simon effect occurs rapidly and decays slowly. Because ex-Gaussian analysis can distinguish these distribution properties, it is a potentially informative tool for understanding the time course of the Simon effect and providing more detailed information about the way in which an experimental manipulation influences RT across the distribution.

Beginning with De Jong, Liang, and Lauber (1994), many authors have reported analyses of the RT distributions in delta plots (RT difference between non-corresponding and corresponding trials). In fact, it is now routine to include delta plots in articles on Simon effects and related conflict effects (e.g., Davranche & McMorris, 2009; Ellinghaus, Karlbauer, Bausenhardt, & Ulrich, 2018; Kubo-Kawai & Kawai, 2010; Ulrich, Schröter, Leuthold, & Birngruber, 2015). In these studies, using a Vincentizing procedure (Ratcliff, 1979), a group RT distribution is obtained by partitioning each participant's RTs on the corresponding and non-corresponding trials into percentile bins (e.g., 10%), ranging from shortest to longest, and calculating the Simon effect for each percentile or for each bin (calculating the average of values between two adjacent quantiles).

Across the RT distribution, most findings are that the location-based Simon effect is largest for fast responses but decreases, and even reverses, as responses slow when the imperative stimuli are displayed in a left or right location (Ansorge & Wühr, 2004; De Jong et al., 1994; Pratte, Rouder, Morey, & Feng, 2010). Decreasing delta plots show that the Simon effect is maximal early in the course of processing and decreases for longer RT quantiles (Pratte et al., 2010; Proctor et al., 2011; Schwarz & Miller, 2012). The activation-suppression theory (Ridderinkhof, 2002) asserts that the decreasing delta plot occurs because the location-based automatic response priming is actively suppressed by a top-down inhibitory process that takes time to build up. Other theories propose that the decreasing delta plot is a consequence of the automatic response priming passively decaying over time (e.g., Hommel, 1993, 1994).

Besides using the delta plots, to obtain the RT distributional information and quantify characteristics of the entire RT distribution, researchers also use methods that are based on fitting functional forms like the ex-Gaussian or the Weibull distributions (e.g., Heathcote et al., 1991; Ratcliff, 1979; Spieler, Balota, & Faust, 1996; Yap, Balota, Cortese, & Watson, 2006). This approach assumes an existing explicit

mathematical function, and that fitting the function to the empirical data can yield parameter estimates of the underlying theoretical distribution. These parameters can help to quantify characteristics of the entire RT distribution (e.g., Logan, 1992; Ratcliff, 1978).

Existing studies have shown that the ex-Gaussian distribution has a good fit to empirical RT distributions in a range of tasks, including the Stroop task (Heathcote et al., 1991; Spieler et al., 1996; Spieler et al., 2000; Steinhauser & Hübner, 2009), memory task (Ratcliff, 1978, 1979), and lexical decision task (Reingold, Reichle, Glaholt, & Sheridan, 2012). The stability of the parameter estimates is most fully demonstrated in Ratcliff's (1978, 1979) work testing an explicit model of memory retrieval. The ex-Gaussian distribution is a convolution of Gaussian and exponential distributions. Fitting it to an empirical dataset provides estimates of three parameters: μ and σ reflect the mean and standard deviation of the Gaussian component of the distribution, respectively; and τ reflects the mean and standard deviation of the exponential component. The mean of the ex-Gaussian distribution is simply μ plus τ . A change in μ reflects the shift of the RT distribution, whereas a change in τ reflects the increase of the skew of the RT distribution. Because the algebraic sum of μ and τ is constrained to approximate the empirical distribution closely, one can partition the individual mean RT for a particular condition into distributional shifting or changes in the skew of the distribution (Tse, Balota, Yap, Duchek, & McCabe, 2010). The ex-Gaussian analysis offers a parsimonious way of characterizing the influence of factors on RT-distributions, and it allows one to see whether some experimental effect on mean RT arises from a shift of the RT distribution (a change in μ), an increase in the skew of the RT distribution (a change in τ), or both. Therefore, compared to a delta plot, the ex-Gaussian analysis provides an easier way to test statistically RT distribution differences among different conditions or variables.

In two recent studies, Luo and Proctor (2018a, 2018b) fitted the ex-Gaussian function to the RT data obtained in the location-, word-, and arrow-based Simon tasks, and found that the location-based Simon effect on mean RT arose mainly from a shift of the RT distribution but not a change of skew of the distribution (in other words, the location-based Simon effect occurred on μ but not τ). However, the word-based Simon effect arose mainly from the change of skew of the RT distribution (i.e., on τ), whereas the arrow-based Simon effect arose from both the shift and the tail of the RT distribution (both μ and τ). These outcomes parallel the findings reflected by delta plots, for which the location-based Simon effect decreases gradually as RT increases, whereas the word- and arrow-based Simon effects increase gradually as RT increases (Ansorge & Wühr, 2004; Luo & Proctor, 2017, 2019; Pratte et al., 2010; Proctor et al., 2011). This similarity suggests that ex-Gaussian distribution provides a good fit to empirical RT distributions in the Simon task and another way to characterize the RT distributions.

Present study

That the Simon effects on ex-Gaussian parameters paralleled the findings reflected by delta plots in the Simon task (Luo & Proctor, 2018a, 2018b) provides evidence that the ex-Gaussian distribution has a good fit to empirical RT distributions in the Simon task. However, this parallel relation is not direct evidence. Moreover, the RT distribution of the location-based Simon effect reflected by negative delta plots is different from that of most other related effects, which yield positive delta plots. The differences in delta plot have been used to test many computational cognitive models (Luo & Proctor, 2019; Ulrich et al., 2015; Yamaguchi & Proctor, 2012), and the model fitting results showed that most models have difficulty simulating the location-based Simon effect with decreasing delta plot (Schwarz & Miller, 2012). Consequently, it is necessary to understand more about the RT distribution of the location-based Simon effect.

To that end, in the current study, besides the delta plot, we used additional approaches to examine whether the ex-Gaussian distribution has a good fit to empirical RT distributions in the Simon task. First, we examined whether the ex-Gaussian analysis of Simon effects is reliable between trial blocks. Specifically, we fitted the ex-Gaussian function to the RT data from each condition and each participant per block to obtain the ex-Gaussian parameters, and then calculated the between-block differences and correlations. Second, we performed a Monte Carlo study to evaluate whether the ex-Gaussian distribution has a good fit to empirical RT distributions indicated by a delta plot in the Simon task. This study also allowed us to evaluate possible biases and estimate the standard deviation associated with the parameter estimates with an increase in sample size, in order to determine how many trials for each condition are needed to get a reliable estimation of the ex-Gaussian parameters.

We used the ex-Gaussian function with the parameters obtained from the raw data across blocks to generate 20 samples. Each sample included 256 trials, half for the compatible condition and half for the incompatible condition. As with the raw data, we used these generated data to depict the delta plot: If the delta plots from the raw data and generated data overlap, this outcome will support that the ex-Gaussian distribution fits well to empirical RT distributions indicated by delta plots. Additionally, we generated a large number of samples of fixed size by sampling ex-Gaussian random variables with known parameter values. Parameter estimates were then obtained for each of the samples. This allowed a distribution of estimated parameter values to be reconstructed. For an unbiased estimator, the standard deviation of this sampling distribution for a given parameter should be decreased, and the mean should become closer to the actual parameter value, as sample size increases.

Method

Participants Twenty right-handed participants (eight males; age 18–24 years) took part in this study. All were undergraduates or graduates from universities near the Institute of Psychology, Chinese Academy of Science, Beijing, China. They had normal or corrected-to-normal vision and were naïve to the purpose of the study.

Apparatus, stimuli, procedure, and design Stimuli were presented on a super VGA high-resolution color monitor with gray background. A personal computer, running E-Prime 1.1 software, controlled the presentation of stimuli, timing operations, and data collection. Participants placed their heads on a chinrest and viewed the monitor from a distance of 58 cm in a dimly lit room. The stimuli were red and green squares ($0.85^\circ \times 0.85^\circ$), whose centers were 4.0° to the left or right of the center of screen. Responses were made by pressing a left key (V) for the red ink color or right key (M) for the green ink color on the computer keyboard with the left or right index finger.

Each participant performed two blocks of trials, with a 5-min interval between the two blocks. Each block included eight practice trials followed by 128 test trials. Each trial began with the onset of a white central fixation cross ($0.4^\circ \times 0.4^\circ$). After 1 s, a square in red or green appeared for 150 ms. After that, the gray screen became blank, during which the trial terminated if the participant responded or after 1.5 s if no response had been made. After the response, a 1-s inter-trial interval occurred, during which the screen remained blank. The mapping of colors to left and right responses was counterbalanced across participants. The response keys and computer screen were aligned such that the fixation point and the midway point between the two response keys were on the participant's sagittal midline. Participants were told to maintain fixation and to respond to the targets as quickly and accurately as possible. This study had two independent variables, block (block 1, block 2) and location-based Simon (compatible, incompatible), with 64 observations for compatible and 64 for incompatible condition per block.

Data analysis The practice trials were excluded from the RT and percent error (PE) analysis, as well as one of the total test trials across participants for which responses were not recorded. The PE data were then analyzed as follows. Firstly, RTs for all responses (including error and correct responses) for each block were rank ordered from shortest to longest in each experimental condition for each participant, and divided into ten equally sized bins. Secondly, mean PE of each bin per experimental condition for each participant per block was calculated. The mean PEs for each condition across participants and per block or across blocks are shown in Table 1. Lastly, a repeated-measures analysis of variance (ANOVA) was performed on PE, with bin, block, and location-based Simon as within-subject variables.

Table 1 Mean percentage of error (PE), mean reaction time (RT, in ms), μ , σ , τ , and standard deviation (in parentheses) for the compatible and incompatible conditions in block 1, block 2, and overall

		PE	RT	μ	σ	τ
Block 1	Compatible	3.3 (0.03)	264(73)	210(72)	40(22)	56(39)
	Incompatible	4.4 (0.04)	291(76)	248(57)	44(18)	42(33)
Block 2	Compatible	1.5(0.03)	266(72)	207(67)	34(30)	64(38)
	Incompatible	2.5(0.04)	292(70)	242(58)	39(21)	54(34)
Overall	Compatible	2.2(0.06)	265(69)	213(67)	49(21)	53(34)
	Incompatible	7.4(0.07)	292(71)	242(57)	39(20)	51(40)

In the RT data analysis, we excluded test trials wherein participants responded incorrectly to the target (2.1%) and test trials (1.3%) with RTs beyond 3 standard deviations of the mean in each condition for each participant per block. The mean RTs for the remaining RTs in each condition for each block or across blocks are presented in Table 1. The remaining RTs were rank ordered from shortest to longest in each condition for each participant per block or across blocks; percentiles (5, 15, ..., 95%) of correct RTs were estimated for each participant and for each condition per block or across blocks. The RTs for each condition and the Simon effects were then calculated for each percentile, as shown in Figs. 1 and 2. A repeated-measures ANOVA was performed on RT, with block, percentile, and location-based Simon as within-subject variables. Considering the way in which the RT data were

grouped, the percentile main effect on RT was significant in all analyses, so it is not reported and discussed.

The same correct RT data were fitted to the ex-Gaussian function for each participant in each condition across blocks by using an algorithm known as quantile maximum likelihood estimation (QMPE; Cousineau, Brown, & Heathcote, 2004; Heathcote, Brown, & Mewhort, 2002). Separate repeated-measures ANOVAs were performed on these parameters, with location-based Simon as a variable. The same analysis was used for each block, and then an ANOVA was performed with an additional variable block. The correlation of Simon effects on ex-Gaussian parameter values obtained from block 1 and those obtained from block 2 were also calculated.

A Monte Carlo study was then performed to evaluate whether the ex-Gaussian distribution fits well to empirical RT distributions indicated by delta plot and evaluate possible biases and estimate the standard deviation associated with the average of parameter estimates obtained for each participant in each condition across blocks.

Results

Mean PE and RT An analysis of variance (ANOVA) was separately performed on PE and RT, with block and location-based Simon (compatible, incompatible) as within-subject variables. The main effect of location-based Simon on PE

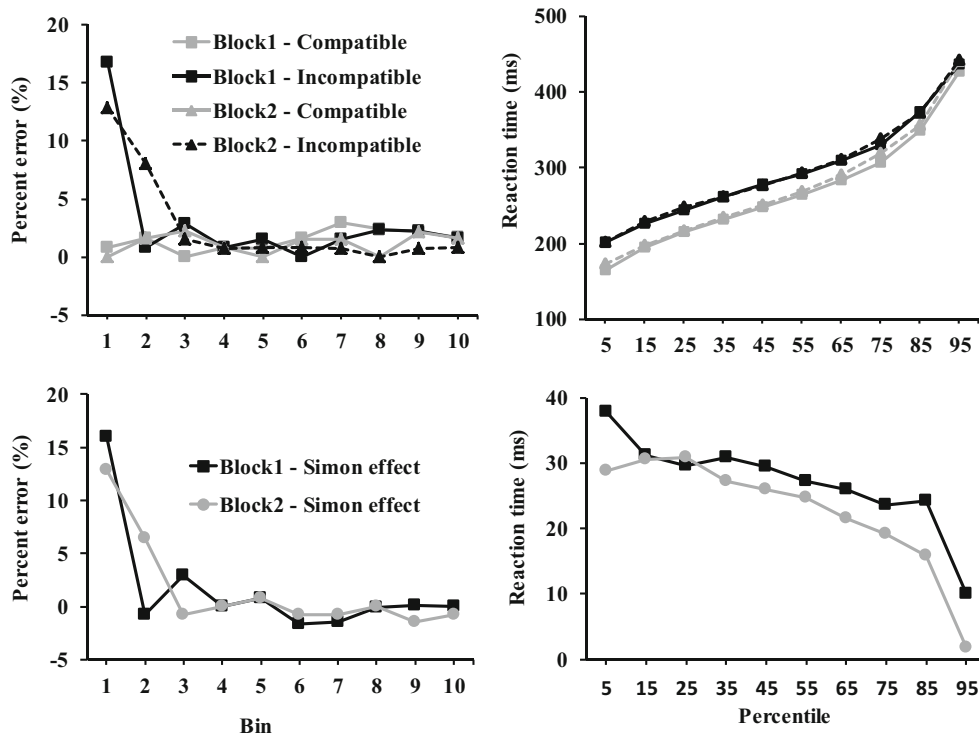


Fig. 1 Mean percent error (top left panel) and error Simon effect (bottom left panel) as a function of block and bin, and mean reaction time (top right panel) and reaction-time Simon effect (bottom right panel) as a function of block and percentile

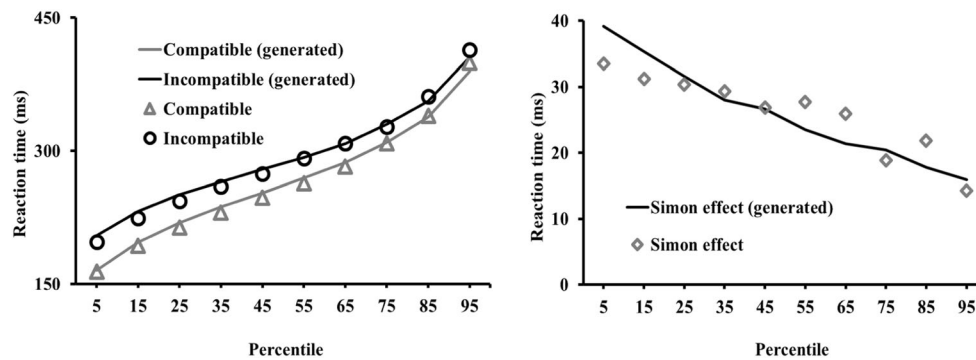


Fig. 2 Mean reaction time (ms) and Simon effect (ms) as a function of percentile for the raw data across blocks and the data generated by ex-Gaussian function with the parameters obtained from the raw data (left and right panels, respectively)

was significant, $F(1, 19) = 6.56$, $p = .019$, $MSE = .001$, $\eta_p^2 = .257$, with 1.3% and 2.9% response errors in the compatible and incompatible trials. There also was a main effect of location-based Simon on RT, $F(1, 19) = 25.84$, $p < .001$, $MSE = 466$, $\eta_p^2 = .576$, with faster responses on compatible trials (274 ms) than on incompatible trials (299 ms). The main effects of block on RT and PE were not significant, and neither was the interaction between block and location-based Simon ($F_s < 1$), which might be because the response speed did not become faster in the second trial block.

Bin analysis on PE A preliminary ANOVA was performed on PE, with block, percentile and location-based Simon (compatible, incompatible) as within-subject variables. This analysis showed neither a main effect of block ($F < 1$), an interaction between it and location-based Simon, $F(9, 171) = 1.63$, $p = .111$, $MSE = .004$, $\eta_p^2 = .079$, nor a three-way interaction between block, percentile and location-based Simon, $F(9, 171) = 1.16$, $p = .324$, $MSE = .004$, $\eta_p^2 = .058$. Therefore, we collapsed the variable block and performed an ANOVA on PE, with percentile and location-based Simon (compatible, incompatible) as within-subject variables. This two-factor ANOVA showed that the main effect of bin was significant, $F(9, 171) = 7.82$, $p < .001$, $MSE = .002$, $\eta_p^2 = .292$, due to more response errors in bin 1 than in the other bins ($ps < .006$) and in bin 2 than in bins 5 and 6 ($ps < .054$). The main effect of location-based Simon was also significant, $F(1, 19) = 6.74$, $p = .018$, $MSE = .003$, $\eta_p^2 = .262$, with 1.3% and 2.8% response errors on compatible and incompatible trials, as was the interaction between bin and location-based Simon, $F(9, 171) = 10.77$, $p < .001$, $MSE = .002$, $\eta_p^2 = .362$. Further analysis of this interaction showed that the Simon effect decreased linearly and quadratically from bin 1 to bin 10, $F(1, 19) = 21.06$, $p < .001$, $MSE = .009$, $\eta_p^2 = .526$; $F(1, 19) = 19.43$, $p < .001$, $MSE = .007$, $\eta_p^2 = .506$, as evident in the left panels of Fig. 1. From the other perspective, the effect of bin was not significant for the compatible condition ($F < 1$), but was for the incompatible condition, $F(9, 171) = 10.59$, $p < .001$, $MSE = .004$, $\eta_p^2 = .358$. Further analysis for the latter showed that PE

decreased linearly and quadratically from bin 1 to bin 10, $F(1, 19) = 20.41$, $p < .001$, $MSE = .006$, $\eta_p^2 = .518$; $F(1, 19) = 19.17$, $p < .001$, $MSE = .007$, $\eta_p^2 = .502$.

Percentile analysis on RT A preliminary ANOVA was performed on RT, with block, percentile, and location-based Simon (compatible, incompatible) as within-subject variables. This analysis showed neither a main effect of block ($F < 1$), an interaction between it and location-based Simon ($F < 1$), nor a three-way interaction between block, percentile and location-based Simon ($F_s < 1$). Therefore, we collapsed the variable block and performed an ANOVA on RT, with percentile and location-based Simon (compatible, incompatible) as within-subject variables. This analysis showed a main effect of location-based Simon, $F(1, 19) = 28.23$, $p < .001$, $MSE = 2,186$, $\eta_p^2 = .598$, reflecting a Simon effect of 25 ms. The interaction between percentile and location-based Simon was also significant, $F(9, 171) = 2.58$, $p = .008$, $MSE = 216$, $\eta_p^2 = .120$. Further analysis showed that the location-based Simon effect decreased linearly from the fifth to the 95th percentile, $F(1, 19) = 5.09$, $p = .036$, $MSE = 1,680$, $\eta_p^2 = .211$ (see Fig. 2, right panels), and the effect was not significant for the 10th percentile ($p = .473$), but was for the other percentiles ($ps < .015$).

Ex-Gaussian analysis The ex-Gaussian parameters for each condition and each block or across blocks are shown in Table 1. The Simon effects on the ex-Gaussian parameters almost equaled those obtained from each block, and equaled the average of those obtained from the two blocks. The analysis of paired t tests on these parameters from the data across blocks showed that the main effects of location-based Simon was not significant on σ (-10 ms), $t(19) = -1.48$, $p = .155$, or τ (-2 ms), $t(19) = -.16$, $p = .878$, but was significant on μ , $t(19) = 2.58$, $p = .018$, with a 30-ms Simon effect.

Repeated-measures ANOVAs were performed on the parameters for each condition, with block and location-based Simon (compatible, incompatible) as within-subject variables. The main effect of location-based Simon on μ was significant,

$F(1, 19) = 14.63, p < .001, MSE = 1,809, \eta_p^2 = .435$, reflecting a Simon effect of 36 ms, but the main effect of block and the interaction between them were not ($F_s < 1$). On σ , the main effects of block and location-based Simon (5 ms), and the interaction between them were not significant, $F(1, 19) = 1.46, p = .241, MSE = 465, \eta_p^2 = .071; F_s < 1$. Also, on τ , the main effects of block and location-based Simon (-12 ms), and their interaction were not significant, $F(1, 19) = 2.86, p = .107, MSE = 686, \eta_p^2 = .131; F(1, 19) = 2.03, p = .170, MSE = 1,450, \eta_p^2 = .097; F < 1$.

Correlations Table 2 shows the correlation coefficients of Simon effects on mean RT and ex-Gaussian parameters obtained from block 1 (mean1, μ_1, σ_1, τ_1) and block 2 (mean2, μ_2, σ_2, τ_2). The Simon effects on the parameters obtained from the same block were correlated with each other ($ps < .001$), but between blocks, only the effects on μ_1 and μ_2 were correlated, $r(20) = .613, p = .004$, but not on σ_1 and $\sigma_2, r(20) = .210, p = .374$, and not on τ_1 and $\tau_2, r(20) = .371, p = .107$. Given that $mean1 = \mu_1 + \tau_1$ and $mean2 = \mu_2 + \tau_2$, a partial correlation analysis, with μ_1 and μ_2 as controlling variables, showed that the Simon effect on τ was reliable, $r(16) = .827, p < .001$. In addition, the Simon effects on mean RT between blocks were correlated, $r(20) = .853, p < .001$, and the Simon effect on mean1 was correlated with $\mu_1, r(20) = .459, p = .042$, and the Simon effect on mean2 was correlated with μ_1 and $\mu_2, r(20) = .454, p = .044; r(20) = .689, p = .001$.

A Monte Carlo study The Monte Carlo study was performed using two sets of parameter values that were the averages of parameter values over blocks obtained for each condition, as shown in Table 1. For the compatible condition, the parameter values (μ, σ and τ) were 213 ms, 49 ms, and 53 ms, and for the incompatible condition, they were 242 ms, 39 ms, and 51 ms. For one test, we used the ex-Gaussian function with these parameters to generate 20 samples. Each sample includes 256 trials, half for compatible trials and the other half for incompatible trials. As with the raw data, we used these

Table 2 Correlation coefficients between the Simon effect on Mean1 and ex-Gaussian parameters (μ_1, σ_1, τ_1) obtained from block 1 and those (Mean2, μ_2, σ_2, τ_2) obtained from block 2

	Mean1	μ_1	σ_1	τ_1	Mean2	μ_2	σ_2
μ_1	.459*						
σ_1	.330	.704**					
τ_1	-.050	-.858**	-.626**				
Mean2	.853**	.454*	.279	-.014			
μ_2	.569*	.613**	.363	-.334	.689**		
σ_2	.195	.205	.210	-.108	.357	.742**	
τ_2	-.192	-.453*	-.297	.371	-.302	-.886**	-.839**

** $p < .001$; * $p < .050$

generated data to depict the delta plot. As shown in Fig. 2, the delta plots by the raw and generated data overlapped, indicating that the ex-Gaussian distribution fits well to empirical RT distributions indicated by the delta plot.

For the other test, for each of the two theoretical distributions, the Monte Carlo study was performed with sample sizes ($N = 16, 24, 32, 64, 128, 512, \text{ and } 1,024$). A Monte Carlo estimation of the sampling distribution was obtained for each sample size by sampling the theoretical distribution 1,000 times and performing a likelihood estimation of the parameters for each sample. Fourteen Monte Carlo simulations (two functions, Compatible and incompatible condition $\times 7$ sample sizes), each based on 1,000 samples, were performed.

For each of the two theoretical functions, the sampling distribution of each parameter was constructed for each sample size. Table 3 summarizes the results. For each sample size, the mean and standard deviation of the sampling distribution are presented along with a 95% confidence interval based on the observed percentile values of the distribution. Figure 3 shows the average estimated parameter values and standard deviations plotted according to sample size for each distribution. As is apparent in Table 3 and Fig. 3, the mean and standard deviation of the sampling distribution were close to the actual parameter values, indicating that they are unbiased estimators.

Table 3 Results of the Monte Carlo study. Mean estimated parameters (MEPs), standard deviations (SDs), and confidence intervals (CIs) for each theoretical distribution and sample size per condition

Sample size	Compatible condition		Incompatible condition	
	MEP (SD)	95% CI	MEP (SD)	95% CI
12	$\mu = 229$ (33) $\sigma = 35$ (27) $\tau = 38$ (33)	[174–278] [0–79] [4–97]	$\mu = 259$ (27) $\sigma = 29$ (24) $\tau = 35$ (30)	[215–303] [0–67] [3–87]
24	$\mu = 223$ (31) $\sigma = 44$ (27) $\tau = 45$ (35)	[175–268] [1–84] [5–105]	$\mu = 252$ (27) $\sigma = 35$ (24) $\tau = 42$ (32)	[212–294] [1–72] [5–93]
32	$\mu = 225$ (27) $\sigma = 42$ (23) $\tau = 42$ (31)	[183–267] [2–75] [5–90]	$\mu = 253$ (24) $\sigma = 33$ (20) $\tau = 40$ (28)	[218–293] [1–62] 4–80]
64	$\mu = 221$ (26) $\sigma = 46$ (20) $\tau = 46$ (30)	[184–262] [5–74] [6–91]	$\mu = 249$ (22) $\sigma = 37$ (18) $\tau = 44$ (26)	[220–287] [4–63] [5–80]
128	$\mu = 219$ (21) $\sigma = 49$ (14) $\tau = 47$ (25)	[191–257] [25–69] [6–81]	$\mu = 249$ (19) $\sigma = 40$ (13) $\tau = 44$ (23)	[226–285] [18–59] [5–73]
512	$\mu = 216$ (14) $\sigma = 49$ (8) $\tau = 50$ (16)	[200–250] [37–64] [9–70]	$\mu = 244$ (9) $\sigma = 39$ (7) $\tau = 48$ (11)	[233–262] [29–51] [28–63]
1024	$\mu = 214$ (8) $\sigma = 49$ (6) $\tau = 52$ (10)	[204–229] [41–59] [33–65]	$\mu = 243$ (6) $\sigma = 39$ (5) $\tau = 50$ (7)	[235–253] [33–47] [38–60]

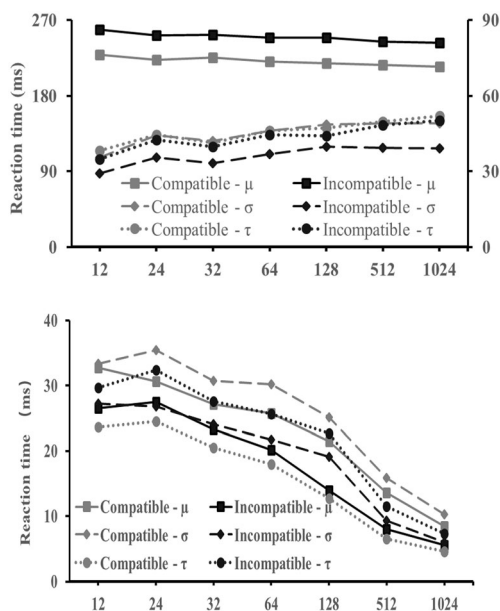


Fig. 3 Results of the Monte Carlo study: Mean estimated parameter values (top panel: the main coordinate axis for μ and the secondary coordinate axis for σ and τ) and standard deviations (bottom panel) for each sample size (12 to 1,024)

Discussion

Besides the delta plot, we provided more approaches to examine whether the ex-Gaussian distribution has a good fit to empirical RT distributions in the Simon task. For one approach, we examined whether there are reliabilities of ex-Gaussian analysis of Simon effects between trial blocks. Specifically, we fit the ex-Gaussian function to the RT data from each condition and each participant per block to obtain the ex-Gaussian parameters, and then calculated the between-block differences and correlations. For the other, we conducted a Monte Carlo study to evaluate (a) whether the ex-Gaussian distribution has a good fit to empirical RT distributions indicated by delta plot in the Simon task and (b) possible biases and estimate the standard deviation associated with the parameter estimates with an increase in sample size. The latter was to determine how many trials for each condition are needed to obtain a reliable estimation of ex-Gaussian parameters.

We observed a location-based Simon effect on PE. It decreased across bins 1 to 10 and was not modulated by block. As shown in Fig. 1, in the compatible condition PE is low across RT bins, whereas in the incompatible condition PE is usually high for the shorter RT bins and reduced as RT becomes longer. Moreover, as shown in Fig. 1, we obtained a Simon effect on RT, and it was reduced gradually as RTs became longer. These results replicate previous findings (Ansorge & Wühr, 2004; De Jong et al., 1994; Luo & Proctor, 2018a, 2018b), and they are compatible with both the activation-suppression theory (Ridderinkhof, 2002), according to which location-based automatic response priming

is actively suppressed, and the theory that asserts the automatic response priming passively decays over time (e.g., Hommel, 1993, 1994).

As displayed in Fig. 2, the delta plots produced by the raw and generated data did overlap, showing that the ex-Gaussian distribution fits well to empirical RT distributions indicated by delta plot. These results demonstrate that the ex-Gaussian distribution had a reliable, good fit to empirical RT-distributions in the Simon task.

Analyzing the parameters obtained from each condition and each participant showed a location-based Simon effect on μ , whereas the effects on σ and τ were not significant. These results, similar to previous findings by Luo and Proctor (2018a, 2018b), suggested that the Simon effect on ex-Gaussian parameters is in parallel with the RT distribution by delta plots.

As can be seen in Table 1, the Simon effect on each parameter was not different between blocks, suggesting that at the group level the Simon effect on each parameter was reliable. However, as shown in Table 2, correlation coefficients of Simon effects between blocks showed moderate correlation on μ (between 0.5 and 0.7), and they were not significant on σ and τ . Given that $\text{mean1} = \mu_1 + \tau_1$ and $\text{mean2} = \mu_2 + \tau_2$, a partial correlation analysis, with μ_1 and μ_2 as controlling variables, showed that the Simon effect on τ was reliable. These results imply that at the individual level the Simon effect on μ and τ is reliable, but is not on σ , which is similar to the findings in the Monte Carlo studies by Ratcliff (1979). That study found that in any practical use, the value of σ is likely to be underestimated and less reliable than the values of μ and τ . These results suggested that for ex-Gaussian analysis, making inferences based on group data is reliable, but based on individual data, making inferences is reliable on the parameters μ and τ .

As noted in the Monte Carlo study, the delta plots from the raw and generated data by ex-Gaussian function overlapped, indicating that the ex-Gaussian distribution fits well to empirical RT distributions indicated by the delta plot. Moreover, the sampling distributions show some small biases for smaller sample sizes. For the specific parameter values used in the study, the means of the sampling distribution do not appear strongly biased for sample sizes of 64 or more. For both of the ex-Gaussian distributions, the results of standard errors show a monotonic decrease with an increase in sample size. The decrease in standard deviation with increasing sample size is sharp up to sample size $N = 512$. The study shows that ex-Gaussian provides good parameter estimations for the ex-Gaussian function, at least, for the test values that were used.

In conclusion, the ex-Gaussian function fitted well to empirical RT distributions: (a) the delta plots by the raw and generated data by ex-Gaussian function could overlap, (b) as shown in the Monte Carlo study, ex-Gaussian parameters show some small biases for smaller sample sizes, and (c) these

ex-Gaussian parameters are reliable between two blocks at the group level and at the individual level μ and τ . The ex-Gaussian function provides a valuable tool for analyzing how conflicting irrelevant information affects performance in comparison to corresponding irrelevant information, and should be considered as an alternative tool for analyzing RT distributions in Simon-type tasks. Ex-Gaussian analysis can help researchers understand whether an increase of mean RT across different conditions or variables is due to an increase of skew of the RT distribution, a shift of the RT distribution, or both. Moreover, ex-Gaussian analysis is helpful for some situations in which RT may be affected by experimental manipulations that have no obvious effect on the mean RT, but on the RT distributions, generating an increase of skew of the RT distribution, a shift of the RT distribution, or both but with opposite directions.

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Compliance with ethical standards

Written consent was obtained from all participants prior to participation. The protocol was approved by the institutional review board (IRB) at the institute of psychology, Chinese Academy of Sciences.

Conflict of interest The authors declare that they have no competing interest.

References

- Ansorge, U., & Wühr, P. (2004). A response-discrimination account of the Simon effect. *Journal of Experimental Psychology: Human Perception and Performance*, *30*, 365–377.
- Balota, D. A., & Yap, M. J. (2011). Moving beyond the mean in studies of mental chronometry: The power of response time distributional analyses. *Current Directions in Psychological Science*, *20*, 160–166.
- Cousineau, D., Brown, S., & Heathcote, A. (2004). Fitting distributions using maximum likelihood: Methods and packages. *Behavior Research Methods, Instruments, & Computers*, *36*, 742–756.
- Davranche, K., & McMorris, T. (2009). Specific effects of acute moderate exercise on cognitive control. *Brain and Cognition*, *69*, 565–570.
- De Jong, R., Liang, C.-C., & Lauber, E. (1994). Conditional and unconditional automaticity: A dual-process model of effects of spatial stimulus-response correspondence. *Journal of Experimental Psychology: Human Perception and Performance*, *20*, 731–750.
- Ellinghaus, R., Karlbauer, M., Bausenhardt, K. M., & Ulrich, R. (2018). On the time-course of automatic response activation in the Simon task. *Psychological Research*, *82*, 734–743.
- Heathcote, A., Brown, S., & Mewhort, D. J. K. (2002). Quantile maximum likelihood estimation of response time distributions. *Psychonomic Bulletin & Review*, *9*, 394–401.
- Heathcote, A., Popiel, S. J., & Mewhort, D. J. K. (1991). Analysis of response time distributions: An example using the Stroop task. *Psychological Bulletin*, *109*, 340–347.
- Hommel, B. (1993). The relationship between stimulus processing and response selection in the Simon task: Evidence for a temporal overlap. *Psychological Research*, *55*, 280–290.
- Hommel, B. (1994). Spontaneous decay of response-code activation. *Psychological Research*, *56*, 261–268.
- Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: Cognitive basis for stimulus-response compatibility—A model and taxonomy. *Psychological Review*, *97*, 253–270.
- Kubo-Kawai, N., & Kawai, N. (2010). Elimination of the enhanced Simon effect for older adults in a three-choice situation: Ageing and the Simon effect in a go/no-go Simon task. *Quarterly Journal of Experimental Psychology*, *63*, 452–464.
- Logan, G. D. (1992). Shapes of reaction-time distributions and shapes of learning curves: A test of the instance theory of automaticity. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *18*, 883–914.
- Lu, C.-H., & Proctor, R. W. (1995). The influence of irrelevant location information on performance: A review of the Simon and spatial Stroop effects. *Psychonomic Bulletin & Review*, *2*, 174–207.
- Luo, C., & Proctor, R. W. (2017). How different location modes influence responses in a Simon-like task. *Psychological Research*, *81*, 1125–1134.
- Luo, C., & Proctor, R. W. (2018a). The location-, word- and arrow-based Simon effects: An ex-Gaussian analysis. *Memory & Cognition*, *46*, 497–506.
- Luo, C., & Proctor, R. W. (2018b). How different direct association routes influence the indirect route in the same Simon-like task. *Psychological Research*. <https://doi.org/10.1007/s00426-018-1024-5>
- Luo, C., & Proctor, R. W. (2019). Shared mechanisms underlying the location-, word- and arrow-based Simon effects. *Psychological Research*. <https://doi.org/10.1007/s00426-019-01175-5>
- Pratte, M. S., Rouder, J. N., Morey, R. D., & Feng, C. (2010). Exploring the differences in distributional properties between Stroop and Simon effects using delta plots. *Attention, Perception, & Psychophysics*, *72*, 2013–2025.
- Proctor, R. W., Miles, J. D., & Baroni, G. (2011). Reaction time distribution analysis of spatial correspondence effects. *Psychonomic Bulletin & Review*, *18*, 242–266.
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59–108.
- Ratcliff, R. (1979). Group reaction time distributions and an analysis of distribution statistics. *Psychological Bulletin*, *86*, 446–461.
- Reingold, E. M., Reichle, E. D., Glaholt, M. G., & Sheridan, H. (2012). Direct lexical control of eye movements in reading: Evidence from a survival analysis of fixation durations. *Cognitive Psychology*, *65*, 177–206.
- Ridderinkhof, K. R. (2002). Activation and suppression in conflict tasks: empirical clarification through distributional analyses. In W. Prinz & B. Hommel (Eds.), *Common mechanisms in perception and action*. Attention and Performance XIX (pp. 494–519). Oxford, UK: Oxford University Press.
- Schwarz, W., Miller, J. (2012). Response time models of delta plots with negative-going slopes. *Psychonomic Bulletin & Review*, *19*, 555–574.
- Simon, J. R. (1990). The effects of an irrelevant directional cue on human information processing. In R. W. Proctor & T. G. Reeve (Eds.), *Stimulus-response compatibility: An integrated perspective* (pp. 31–86). Amsterdam: North-Holland.
- Spieler, D. H., Balota, D. A., & Faust, M. E. (1996). Stroop performance in healthy younger and older adults and in individuals with dementia of the Alzheimer's type. *Journal of Experimental Psychology: Human Perception and Performance*, *22*, 461–479.
- Spieler, D. H., Balota, D. A., & Faust, M. E. (2000). Levels of selective attention revealed through analyses of response time distributions. *Journal of Experimental Psychology: Human Perception and Performance*, *26*, 506–526.
- Steinhauser, M., & Hübner, R. (2009). Distinguishing response conflict and task conflict in the Stroop task: evidence from ex-Gaussian

- distribution analysis. *Journal of Experimental Psychology: Human Perception and Performance*, 35, 1398.
- Tse, C. S., Balota, D. A., Yap, M. J., Duchek, J. M., & McCabe, D. P. (2010). Effects of healthy aging and early stage dementia of the Alzheimer's type on components of response time distributions in three attention tasks. *Neuropsychology*, 24, 300–315.
- Ulrich, R., Schröter, H., Leuthold, H., & Birngruber, T. (2015). Automatic and controlled stimulus processing in conflict tasks: superimposed diffusion processes and delta functions. *Cognitive Psychology*, 78, 148–174.
- Umiltà, C., & Nicoletti, R. (1990). Spatial stimulus-response compatibility. In R. W. Proctor & T. G. Reeve (Eds.), *Stimulus-response compatibility: An integrated perspective* (pp. 89–143). Amsterdam: North-Holland.
- Yamaguchi, M., & Proctor, R. W. (2012). Multidimensional vector model of stimulus–response compatibility. *Psychological Review*, 119, 272–303.
- Yap, M. J., Balota, D. A., Cortese, M. J., & Watson, J. M. (2006). Single-versus dual-process models of lexical decision performance: Insights from response time distributional analysis. *Journal of Experimental Psychology: Human Perception and Performance*, 32(6), 1324–1344.
- Zhang, H., Zhang, J., & Kornblum, S. (1999). A parallel distributed processing model of stimulus–stimulus and stimulus–response compatibility. *Cognitive Psychology*, 38, 386–432.

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