Journal of Experimental Psychology: General
2007, Vol. 136, No. 3, 414–429

0096-3445/07/$12.00 DOI: 10.1037/0096-3445.136.3.414

Individual Differences in Components of Reaction Time Distributions and Their Relations to Working Memory and Intelligence

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The authors bring together approaches from cognitive and individual differences psychology to model characteristics of reaction time distributions beyond measures of central tendency. Ex-Gaussian distributions and a diffusion model approach are used to describe individuals' reaction time data. The authors identified common latent factors for each of the 3 ex-Gaussian parameters and for 3 parameters central to the diffusion model using structural equation modeling for a battery of choice reaction tasks. These factors had differential relations to criterion constructs. Parameters reflecting the tail of the distribution (i.e., τ in the ex-Gaussian and drift rate in the diffusion model) were the strongest unique predictors of working memory, reasoning, and psychometric speed. Theories of controlled attention and binding are discussed as potential theoretical explanations.

Keywords: reaction time distributions, ex-Gaussian, EZ diffusion model, working memory, intelligence

The analysis of reaction time (RT) distributions has a long tradition in cognitive psychology (e.g., Hohle, 1965; Luce, 1986; Ratcliff, 1978). Repeatedly, characteristics of RT distributions beyond measures of central tendency have been hypothesized and shown to capture important aspects of human cognition (e.g., Heathcote, Popiel, & Mewhort, 1991; Spieler, Balota, & Faust, 2000). The use of mathematical models to describe RT distributions comprehensively and to connect their characteristics to theoretical models has proven fruitful. For a number of cognitive paradigms, different aspects of the shape of RT distributions have been shown to be differentially related to experimental manipulations (e.g., Andrews & Heathcote, 2001; Heathcote et al., 1991; Hockley, 1984; Hohle, 1965; Rohrer & Wixted, 1994; Spieler et al., 2000). This information is overlooked if only RT means or medians are considered.

In individual differences research, there is also a continuing interest in examination of RT distributions because of the robust—though not impressively high—correlations of RTs on seemingly simple tasks with measures of higher cognition, such as fluid or general intelligence. The theoretical reasons for this empirical link of simple task RTs to higher cognition, however, are not understood, despite a host of studies and theoretical propositions (for reviews, see Deary, 2000; Jensen, 1998a). It has been claimed that aspects of RT distributions beyond means or medians, for example RT variability, might carry important information regarding the relationship to intelligence (Jensen, 1992, 1993). The so-called *worst performance rule* (Larson & Alderton, 1990) denotes the replicated finding that the slower, and especially the slowest, response times of individuals are more strongly related to general intelligence than faster ones (for a review, see Coyle, 2003). Theoretical explanations of this phenomenon are based mainly on the idea that lapses of attention and/or working memory lead to longer RTs and that individuals of higher intelligence have generally better capacities of attention control, preventing such lapses (Jensen, 1992; Larson & Alderton, 1990; cf. Engle, 2002).

In this article, we sought to bridge these fields of research by (a) drawing theoretical connections between them, (b) parameterizing individual RT distributions with mathematical models, and (c) demonstrating that parameters that can be linked to the quality of information processing carry the main contribution in predicting constructs of higher cognition, in particular, working memory (WM) and reasoning. We achieved this using a multivariate ap-

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Florian Schmiedek is now also at Humboldt University at Berlin. This research was supported by German Research Foundation Grant Wi 1390/1–2.

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proach together with structural equation modeling (SEM) techniques with which one can overcome problems of parameter dependencies that one faces if using individually estimated model-based parameters. We first briefly review evidence regarding the connection of RTs from the tails of RT distributions to intelligence. This research can be linked to theories of controlled attention or goal maintenance (Duncan, Emslie, Williams, Johnson, & Freer, 1996; Engle, 2002; Kane & Engle, 2002) as the basis for WM and reasoning. Then, we discuss ex-Gaussian analyses for deriving parameters that comprehensively describe RT distributions of individuals. Subsequently, we use the diffusion model (Ratcliff, 1978; Ratcliff & Rouder, 1998) to show connections of the ex-Gaussian parameters to underlying cognitive processes. A problem of statistical parameter dependencies when one uses individually estimated parameters in a multivariate context is discussed next, together with a solution based on SEM procedures.

In the empirical part, we describe how this method allows the disentangling of latent factors of RT distribution components across a set of choice reaction tasks (CRTs). It is shown that the factor most likely to capture the evidence accumulation part of the decision process predicts WM performance, reasoning, and psychometric speed (PS) to a substantial degree.

Lines of Research on RT Distributions

The Worst Performance Rule

The worst performance rule states that the slowest RTs on a cognitive task are more strongly related to general intelligence than are the faster RTs. In a recent review, Coyle (2003) summarized empirical findings on this hypothesis and discussed theoretical accounts. The term *worst performance rule* was introduced by Larson and Alderton (1990). In their analyses, each individual's RTs were rank ordered from fastest to slowest. These ranked RTs were grouped into consecutive RT bands. The median RT of each band was correlated with measures of general intelligence, WM, and PS. The correlations linearly increased from the fastest (Spearman $r_s = -.20$, $-.21$, and $-.10$, for general intelligence, WM, and speed, respectively) to the slowest band ($r_s = -.37$, $-.36$, and $-.17$), indicating a stronger link to higher cognitive functioning for the slower parts of RT distributions.

Among the eight studies reviewed by Coyle (2003), seven supported the worst performance rule (the exception being a study by Salthouse, 1998). One theoretical account for these relations is that occasional lapses of attention guided toward the task or lapses in WM lead to slow RTs on a portion of trials. Individuals of lower intelligence are assumed to be more susceptible to such lapses. This attentional lapse account can be linked to theoretical considerations that propose WM as the key explanatory construct for general intelligence, as explained below.

A methodological limitation of the analyses supporting the worst performance rule is the use of separate RT bands. Given a limited total number of trials, often only relatively small numbers of trials can be used within each band, reducing the reliability of the estimates. If fluctuations of attention are seen as a continuous phenomenon—rather than a discrete one that only manifests in the slowest RTs and not so in all other RTs—it is preferable to extract information about slowed responses from the whole set of available RTs. This information is contained in the skewness of the RT distributions. Measured as the third-order moment of a distribution, however, skewness is not a very reliable measure either, being strongly influenced by outlying data points (Ratcliff, 1979). Ex-Gaussian analyses provide a preferable method of comprehensively describing RT distributions, as discussed in the following paragraph.

The Ex-Gaussian Model as a Descriptive Approach for Analyzing RT Distributions

A number of mathematical models can be used to describe RT distributions (Luce, 1986). A prominent distribution in the cognitive literature is the ex-Gaussian, which results from a convolution of a Gaussian and an exponential distribution. It has repeatedly been found to provide a good fit to empirical RT data from a number of different paradigms (e.g., Heathcote et al., 1991; Hockley, 1984; Mewhort, Braun, & Heathcote, 1992; Ratcliff, 1979). The ex-Gaussian distribution is characterized by three parameters: μ and σ, reflecting the mean and standard deviation of its Gaussian part, and τ, reflecting the exponential part. The mean of the total distribution is simply the sum of μ and τ. The overall variance is the sum of σ^2 and τ^2. The skewness—measured as the third central moment—of the combined distribution is $2\tau^3$. Although μ characterizes the leading edge of the distribution, τ is more strongly related to the thickness of its tail and overall skewness. With a τ of zero, the distribution would be symmetric. However, τ is a more reliable measure of skewness than is the third central moment (Ratcliff, 1979). A particular strength that one gains in using the τ parameter to characterize the comparatively longer RTs in the tail of the RT distribution is that it integrates information from all RTs—as compared with splitting the tail into bins, as is done in most analyses testing the worst performance rule. If attention fluctuations are seen as a probabilistic phenomenon with varying durations of attentional lapses, a qualitative distinction between "normal" and attention lapse RTs obtained through splitting up the RT distribution at some arbitrary point is not a desirable option. Therefore, τ seems to be a good candidate to capture attention fluctuations.

A theoretical interpretation of the ex-Gaussian parameters is not straightforward. From early on, there has been the idea that the Gaussian component reflects more peripheral sensory–motor and automatic processes and the exponential component more central, controlled, and decision-related processes (Hohle, 1965; but see Luce, 1986, for a discussion). This idea has guided the interpretation of findings in several studies (e.g., Gordon & Carson, 1990; Madden et al., 1999; Rohrer & Wixted, 1994). Further support for the idea that the exponential component is more related to attention-demanding processes comes from individual differences studies comparing groups of participants who can be hypothesized to differ in attention capacities. In studies comparing different age groups (Spieler, Balota, & Faust, 1996; West, Murphy, Armilio, Craik, & Stuss, 2002) and children with and without a diagnosis of attention-deficit/hyperactivity disorder (Leth-Steensen, Elbaz, & Douglas, 2000), the τ parameter has been found to discriminate best among groups, especially in tasks involving executive control demands.

To summarize, the ex-Gaussian model provides a parsimonious and usually well-fitting description of RT distributions. Even though its parameters do not have a direct theoretical interpretation, it makes sense to link the τ parameter to fluctuations of attention at a more coarse level of cognitive processes. One might shed some further light on the interpretation of these parameters by linking them to a prominent theoretical processing model of CRTs, as we do in the section on links to the diffusion model.

Theoretical Links of RT Distribution Parameters to WM and Attention

WM has been shown repeatedly to be highly correlated with reasoning (e.g., Engle, Tuholski, Laughlin, & Conway, 1999; Kyllonen & Christal, 1990; Süβ, Oberauer, Wittmann, Wilhelm, & Schulze, 2002). Engle, Kane, and their colleagues have argued that the capacity of WM reflects the ability to control attention, that is, to maintain information active in the presence of interference (e.g., Conway, Kane, & Engle, 2003; Engle, 2002; Kane & Engle, 2002). Applied to CRTs, this could mean that occasional distraction by external or internal events leads to lapses of attention, in particular if WM capacity is low. Along similar lines, Duncan et al. (1996) proposed that intelligence is related to the ability to maintain goals in an active state so that they influence behavior. Low intelligence, they argued, is associated with occasional goal neglect in situations involving strong distraction. A less severe form of goal neglect would be a temporary lapse of attention, resulting not in an omission but a delay of action.

These theoretical approaches, therefore, converge on the prediction that low WM capacity and low reasoning ability are associated with a higher probability of temporary interruptions in information processing on a subset of trials, which could be called lapses of attention. Such lapses on some trials result in a more extended tail of the RT distribution, whereas the speed of the remainder of trials is largely unaffected, so that the leading edge of the distribution should be less correlated to WM and intelligence.

Theoretical Links of RT Distributions to the Diffusion Model

Another approach to theoretically interpreting the parameters of the descriptive ex-Gaussian model is through their links with theoretical models of RTs. The most successful among these models so far is the diffusion model (e.g., Ratcliff & Rouder, 1998; Ratcliff & Smith, 2004). Its major strengths are the applicability to a wide range of two-choice tasks (e.g., brightness discrimination, signal detection, letter discrimination, lexical decision, and recognition memory) and the fact that it provides a theoretical basis as well as good empirical fit for all aspects of RT data, including accuracy and the shapes of distributions for correct and error RTs.

The diffusion model belongs to the class of random walk models and assumes continuous accumulation of information over time. Information accumulation begins at a starting point and continues until total information accumulated reaches one of two boundaries, resulting in a positive or negative response. Central parameters of the diffusion model are the response criterion and the drift rate. The response criterion, a, defines the separation of the response boundaries around the starting point. More conservative response criteria imply that more information needs to be accumulated in favor of one of the response alternatives before a response is made. The drift rate, ν, is the mean rate at which the decision process approaches a boundary. It characterizes the quality of evidence accumulation and can be influenced by stimulus characteristics as well as by individual differences in processing efficiency. Other parameters in the model are the combined nondecision components of RT, T_{er}, and trial-to-trial variability in starting point, nondecision time, and drift rate. These variability parameters allow for important characteristics of the model, like accounting for complex interactions of correct and error RTs (Ratcliff & Rouder, 1998).

Regarding the shape of correct RT distributions, which is the focus of the present article, links of the diffusion model parameters to characteristics of RT distributions can be made. The geometry of the diffusion process predicts that differences in the response criterion primarily affect the leading edge of the distribution, which is strongly linked to the μ parameter in the ex-Gaussian model. Differences in drift rate more strongly influence slower RTs, leading to more skewed distributions for smaller drift rates, which are captured primarily by the τ parameter. Using simulations, Spieler (2001) showed that of the three ex-Gaussian parameters, τ is most strongly related to the drift rate, with faster drift rates leading to smaller estimates of τ. Changes in the response criterion were primarily reflected in the μ parameter, with more conservative criteria being related to larger estimates of μ.

Even though the picture obviously becomes more complex once the other diffusion model parameters are taken into account, for our present purpose the above considerations provide a connecting link between the diffusion model and ex-Gaussian analyses of empirical RT data. It can be expected that μ should correlate positively with observed accuracy across persons, because individual differences in response criterion setting are related to both. For σ, it is difficult to derive hypotheses about potential correlates, but we can make clear predictions for the τ parameter. The drift rate, which characterizes the quality of decision-related information processing, is most strongly related to τ among the ex-Gaussian parameters. If we assume that the efficiency of information processing in simple two-choice decisions is related to the efficiency of information processing in more complex tasks, this leads to the prediction that the τ parameter should be correlated more strongly than the other ex-Gaussian parameters with measures of WM and reasoning. The τ parameter also can be expected to correlate negatively with accuracy across individuals, because higher drift rates are also associated with a higher probability of the diffusion process reaching the correct response boundary.

Obviously, the most preferable way of investigating the correlation of diffusion model parameters and measures of higher cognition would be to directly estimate these parameters for each individual. Obtaining reliable estimates, however, would require very large numbers of RTs for each participant, much larger than those available in the study from which data are analyzed in this article. Therefore, we used two different ways to approach the diffusion process. One was to use the indirect links of ex-Gaussian parameters to diffusion model parameters discussed above. The other was to make use of recent results by Wagenmakers, van der Maas, and Grasman (in press), who showed that parameters of a simplified version of the diffusion model, which they called the *EZ-diffusion model*, can be directly calculated in closed form from empirical data. The EZ-diffusion model has only three parameters:

drift rate, boundary separation, and nondecision time. The corresponding trial-to-trial variability parameters are dropped from the model. Even though these are nontrivial constraints, particularly if one wants to draw links to theories of attentional lapses, the EZ-diffusion model allows one to make a more direct estimation of theoretically meaningful parameters from RT distributions than using ex-Gaussian parameters as proxies. We therefore computed EZ-diffusion parameters and related them to WM and intelligence. The main goal of this endeavor was to investigate whether individual differences in drift rate are sufficient to explain the relation of the τ parameter to WM and intelligence. We tested this hypothesis via a simulation study that is based on the results from the empirical study.

In summary, two lines of theoretical reasoning lead to the same prediction: Common variance of τ parameter estimates across a set of cognitive tasks should carry most of the relation between performance on CRTs of trivial difficulty and measures of higher cognition, such as WM. The first line of reasoning derives from theoretical considerations concerning the role of WM in CRTs. This role has been hypothesized to lie in the control of attention to resist distraction (Engle, 2002; Kane & Engle, 2002) or the maintenance of goals (Duncan et al., 1996). These hypotheses converge on the expectation that the τ component is most important because fluctuations of processing that result from low WM capacity should lead to more skewed RT distributions even on very simple tasks. Engle, Kane, and colleagues see control of attention as a domain general ability involved in WM tasks from different content domains (Kane et al., 2004) as well as in various interference tasks (for a review, see Kane & Engle, 2002) and as a mediator of the link between WM and reasoning (Engle et al., 1999). Therefore, it can be hypothesized that the common variance of the τ parameter across a set of tasks should have a particularly strong relation to WM and reasoning.

The second line of reasoning derives from the diffusion model for two-choice decision tasks and predicts that of the three ex-Gaussian parameters, τ should relate most strongly to measures of higher cognition because it is predominantly reflecting the drift rate and therefore the quality of evidence accumulation. Assuming that this aspect of quality of information processing in simple choice tasks is related to capacity limits on more complex tasks, one is led to the expectation that τ should be at least moderately correlated with measures of WM capacity and reasoning. If that turns out to be the case, the interesting question is whether such a relatively simple account, which does not invoke the concept of attentional lapses, might be sufficient to fully account for the relation of τ to WM, which is the essence of the worst performance rule. Ratcliff, Schmiedek, and McKoon (in press) have shown with simulations that individual differences in drift rate can produce the worst-performance-rule pattern, whereas individual differences in boundary separation or nondecision time cannot account for it. One of our important goals in the present work was to investigate whether such a drift rate account is indeed sufficient to explain the relation of RT distribution characteristics to WM and intelligence in empirical data. We pursued this goal with the following steps. First, we showed that the τ parameter contributes most strongly and uniquely to the prediction of WM and intelligence, a finding that could be explained by lapses of attention as well as by a drift rate account. Second, we used the EZ-diffusion model and simulations based on empirical results to show that a drift rate account indeed is sufficient to explain the strong relation of τ to WM and intelligence. The drift rate account is theoretically simpler because it uses only concepts that are independently motivated—drift rate and WM capacity—whereas the attentional-lapse account requires an additional concept, lapses of attention, to mediate between RT distributions and concepts of higher order cognition such as WM capacity or goal neglect.

A necessary precondition for showing differential correlations of the ex-Gaussian parameters, however, is to show that the different parameters capture reliable and, to some degree, independent information about individual differences. If the parameters reliably capture distinct and basic characteristics, it should be possible to show common variance of those parameters across a set of cognitive tasks. From a factor analytic perspective, separate common factors of μ, σ, and τ parameters should be identifiable. A demonstration of such factors was another of our major goals in this article. The same applies to the parameters of the EZ-diffusion model. To the degree that they reflect individual differences in general underlying processes, common factors should be identifiable. If we identify separable factors for the three parameters, our primary interest becomes how strongly the drift rate factor is related to WM and intelligence.

Earlier attempts to link ex-Gaussian parameters to intelligence have led to mixed results. Although Blanco and Alvarez (1994) reported differences in the τ parameter of a flanker task between groups of participants who were low and those who were high in general intelligence, Juhel (1993) did not find significant correlations between ex-Gaussian parameters of a discrimination task and intelligence. Use of only single tasks and insufficient consideration of statistical dependencies between the ex-Gaussian parameters, however, are severe limitations of these studies. This technical issue will be addressed next.

The Problem of Parameter Dependency

When parameters are estimated for individual subjects' data and are used consecutively for correlational analysis in an individual differences context, statistical dependencies among the parameters become an issue. Statistical relations among parameters that result from the functional form of the model lead to correlations among estimated parameters. This has been recognized as a problem for the interpretation of parameter estimates, for example, of individually estimated linear regression parameters (Jensen, 1998b; Valentine, Wilding, & Mohindra, 1984), the diffusion model (Ratcliff & Tuerlinckx, 2002), and also the ex-Gaussian model (Spieler et al., 2000, Footnote 3). The statistical dependencies arise from trade-offs between parameter estimates in the data-fitting procedure that introduce correlated deviations of these estimates from the true values of the parameters. The observed correlations among the ex-Gaussian parameters are, therefore, a combination of true relations and statistical dependencies, which introduce correlated errors. The statistical dependencies of ex-Gaussian parameters are positive for μ and σ and negative for μ and τ and for σ and τ, respectively, as shown in Appendix A. This affects all further multivariate analyses in which these correlations are used as information, such as regression analysis, factor analysis, or SEM. In regression analysis, for example, the relative contribution of the three ex-Gaussian parameters for predicting an external criterion cannot be determined unambiguously because regression weights take the correlations among predictor variables into account.

A potential solution to this problem is based on a multivariate approach using SEM. This approach requires multiple tasks that represent a common construct. Then, one can model μ, σ, and τ as common factors of the μ, σ, and τ parameter estimates of the individual tasks, while at the same time allowing for correlated errors for the three parameters within tasks. These correlated errors account for the statistical dependencies. The latent factors only capture what is common to the same ex-Gaussian parameter across separate tasks and therefore are free from statistical dependencies. Appendix B provides more detailed information on this approach. For the EZ-diffusion model, parameter dependencies are less of a problem because parameters do not have to be estimated but are directly calculated from empirical moments and accuracies. As additional simulations not reported here showed, simulating data according to an EZ-diffusion model with true parameters being uncorrelated across individuals results in uncorrelated recovered EZ-diffusion parameters.

Overview of Study and Hypotheses

In the empirical part of this article, we used data from a study on individual differences in WM and psychometric intelligence (Oberauer, Süβ, Wilhelm, & Wittmann, 2003) to test the hypotheses summarized below. This study included eight different two-choice RT tasks, allowing us to conduct multivariate analyses of ex-Gaussian parameters estimated separately for each task. Because the sample size of the study was large enough to conduct SEM, it was possible to disentangle correlated estimation error from common variance of ex-Gaussian parameters across experimentally independent and different tasks. The latent factors modeling this common variance were capturing task-general aspects of the ex-Gaussian parameters and therefore allowed us to examine how such general aspects of RT distributions relate to constructs of higher cognition. The study includes comprehensive measurements of WM (six marker tasks), reasoning (nine tasks), and PS (nine tasks).

Our hypotheses were, first, that the ex-Gaussian parameter estimates should show substantial loadings on their respective common latent factors. That is, the different ex-Gaussian parameters should measure an aspect of individual differences that is, to some degree, generalizable across different tasks. Second, factors for the μ, σ, and τ parameters should be separable but positively correlated. Third, the μ factor should correlate positively with overall task accuracy because differences in response criterion setting primarily lead to shifts of the leading edge of the RT distribution—reflected by μ. Fourth, the τ factor should correlate negatively with WM and reasoning, implying better performance for smaller estimates of τ, and should have the strongest regression weight for the prediction of both constructs, relative to the other factors. Furthermore, the τ factor should correlate negatively with accuracy across individuals. Regarding PS, we did not have any specific hypotheses on correlations with individual parameters.

For the EZ-diffusion parameters, we were expecting that common factors for each parameter should be identifiable. For drift rate, a common factor would indicate that individual differences in the quality of information accumulation generalize across different tasks, which should be an important source of the observed positive correlations between mean RTs of different CRTs. A common factor for the nondecision components would reflect individual differences in sensory and motor components that generalize across tasks, which also should be expected, given that all tasks were visual tasks administered within the same computerized setup and required manual responses on the same response keys. For boundary separation, identification of a common factor would indicate individual differences in response criterion setting that are, to some degree, general across tasks. Given that response criteria should at least partly be influenced by personality characteristics, this seemed a reasonable assumption.

We expected positive correlations of the drift rate factor with PS because of the simple decision processes involved. Because of the different sensory and particularly motor requirements of paper-and-pencil PS and computerized CRTs, a nondecision component factor should show a much weaker relation to PS. To the degree that efficient decision processes in two-choice RT tasks reflect a source of variance that also determines efficient information processing in higher order cognitive tasks, a drift rate factor should also be correlated positively to the factors of WM and reasoning.

Method

Participants and Procedure

The original sample consisted of 135 students and other participants from the University of Mannheim who received 80 DM (~U.S. $50) for participation. The mean age of the sample was 25.8 years ($SD = 3.8$); 44% were women. Because of missing data on at least four of the CRTs, 4 subjects were excluded from the analyses. Groups of about 10 participants were tested in two sessions of 4.5 hr each, separated by 2–4 weeks.

Choice Reaction Time Tasks

Eight different CRTs were conducted. For each CRT, there were five blocks of 16 trials, resulting in a total of 80 RTs. Participants were instructed to decide about each stimulus as quickly as possible by pressing one of two keys on the left side and the right side of the computer keyboard, respectively. The assignment of stimulus categories to the response keys was displayed continuously in the upper third of the screen.

> CRT 1: In this verbal classification task, single words were presented on the screen, and participants had to classify them into the categories of plant or animal.
>
> CRT 2: In the second verbal classification task, participants had to decide whether words had one or two syllables. The words were distinct from the words used in CRT 1.
>
> CRT 3: In this quantitative task, three-digit numbers were presented at the center of the screen. Participants had to classify them as odd or even.
>
> CRT 4: In the second quantitative task, again three-digit numbers were presented, and participants had to decide whether they were smaller or larger than 500.
>
> CRT 5: In this spatial task, participants had to decide whether an arrow displayed at the center of the screen was pointing

upward or downward. Arrows were either pointing in a direction between 300° and 60° (upward) or in a direction between 120° and 240° (downward).

CRT 6: In the second spatial task in which arrows were stimuli, participants had to decide whether arrows were displayed in the upper or lower half of the screen. The sequence of arrows was distinct from the sequence applied in CRT 5.

CRT 7: In this spatial task, participants saw 3 × 3 grids with individual cells either filled or not filled. Participants had to decide whether the filled area was one coherent area or two areas. A pattern had to be classified as one area if each filled cell shared at least one side with another filled cell.

CRT 8: In the second task with 3 × 3 grids, participants had to decide whether the patterns were symmetrical along a vertical or horizontal axis. The sequence of patterns was distinct from the sequence applied in CRT 7.

WM and Intelligence Tasks

Six WM marker tasks were used in the study. These were variants of the reading span (Daneman & Carpenter, 1980), computation span (Turner & Engle, 1989), spatial short-term memory (Oberauer, 1993), spatial coordination (Oberauer, 1993), memory updating spatial, and memory updating numerical (Oberauer, Süβ, Schulze, Wilhelm, & Wittmann, 2000; adapted from Salthouse, Babcock, & Shaw, 1991) tasks. Further information on these tasks is given in Oberauer et al. (2000). A latent factor of the tasks was used as a comprehensive measure of WM. In the measurement model of this factor, correlated residuals (based on modification indices) for reading span and computation span tasks were included. Those two tasks share very similar demands and differ only in having verbal versus numerical content.

Reasoning and PS were each measured with nine paper-and-pencil tasks of the Berlin Structure of Intelligence Test (Jäger, Süβ, & Beauducel, 1997, and Süβ & Beauducel, 2005). Those tasks were aggregated into three parcels of one numerical, figural, and verbal task each and then modeled as latent factors, with these parcels as indicator variables.

Analyses and Outlier Identification

We conducted ex-Gaussian analyses using the quantile maximum probability estimator QMPE (Version 2.18; Cousineau, Brown, & Heathcote, 2004; Heathcote, Brown, & Mewhort, 2002). Only correct RTs were used for these analyses. RT outliers were identified by an iterative procedure based on individual RT distributions. For each participant and each task, RTs faster than 200 ms and slower than four individual standard deviations above the individual mean were defined as outliers. These outliers were deleted, and the procedure was repeated until no further outliers were detected. Careful visual inspection of all individual RT distributions indicated that this definition of cutoff values was the best compromise between discarding RTs that clearly were far apart from the rest of the distribution on the one hand and not cutting into the tail of the distributions on the other hand. An average of fewer than one RT per task and participant was excluded. With the exception of 1 participant, who had 17 outlying RTs in one task, the maximum number of discarded RTs was four. On average, 75.1 RTs were available per individual and task. In 98.5% of the individual/task combinations, at least 60 correct RTs were available, and in 92.0% at least 70 correct RTs were available.

As shown in Table 1, accuracies were high on all tasks. Raw accuracies were subjected to a probit transformation. This transformation is based on the assumptions that the psychological construct underlying performance accuracy is normally distributed and that the observed accuracies correspond to the cumulative normal distribution. In the present data, this transformation was very much linear up to accuracies of .90 but stretched out individual differences in accuracy between .90 and 1.00. This made the skewed accuracy distributions much more normal, as normal-quantile and normal-probability plots indicated. For perfect accuracies, we used adjusted values according to Cohen and Cohen (1983). Compared with other often-used transformations for accuracy data, like the arcsine or the logit transformations, the stretching effect of the probit is intermediate.

Regarding interindividual differences in the ex-Gaussian parameter estimates, outliers were defined in just the same way as for the intraindividual RT distributions. Each task and each parameter

Table 1
Mean Values (Between-Person Standard Deviations) of Intraindividual Reaction Time (RT) Means; RT Standard Deviations; Accuracies; Ex-Gaussian Parameters of μ, σ, and τ; and EZ-Diffusion Parameters of υ, a, and T_{er} for the Eight Choice Reaction Tasks (CRTs)

Choice reaction task	*M*	*SD*	Accuracy	μ	σ	τ	Drift rate (υ)	Boundary separation (*a*)	Nondecision time (T_{er})
CRT1	678 (98)	175 (90)	.95 (.05)	530 (58)	52 (20)	146 (65)	.26 (.08)	.14 (.04)	431 (64)
CRT2	637 (135)	169 (99)	.96 (.04)	482 (62)	50 (22)	145 (83)	.28 (.09)	.13 (.04)	398 (56)
CRT3	553 (69)	132 (42)	.96 (.03)	432 (44)	49 (17)	121 (55)	.30 (.07)	.12 (.03)	350 (47)
CRT4	511 (59)	110 (33)	.97 (.03)	410 (44)	43 (15)	100 (37)	.34 (.06)	.11 (.02)	345 (39)
CRT5	434 (62)	113 (37)	.95 (.04)	324 (44)	34 (14)	110 (37)	.31 (.07)	.11 (.02)	272 (37)
CRT6	469 (53)	112 (36)	.94 (.06)	366 (38)	40 (16)	101 (41)	.30 (.08)	.11 (.02)	306 (38)
CRT7	676 (110)	172 (77)	.94 (.05)	517 (60)	62 (25)	155 (80)	.25 (.07)	.13 (.03)	423 (66)
CRT8	824 (223)	287 (174)	.92 (.08)	552 (67)	59 (30)	260 (167)	.20 (.09)	.15 (.04)	431 (83)

Note. Because outlying subjects were determined independently for different parameters, the number of subjects for different entries of this table range from 124 to 131. μ = mean of the Gaussian distribution; σ = standard deviation of the Gaussian distribution; τ = exponential distribution.

data were treated as missing for participants whose estimated value was beyond the mean plus or minus four standard deviations of the individual differences distributions. This resulted in a total of 21 of 3,144 data points (131 participants × 8 tasks × 3 parameters) being set to missing for the analyses. We conducted SEM analyses with Mplus (Version 3.12, Muthén & Muthén, 2004) using raw data maximum likelihood estimation procedures to allow for parameter estimation, including the few participants with outlying values set to missing.

We calculated the EZ-diffusion parameters using the equations given in Wagenmakers et al. (in press). Means and variances of correct RTs, together with accuracies, were sufficient to recover the diffusion model parameters under the assumptions that trial-to-trial variability is zero and that the starting point is equidistant from the response boundaries. Outliers of the EZ-diffusion parameters were identified with the same procedure as for the ex-Gaussian parameter estimates. In addition, T_{er} values smaller than 100 ms were treated as outliers. All together, this procedure resulted in 19 of the 3,144 data points being set to missing.

Results

Descriptives of Ex-Gaussian and EZ-Diffusion Parameters

Table 1 shows the means, standard deviations, accuracies, and mean estimates of the ex-Gaussian and EZ-diffusion parameters for the eight CRTs. For all tasks, mean RT, which is the sum of μ and τ, is explained primarily by μ, whereas RT variance, which is the sum of σ^2 and τ^2, is dominated by τ. Across tasks, more difficult tasks, as defined by larger mean RTs, are characterized by lower average drift rates but also by more conservative criterion settings and slower nondecision times.

Ex-Gaussian Measurement Model

The initial model that we tested was a confirmatory factor analysis with correlated μ, σ, and τ factors. Each ex-Gaussian parameter estimate from the eight tasks loaded only on its corresponding factor. Correlations were allowed for the three pairs of error terms within each task. The fit of this initial model was acceptable, $\chi^2(225) = 341.3$, root-mean-square error of approximation (RMSEA) = .06, comparative fit index (CFI) = .89, standardized root-mean-square residual (SRMR) = .09. In comparison, a model without correlated residuals within tasks did have a bad fit, $\chi^2(249) = 766.8$, RMSEA = .13, CFI = .52, SRMR = .10, indicating the necessity of accounting for the statistical dependencies between the ex-Gaussian parameters.[1]

Because pairs of tasks had the same stimulus content material, such pairs were more similar to each other than to the remaining tasks. This overlap of stimulus and task features made it necessary for us to also allow for correlations between the corresponding ex-Gaussian parameter residuals of some of the tasks with the same stimulus material. Using modification indices, we introduced correlations among the μ residuals of CRT 3/CRT 4 and CRT 5/CRT 6. This improved the fit significantly, $\Delta\ \chi^2(2) = 27.0$, $p < .001$. In the next step, we also introduced a correlation for the CRT 5/CRT 6 pair of τ residuals, again improving fit significantly, $\Delta\ \chi^2(1) = 15.1$, $p < .001$. Model fit could not be improved further by correlations of σ residuals. Therefore, the model with three correlated residual terms was accepted as the final measurement model for further analyses. The fit of this model was satisfactory, $\chi^2(222) = 299.1$, RMSEA = .05, CFI = .93, SRMR = .09.

Table 2 shows the standardized factor loadings and the correlations of error terms within tasks. Factor loadings were substantial for the μ and τ factors and more heterogeneous for the σ factor. On average, 43% of the variance in μ, 14% of the variance in σ, and 26% of the variance in τ could be explained by the common factors.

After having shown that the common factors for each ex-Gaussian parameter explained a substantial amount of variance for the different tasks, we could interpret the resulting factor correlations as reflecting the relationship among different aspects of RT distributions, uncontaminated by parameter dependencies. As shown in Figure 1, these correlations were .46 for the μ and σ factors, $\Delta\ \chi^2(1) = 15.8$, $p < .001$; .51 for the μ and τ factors, $\Delta\ \chi^2(1) = 22.7$, $p < .001$; and .75 for the σ and τ factors, $\Delta\ \chi^2(1) = 33.4$, $p < .001$. These positive correlations indicated that faster responses were associated with less variability and less skewness of RT distributions. However, the correlations were far from unity, therefore also proving that the three ex-Gaussian parameters captured separate aspects of individual differences in RT distributions. In Appendix C, a simulation study based on the presented empirical factor structure of the ex-Gaussian parameters shows that modeling their relations with the proposed SEM approach allows the true correlation values to be recovered.

Relations of Ex-Gaussian Parameters to Accuracy

The fit of the measurement model that included an additional factor for accuracies was satisfying, $\chi^2(407) = 564.5$, RMSEA = .05, CFI = .91, SRMR = .09. Loadings on the accuracy factor were all significant and of substantial to strong magnitude, with values ranging from .46 to .81. Correlations with the accuracy factor were .49 for μ, $\Delta\chi^2(1) = 24.9$, $p < .001$; $-.11$ for σ, $\Delta\chi^2(1) = 0.9$; and .02 for τ, $\Delta\chi^2(1) = 0.0$. Therefore, the only significant relation was found between the μ factor and accuracy.

Relations of Ex-Gaussian Parameters to Criterion Constructs

Working memory. Correlations of the μ, σ, and τ factors with the WM factor were $-.36$, $-.43$, and $-.72$, respectively. All three correlations were significant, as shown by the decreases of fit resulting from their elimination from the model (Table 3). In a latent regression model, only the τ factor had a significant and strong regression weight of $-.90$ (Figure 2A). The two models were mathematically equivalent and therefore had identical fit indices. This fit was acceptable, $\chi^2(371) = 530.9$, RMSEA = .06,

[1] The strength of the potential influence of the statistical interdependencies among ex-Gaussian parameters in the present empirical data could be estimated by averaging the estimated parameter correlations, as provided by the QMPE program, across individuals and tasks. The average estimated parameter correlations were .61 for the μ and σ, $-.64$ for the μ and τ, and $-.46$ for the σ and τ parameter estimates. The average observed correlation between the parameter estimates, which were .36 for the μ and σ, .02 for the μ and τ, and $-.15$ for the σ and τ parameters, therefore have to be expected to be influenced to a large degree by statistical dependencies.

Table 2
Factor Loadings and Correlations of Residuals of the Ex-Gaussian Parameters

Choice reaction task	Parameter	Factor loading μ	Factor loading σ	Factor loading τ	Residual correlation μ	Residual correlation σ
1	μ	.60				
	σ		.28		.33	
	τ			.47	.05	−.24
2	μ	.70				
	σ		.26		.39	
	τ			.58	.17	.03
3	μ	.65				
	σ		.35		.46	
	τ			.52	−.05	−.22
4	μ	.73				
	σ		.67		.23	
	τ			.55	−.17	−.25
5	μ	.60				
	σ		.45		.42	
	τ			.60	.03	.00
6	μ	.69				
	σ		.33		.24	
	τ			.39	−.14	−.32
7	μ	.66				
	σ		.33		.45	
	τ			.54	−.05	−.08
8	μ	.64				
	σ		.10		.32	
	τ			.37	.33	−.14

Note. $N = 131$. μ = mean of the Gaussian distribution; σ = standard deviation of the Gaussian distribution; τ = exponential distribution.

CFI = .89, SRMR = .09. The amount of explained variance of the latent WM factor was .55.

Reasoning. The fit of this model was acceptable, $\chi^2(291) = 425.4$, RMSEA = .06, CFI = .90, SRMR = .09. Latent correlations and regression weights for the reasoning factor are shown in Table 3. The only significant unique predictor of reasoning was τ. The total reasoning factor variance accounted for was .51.

Psychometric speed. The fit of this model with PS as a criterion construct was acceptable, $\chi^2(291) = 437.5$, RMSEA = .06, CFI = .89, SRMR = .09. Latent regression weights indicated that only σ contributed significantly to the prediction of PS (Table 3). Total variance explained was .52.

EZ-Diffusion Measurement Model

A measurement model with three latent factors for drift rate, nondecision time, and boundary separation, as well as correlated residuals of the three parameters within each task, resulted in acceptable fit, $\chi^2(225) = 367.1$, RMSEA = .07, CFI = .90, SRMR = .10. We found this model could be further improved by allowing correlated residuals for nondecision time parameters from task pairs with the same stimulus content, $\Delta\chi^2(4) = 41.1$, $p < .001$. This model was accepted as the final measurement model, $\chi^2(221) = 326.0$, RMSEA = .06, CFI = .92, SRMR = .10. As shown in Table 4, most of the factor loadings were of substantial to high magnitude.

The correlations between the three factors were −.32 for the ν and a factors, $\Delta\chi^2(1) = 10.1$, $p < .01$; .38 for the ν and T_{er} factors, $\Delta\chi^2(1) = 10.0$, $p < .01$; and .05 for the a and T_{er} factors, $\Delta\chi^2(1) = 0.2$. These correlations indicate that on a task-general level, higher drift rates were associated with more liberal boundary separations but also with slower nondecision times, whereas boundary separation and nondecision times were unrelated.

Relations of EZ-Diffusion Parameters to Accuracy

Including a latent factor for the probit-transformed accuracies resulted in a model with acceptable fit, $\chi^2(406) = 608.5$, RMSEA = .06, CFI = .96, SRMR = .10. Correlations with the accuracy factor were .62 for ν, $\Delta\chi^2(1) = 46.3$, $p < .001$; .53 for a, $\Delta\chi^2(1) = 31.4$, $p < .001$; and .41 for T_{er}, $\Delta\chi^2(1) = 10.7$, $p < .01$. The strong positive relations of ϑ and a with accuracy could have been expected because of the nature of the assumed diffusion process; higher drift rates as well as more conservative response boundary settings should lead to higher probabilities of correct responses. The positive correlation of T_{er} with accuracy, indicating higher accuracy for participants with slower nondecision times, cannot be derived from assumptions about the diffusion process.

Relations of EZ-Diffusion Parameters to Criterion Constructs

Working memory. Correlations of the ϑ, a, and T_{er} factors with the WM factor were .68, −.45, and .11, respectively (Table 3). In a latent regression model, the ν factor had the strongest regression weight of .65 (Figure 2B). The two equivalent models had acceptable fit, $\chi^2(370) = 593.6$, RMSEA = .07, CFI = .88, SRMR = .09. The amount of explained variance of the latent WM factor was .53.

Reasoning. A latent factor for the three parcels of reasoning tasks had a strong correlation with ν of .79, a correlation of −.48 with a, and a correlation of .25 with T_{er}. The corresponding regression weights in Table 3 show that ν was by far the strongest predictor of reasoning. Fit of both models was good, $\chi^2(290) =$

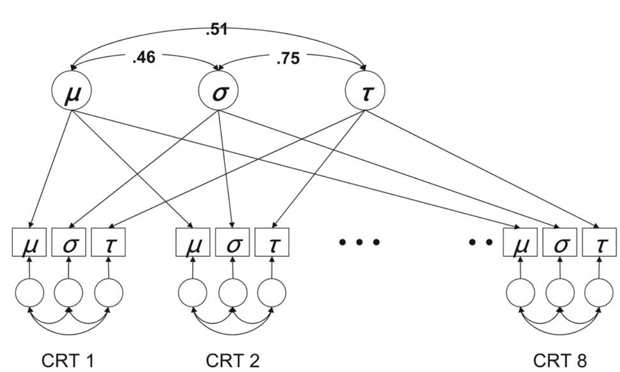

Figure 1. Simplified graphical representation of the structural equation modeling for the eight choice reaction tasks (CRTs). The ex-Gaussian distribution is characterized by three parameters: μ and σ, reflecting the mean and standard deviation of its Gaussian part, and τ, reflecting the exponential part.

Table 3
Latent Correlations and Regression Weights for the Prediction of Working Memory, Reasoning, and Psychometric Speed With Ex-Gaussian and EZ-Diffusion Parameters

	Working memory		Reasoning		Psychometric speed	
Parameter	r	β	r	β	r	β
Ex-Gaussian						
μ	−.36*** (13.0)	−.02 (0.0)	−.38*** (12.8)	−.02 (0.0)	−.43*** (17.5)	−.12 (1.2)
σ	−.43*** (13.4)	.25 (1.2)	−.56*** (21.3)	−.07 (0.1)	−.71*** (38.2)	−.62** (6.7)
τ	−.72*** (50.9)	−.90*** (12.2)	−.71*** (42.8)	−.66* (6.3)	−.58*** (26.6)	−.05 (0.0)
EZ-diffusion						
υ	.68*** (51.9)	.65*** (35.9)	.79*** (66.3)	.71*** (36.6)	.59*** (32.9)	.62*** (28.8)
a	−.45*** (21.3)	−.23* (6.4)	−.48*** (22.4)	−.25** (7.1)	−.42*** (17.0)	−.20* (4.1)
T_{er}	.11 (0.8)	−.12 (1.3)	.25* (4.0)	.00 (0.0)	−.04 (0.1)	−.26* (4.6)

Note. Values in parentheses are chi-square difference test statistics with one degree of freedom from tests of individual parameters against constrained models with those parameters fixed to zero. r = latent correlation; β = latent regression weight (standardized); μ = mean of the Gaussian distribution; σ = standard deviation of the Gaussian distribution; τ = exponential distribution; υ = drift rate; a = boundary separation; T_{er} = nondecision time.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

430.5, RMSEA = .06, CFI = .91, SRMR = .09. The total reasoning factor variance accounted for was .68.

Psychometric speed. The latent factor of PS correlated .59 with ν, −.42 with a, and −.04 with T_{er}. Latent regression weights indicated that ν was the strongest predictor of PS (Table 3). Fit of both models was good, $\chi^2(290) = 428.9$, RMSEA = .06, CFI = .91, SRMR = .09. The total PS factor variance accounted for was .46.

Discussion

In this study, we have shown how SEM allows separating common factors of different aspects of RT distributions from each other and from statistical dependencies among them. For a set of CRTs, we have shown that for each of the three ex-Gaussian parameters, μ, σ, and τ, a common factor could be identified, with the correlations of these factors being positive but far from unity. This means that each factor captured relatively independent individual differences that shared a substantial part of their variance across different tasks. We compared these findings with models with latent factors for more traditional measures to describe RT distributions, like individually calculated quantiles or moments of the RT distributions (see Appendix D for details). Distribution moments map what Cronbach and Gleser (1953) termed the *level* (first moment), *scatter* (second moment) and *shape* (a mixture of second, third, and still higher moments) of a distribution. Latent factors of these traditional measures showed less differentiated relations to the criterion constructs. Also, correlations among latent factors of means, standard deviations, and skewness or of different quantiles were much higher than among the ex-Gaussian or EZ-diffusion factors. Therefore, simultaneous multivariate analyses would be complicated by collinearities. In terms of Wittmann's (1988) framework of a multivariate reliability and validity theory, which distinguishes between wanted and unwanted sources of reliable variance, moments and quantiles might capture reliable individual differences but would not allow separating different components of reliable variance in the same way as the ex-Gaussian or the EZ-diffusion parameters do. Each factor seems to contain individual differences variance from the other factors, which is reliable but unwanted variance in this case. The ex-Gaussian distribution, as a descriptive model, and the EZ-diffusion parameterization, as a theoretical process model, seem to be preferable in that they both allow a better separation of different aspects of RT distributions.

Correlating the factors with other variables sheds light on what these underlying common aspects might be. The μ factor correlated positively with accuracy on the same tasks, a finding that was predicted by the diffusion model: Individual differences in setting the response criterion affect μ and accuracy in the same direction. If individual differences in criterion setting are relatively stable across tasks, the observed relation between latent factors of μ and accuracy can be expected. Other than expected, however, the τ factor did not correlate with accuracy. Whether the expected negative correlation between τ and accuracy could be found for more difficult tasks, in which average accuracies are lower, should be investigated in future research.

The τ factor was strongly related to a composite of WM tasks and to reasoning and was the only significant unique predictor of these constructs. A simple potential explanation that one must first rule out before links to theories of attentional lapses and diffusion processes can be drawn is that individual differences in τ could just reflect general slowing. There are theories that propose general information processing speed to be the most important cognitive resource underlying WM and intelligence (e.g., Eysenck, 1998; Jensen, 1998a; Vernon, 1983). According to such views, people of lower WM capacity should be generally slower on CRTs. This slowing should affect all RTs equally, implying a linear transformation of the RT distribution of low-WM people relative to high-WM people. Linear relationships of RTs of slow versus fast participants have been found before (Hale & Jansen, 1994; Zheng, Myerson, & Hale, 2000). The general slowing hypothesis predicts the same linear relationship when people are contrasted by their WM capacity or reasoning ability. Such a linear transformation would equally affect all three ex-Gaussian parameters. Then, however, all three factors should be equally good predictors of WM. The finding that τ did correlate much higher with WM and was the only unique predictor of it is clear evidence against such an interpretation.[2]

This consideration leads to a related potential objection against our findings. Given that the different ex-Gaussian parameters had different variability across subjects and different loadings on the factors, restrictions of variability or reliability in μ and σ could lead to an advantage for τ in correlational analyses. The findings that the μ factor was the only component with a significant relation to accuracy and that the σ factor was the only unique predictor of PS, however, provide arguments against such concerns. Apparently, each ex-Gaussian factor had enough variability and reliability to be the strongest predictor of a criterion variable—in competition with the other two factors—depending on the criterion variable used.

The finding that the τ factor is the strongest predictor of WM and reasoning is in line with theoretical propositions of controlled attention being an important aspect of these constructs but can also be interpreted within a diffusion model account: Individual differences in drift rate, which represents the efficiency of information processing, are reflected largely in variation of τ. Results of the latent factor models for the EZ-diffusion parameters were in line with such an account. Among these parameters, the drift rate factor clearly had the strongest correlation with WM and reasoning. The correlation of the drift rate factor and WM was of about the same size as the correlation of τ and WM. The same pattern of relations was found for reasoning and PS. Therefore, one could argue that individual differences in τ do not reflect more than individual

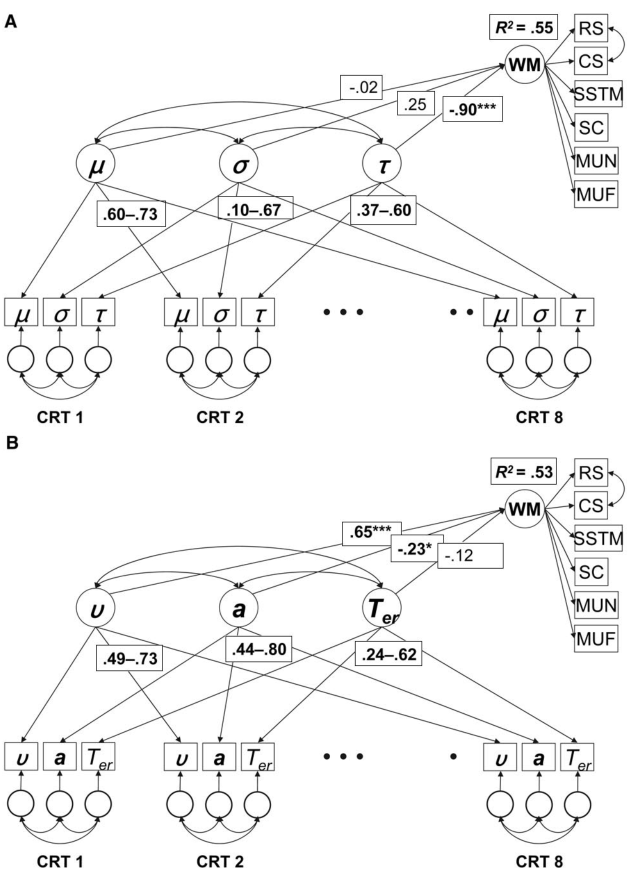

Figure 2. A: Prediction of the working memory (WM) factor with latent factors of ex-Gaussian parameters (μ and σ, reflecting the mean and standard deviation of the Gaussian distribution, and τ, reflecting the exponential distribution). B: Prediction of the WM factor with latent factors of EZ-diffusion parameters (a = boundary separation, ν = drift rate, T_{er} = nondecision time). For simplification, only three of the eight factors are shown, and ranges of the factor loadings are given. R^2 = variance; RS = reading span; CS = computation span; SSTM = spatial short-term memory; SC = spatial coordination; MUN = memory updating numerical; MUF = memory updating spatial; CRT = choice reaction task. $^{*}p < .05$; $^{***}p < .001$.

Table 4
Factor Loadings and Correlations of Residuals of the EZ-Diffusion Parameters

Choice reaction task	Parameter	Factor loading υ	Factor loading a	Factor loading T_{er}	Residual correlation υ	Residual correlation a
1	υ	.49				
	a		.58		−.51	
	T_{er}			.24	.32	−.53
2	υ	.50				
	a		.62		−.40	
	T_{er}			.35	−.04	−.08
3	υ	.73				
	a		.62		−.29	
	T_{er}			.35	.30	−.46
4	υ	.67				
	a		.71		−.12	
	T_{er}			.49	.19	−.27
5	υ	.62				
	a		.80		−.01	
	T_{er}			.62	.05	−.13
6	υ	.65				
	a		.72		−.16	
	T_{er}			.56	.27	−.34
7	υ	.66				
	a		.72		−.17	
	T_{er}			.48	.14	−.33
8	υ	.52				
	a		.44		−.39	
	T_{er}			.53	.00	−.29

Note. N = 131. υ = drift rate; a = boundary separation; T_{er} = nondecision time.

[2] Another kind of analyses to test the possibility that individual differences in WM are really related to a change in the shape of RT distributions—and not just to a linear transformation of the whole distribution—is to inspect Q–Q plots of RT distribution quantiles for subjects with high versus those with low WM, as suggested by one of the reviewers. We created such Q–Q plots on the basis of 10 quantiles. Quantiles were calculated separately for each individual and then averaged for a group of individuals with high WM and a group of individuals with low WM, defined as the upper and lower 25% of individuals on a composite of the six WM tasks. We tested the relation of these mean quantiles in the two groups for nonlinearity by hierarchical regression analyses that in a first step included a linear trend and in a second step an additional quadratic trend. For seven out of the eight CRTs, this resulted in significant quadratic trends, indicating that the relative slowing of the low versus the high WM subjects was particularly strong for the slowest quantile.

differences in the underlying drift rates. To test whether this is a viable explanation of the observed empirical relations, we conducted an additional simulation study based on the empirical results.

Simulation Study

To investigate whether individual differences in drift rate could fully explain the observed relations of τ and WM/reasoning, we simulated data that were based on the EZ-diffusion model with parameters set to the calculated values for each participant and each task. In Figure 3, the logic of this simulation is displayed. By generating data based on the EZ-diffusion model and estimating again ex-Gaussian parameters for these data, we could evaluate how high the τ–WM relation would be expected to be if individual differences in τ were based on an EZ-diffusion model, which does not contain mechanisms and parameters corresponding to lapses of attention. If the τ–WM relation were as high for the simulated as for the empirical data, individual differences in drift rate would be sufficient to explain this relation.

We simulated data using the EZ-diffusion parameters estimated from the empirical data. For each participant/task-combination, 1,000 RTs were simulated to prevent an attenuation of the correlation with WM because of estimation error. As apparent in Figure 3, the recovered correlation of drift rate and WM was as high as the empirical one. This was to be expected, because data were generated according to the EZ-diffusion model. The fact that the correlation of τ and WM was only slightly lower for the simulated than for the empirical data, however, showed that a diffusion model account indeed was sufficient to explain the observed τ–WM relation. Results for reasoning and PS showed the same pattern: Latent correlations with the τ factor were as high for the original data as for the data generated by the EZ-diffusion model. If the recovered correlations had been lower, this would have been an indication that τ reflected individual differences beyond those produced by individual differences in drift rate. We conclude that lapses of attention are not necessary to account for the τ–WM relation in our data.

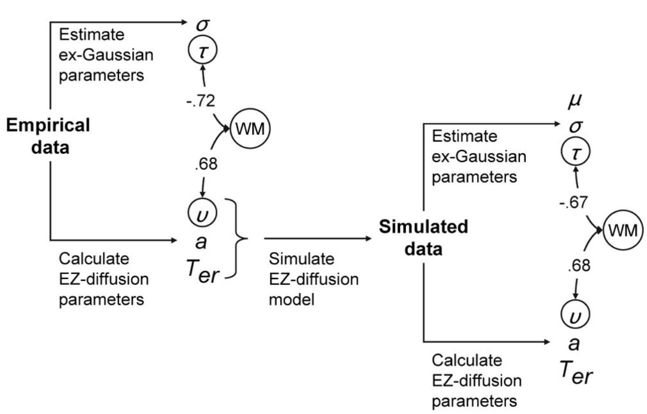

Figure 3. Rationale of the simulation study. We simulated data based on the EZ-diffusion model using parameter values from the empirical data. Then, we again estimated ex-Gaussian parameters (μ and σ, reflecting the mean and standard deviation of the Gaussian distribution, and τ, reflecting the exponential distribution) and EZ-diffusion parameters (a = boundary separation, ν = drift rate, T_{er} = nondecision time) to evaluate whether the empirical relation of the τ factor to the working memory (WM) factor can be recovered with an EZ-diffusion process. Circles denote latent factors.

We conducted a second simulation to investigate whether an account based on attentional lapses could provide an equally parsimonious account of the data. To this end, we integrated the idea of attentional lapses into the diffusion model. We assumed that attentional lapses are temporary interruptions of the information accumulation in the decision process that occur on some but not all trials. Therefore, they introduce variability in the drift rate from trial to trial. Variability in drift rate is an important parameter in the full diffusion model, accounting for slower response times for incorrect than for correct responses (Ratcliff & Rouder, 1998).

Variability of drift rate is not represented in the EZ-diffusion model, and if present in the data, it is captured by the drift rate parameter itself (Wagenmakers et al., in press). Therefore, the possibility remains that the observed relation of mean drift rate and WM could have been produced by true individual differences in trial-to-trial variability in drift rate. Our second simulation revealed that it is highly unlikely that individual differences in EZ-diffusion drift rates are only related to WM because they reflect individual differences in trial-to-trial variability. Even if trial-to-trial variability in drift rate and individual differences therein were simulated to be larger than what is usually observed in empirical studies and if those individual differences were simulated to be perfectly correlated with WM as a latent construct, resulting correlations of τ and WM were lower than the empirical ones. It would therefore be difficult to account for the observed relation of τ and WM only in terms of trial-to-trial variability in a drift rate that is due to attentional fluctuations. The possibility that such effects contributed to the observed correlations with WM and reasoning cannot be ruled out, but the more parsimonious account for the present data is that WM and reasoning are related to individual differences in mean drift rate, and attentional lapses play no role in an explanation of this relationship.

Conclusions

How does this study inform research based on the ex-Gaussian model? To our knowledge, this study is the first to support the interpretation of the τ parameter as being linked to higher cognitive functioning with evidence from individual differences among young adults. Researchers using ex-Gaussian analysis often have speculated about τ reflecting the controlled aspects of information processing, but evidence for this so far only have come from experiments showing that τ is the most sensitive parameter for experimental manipulations of executive control demands or from studies comparing different populations like different age groups. The fact that within a group of university students, individual differences in τ were strongly and uniquely predictive of individual differences in WM and reasoning aids future interpretations of findings on τ parameter effects. Also, the finding that individual differences in different ex-Gaussian parameters are to some degree generalizable across different tasks opens a new perspective for research on RT distributions in experimental cognitive psychology, where studies so far primarily have used single paradigms. The construction of the tasks, carefully balancing stimulus features and varying task demands, assured that explanations based on task-specific components or operational issues cannot provide an alternative account of the results. The SEM methods put forward here provide an approach that could be used for all sorts of models in which individual differences in model parameters could be of interest but are confounded with statistical dependencies because of the estimation process.

How does this study inform research on the diffusion model? The present results are of particular interest for researchers who work with diffusion models of CRTs. First, it could be shown that individual differences in all central diffusion model parameters generalize across different tasks. This suggests that the underlying mechanisms could be relatively task-independent. Second, the correlations among the latent factors are of interest. The negative correlation of the drift rate and boundary separation factors indicates that people with higher drift rates choose smaller boundary separation values. This makes sense, because these individuals can allow more liberal response criteria while keeping the same accuracy level. The positive correlation of the drift rate and nondecision time factors, however, is difficult to interpret, because it means that there is a tendency of people with faster drift processes to have slower nondecision times. This relation could reflect biases because of the simplification involved in use of the EZ-diffusion model and therefore warrants investigations using the full diffusion model to fit individual RT distributions. The method we have presented of using SEM to disentangle true relations of the parameters from statistical dependencies offers an interesting possibility to overcome problems of strong parameter dependencies in the diffusion model (see Ratcliff & Tuerlinckx, 2002, for a demonstration of such parameter correlations). Such analyses did not seem feasible, however, with the number of RTs available per subject and task in the present data.

Third, the strong correlations of the drift rate factor with WM, reasoning, and PS indicate an important role of drift rate for higher order cognition. Assuming that drift rate reflects a general source of variance in efficiency of information processing that is also relevant for more complex cognitive tasks provides a parsimonious account of worst performance rule patterns in the relationship between RT and intelligence, as also put forward from simulation results by Ratcliff et al. (in press).

How can the relation of simple speed tasks to WM and fluid intelligence be explained? Our study extends evidence on slower RTs being more strongly related to intelligence than faster RTs through methods that capture information from the whole shape of RT distributions. In a multivariate approach, the relations in latent factor space are much stronger than the observed intelligence–slow RT correlations reported so far. These findings are compatible with the view that individual differences in WM and reasoning are largely determined by variations in controlled attention (Engle et al., 1999; Kane & Engle, 2002). The combined picture of the results with the ex-Gaussian and EZ-diffusion models, however, poses a challenge to theories invoking concepts such as resistance to interference and lapses of attention to explain the association of RTs with WM and intelligence.

So far, the link of WM capacity and attention control has been investigated through comparisons of performance on several interference tasks between groups with extremely high and low WM capacity. The present results show that measures of variability on very simple tasks, which do not require resistance to interference in any obvious way, are key predictors of WM performance and that the assumption of lapses of attention is not necessary to account for the relation of RT to WM and reasoning. These observations cannot be predicted directly from a theory that highlights the role of WM in resisting distraction. It can be derived easily, however, from a theory that assigns WM the function of establishing and maintaining ad hoc bindings between component representations (Oberauer, Süβ, Wilhelm, & Sander, in press). Oberauer et al. proposed that WM capacity reflects the ability to maintain temporary bindings between representations. Many CRTs—including those used in the present study—involve arbitrary mappings between stimulus categories and response categories. Bindings between stimulus and response representations in WM are needed to mediate the selection of appropriate responses to stimuli, at least at the beginning of a new task. Even after moderate amounts of practice, when more durable associations between stimuli and responses are built in long-term memory, bindings in WM might still contribute to efficient response selection. According to this hypothesis, WM reflects the strength of temporary bindings, which determines the efficiency of information transmission between stimuli and responses. Support for this hypothesis comes from a study of Wilhelm and Oberauer (2006) showing that WM was correlated specifically to CRTs with arbitrary stimulus–response mappings.

Neural network models in which age-related cognitive changes are simulated by decreasing the signal-to-noise ratio of the activation function resulting from declining dopaminergic neuromodulation also predict an increase in intraindividual item-to-item variability (Li, Lindenberger, & Sikström, 2001). Such a decrease in processing robustness, as indicated by increasing RT variability on simple cognitive tasks, seems to play a unique role in predicting age differences in fluid intelligence (e.g., Li et al., 2004). Another explanation of variability in cognitive performance on simple tasks as well as impaired performance on tasks of higher cognition (Li, Huxhold, & Schmiedek, 2004) is that neuronal noise and the individual differences therein apparently can reduce distinctiveness of internal representations and also lead to deficits in associative bindings (Li, Naveh-Benjamin, & Lindenberger, 2005). These neural network approaches, however, so far have only rarely been used to model RTs and to predict aspects of RT distribution shapes (but see Ratcliff, Van Zandt, & McKoon, 1999), which opens a promising avenue for future research.

Our results, in particular the simulation based on the EZ diffusion model parameters, strongly point toward an association between general drift rate in CRTs on the one hand and general WM and reasoning on the other hand. We cannot rule out that fluctuations of attention control might add, in a top–down manner, to the correlation of RT distribution tails and higher order cognition. At present, such an additional assumption is not necessary to account for the data on the relation between CRTs and the WM–reasoning complex. It seems that the correlation between speed on easy cognitive tasks and performance in more complex tasks such as measures of WM and reasoning can be explained parsimoniously by a simple assumption: The same source of individual differences that governs the general efficiency of information accumulation in the decision component of speeded choice tasks is also the common determinant of performance on a large range of WM and reasoning tasks. Our data do not allow firm conclusions on the nature of this general source of variance. We believe, however, that two concepts, neural noise (Li et al., 2001) and the robustness of temporary bindings (Oberauer et al., in press; Wilhelm &

Oberauer, 2006), are particularly well suited to fill the role of determining drift rate in the diffusion model on the one hand and acting as a general limiting factor for complex cognition on the other hand.

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(*Appendixes follow*)

Appendix A

Statistical Dependencies of Ex-Gaussian Parameters

To illustrate the impact of statistical dependencies among ex-Gaussian parameters that are estimated for individual subjects' data, we conducted a simulation. True values of μ, σ, and τ were drawn from independent normal distributions for 1,000 subjects with means of 500, 100, and 250 and standard deviations of 50, 10, and 25, for μ, σ, and τ, respectively. Observed correlations between the three parameters ranged from .00 to −.02. For each individual, we generated 80 RTs by adding values drawn from normal and exponential distributions with the corresponding individual parameters. Then, we estimated the ex-Gaussian parameters separately for each individual, using QMPE. Correlations of these estimated parameters were substantial and highly significant, specifically .37 for μ and σ, −.34 for μ and τ, and −.48 for σ and τ (all $ps < .001$). This shows that correlations of individually estimated ex-Gaussian parameters are strongly influenced by statistical dependencies. These dependencies are positive for the two Gaussian parameters and negative for their correlations with the τ parameter of the exponential distribution. A compensatory relationship of the two distributions combined in the ex-Gaussian is apparent here. If sampling error, for example, leads to an overestimation of μ, an underestimation for τ must follow because the sum of μ and τ has to fit the observed mean of the distribution. Because τ also determines the variance, an underestimation of τ leads to an overestimation of σ—therefore, the positive relation of μ and σ.

Appendix B

Using Structural Equation Modeling to Disentangle True and Statistical Correlations of Reaction Time Distribution Parameters

If ex-Gaussian parameters are estimated separately for each individual on a set of tasks, SEM can be used to disentangle statistical dependencies from true relations among the common factors of those parameters across tasks. Figure B1 shows how this is achieved. In this example, ex-Gaussian parameters are estimated separately for each individual and each of the two tasks. The resulting μ, σ, and τ parameter estimates load on corresponding latent μ, σ, and τ factors. Within tasks, error terms are allowed to correlate. These correlations reflect a combination of true task-specific correlations and statistical dependencies among these parameters. Their estimated values are therefore not interpretable without knowledge of the amount of statistical dependency. Even though we estimated the dependencies for each individual using QMPE, these estimated parameter correlations vary across individuals, complicating a separation of statistical dependencies and true correlations within tasks. Across tasks, however, the latent common factors capture variance that is common to μ, σ, and τ estimates across the different tasks (or parallel versions of the same task). These latent factors are free from error of the ex-Gaussian parameter estimates. Therefore, correlations of the latent μ, σ, and τ parameters are not influenced by statistical dependencies and reflect true relations among the parameters. With a Monte Carlo simulation based on empirical parameter values presented in the Results section, we show in Appendix C that this method indeed recovers the true parameter correlations. With two tasks and three ex-Gaussian parameters each, the model is just identified. With more than two tasks, the model gains more and more degrees of freedom.

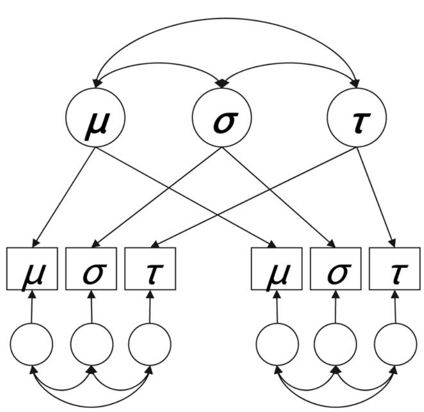

Figure B1. Graphical representation of the structural equation modeling approach to disentangle statistical dependencies from true correlations of the ex-Gaussian parameters. The correlated residual factors account for the statistical dependencies. The latent factors capture common variance across tasks.

Appendix C

Monte Carlo Analyses Showing the Validity of Empirical Models

To validate the results of the SEM model for the eight CRTs, we conducted a Monte Carlo study, using the parameter estimates of the empirical study as the true model. The question to be answered by this simulation study therefore was, If the parameter estimates resulting from modeling the empirical data were true, would the model be able to recover them within the usual range of sampling error? If this were the case, it would show that the SEM approach can be used to disentangle true relations among the ex-Gaussian parameters from their statistical dependencies in the given empirical situation.

In the Monte Carlo study, we used the estimated factor correlations, factor loadings, and error variances to generate simulated data for 1,000 subjects with a covariance matrix of the 8 tasks × 3 parameter variables that is based only on the common loadings on the latent factors and the factor correlations—not on any statistical dependencies. Then, for each individual, we generated RT data with 80 trials on the basis of these simulated values plus the observed means of the parameters (because the individual data generated from the covariance matrix only reflect individual deviations from the means) by inserting simulated parameters into the ex-Gaussian equation. In the next step, ex-Gaussian parameters were estimated again for each individual and each task from the generated RTs. Correlations of these estimates were again influenced by statistical dependencies. In the final step, we modeled these estimates just the same way (after deleting outlying data points on the basis of the criterion of four *standard deviation*s above the mean for each task) as we did with the real data, allowing for correlated errors within tasks.

Results showed that, indeed, the model did recover the true parameter values of the factor correlations with satisfactory accuracy in the sense that 95% confidence intervals of the estimated parameters did cover the true values (with the precision of these confidence intervals being increased by the large sample size of $N = 1{,}000$ used in this simulation). While the true correlations among the ex-Gaussian parameters on which the simulation was based were .46 for μ and σ, .51 for μ and τ, and .75 for σ and τ, the corresponding estimates were .53 (SE = .043), .55 (SE = .033), and .79 (SE = .049).

Appendix D

Pairwise Estimates of Latent Correlations of Distribution Moments, Quantiles, Ex-Gaussian Parameters, Ex-Diffusion Parameters, and Criterion Constructs

Variable	*M*	*SD*	Skew	Q1	Q2	Q3	μ	σ	τ	υ	*a*	T_{er}
M	—											
SD	.86	—										
Skew	.78	.86	—									
Q1	.93	.65	.61	—								
Q2	.99	.83	.68	.96	—							
Q3	.98	.95	.78	.84	.96	—						
μ	.88	.53	.46	.99	.92	.78	—					
σ	.68	.67	.23	.43	.64	.74	.46	—				
τ	.85	1.00	.80	.62	.82	.94	.51	.75	—			
υ	−.53	−.73	−.53	−.23	−.45	−.63	−.14	−.64	−.80	—		
a	.88	.83	.74	.79	.87	.89	.71	.53	.84	−.32	—	
T_{er}	.22	−.23	−.09	.57	.37	.12	.68	.03	−.28	.38	.05	—
WM	−.58	−.65	−.59	−.43	−.55	−.65	−.36	−.43	−.72	.68	−.45	.11
Reasoning	−.57	−.71	−.77	−.41	−.54	−.64	−.38	−.56	−.71	.79	−.48	.25
PS	−.53	−.52	−.29	−.41	−.52	−.57	−.43	−.71	−.58	.59	−.42	−.04

Note. $N = 131$. Correlations were estimated separately for each pair of latent factors. Residuals for each pair of parameters corresponding to the same task were allowed to correlate. Q1–Q3 = quantile reaction times (RTs) calculated by averaging RTs from the slowest, medium, and fastest third of each individual's RT distribution; μ = mean of the Gaussian distribution; σ = standard deviation of the Gaussian distribution; τ = exponential distribution; υ = drift rate; *a* = boundary separation; T_{er} = nondecision time; WM = working memory; PS = psychometric speed.

Received December 28, 2004
Revision received November 28, 2006
Accepted December 4, 2006 ■