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An integrated perspective on the relation between response speed and intelligence

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ABSTRACT

Research in the field of mental chronometry and individual differences has revealed several robust regularities (Jensen, 2006). These include right-skewed response time (RT) distributions, the worst performance rule, correlations with general intelligence (*g*) that are more pronounced for RT standard deviations (RTSD) than they are for RT means (RTm), an almost perfect linear relation between individual differences in RTSD and RTm, linear Brinley plots, and stronger correlations between *g* and inspection time (IT) than between *g* and RTm. Here we show how all these regularities are manifestations of a single underlying relationship, when viewed through the lens of Ratcliff's diffusion model (Ratcliff, 1978; Ratcliff, Schmiedek, & McKoon, 2008). The single underlying relationship is between individual differences in general intelligence and individual differences in "drift rate", which is just the speed of information processing in Ratcliff's model. We also test and confirm a strong prediction of the diffusion model, namely that the worst performance rule generalizes to phenomena outside of the field of intelligence. Our approach provides an integrative perspective on intelligence findings.

1. Introduction

Sir Francis Galton (1822–1911), one of the founders of differential psychology, believed that "general mental ability" manifests itself by the speed with which people perform elementary cognitive tasks. That is, intelligent people should be faster than less intelligent people at deciding, say, whether a clearly presented arrow points to the left or to the right. Galton's idea could be taken to imply that individual differences in intelligence are caused by individual differences in fundamental, low-level neurophysiological characteristics (e.g., Anderson & Reid, 2005) such as brain glucose metabolic rate, intracellular pH levels, or the degree of neural myelinization.

Galton's idea was reductionist to such an extent that it struck many people as counter-intuitive: how can something so complex and multidimensional as human intelligence be captured by something so simple and unidimensional as response speed in elementary cognitive tasks? The initial opposition to Galton's idea was strong enough to have it be rejected and ignored until the 1980s. Since then, overwhelming empirical evidence has been gathered in support of Galton's idea (for reviews see Deary, 1994; Jensen, 2006). Indeed, there is now an entire subfield called "differential mental chronometry", the goal of which is to study the relation between measures of general intelligence (*g*) and response time (RT) in elementary cognitive tasks.

Over the course of several decades, researchers in the field of differential mental chronometry have discovered various regularities that any theory of the relation between RT and *g* should try to accommodate (e.g., Jensen, 2006, chap. 11). Here we focus on the following key regularities:

1. Right-skewed RT distributions. RT distributions have a pronounced right skew. In addition, low-*g* people

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generate RTs that are more spread-out than those for high-g people (e.g., Baumeister, 1998).

2. The Worst Performance Rule. Slow RTs are more indicative of g than are fast RTs (e.g., Larson & Alderton, 1990; Unsworth, Redick, Lakey, & Young, 2010; for a review see Coyle, 2003).
3. Stronger correlation between g and the standard deviation of RT (RTSD) than between g and the mean of RT (RTm). It is generally found that RTSD correlates slightly higher with g than does RTm, which – as suggested by Jensen (2006) – in turn correlates slightly higher with g than does the median RT (Baumeister, 1998; Jensen, 1992; Walhovd & Fjell, 2007).
4. Linear relation between RTm and RTSD. As observed by Jensen (2006, p. 202): "(…) there is a near-perfect correlation between individual differences in RTm and RTSD. (…) Empirically measured diameters and circumferences of different-size circles are no more highly correlated than are RTm and RTSD. The slight deviations of their correlation coefficient from unity are simply measurement errors."
5. Linear Brinley plots. Across several tasks that vary in difficulty, the RTm of a group of low-g people is a constant multiple of the RTm of a group of high-g people (e.g., Rabbitt, 1996).
6. Stronger correlation between g and inspection time (IT) than between g and RTm. The time needed to obtain a predetermined level of accuracy in a simple visual inspection task is more strongly related to g than is RTm from a response time task (Jensen, 1998, 2006).

We demonstrate that all of the above regularities can be viewed as manifestations of a single latent relationship. We make this argument using one of the most popular models for RT tasks: the *diffusion model* (e.g., Ratcliff, 1978; Ratcliff et al., 2008). This single latent relationship is between individual differences in "drift rate" and individual differences in g. Drift rate is a diffusion model parameter that quantifies the signal-to-noise ratio of the information-accumulation process. Since drift rate represents a signal-to-noise ratio, it can be affected by stimulus manipulations and task demands. However, even in identical decision environments, different people will evince different drift rates, and we assume that these individual differences are associated with intelligence, with high-g people having high drift rates. The primary aim of this article is to demonstrate that, although each of the six benchmark phenomena may appear different, and have inspired different research efforts, they can all be accounted for by this one common assumption. The diffusion model provides a unifying account of these six benchmark phenomena, but also makes testable predictions about different, related, phenomena. The secondary aim of this article is to outline the advantages of a diffusion model analysis as a tool in the study of the relation between response speed and general intelligence.

The outline of this paper is as follows. The first section briefly outlines Ratcliff's diffusion model. The second section describes how the single assumption that individual differences in the diffusion model's drift rate parameter correlate with g naturally predicts the six key phenomena in the field of differential mental chronometry. Earlier papers on this relationship laid the groundwork for establishing some results in this section (right-skewed RT distributions, the worst performance rule, the linear relation between RT mean and RT standard deviation, and linear Brinley plots). We add to these results the stronger correlation between g and RT standard deviation than between g and RT mean, the stronger correlation between g and inspection time than between g and RT mean, and a non-trivial prediction of the worst performance rule: that the worst performance rule is not specific to g, but generalizes to other phenomena that affect drift rate, such as stimulus difficulty. The third section lists the conceptual and practical advantages, as well as two drawbacks, of a diffusion model approach to the study of intelligence. The fourth, concluding section discusses what we have learned by attributing g to drift rate.

2. The diffusion model

In the diffusion model (Ratcliff, 1978; Ratcliff & Rouder, 2000; van Ravenzwaaij & Oberauer, 2009; Wagenmakers, 2009), stimulus processing is conceptualized as the noisy accumulation of evidence over time. A response is initiated when the accumulated evidence reaches a predefined threshold (Fig. 1).

The model applies to tasks in which the participant has to decide quickly between two alternatives. For instance, in a *lexical decision task*, participants have to decide whether a letter string is an English word, such as TANGO, or a nonword, such as TANAG. The RTs in this task generally do not exceed 1.0 or 1.5 s. The four key parameters of the diffusion model are (1) the speed of information processing, quantified by mean drift rate v; (2) response caution, quantified by boundary separation a; (3) a priori bias, quantified by mean starting point z; and (4) mean non-decision time, quantified by T_{er}.

The model assumes that the decision process starts at z, after which information is accumulated with a signal-to-noise ratio that is governed by mean drift rate v.[1] Conceptually, drift rate captures a range of factors that affect information accumulation, including characteristics of the stimuli, the task, and the participant. Small drift rates (near $v = 0$) produce long RTs and high error rates. Boundary separation (a) determines the speed-accuracy tradeoff; lowering boundary separation leads to faster RTs at the cost of a higher error rate. A starting point of $z = .5a$ indicates and unbiased decision process (an assumption we maintain throughout the paper). Together, these parameters generate a distribution of decision times DT. The observed RT, however, also consists of stimulus-nonspecific components such as response preparation and motor execution, which together make up non-decision time T_{er}. The model assumes that non-decision time T_{er} simply shifts the distribution of DT, such that $RT = DT + T_{er}$ (Luce, 1986). The full diffusion model includes parameters that specify across-trial

[1] Mathematically, the change in evidence X is described by a stochastic differential equation $dX(t) = \xi \cdot dt + s \cdot dW(t)$, where $W(t)$ represents the Wiener noise process (i.e., idealized Brownian motion). Parameter s represents the standard deviation of $dW(t)$ and is usually fixed.

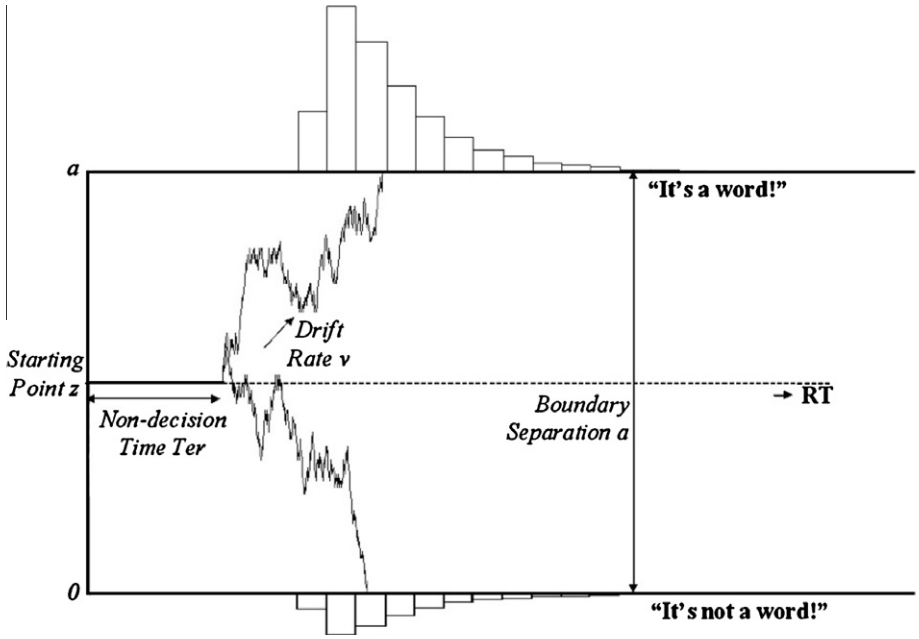

Fig. 1. The diffusion model and its key parameters. Evidence accumulation begins at *z*, proceeds over time guided by drift rate *v*, is subject to random noise, and stops when either the upper or the lower boundary is reached. The distance between the boundaries is *a*. The predicted RT is just the accumulation time, plus a constant value for non-decision processes T_{er}.

variability in drift rate, starting point, and non-decision time (Ratcliff & Tuerlinckx, 2002), but these are fixed to zero throughout this paper.

The advantages of a diffusion model analysis over standard analyses that separately consider accuracy and mean response time are twofold. First, the model takes into account entire RT distributions, both for correct and incorrect responses. Second, the model allows researchers to decompose observed RTs and error rates into latent psychological processes. The diffusion model has been successfully applied to a wide range of experimental paradigms, including brightness discrimination, letter identification, lexical decision, recognition memory, and signal detection (e.g., Dutilh, Wagenmakers, Vandekerckhove, & Tuerlinckx, 2009; Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007; Ratcliff, 1978; Ratcliff, Gomez, & McKoon, 2004; Ratcliff, Thapar, & McKoon, 2006b, 2010; van Ravenzwaaij, van der Maas, & Wagenmakers, in press; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008).

3. Key phenomena in intelligence research captured by drift rate

We discuss six important phenomena in the study of mental chronometry in turn, each with a demonstration that the diffusion model naturally predicts the data, with the common assumption that *g* manifests itself through drift rate *v*.

3.1. Right-skewed RT distributions

Distributions of RT are almost always right-skewed (e.g., Baumeister, 1998). Typically, the spread of the distribution is negatively correlated with the participant's *g* (i.e., low-*g* participants have a more spread-out RT distribution than high-*g* participants). The diffusion model not only predicts RT distributions with a right-skew, but also cannot account for RT distributions with any other shape (cf. Ratcliff, 2002).

Fig. 2 shows how right-skewed RT distributions follow naturally from the geometry of the diffusion model (see also Ratcliff, Spieler, & McKoon, 2000, Fig. 6). The figure shows 10 lines with slopes $\phi = \{1,2,\ldots,10\}$, which can be thought of as different accumulation paths for a single participant that vary over trials. For presentational convenience, we have omitted the noise from the accumulation paths (but adding noise does not lead to a qualitatively different pattern). Fig. 2 shows how the spread between the

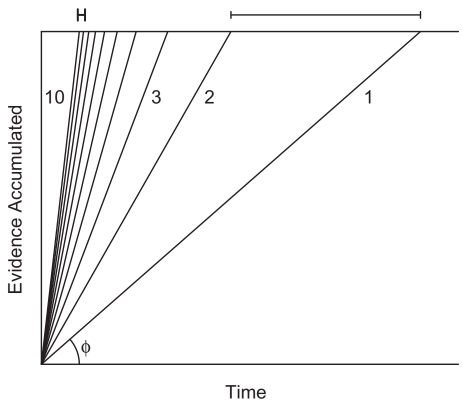

Fig. 2. Increasing slopes lead to a right-skewed distribution. Displayed are 10 lines with slopes $\phi = \{1,2,\ldots,10\}$. The spread between lines with slopes 1 and 2 is much larger than the spread between lines with slopes 9 and 10.

points where the lines hit the upper boundary increases as we move to the right.

The figure with noiseless data provides an intuition about why the diffusion model always predicts right-skewed RT distributions. The same line of reasoning implies that low-*g* participants have an RT distribution that is more spread-out than high-*g* participants, as observed in mental chronometry (e.g., Baumeister, 1998). In this case, a lower *g* is associated with a lower drift rate v, which leads to a lower slope ϕ, which results in an RT distribution that is more spread-out; as in the right-hand end of Fig. 2.

In order to demonstrate more concretely how the diffusion model accounts for the fact that low-*g* participants have an RT distribution that is more spread-out than high-*g* participants, we conducted a simulation in which we varied drift rate for five synthetic participants. We generated 50,000 RT trials from synthetic participants with drift rates of $v = 0.1$, $v = 0.2$, $v = 0.3$, $v = 0.4$, and $v = 0.5$. For all participants, boundary separation was fixed to $a = 0.12$ and non-decision time was fixed to $T_{er} = 0.25$, values that are within a plausible range (e.g., Matzke & Wagenmakers, 2009; Wagenmakers, van der Maas, & Grasman, 2007). Fig. 3 shows that the RT distributions for five different drift rates increase in spread as drift rate decreases. To quantify this, we divided the RT data into five bins and found the cut-points between bins: these are called *quantiles*, represented by the dots under the densities. Both the densities and the quantiles show that the spread of the RT distribution increases for smaller drift rates. Note that for different drift rates, the fastest RTs differ only a little, but the slowest RTs differ a lot.

In sum, the diffusion model automatically produces RT distributions that are skewed to the right. Furthermore, people with a lower drift rate will have a more spread-out RT distribution. Fig. 3 shows two other phenomena in addition to the right-skewed RT distributions. First, the differences in drift rate are related more strongly to the slower RT quantiles than to the faster RT quantiles. This phenomenon, called the worst performance rule, will be the topic of the next section. Second, changes in drift rate have a large influence on RTSD, but a somewhat weaker influence on RTm. This observation relates to another phenomenon in intelligence research: a larger correlation between *g* and RTSD than between *g* and RTm. We will discuss this topic after the worst performance rule.

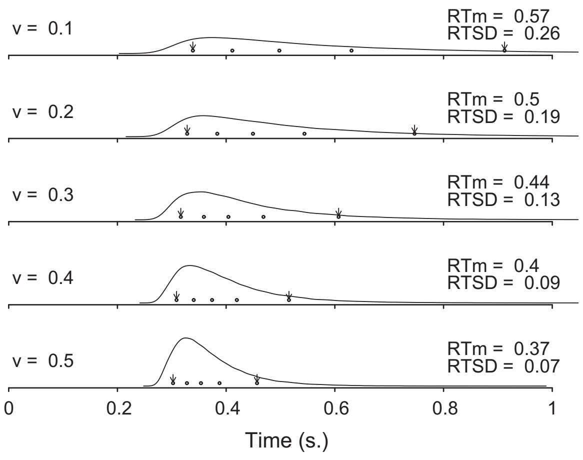

Fig. 3. Predicted RT distributions from the diffusion model spread out as drift rate decreases: five RT distributions of 50,000 RT trials, generated from the diffusion model with drift rate $v = 0.1$, $v = 0.2$, $v = 0.3$, $v = 0.4$, and $v = 0.5$. The dots under the densities represent the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles of the RT distribution. The five arrows to the left of the figure highlight the fastest RT quantiles, the five arrows to the right highlight the slowest RT quantiles.

3.2. The worst performance rule

The worst performance rule refers to the finding that differences in slow RTs between people correlate more strongly with *g* than differences in fast RTs. The original worst performance rule was identified by Larson and Alderton (1990) and their result is displayed in Fig. 4. This effect has since been found in several studies (for a review, see Coyle, 2003). In this section we show how the diffusion model produces data consistent with the worst performance rule.

3.2.1. Worst performance rule for ability

The standard WPR effect entails a correlation between *g* and slow RTs. Specifically, across people, the correlation between *g* and the speed of each person's slowest RTs is stronger than the corresponding correlation for the fast RTs. In a simulation study, Ratcliff et al. (2008) generated data that showed the diffusion model predicted the worst performance rule when drift rate was used as a proxy measure for *g* (i.e., they showed a higher correlation between slow RTs and drift rate v than between fast RTs and drift rate v).

In nine different simulations, Ratcliff et al. (2008) generated data for 1000 synthetic participants. For all simulations, each participant had a drift rate v, boundary separation a, and non-decision time T_{er} that were sampled from a normal distribution. Drift rate v had mean $v_m = .4$ and standard deviation $v_s = .01$ or .10. Boundary separation a had mean $a_m = .1$ and standard deviation $a_s = 0$, .02, or .04. Non-decision time T_{er} had mean $T_{er_m} = .4$ and standard

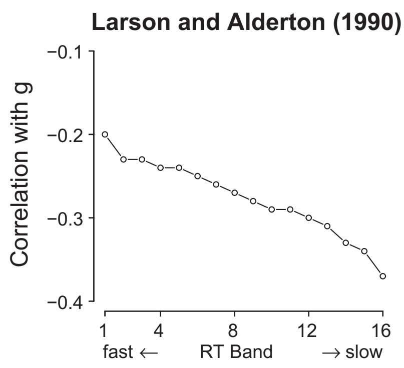

Fig. 4. The worst performance rule. The RT data from the original experiment by Larson and Alderton (1990, Table 4) were divided into 16 bands, the mean of which was correlated with *g*. Mean RT from the slowest bands correlates more strongly with *g* than the mean RT from the fastest bands.

deviation $T_{er_s} = 0$, .05, or .10. For each synthetic participant's data set, five different quantiles were calculated, to estimate the shortest through to the longest RTs in the distribution (.1, .3, .5, .7, and .9 quantiles).

Ratcliff et al. (2008) found a worst performance rule for drift rate: the slowest quantile (.9) correlated more strongly with drift rate than did the fastest quantile (.1). The difference between the correlation between the fastest RT quantile and drift rate and the correlation between the slowest RT quantile and drift rate ranged from .19 to .42, depending on the values of the parameters.

In Ratcliff et al.'s (2008) work, different drift rates were associated with different (synthetic) participants, but their mathematical result does not depend on this interpretation. This means that the diffusion model predicts that the worst performance rule should not be limited to differences between individual participant, but should also be found for any manipulation that creates drift rate differences. For example, different stimuli produce different drift rates, so the diffusion model predicts that a worst performance rule should be found when RTs are grouped based on stimulus difficulty: slow RT bins should correlate more strongly with stimulus difficulty than fast RT bins. In the next section, we will explain this strong prediction of the diffusion model and demonstrate a worst performance rule for stimulus difficulty.

3.2.2. New prediction: worst performance rule for stimulus difficulty

In the diffusion model, drift rate represents the quality of information processing. A high drift rate means that information is accumulated quickly and a low drift rate means that information is accumulated slowly. Many factors influence the drift rate for a particular participant performing a particular task. For one, the participant may have a very high ability, being superior to other participants in this task. Alternatively, the task itself may be very easy, leading to higher drift rates for this task than other tasks (for all participants). In the previous section, we saw how a worst performance rule for ability may translate to a worst performance rule for drift rate. Since drift rate may also manifest itself on the level of the stimulus, the diffusion model predicts that a worst performance rule for stimulus difficulty – a higher correlation between slow RTs and stimulus difficulty than between fast RTs and stimulus difficulty. We test this prediction using empirical data.

To test for a worst performance rule for stimulus difficulty, we have taken data from a stimulus brightness experiment (Ratcliff & Rouder, 1998) in which three participants had to categorize the brightness of a stimulus as "high" or "low". The stimuli varied in brightness, and so produced greatly differing decision difficulty. The experiment was divided into blocks, and for half of those blocks the participants were instructed to focus on response speed, whereas for the other half, they were instructed to be as accurate as possible. We binned the data according to 17 different levels of stimulus difficulty. For each level of difficulty, we calculated five RT quantiles (i.e., .1, .3, .5, .7, and .9) per emphasis condition (i.e., "speed" and "accuracy") for each participant, and did so separately for correct and error responses. We correlated each of the five quantiles with the 17 levels of stimulus difficulty, numbered from least to most difficult. These correlations were calculated for each condition, participant, and response (i.e., correct or error). The results can be seen in Fig. 5.

The panels in the figure show the worst performance rule, separated by condition and by response accuracy. All four panels show a worst performance rule for stimulus easiness which is most clearly seen in the group average (solid line on each panel). The worst performance rule is most pronounced for the correct responses from the "speed" condition for correct RTs, where the difference in correlations between the highest and the lowest RT quantiles is .53. For the incorrect responses from the "speed condition", this difference is .40. In the "accuracy" condition the difference in correlations between the highest and the lowest RT quantiles is .21 for correct responses[2] and .45 for incorrect responses.

In sum, the worst performance rule is not limited to participant-specific effects. Here, we demonstrated that the worst performance rule can hold for individual-participant data. The size of this worst performance rule for stimulus difficulty was in the range of .21 to .53, depending on the condition and on the accuracy of the RTs. In this section, we have verified a strong and novel prediction that follows from a drift rate account of *g*, namely that the worst performance rule is not just an effect found in intelligence research. Instead, our findings suggest that it is a more general effect, just as the diffusion model predicts, and is also found for stimulus difficulty.

3.3. Stronger correlation between g and RTSD than between g and RTm

A persistent phenomenon in intelligence research is that *g* correlates more strongly with RTSD than with RTm (e.g., Baumeister, 1998; Jensen, 1992; Walhovd & Fjell, 2007). In this section, we will investigate under what conditions this finding might be accounted for by the drift rate parameter. We generated diffusion model parameters for 10,000 synthetic participants in many different simulation conditions. In all simulations, the drift rate for each synthetic participant was drawn from a normal distribution with mean 0.2, which instantiates the assumption that different participants have different drift rates (and different *g*). We repeated the simulation with different standard deviations for the distribution of drift rates (v_σ), between zero and 0.1, to observe what happened when participants were assumed to be either more alike (small standard deviation) or more variable (large standard deviation). For the first simulation, we also allowed two other parameters (boundary separation *a* and non-decision time T_{er}) to vary randomly across participants. We then explored the consequences of fixing these parameters across participants in three further simulations. For every simulation, we calculated RTm and RTSD using the following equations (cf. Wagenmakers, Grasman, & Molenaar, 2005):

[2] This relatively low difference in correlations was probably caused by a ceiling effect, as the lowest RT quantile already correlates −.70 with stimulus easiness.

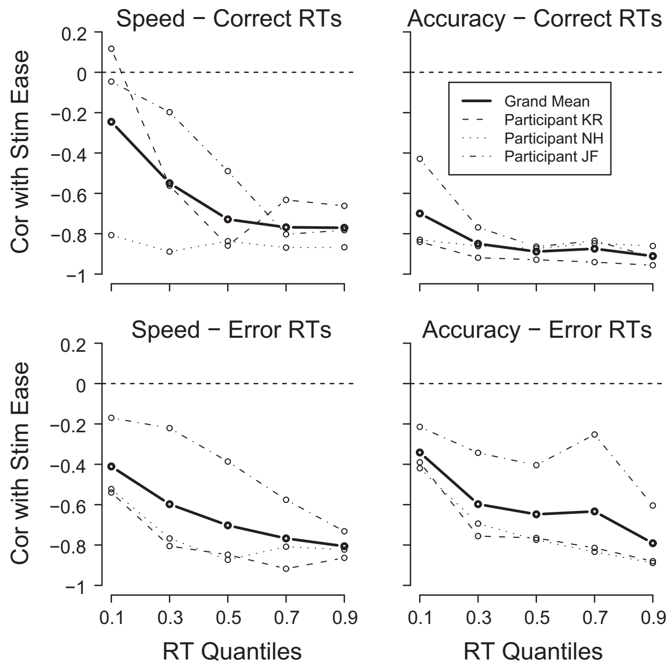

Fig. 5. The worst performance rule for the reverse of stimulus difficulty (i.e., stimulus easiness). The bold lines correspond to the correlation between RT quantiles and stimulus difficulty, averaged over the three participants. The dashed, dotted, and dash–dotted lines represent data from participants "KR", "NH", and "JF", respectively. Top left panel: correct RTs in the "speed" condition. Top right panel: correct RTs in the "accuracy" condition. Bottom left panel: error RTs in the "speed" condition. Bottom right panel: error RTs in the "accuracy" condition.

$$\mathrm{RTm} = \frac{a}{2v} \times \frac{1-e^{-va/s^2}}{1+e^{-va/s^2}} + T_{er},$$
$$\mathrm{RTSD} = \sqrt{\frac{a}{2v} \times \frac{s^2}{v^2} \times \frac{-2va/s^2 e^{-va/s^2} - e^{-2va/s^2} + 1}{(1+e^{-va/s^2})^2}}, \quad (1)$$

Finally, we compared the correlations between drift rate v and RTSD with the correlations between drift rate v and RTm. In the first set of 40 simulations, in addition to the random drift rates, individual values for boundary separation a were drawn from a uniform distribution with minimum 0.08 and maximum 0.12. Individual values for non-decision time T_{er} were drawn from a uniform distribution with minimum 0.20 and maximum 0.40.

In the second, third, and fourth simulations, we fixed non-decision time T_{er}, or boundary separation a, or both, respectively. Fixing these parameters allowed us to investigate the underlying causes of the observed results. The key aspect of all simulations was that we calculated RTm and RTSD for each synthetic participant and correlated them with drift rate v, separately for each of the many levels of between-subject variability in drift rate (v_σ). We were most interested in what conditions predicted the observed finding; that the correlation between RTm and drift rate is weaker than the correlation between RTSD and drift rate.

The top left panel of Fig. 6 shows that the correlation between drift rate v and RTSD (filled dots) is stronger than the correlation between drift rate v and RTm (open dots). One reason for this could be that RTSD is not influenced by individual differences in non-decision time T_{er} – these only shift the RT distribution, without affecting variance – whereas non-decision time T_{er} differences do affect RTm. Therefore, fixing non-decision time T_{er} between participants should lead to a smaller difference between these correlations.

In the second set of simulations, parameters drift rate v and boundary separation a varied between participants as before, but non-decision time T_{er} was fixed to .3 for all participants. The results, found in the top right panel of Fig. 6, show that removing individual differences in non-decision time T_{er} weakens the difference between the two correlations, but still maintains the order: drift rate v always correlates more strongly with RTSD than RTm.

In the third set of simulations, parameters drift rate v and non-decision time T_{er} varied between participants as in the first simulations, but this time boundary separation a was fixed to .1 for all participants. The results, found in the bottom left panel of Fig. 6, show that when individual differences in boundary separation a are removed, the correlation between drift rate v and RTSD becomes close to 1. This is not surprising, as variation in RTSD now exclusively depends on drift rate (cf. Eq. (1)). The increase in strength of the correlation between drift rate v and RTm resulting from fixing boundary separation a is much less pronounced. Therefore, the difference between both correlations has increased.

In a final set of simulations, parameter drift rate v varied between participants as in the previous simulations. We investigated whether removing individual differences in *both* boundary separation a and non-decision time T_{er} similarly leads the correlation between drift rate v and RTm to approach 1. Boundary separation a was fixed to 0.1 and non-decision time T_{er} was fixed to 0.3 for all participants.

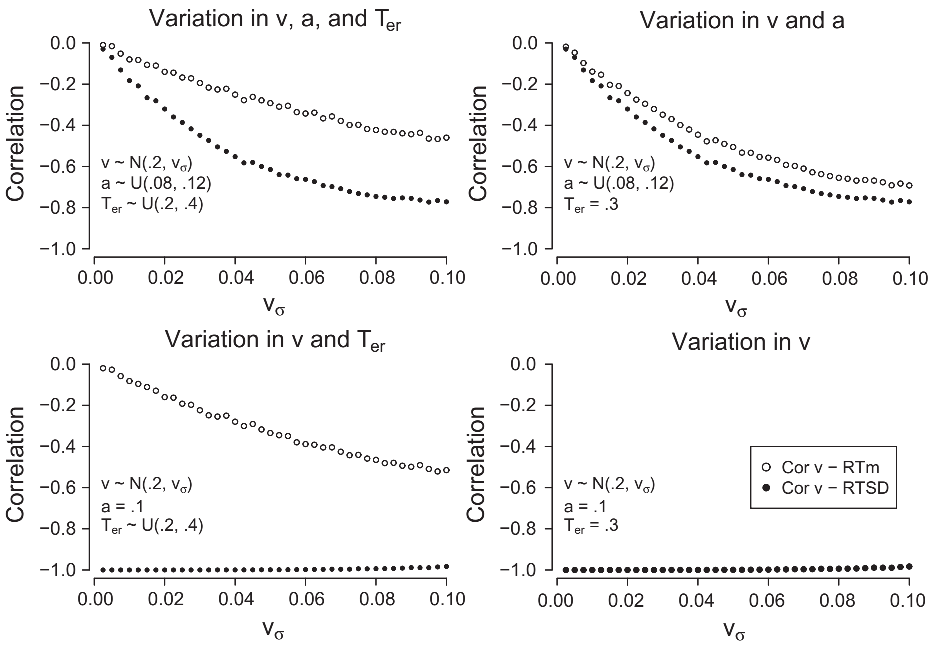

Fig. 6. The correlation between RTSD and drift rate v (filled dots) is larger than the correlation between RTm and drift rate v (open dots). All panels show data from simulations in which the standard deviation of drift rate over participants, $v_\sigma = \{.0025,.005,\ldots,.1\}$. In the top left panel, boundary separation a and non-decision time T_{er} vary between participants. In the top right panel, boundary separation a varies between participants, but non-decision time T_{er} is fixed. In the bottom left panel, non-decision time T_{er} varies between participants, but boundary separation a is fixed. In the bottom right panel, both boundary separation a and non-decision time T_{er} are fixed.

The results, found in the bottom right panel of Fig. 6, show that both correlations approached 1, so there was no longer any appreciable difference between the two correlations.

In sum, as long as individuals differ when described in terms of diffusion model parameters, the correlation between drift rate and RTSD is likely to be larger than the correlation between drift rate and RTm. The difference between these two correlations gets stronger as individual differences in drift rate increase. Removing individual differences in non-decision time does not lead to a qualitative difference in the pattern of results, whereas removing individual differences in boundary separation leads the correlation between drift rate and RTSD to approach unity. Removing individual differences in both boundary separation and non-decision time leads to both the correlation between drift rate and RTSD and between drift rate and RTm to approach unity, and no appreciable difference between the two correlations.[3]

3.4. Linear relation between RTm and RTSD

The linear relation between RTm and RTSD is well-known in the field of intelligence. Jensen even suggests that the correlation between RTm and RTSD is in principle 1.0, and the lower correlations we obtain in practice are simply due to measurement error (Jensen, 2006, p. 202). Despite the fact that the linear relationship between RTm and RTSD is a familiar phenomenon in research on intelligence (e.g., Berkson & Baumeister, 1967; Jensen, 1992), surprisingly little research has been conducted to explain this correlation.

The linear relationship between RTm and RTSD has also been studied by RT researchers (e.g., Luce, 1986; Wagenmakers et al., 2005; Wagenmakers & Brown, 2007). In a theoretical study, Wagenmakers et al. (2005) formalized the relationship between RTm and RTSD in terms of diffusion model parameters (see Wagenmakers et al., 2005, Eq. 12). In order to visualize this relationship, we plotted RTSD against RTm for a range of values of boundary separation a and drift rate v (see Fig. 7, adapted from Wagenmakers et al., 2005, Fig. 3).

The figure shows that for different values of boundary separation, when drift rate varies between participants, $v = \{.1,.15,\ldots,.5\}$, the relationship between RTSD and RTm is almost perfectly linear. Put another way, if participants vary in drift rate on some task, the RTSD of those participants will be linearly related to their mean RTs. Wagenmakers and Brown (2007) also found the linear relation between RTm and RTSD for a range of empirical data outside the field of intelligence involving memory, perception, categorization, and problem solving. The authors conclude that for nearly 75% of the participants, the correlation between RTm and RTSD is at least .85.

In sum, the precise relationship between RTm and RTSD is predicted by the diffusion model (cf. Wagenmakers et al., 2005, Eq. (12)). When diffusion model parameters vary in a realistic range (Matzke & Wagenmakers, 2009), this relationship is approximately linear, as can be seen in Fig. 7.

[3] In simulations not reported here, we found that setting non-zero values for the across-trial variability in drift rate, starting point, and non-decision time led to lower correlations in general, but did not change the qualitative pattern of results.

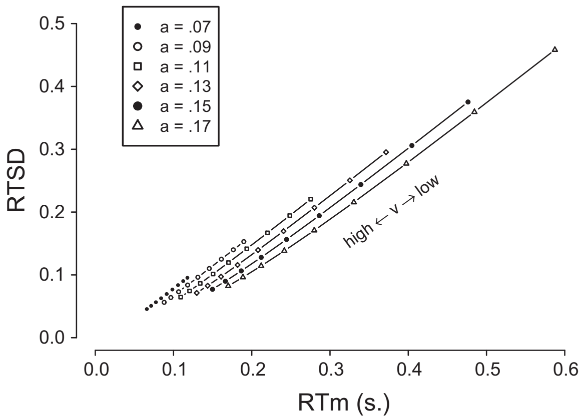

Fig. 7. The close-to-linear relationship between RTm and RTSD in the diffusion model. Lines represent, from left to right, values of boundary separation a = {.07,.09,...,.17}. Points in each line represent, from right to left, values of drift rate v = {.1,.15,...,.5}.

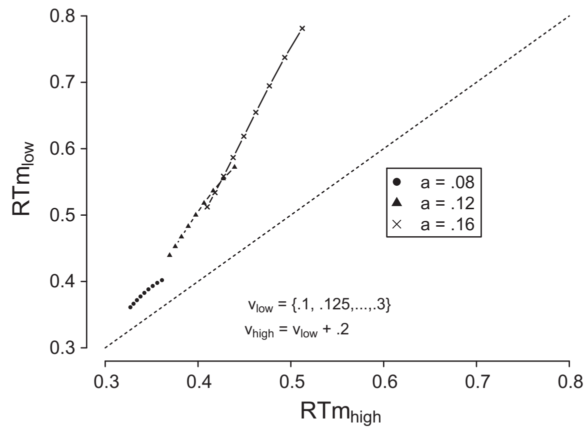

Fig. 8. Approximately linear Brinley plots predicted by the diffusion model. Parameter v_{low} = {.1,.125,...,.3}, parameter $v_{high} = v_{low} + .2$.

Recent work by Schmiedek, Lövdén, and Lindenberger (2009) showed that the linear relationship between RTm and RTSD may not be invariant across age-groups, suggesting that the relationship displayed in Fig. 7 may be an idealized representation.

3.5. Linear Brinley plots

First introduced in the context of cognition and aging, *Brinley plots* (Brinley, 1965; Salthouse, 1996) are now also used in the area of intelligence (e.g., Rabbitt, 1996). In the original Brinley plot, the mean RT of older participants is plotted against the mean RT of younger participants, for a number of experimental conditions that vary in difficulty. Typically, Brinley plots are linear with a slope larger than one and a negative intercept. Brinley plots are usually interpreted as an indication of the general slowing of cognitive processes (e.g., Cerella, 1985).

In intelligence research, the role of the participant's age is played instead by their intelligence: Brinley plots show the mean RT of low-*g* people against the mean RT of high-*g* people, for conditions with different task difficulties. These plots are also usually linear with a slope larger than one and a negative intercept. Analogous to the research on aging, this pattern of results is interpreted as an indication of global (as opposed to specific) differences in mental ability (e.g., Fry & Hale, 1996; Kail, 1991, for an overview, see Jensen, 2006, for a modeling approach, see Faust, Balota, Spieler, & Ferraro, 1999; Myerson, Hale, Wagstaff, Poon, & Smith, 1990).

In terms of diffusion model parameters, the relationship between RTm and drift rate v is given by Eq. (1), provided that there is no a priori bias and no across-trial variability parameters (Wagenmakers et al., 2005). Since the within-trial noise of drift rate s is fixed arbitrarily, the shape of a Brinley plot for two people with different drift rates can be calculated analytically if one is willing to make an assumption about their boundary separations.

Based on Eq. (1), we constructed a set of Brinley plots, in which RT means of a synthetic high-*g* participant (with drift rate v_{high}) are displayed against a synthetic low-*g* participant (with drift rate v_{low}). For this set of Brinley plots, we assumed that v_{high} was larger than v_{low} by a fixed amount (i.e., $v_{high} = v_{low} + .2$). We set boundary separation a to be equal for the high-*g* participant and the low-*g* participant. The Brinley plots are displayed in Fig. 8.

Displayed in the figure are data from the low-*g* and the high-*g* participants on a task with nine conditions of decreasing difficulty, modeled using v_{low} = {.1,.125,...,.3}.[4] As observed empirically, the Brinley plots are approximately linear with a slope greater than 1 and a negative intercept. For larger values of boundary separation a, the slope increases and the intercept becomes lower.

For the full diffusion model with across-trial variability in drift rate, starting point, and non-decision time, an analytical approach is not practical. However, Ratcliff et al. (2000) used simulation to demonstrate linear Brinley plots with the full diffusion model (see also Myerson, Adams, Hale, & Jenkins, 2003). Ratcliff et al. generated RT data with the diffusion model for synthetic older and younger participants. The participants differed on either drift rate or boundary separation: the older group had either a lower drift rate, or a higher boundary separation than the young group. As a result, the older group had larger RTs than the younger group. Brinley plots were constructed that showed all the standard features, such as linearity, a slope higher than one, and a negative intercept Ratcliff et al., 2000, see Fig. 8. In sum, the diffusion model is capable of generating linear Brinley plots by varying either drift rate or boundary separation.

3.6. Stronger correlation between g and IT than between g and RTm

The inspection time, or IT, task is another simple paradigm that has often been studied in relation to intelligence (Deary & Stough, 1996; Jensen, 2006). In a typical IT task, a

[4] Non-decision time T_{er} was set to .25 for both the high-*g* and the low-*g* participants, but since non-decision time T_{er} is an additive component that is assumed not to vary across conditions, it cannot influence the shape of the Brinley plots.

participant is simultaneously presented with two lines and has to judge which of the two is the longest. While there is no time limit for this judgment, the task is made difficult by displaying the lines only for a limited duration, which is varied over trials. For each participant, a display duration is found that leads to a predetermined level of accuracy (e.g., 90%). This duration is called the IT for that particular participant.

Typically, the correlation between IT and g ranges from about −.30 to −.50 (Deary & Stough, 1996; Grudnik & Kranzler, 2001) and is therefore more pronounced than the correlation between RTm and g, which ranges from about −.20 to −.30 (Jensen, 1998, 2006). Here we show that the diffusion model predicts such a pattern of correlations when the plausible assumption is made that boundary separation and non-decision time vary between participants.

First, we express IT in terms of drift rate. An inspection time paradigm can be modeled by a diffusion process with no response boundaries; that is, the evidence accumulation process begins at some starting point and gathers information from the stimulus as long as the stimulus is available. When the stimulus is removed, at time IT, the diffusion process stops.[5] A response is chosen depending on whether the diffusion process terminated above or below its starting point, corresponding to a balance of evidence in favor of one response or the other. Across trials, the finishing point of the evidence accumulation process will be normally distributed with mean $v \times IT$ and standard deviation $s \times \sqrt{IT}$, where v is drift rate and s is the within trial noise of drift rate (e.g., Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006). The decision maker's accuracy, p_c, will thus be given by the mass of this distribution that lies above 0 (see Fig. 9), which can be defined in terms of the standard normal distribution. Inverting that relationship shows that IT is given by:

$$p_c = \Phi\left(\frac{v}{s}\sqrt{IT}\right) \tag{2}$$

where Φ denotes the standard normal cumulative distribution. Now, by rearranging the equation, we can express IT in terms of the decision maker's accuracy p_c and drift rate v

$$IT = \left(\frac{s}{v} \times \Phi^{-1}(p_c)\right)^2. \tag{3}$$

With IT defined, we can investigate under what contingencies drift rate can account for a stronger correlation between g and IT than between g and RTm. In order to do so, we have reused the simulation data presented in Section 4. Correlations between drift rate v and IT (open dots) and correlations between drift rate v and IT (filled dots) are shown in Fig. 10. Note that all four panels contain the same data, as IT only depends on drift rate.

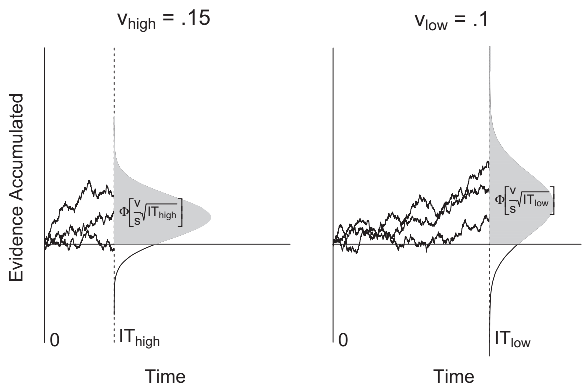

Fig. 9. The relationship between drift rate v, inspection time IT and percentage correct p_c. The percentage correct is defined as the proportion of decision processes that terminate above the starting point at time IT. The two panels represent low- and high-g participants. Response accuracy is identical in both panels (p_c = .9), showing how a low drift rate v leads to a high inspection time IT, and vice versa.

Recall that in Section 4, synthetic data were generated from the diffusion model while allowing drift rate v to vary across participants. The magnitude of variability between participants was varied from $v_\sigma = \{.0025, .005, \ldots, .1\}$, and this manipulation is shown on the x-axis of Fig. 10. For these same parameter settings, we calculated RTm and IT for each participant and correlated them with drift rate v.

The top left panel of Fig. 10 shows that the correlation between drift rate and IT becomes weaker as between-subject variability in drift rate increases. This occurs because drift rate v is inversely related to the square root of IT – not a linear relationship. Therefore, the measured linear correlation must decrease when a wider range of values of drift rate over participants is observed, and eventually approach the asymptote 0.[6] In all four simulation conditions, the correlation of drift rate v with RTm becomes stronger than the correlation of drift rate v with IT whenever the variation in drift rate between participants is large enough (greater than about $v_\sigma = 0.05$).

In sum, we found a stronger correlation between drift rate and IT than between drift rate and RTm when the between-subject standard deviation in drift rate is below 0.05. Empirically found correlations between IT and g from about −.30 to −.50 (Deary & Stough, 1996; Grudnik & Kranzler, 2001) and correlations between RTm and g from about −.20 to −.30 (Jensen, 1998, 2006) match our simulation results when the between-subject standard deviation in drift rate is somewhere between 0.04 and 0.05. Values of the between-subject standard deviation in drift rate in this range are plausible and have been found empirically for the mean drift rate value of 0.02 which we used in our simulations (e.g., Ratcliff, Thapar, & McKoon, 2001).

[5] Different assumptions about the termination of the diffusion process could be reasonable. A plausible assumption is that the diffusion process could continue for a fixed time after time IT (e.g., 100 ms longer). For instance, Ratcliff and Rouder (2000) found that after masking the stimulus in a two-choice letter identification task, the decision process continued with a full drift rate. This assumption would only add a constant amount of time to each IT (e.g., 100 ms) and would not alter the correlation between drift rate v and IT.

[6] As an example, consider the correlation between fictional variables x_1 and x_2, with $x_1 = \{1, 2, \ldots, n\}$ and $x_2 = (1/x)^2$. So, variable x_2 is inversely related to the square root of variable x_1, like the relation between drift rate and IT. Increasing values of n lead to lower correlations between x_1 and x_2; n = 10 gives a correlation of −0.67, n = 100 gives a correlation of −0.26, n = 1000 gives a correlation of −0.09. Increasing the variability in drift rate leads to an analogous decrease in the correlation between drift rate and IT.

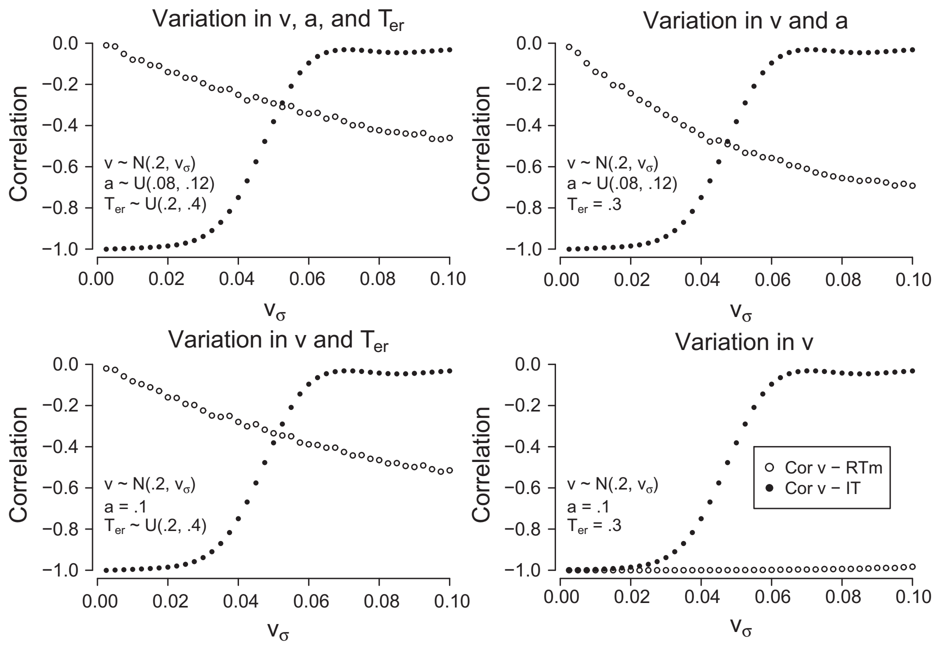

Fig. 10. The correlation between IT and drift rate v (filled dots) is larger than the correlation between RTm and drift rate v (open dots) for low standard deviations of drift rate, v_σ, but smaller for high values of v_σ. All panels show data from simulations in which the standard deviation of drift rate over participants, $v_\sigma = \{.0025, .005, \ldots, .1\}$. In the top left panel, boundary separation a and non-decision time T_{er} vary between participants. In the top right panel, boundary separation a varies between participants, but non-decision time T_{er} is fixed. In the bottom left panel, non-decision time T_{er} varies between participants, but boundary separation a is fixed. In the bottom right panel, both boundary separation a and non-decision time T_{er} are fixed.

We have demonstrated that three of the phenomena reviewed earlier (the worst performance rule, stronger correlations between g and RTSD, and linear Brinley plots) all continue to hold when the between-subject standard deviation in drift rate is smaller than 0.05. Two other phenomena (right skewed RT distributions and the linear relation between RTm and RTSD) are not affected by the between-subject standard deviation in drift rate. These results agree with this new result – a stronger correlation between drift rate and IT than between drift rate and RTm. All six phenomena will be observed whenever the between-subject standard deviation in drift rate is not too large.

4. Advantages and limitations of a diffusion model approach to the study of intelligence

We have shown how a simple assumption in a computational model can provide a unifying account of six different phenomena from the intelligence literature. When we assume that differences in drift rate in the diffusion model are associated with differences in intelligence (g), we find that the model predicts: right-skewed RT distributions; the worst performance rule; the fact that g correlates stronger with RTSD then with RTm; the linear relation between RTm and RTSD; linear Brinley plots; and the stronger correlation between g and IT than between g and RTm. The diffusion model also provides a theoretical framework for interpreting these phenomena. We will now list an additional set of advantages of using the diffusion model in intelligence research.

1. The diffusion model is a quantitative model. Precise predictions can be obtained through analytics or simulation; verbal accounts are less precise and notoriously susceptible to alternative interpretation.
2. The diffusion model allows for a decomposition of RTs in terms of meaningful psychological processes. The model can filter out the processes that may be related to psychometric g (e.g., drift rate or variability in drift rate) from those that are not (e.g., nondecision time T_{er}). The diffusion model therefore solves an important problem that was most recently articulated by Jensen: "The RT literature is made problematic by the inconsistency across studies to employ methods that distinguish between the cognitive decision and the motor components of the task, treating them as if they are equivalent or indistinguishable." (Jensen, 2006, p.234).
3. The diffusion model takes into account entire distributions of response times, for both correct and error decisions, as well as error rate.
4. The diffusion model makes qualitative predictions and can be falsified. In a series of simulations, Ratcliff (2002) showed that the diffusion model is incapable of fitting many apparently reasonable patterns of RT data. That such data have not been observed is strong evidence in favor of the model. Even more powerfully, we demonstrated that a novel prediction from the diffusion model account was supported in data.

5. The diffusion model is now easy to apply, thanks to several purpose-built software packages: EZ (Wagenmakers et al., 2007), fast-dm (Voss & Voss, 2007), DMAT (Vandekerckhove & Tuerlinckx, 2007, 2008), and a hierarchical Bayesian version (Vandekerckhove, Tuerlinckx, & Lee, in press).
6. Drift rate is theory-neutral; it is a general parameter to capture signal-to-noise ratio in the evidence accumulation process, and is not particular to the diffusion model alone. The deeper meaning of the drift rate parameter can be further explored through developments in neuroscience or quantitative modeling (Gold & Shadlen, 2007; Heekeren, Marrett, & Ungerleider, 2008; Ho, Brown, & Serences, 2009; Lo & Wang, 2006; Ma, Beck, & Pouget, 2008; Soltani & Wang, 2010).
7. The diffusion model builds a bridge between theorizing in related fields, such as aging (e.g., Ratcliff et al., 2000, 2001, 2006b; Ratcliff, Thapar, & McKoon, 2003, 2004, 2006a).
8. There is a growing link between neuroscience and the diffusion model (e.g., Gold & Shadlen, 2007). Neuroscience will also become more important for the study of intelligence (Jensen, 2006). Further integration between these different research agendas will most likely benefit both lines of research.

These per usual, these benefits do not come without cost. Quantitative modeling is a powerful approach, and the diffusion model in particular is very useful, but also brings inherent limitations. The most important limitations are:

1. The diffusion model requires a substantial number of observations per condition in order to be able to obtain reliable parameter estimates. For instance, for an error rate of 5%, approximately 200 RTs are necessary to get a reliable estimate of the RT distribution for errors (Wagenmakers, 2009). This limitation may be partly solved by including multiple experimental conditions in the experiment, in which only a single parameter (e.g., drift rate) is manipulated.
2. The diffusion model can only be applied to two-alternative forced-choice data. Cognitive tasks that allow for multiple response alternatives are unsuitable for a diffusion model analysis. Fortunately, there are several alternative models that feature a drift rate parameter and do allow for multiple alternatives. Two of those models are the leaky, competing accumulator model (LCA Usher & McClelland, 2001) and the linear ballistic accumulator model (LBA Brown & Heathcote, 2008). We will return to these models in the concluding comments.
3. The diffusion model is essentially a single-process model. Stimulus–response incompatibility tasks (e.g., the Stroop task, MacLeod (1991) or the Simon task, Simon (1990)), may not be suited to a standard analysis with the diffusion model, because there are two processes at work simultaneously: the relevant and the irrelevant stimulus dimension (e.g., Kornblum, Stevens, Whipple, & Requin, 1999). As such, the one-dimensional diffusion model is not naturally suited to deal with these kinds of tasks. Modifications of the model may work (e.g., one may assign a drift rate to the relevant stimulus dimension and a drift rate to the irrelevant stimulus dimension), as may other response time models with independent accumulators for each response (e.g., the dimensional overlap model, Kornblum et al., 1999).
4. Drift rate is theory-neutral. In some ways this is an advantage (Item 6 above) but in others it is a disadvantage. For example, thinking of g as a drift rate does not automatically suggest an underlying theory for changes in g. However, modern developments have linked the diffusion model (and the LBA and LCA models) to underlying physiological processes, using neuroscientific methods (e.g., Bogacz & Gurney, 2007; Gold & Shadlen, 2007; Ratcliff & McKoon, 2008). These findings provide the beginnings of a "theory for drift rates".

5. Concluding comments

The diffusion model provides an elegant, quantitative, and unifying account of previously disparate empirical phenomena. This means that while substantial research efforts have been devoted to each of the individual phenomena, these efforts represent an ill-advised division of labor. We combined results from previous research with new results regarding the stronger correlation between g and RT standard deviation than between g and RT mean, the linear relation between RT mean and RT standard deviation, and the stronger correlation between g and inspection time than between g and RT mean. We also showed that the worst performance rule is not specific to g, but generalizes to other phenomena, such as drift rate and stimulus difficulty. To our knowledge, this is the first attempt to demonstrate that six seemingly disparate phenomena are in fact all the same and can be accounted for by a single entity: the drift rate parameter of the diffusion model.

It is not a new idea that information-accumulation processes, such as drift rate, might represent neural firing rate and therefore also represent mental speed. Both Lo and Wang (2006) and Usher and McClelland (2001) propose neurally based models using evidence accumulation frameworks. Shadlen and Newsome (1996) showed that when monkeys choose to saccade to one of two directions, their neurons display selective activation for each direction. Moreover, the monkeys reliably responded when neuronal activation reached a fixed response threshold. Gold and Shadlen (2007) draw a parallel between evidence accumulation parameters from sequential sampling models (such as drift rate) and neuronal firing rates in the brain. The authors show how these evidence accumulation parameters may be implemented in the brain of a monkey. Smith and Ratcliff (2004) compared results from single-cell studies to behavioral results in psychology, and concluded that for both cases, decisions are made when a noisy accumulator (i.e., drift rate) reaches a response threshold.

It must be noted that drift rate only accounts for the percentage of variance in individual differences in intelligence that was previously explained by the six benchmark phenomena. It is likely that higher-order models, featuring memory and higher cognitive functions, are needed to fully explain all factors that affect individual differences in intelligence.

The assumption that drift rate partly reflects the speed of mental processing is plausible and parsimonious. Schmiedek, Oberauer, Wilhelm, Süß, and Wittmann (2007) showed that drift rate is a strong predictor of working memory, reasoning, and psychometric speed. They conjectured that "drift rate reflects a general source of variance in efficiency of information processing that is also relevant for more complex cognitive tasks". Ratcliff et al. (2010) found that a common factor for drift rate explains a large proportion of the variance across subjects in two IQ measures, matrix reasoning and vocabulary. However, it is certainly possible that other diffusion model parameters also reflect individual differences in *g*. This is an exciting and open research question – so far, the diffusion model has seen only limited application in the field of intelligence research.

Although we have presented our analyses using the diffusion model, there are many related evidence accumulation models. Two examples are the leaky, competing accumulator model (LCA Usher & McClelland, 2001) and the linear ballistic accumulator model (LBA Brown & Heathcote, 2008). These models differ from the diffusion model mainly in that they feature multiple accumulators and hence allow for more than two response alternatives. Apart from this structural difference, the models share many basic assumptions – importantly, they all have similar definitions for drift rates, boundary separation, and non-decision time. It is reasonable to expect that the LCA and the LBA would provide a similar account of the six benchmark phenomena as the diffusion model, given their similarities. In fact, a recent simulation study demonstrated that fluctuations in diffusion model drift rates map uniquely onto fluctuations in LBA model drift rates (Donkin, Brown, Heathcote, & Wagenmakers, in press). Thus, what is important in our linking of intelligence and drift rate is that drift rate measures the speed of evidence accumulation.

So what have we learned about intelligence by associating it with drift rate in the diffusion model? Arguably, almost nothing! However, we have shown that many benchmark phenomena in the field of intelligence research can originate from fluctuations in a single, theory-neutral parameter – drift rate – that quantifies processing speed.

Therefore, our work suggests that in order to learn something unique about *g*, one should:

1. go beyond the benchmark phenomena discussed above;
2. find an empirical phenomenon, associated with *g*, which cannot be accounted for by drift rate;
3. explain in what way *g* differs from drift rate.

We have outlined the advantages of a diffusion model analysis as a tool in the study of the relation between response speed and general intelligence. We hope that this research may further the integration between the field of intelligence research and the field of quantitative modeling. The diffusion model, with its drift rate parameter, provides a new way of thinking about the concept of intelligence.

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