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Using the diffusion model to study individual differences

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Manuscript 2

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Manuscript 3

Theisen, M., Lerche, V., von Krause, M., & Voss, A. (2020). Age differences in diffusion model parameters: a meta-analysis. *Psychological Research*, 1-10.

Manuscript 4

von Krause, M., Lerche, V., Schubert, A. L., & Voss, A. (2020). Do Non-Decision Times Mediate the Association between Age and Intelligence across Different Content and Process Domains?. *Journal of Intelligence*, *8*(3), 33.

Manuscript 5

von Krause, M., Radev, S.T., & Voss, A. (submitted). Processing speed is high until age 60 - Insights from Bayesian modeling in a one million sample (with a little help of deep learning). *Proceedings of the National Academy of Sciences of the United States of America*.

1 Introduction

Already since the days of Gordon W. Allport (1937), psychological science has been partly divided. On the one hand, fields such as cognitive or experimental psychology have focused on principles and laws that supposedly generalize across people, possibly even all humans (Reisberg, 2013). On the other hand, fields such as personality psychology have focused on the individual differences between people (John et al., 2008). Though of course there has always been an exchange between these two "blocks" of psychology, the gap between them has more often than not proved hard to bridge. For example, there has been an abundance of research on individual differences in cognition, cognitive abilities like mental speed, and intelligence, dating back as far as Francis Galton (1908) and Alfred Binet (1904). Mostly separately from that, in the field of cognitive psychology, people have tried to understand the exact "hows" of cognitive processes in general, quite often by means of experimental methods and, in the past decades, mathematical or computational models of cognition (Busemeyer & Diederich, 2010). Through cognitive modeling, scientists try to map the distinct processes hypothesized to create certain behavioral data to parameters in a mathematical formulation (Farrell & Lewandowsky, 2018), ideally allowing for formalized testing of the theories underlying the models. As the hypothesized processes are usually not directly observable, modeling approaches also often have the advantage of providing estimates of these hidden or latent parameters, even on the level of an individual person. In this way, cognitive models provide a link between experimental psychology and research on individual differences.

One such cognitive model that has seen a huge rise in popularity over the past 40 years is the diffusion model (Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998; Voss et al., 2013). Roger Ratcliff originally developed the model in the 1970s, building on older work from Laming (1968) and Link and Heath (1975). It is a stochastic model of the decision process in simple binary decision tasks and part of the family of evidence accumulation models. Other models belonging to the same model family are the leaky competing accumulator model (LCA; Usher & McClelland, 2001) and the linear ballistic accumulator model (LBA; Brown & Heathcote, 2008). These latter models have several distinct properties when compared to the diffusion model, the most important ones probably being that they are applicable not only to binary decision tasks but also to multiple choice tasks, and try to (in case of the LCA) model the neural processes underlying decision making. Since I will only study binary decisions and this thesis will be concerned with the neural basis of decisions only to a minor extent, and because the diffusion model has been tried, tested, and validated by far most extensively in previous research, this model will also be the focus of my work. However, I will refer back to the LCA and LBA in the discussion.

The basic idea of the diffusion model is that people, for example when solving a recognition memory task (Ratcliff, 1978), continuously accumulate information until one of two thresholds is reached. These thresholds represent the two possible decision outcomes. The diffusion model uses response time distributions and accuracy rates to estimate different aspects of the decision process underlying the data obtained in an experimental setting. The main advantage of the model lies in its ability to disentangle the speed of information accumulation (called drift rate in the model) from speed-accuracy trade-offs (represented by the so-called boundary separation), decision biases, and the time needed for non-decisional processes like encoding and motor response execution (Voss et al., 2004). In this way, the model allows the specification of well-defined research questions, in contrast to, for example, the mere comparison of mean correct response times between different experimental conditions. For instance, the model can help explain whether the slower response times found in one experimental condition compared to another are due to higher average decision caution (maybe because of differently worded instructions) or differences in speed of information accumulation – both should map to different diffusion model parameters, namely boundary separation and drift rate.

There has been a great variety of studies employing the diffusion model, mostly in experimental or cognitive psychology, with a focus on research in memory (Arnold et al., 2015; Ball & Aschenbrenner, 2018; Boywitt & Rummel, 2012; Horn et al., 2013; McKoon & Ratcliff, 2012; Ratcliff, 1978; Spaniol et al., 2006; Voskuilen et al., 2018), perception (Dully et al., 2018; Kühn et al., 2010; McGovern et al., 2018; Ratcliff et al., 2003; Spaniol et al., 2011), language (Ratcliff, Gomez, et al., 2004; Ratcliff, Thapar, et al., 2004; Yap et al., 2012), and executive control (Madden et al., 2010). However, over the past two decades, more and more researchers have also started using the diffusion model to study individual differences in diffusion model parameter estimates.

When linking cognitive modeling and individual differences research in such a way, it is vital to first establish a clear definition of the diffusion model parameters as markers of individual differences. Do they represent trait-like entities? If this is the case, according to generally accepted definitions of personality and traits, they should exhibit consistency across tasks and time (John et al., 2008). Moreover, it is important that they are valid representations of the decision processes they are theorized to measure, and, in a correlational setting with other traits, show concurrent and discriminant validity. In the end, these issues lead to the question of how such parameters may help us tackle problems posed in individual differences research - a question I pursued in my dissertation project by employing the diffusion model to better understand the relations of the processes represented by the diffusion model parameters, intelligence, and age.

In doing so, I tried to bridge the gap between experimental psychology methodology and substantial individual differences research in two ways. On the one hand, I used the diffusion model, with its background in cognitive psychology, to obtain better-informed inferences regarding questions on individual differences in cognition than are achievable when solely relying on raw data. On the other hand, and this is the major novelty of my research program, I applied principles deemed important in individual differences research to diffusion model analyses, by using rich and diverse data to improve the reliability and scope of my results. Most previous diffusion model studies reporting on individual parameter values focused on very specific research questions grounded in experimental psychology and often not followed up on in a systematic way in subsequent research. In contrast to that, throughout the work that forms this thesis, my aim was to take the diffusion model parameters seriously primarily as constituents of individual differences and systematically probe their applicability and usefulness in such a framework throughout an entire research program.

My dissertation can roughly be divided in two parts, with the first, much shorter and more methodological part, setting the stage for the substantial research questions tackled in part two. Both parts are concerned with the question whether the diffusion model can help us study individual differences in cognition better and more precisely than by relying on raw data.

In the first section, I follow up on the previous literature on the question whether diffusion model parameters should be considered trait-like entities by studying a large sample of participants longitudinally over two years (*Manuscript 1*). There have been some attempts at systematically conceptualizing the study of individual differences with the diffusion model and establishing a framework for the interpretation of diffusion model parameters as person-specific measures of distinct cognitive processes (Lerche & Voss, 2017b; Ratcliff & Childers, 2015; Schubert et al., 2016). Lerche and Voss (2017b) reported that the main diffusion model parameters showed at least acceptable retest stability over a one week interval, while Schubert and colleagues (2016) used a latent state-trait model to establish their consistency (especially of drift rates) across two tasks as well as over an eight month interval. In our study, we go beyond the previous literature on temporal patterns in diffusion model parameters in several ways. We analyzed four different types of stability and change in diffusion model parameters in a large sample across four measurement occasions over two years.

In the second section, I use the estimates of individual differences in cognitive parameters provided by the model to better understand research questions on individual differences in cognition. An abundance of literature relies on mean response times as a measure of processing speed (Jensen, 2006; Sheppard & Vernon, 2008). As response times are composites of several processes, it is often hard to understand what exactly is measured in mean response times and how to interpret the corresponding literature that analyzes such data. Here, I focus on two "puzzles" in cognitive individual differences research that I hope to help better understand by means of disentangling the decision process components through diffusion modeling.

The first puzzle concerns the across-task structure of processing speed and its relationship to intelligence. Intelligence and processing speed were found to be positively related in numerous studies (Jensen, 2006; Sheppard & Vernon, 2008). Intelligence is also thought to be in parts content-specific, with the across-task structure showing both a general factor (*g*) and domain factors such as verbal or figural intelligence (Sternberg, 2000). Yet processing speed, as measured in mean response times, has in the past repeatedly been found to be largely unitary, that is, when analyzing the correlational pattern of processing speed across several tasks, their common variance seems best represented by a single general factor similar to *g* in intelligence research (Jensen, 2006; Schubert et al., 2017). Content-domain specific aspects, for example of processing speed specific to verbal or figural tasks, could not be found in previous research.

Taken together, these findings reported in the literature might seem somewhat puzzling: processing speed and intelligence are closely related, although the former does not exhibit the complex correlational patterns of the latter. The idea behind *Manuscript 2* is that this configuration of results can be attributed to the fact that response times are composite scores of several distinct processes. To get a theoretically pure measure of processing speed or speed of information accumulation, we focused on the drift rate diffusion model parameter in a study utilizing 18 tasks. We investigated the structure of processing speed and its relationship to intelligence across the figural, numerical, and verbal content domains. In this way, we could study the relative strength of domain-specific and domain-general aspects of drift rates and their correlational patterns to the respective intelligence components.

The second puzzle is already grounded in past diffusion model research. Older people often show longer response times across a great variety of cognitive tasks - this is a consistent finding in the literature on cognitive aging (Jensen, 2006). Repeatedly, this observation has been interpreted as representing a mental slow-down, that might even be the root of cognitive decline as a whole, including the lower intelligence scores found in older people (Salthouse, 1996). Yet studies employing the diffusion model, comparing college-aged persons with older adults aged 65 or more, have repeatedly shown that drift rates (as indices of processing speed) are unrelated to age – instead, older people tend to sample more information before taking a decision and need more time for encoding and motor response execution (e.g., Ball & Aschenbrenner, 2018; McKoon & Ratcliff, 2012, 2013; Ratcliff et al., 2003; Ratcliff, Thapar, et al., 2004; Spaniol et al., 2006; Thapar et al., 2003; Voskuilen et al., 2018). It must be noted that some studies did find drift rates to be negatively related to age, while others found a positive relation, making the overall picture quite unclear (Ratcliff, Thapar, et al., 2004; Voskuilen et al., 2018).

We used a three-step approach to better understand the inconsistent results regarding the effects of age on drift rates. First, we studied age differences in diffusion model parameters and especially drift rates in a meta-analysis to gain a quantitative description of the overall patterns reported in the literature (*Manuscript 3*). Second, we employed mediation analyses to study which of the diffusion model parameters mediate age-related differences in intelligence (*Manuscript 4),* once more using the dataset of 18 different tasks also analyzed in *Manuscript 2*, to be able to scrutinize task-specificities within one sample. In this way, we could assess directly whether it was speed of information accumulation, boundary separation, or non-decision time that explained the slower response times found with increasing age, thus providing a test of the assumption that changes in processing speed are at the core of age-related cognitive decline. Finally, we studied age differences in mean response times and diffusion model parameters in a very large implicit association test (Greenwald et al., 1998, 2003; Nosek et al., 2007) dataset (N > 1,000,000; *Manuscript 5*). To obtain parameter estimates, we used a novel parameter estimation approach based on a deep neural network that makes handling such sample sizes feasible (Radev et al., 2020). The large number of participants allowed us to robustly analyze cross-sectional age differences on a year-specific level, yielding very interesting results on the age relationships of processing speed, decision caution, and non-decision time, almost over the entire lifespan (ages 10 to 80).

Together, the studies presented in this dissertation constitute an important step in the direction of a systematic use of the diffusion model in the study of individual differences. After introducing the five manuscripts on the following passages, I will then discuss their implications, possible limitations, and give some ideas on possible future research.

2 Stability and change in diffusion model parameters (Manuscript 1)[1]

Utilizing the full data resulting from binary decision tasks, the diffusion model allows researchers to obtain individual parameter estimates of processing speed (drift rates), decision caution (boundary separation), non-decision times, and response biases (Ratcliff & McKoon, 2008). These parameters have been validated both experimentally (Arnold et al., 2015; Voss et al., 2004) and neurophysiologically (McGovern et al., 2018; Ratcliff et al., 2007). However, in most studies using the diffusion model, the focus is on comparing differences in model parameter between experimental conditions. For example, one might study the question whether the IAT effect measured in implicit association tests (Greenwald et al., 1998, 2003; Nosek et al., 2007), that supposedly measures implicit bias, maps onto differences in drift rates, boundary separations, or non-decision times (Klauer et al., 2007). When employing the diffusion model in such a manner, that is, for studying group differences, the reliability and exact properties of each of the individual parameter estimates is of secondary importance to the general validity of the parameters. Contrarily, when researchers are interested in the diffusion model parameters as characterizing individuals, some new questions gain priority. Are the model parameters truly person specific? Is there reliable between-person variance? Are between-person differences in model parameters related across different paradigms? Are between-person differences stable across time? How do individual parameter estimates develop?

These questions relate to the concept of *traits* that is of central importance in theories of individual differences. Traits are often defined as characteristic patterns of thoughts, feelings and behaviors that show consistency across situations and stability across time (Allport, 1937; John et al., 2008). Whether the diffusion model parameters, for example, processing speed as measured by drift rates, can be interpreted as traits in the way they were just defined, is still unclear from past diffusion model studies. While a number of studies have started to employ the individual parameter estimates in correlational research, for example focusing on their relationships with intelligence (McKoon & Ratcliff, 2012; Ratcliff et al., 2010; Schmiedek et al., 2007), the underlying assumptions have rarely been tested systematically. The aspect that has received by far the most attention is whether the diffusion model parameters show consistency across tasks. Several studies have reported medium to high across-task correlations

[1] von Krause, M., Radev, S. T., Voss, A., Quintus, M., Egloff, B., & Wrzus, C. (submitted). Stability and Change in Diffusion Model Parameters Across Two Years. *Journal of Intelligence*.

for all of the core diffusion model parameters (e.g., Ratcliff et al., 2010; Schmiedek et al., 2007; Schubert et al., 2016). In contrast, their temporal stability has received far less attention.

The first study reporting test-retest correlations over a time period of at most a week found strong across-time correlation for drift rates, boundary separations, biases, and non-decision times (all correlations r >.70, Yap et al., 2012). In contrast, Lerche et al. (2017b) found far weaker across-time correlations for non-decision times (all *r*s <.50), although they did find strong stability for drift rates, boundary separations and biases (all *r*s >.70). Finally, Schubert et al. (2016) conducted a first systematic study of the trait characteristics of diffusion model parameters. Studying two different tasks over two measurement occasions eight months apart, the authors employed latent-state-trait structural equation models to separate the parts of diffusion model parameter variance specific to each task and each time point from trait variance. According to their analyses, drift rates show by far the greatest across-task and across-time stability, with boundary separation and non-decision times being less trait-like in their composition of variance (the authors did not study response bias).

While these studies were important first steps on the path of establishing the trait-like qualities of individual diffusion model parameter estimates in a temporal sense, they had several shortcomings. First, the time period studied was limited, with at most eight months separating the first form the second measurement occasion (Schubert et al., 2016). If diffusion model parameters should be considered trait-like entities, they might be expected to show stability over time periods of one year or even several years. Second, sample sizes were generally limited and so was the samples' heterogeneity – most participants were college-aged students. Third, the studies mostly focused on one aspect of temporal stability, namely test-retest correlations or the trait-factor in the structural equation model. Both these measures relate to the concept of rank-order stability, that is, the stability of the across-person relative positions of participants on the range of possible parameter values. Yet in the study of individual differences, a number of additional ways of studying stability and change has been proposed – not only rank-order stability, but also mean-level changes, inter-individual differences in change, and profile stability (Roberts, Brent et al., 2008). These aspects have been extensively studied for the Big Five personality traits (e.g., Roberts et al., 2001, 2006; Roberts & DelVecchio, 2000), but have received little attention in the literature on cognitive parameters and none in the diffusion model literature.

Our study that comprised Manuscript 1 seeks to address all three gaps just outlined. We studied diffusion model parameters in a personality IAT (Back et al., 2009; Schmukle et al., 2008) across four measurement occasions over two years, employing a hierarchical Bayesian parameter estimation approach (Wiecki et al., 2013). We used a diverse sample that included both college-aged people and old adults, and in both age groups included students and non-students. Finally, we studied four types of stability and change: rank-order stability, mean-level changes, inter-individual differences in change, and profile stability.

In short, we found all three diffusion model parameters studied (drift rates, boundary separations, non-decision times) to exhibit high rank-order stability over time, with drift rates over a time period of two years showing the lowest correlation (r = .64). Most across-time correlations of the three parameters each assessed at the four measurement occasions were even higher, in the range from r = .80 to r = .90. Regarding mean-level changes, the group-level drift rate parameters increased over time, while the boundary separations decreased. Non-decision times showed no changes. In terms of the rate of change, only drift rates exhibited credible individual differences. Finally, average profiles of the three core diffusion model parameters proved to be very stable across time.

All these results can be interpreted as supportive of the notion of individual diffusion model parameters as trait-like entities, at least regarding temporal aspects. Most importantly, the high rank-order stabilities, as well as the profile stabilities, make it clear that the individual relative expressions of processing speed, decision caution, and non-decision time most often remain stable even across longer time periods. Interestingly, rank-order stability was considerably higher than what has been suggested by previous studies (Lerche & Voss, 2017b; Schubert et al., 2016; Yap et al., 2012). Three main reasons for the higher stability found in our study might be a) the relatively high number of trials per person (600), b) the very robust hierarchical Bayesian modeling approach employed (both of which might have led to more reliable estimates), and c) the great heterogeneity in participant demographics in our sample, with the greater variance in diffusion model parameters possibly also leading to stronger covariances. The mean-level changes found for drift rates and boundary separations can be interpreted as practice effects – people sample information more efficiently and become less cautious over time. This is in line with previous studies on practice effects in diffusion model parameters, though it must be noted that these previous results (of within-session practice effects) also included decreases in non-decision time (Dutilh et al., 2009, 2011; Evans & Brown, 2017). Interestingly, in our study we could show the practice effects seem to persist over time periods of up to one year. Finally, we found that people differ in the extend they profit from the practice effect on processing speed.

All these results lead to the same conclusion: As the diffusion model parameters show considerable across-time rank-order and profile stability even over a period of two years and display interpretable mean-level changes, the notion of parameters-as-traits seems in this way justified. Our findings thus strengthen and expand the accounts presented in previous studies on individual differences in diffusion model parameters. In the following manuscript, we continued to test their applicability and usefulness for individual differences research, with the first application focusing on the relationship of the parameter drift rate, representing processing speed, with intelligence.

3 Diffusion modeling and intelligence (Manuscript 2)[2]

Cognitive processing speed is known to be related to general intelligence (*g*; Jensen, 2006; Sheppard & Vernon, 2008). Drawing on 172 studies, Sheppard and Vernon (2008) found small to medium correlations between mental speed as measured by mean response times (RTs) and intelligence across a variety of paradigms and heterogeneous types of sample; people with lower RTs tended to have higher intelligence (IQ) scores. Cognitive processing speed has also been hypothesized to contribute to age-related cognitive decline. Salthouse (1996) proposed the idea that a general slow-down of cognitive processes might be the reason for lower IQ scores found in older adults, highlighting the close relationship between processing speed and intelligence.

In the past two decades, a number of studies utilizing the diffusion model have started investigating the relationship between the model parameter drift rate and intelligence (McKoon & Ratcliff, 2012; Ratcliff et al., 2010; Schmiedek et al., 2007). The use of drift rates as measure of processing speed instead of mean RTs has several important advantages. First, by utilizing the full response time distributions of correct and error responses and also the accuracy rates, one can draw on a larger proportion of the available data. Second, by separating processing speed from decision caution and non-decision time, the diffusion model provides a theoretically pure measure of processing speed in its drift rate parameter, that should show more clearly interpretable correlational patterns to external criteria than mean RTs, which are a composite of several distinct processes. Schmiedek and colleagues (2007) found drift rates to strongly predict scores in reasoning, working memory, and psychometric speed. In a similar way, Ratcliff and colleagues found high positive correlations between drift rates and general

[2] Lerche, V., von Krause, M., Voss, A., Frischkorn, G. T., Schubert, A. L., & Hagemann, D. (2020). Diffusion modeling and intelligence: Drift rates show both domain-general and domain-specific relations with intelligence. *Journal of Experimental Psychology: General*. Advance online publication.

intelligence across three different age groups (college-aged, 60-74 years old, 75-90 years old; Ratcliff et al., 2010). Both these studies used structural equation modeling to aggregate the drift rates from several tasks to a latent factor – eight in the case of Schmiedek and colleagues, while Ratcliff and colleagues used three. There is thus initial evidence that drift rates predict measures of intelligence in a similar way that raw mean RTs do.

When looking at the relationship between processing speed and intelligence more closely, a slightly puzzling finding becomes salient. Intelligence is typically assumed to have a hierarchical structure that contains both a strong general factor (*g*) and domain-specific abilities (Sternberg, 2000). Conversely, processing speed as measured by mean response times has been shown to be largely unitary, although it is linked to intelligence (Jensen, 2006). In order to better understand this issue, we analyzed the structure of processing speed (as measured by drift rates) and its relationship to intelligence in Manuscript 2.

We tested performance of 125 participants in a wide range of binary decision tasks. Six tasks stemmed from the verbal, figural and numerical content domains, respectively. In addition, we varied task complexity, with half of the tasks in each domain being simple tasks (mean RTs < 1 second), and the other half more complex tasks (mean RTs > 2 seconds). The rationale behind the latter distinction was as follows. Typically, the types of tasks analyzed with the diffusion model have been quick and simple tasks with very low response times (under one second). The reason is that basic assumptions of the diffusion model, namely within-trial stability of parameters and the idea that a single evidence accumulation process underlies the decision process, were thought to be violated in more complex tasks (Ratcliff & McKoon, 2008). However, in recent years it has been proposed that the diffusion model is also applicable to slower response time paradigms, with initial validation studies showing promising results (Lerche & Voss, 2017a). Following up on this research, we wanted to systematically include slow response time tasks from each content domain in our study, in order to better judge the applicability of the model to such tasks. Another reason was that in studies drawing on mean RTs, more complex tasks were shown to show stronger relationships to intelligence than simple, fast tasks (Sheppard & Vernon, 2008). We wanted to test whether the same holds true when using drift rates as the measure of processing speed.

As outcomes, we used the scores of a standard intelligence test (Jäger et al., 1997) for general intelligence and the verbal, figural and numerical content domains. Through structural equation modeling, we tested whether the latent general intelligence factor was related to a latent general factor of drift rates and a method factor representing the shared variance of drift rates in the slow response time tasks. In addition, we included content-domain specific factors for verbal, figural, and numerical intelligence, as well as for the respective drift rate content domains, and studied their cross-relationships.

Our results showed a very distinct pattern. General intelligence was related to the general drift rate factor (r = .45) and the factor encompassing the variance specific to drift rates in complex tasks (r = .68). Both drift rate factors jointly explained 67% of the variance in general intelligence. Regarding the latent content domain factors of drift rates, all of them showed strong correlations with the respective intelligence content domains (verbal: r = .50; figural: r = .90; numerical: r = .74), but not with the theoretically unrelated intelligence content domains. It should be noted that while both the verbal and numerical drift rate (residual) factor showed statistically significant variance, this was not the case for figural drift rates. Finally, non-decision times also showed strong relationships to intelligence, but here the latent structural equation models all failed to show satisfying fit.

Our results support the notion that processing speed, as measured by drift rates, is not unitary, but contains content-domain specific aspects. The fact that these were related to the respective intelligence content domains speaks in favor of the validity of the measurement of these aspects in our structural equation model. It might be that the domain-specificity of processing speed was hidden in previous studies utilizing mean correct response times due to composites of processes contributing to RTs. In our analyses, we did not find a latent measurement model of (raw or logarithmized) correct mean RTs incorporating all 18 tasks with acceptable model fit, no matter if we used a *g* factor only model or more complex models also representing content domains and specifics of the slow tasks. Mean RTs, possibly due to the entanglement of processing speed in speed-accuracy trade-offs and non-decision times, seem to be both less domain-specific and show stronger correlations between particular dyads of tasks, represented by implied residual covariances in a structural equation modeling framework.

We also found strong additional evidence for a positive relationship between drift rates and general intelligence. This was especially pronounced for the more complex, slower response time tasks. While this mirrors findings reported for mean RTs (Sheppard & Vernon, 2008), ours was the first study to analyze the implied moderation with drift rates.

Taken together, this attempt at utilizing individual estimates of diffusion model parameters, namely drift rates, as measures of individual differences, brought important insights into both the across-task structure of processing speed and the relationships of the obtained structural components to intelligence. By employing the diffusion model, a clear pattern of results emerged, that was in contrast to the state-of-the-art based on raw data. In this way, the model-based approach of obtaining individual decision process parameters to better understand cognition and mental abilities proved to be a promising avenue. We continued to probe its utility in the following manuscripts, which focused on an aspect of cognition that was only briefly touched in this thesis up to this point: the question of whether there are age differences in decision process parameters.

4 Age differences in diffusion model parameters – a meta-analysis (Manuscript 3) [3]

Older people show longer response times in elementary cognitive decision tasks. This finding has been replicated numerous times over the past decades and holds true across a variety of paradigms (Jensen, 2006). Already in young adulthood, increasing age is associated with longer mean RTs (Salthouse, 1996, 2004, 2010).

However, over the past twenty years, a number of studies utilizing the diffusion model have started to challenge the assumption that processing speed declines with age. When disentangling the decision process components contributing to empirical raw data, one finds that higher mean RTs can have at least three different (though possibly correlated) causes: lower processing speed (drift rates), higher decision caution (boundary separation), or slower encoding and motor response processes (non-decision times).

Several studies compared young college-aged adults to old adults aged at least 60 regarding their individual diffusion model parameter estimates (e.g., Ball & Aschenbrenner, 2018; McKoon & Ratcliff, 2012, 2013; Ratcliff et al., 2003; Ratcliff, Thapar, et al., 2004; Spaniol et al., 2006; Thapar et al., 2003; Voskuilen et al., 2018). Generally, older adults exhibited higher decision caution and slower non-decision times. For drift rates, findings were more complex and also differed across studies. While in most cases there were no differences in processing speed as measured by drift rates between young adults and old adults, in some cases drift rates were higher for the younger group (Voskuilen et al., 2018). Conversely, there are even reports of slightly higher drift rates in the older age group (Ratcliff, Thapar, et al., 2004). To address these issues more systematically, we conducted a meta-analysis, with the aim to study the age effects on drift rates (and the other two core diffusion model parameters) thoroughly and quantitatively.

Our multi-level meta-analysis comprised 25 samples with a total *N* of 1,503. In addition to the main effect of age group, we tested two potential moderators of this effect. One of them was

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[3] Theisen, M., Lerche, V., von Krause, M., & Voss, A. (2020). Age differences in diffusion model parameters: a meta-analysis. *Psychological Research*, 1-10.

the type of task – we categorized the studies as either using a perceptual task, a lexical decision task, or a memory task. The second moderator in our model was task difficulty as measured by across-person mean drift rates.

We found strong age effects for boundary separations and non-decision times: The older age group showed on average higher boundary separations and longer non-decision times. For these parameters, the inclusion of the moderators did not lead to a better model fit. For drift rates, the model including both moderators and their interaction showed a significantly better fit than the more parsimonious models. Results indicate that older adults have lower drift rates in perceptual tasks and memory tasks, but slightly higher drift rates in lexical decision tasks. Older adults also performed relatively better in more difficult tasks. Regarding the interaction between the moderators, we found that older adults showed higher drift rates in more difficult settings only for perceptual and lexical decision tasks, not for memory tasks. Finally, there was a large proportion of between-study variance in age effects sizes that was not explained by either moderator.

Our meta-analysis highlighted the importance of type of task and task difficulty in determining the difference in drift rates found between college-aged and old adults. At the same time, there were of course also many other factors potentially contributing to differences between the studies – most importantly, the studies were based on different samples. In Manuscript 4, we therefore studied age differences in diffusion model parameters across 18 different tasks within the same sample, utilizing the data we had already analyzed in Manuscript 2. This data set also had the advantage of incorporating people from a continuous age range (18 to 62 years) – including participants from middle adulthood, a period of life rarely analyzed in diffusion model studies so far. Finally, we also wanted to study the specific associations between age, the diffusion model parameters, and intelligence.

5 Relationships of age, intelligence, and diffusion model parameters (Manuscript 4)[4]

Increasing age is not only associated with longer mean response times, but also with decreases in a wide range of other cognitive abilities, including general intelligence (Hartshorne & Germine, 2015; Jensen, 2006; Salthouse, 2004; Verhaeghen & Salthouse, 1997). As was

[4] von Krause, M., Lerche, V., Schubert, A. L., & Voss, A. (2020). Do Non-Decision Times Mediate the Association between Age and Intelligence across Different Content and Process Domains?. *Journal of Intelligence*, *8*(3), 33.

already mentioned, the associated deterioration of mean response times and other cognitive abilities has given rise to the theory that cognitive slow-down might be part of the causal basis of general cognitive decline (Salthouse, 1996). Specifically, mean RTs were repeatedly found to mediate the association between age and intelligence, both in cross-sectional and (to a lesser degree) in longitudinal studies (Finkel et al., 2007; Salthouse, 1996; Zimprich & Martin, 2002).

Yet drift rates, as a theoretically process-pure measure of cognitive speed, fail to show clear-cut associations with age – instead, the relation to age depends strongly on the type and difficulty of the task. This gives rise to the question which of the decision process components are responsible for the age association found for mean RTs and ultimately for the mediation of age differences in intelligence through mean RTs. As both boundary separations and non-decisions were linked to age in our meta-analysis, both were potential candidate mediators.

Schubert and colleagues (2020) tested several mediation models of age, fluid intelligence, and the core diffusion model parameters in a sample of 223 participants, while also including the P3 event-related potential (ERP) latency from an electroencephalogram as a potential mediator. They found that while both drift rates and boundary separation failed to mediate the negative relationship between age and fluid intelligence, non-decision times and the P3 latency jointly fully mediated said association. The P3 latency is thought to be linked to anterior brain regions associated with response planning, as well as higher-order processing (Schubert et al., 2020). The authors offered two alternative explanations of this mediation via non-decision times and the P3 latency. As they did not find non-decision times to be related to ERPs associated with encoding processes (i.e., N1 and P1), they inferred that it should be the motor processes reflected in non-decision times that are the basis of the mediation. First, these motor response times might reflect age-related differences in anterior brain regions associated with response planning and response execution, as well as higher order processing, as they showed to be closely linked to the P3 latency. Second, the mediation might reflect the influence of motor response processes on the intelligence test scores. As the IQ test had strict time limits for each task and relied on hand-writing for recording the answers, motor response speed should have influenced the scores obtained.

In Manuscript 4, we followed up on these questions in several ways. First, we examined the associations between the diffusion model parameters and age across 18 different tasks from the verbal, figural, and numeric content domains to study the generalizability of previous results. Second, we estimated mediation models of age, the diffusion model parameters, and different aspects of intelligence, utilizing a broad range of outcomes. Schubert and colleagues (2020) had used a single outcome measure, fluid intelligence. We estimated mediation models for general (fluid) intelligence, for three different intelligence content domains (verbal, figural, numerical), as well as for three different intelligence process domains (processing capacity, memory, psychometric speed).

The differentiation of process domains allowed us to directly study the two different explanations offered by Schubert and colleagues (2020) for the mediation via non-decision times. If age differences in non-decision times reflected age-related differences in anterior brain regions associated with response planning, response execution, but also higher order processing, then the mediation should occur similarly across all intelligence process domains. Conversely, if the mediation of the relationship between age and fluid intelligence via non-decision times reflected non-decisional aspects influencing the intelligence test scores, then the mediation should be especially distinct for the psychometric speed tasks of the intelligence test, that relied extensively on quick handwriting; on the contrary, the mediation should be less pronounced for the processing capacity tasks, that were closest to a power test among the intelligence test tasks.

In our sample of 125 participants that covered an age range of 18 to 62, we found that boundary separations and non-decision times showed positive correlations with age. This generally held true across the 18 different tasks studied, although the magnitude of the correlations sometimes differed between tasks. Drift rates mostly did not show any linear age trends, although there were some tasks where older adults had lower, and there was even one task where they had higher drift rates. The distribution of drift rate correlations showed no interpretable pattern, neither when comparing the content domains, nor between simple/fast and more complex/slow tasks. In post-hoc analyses, we found that many of the task-specific drift rates showed non-linear age trends, in that they exhibited cross-sectional increases until age 30, and a slow decline thereafter. Given the exploratory nature of these results and the sparse sample size representing middle adulthood, these findings should be interpreted cautiously.

In our mediation models, we replicated the mediation of the association between age and intelligence via non-decision times. Neither boundary separation nor drift rates were a significant mediator in any of our models. However, non-decision time mediated the link for all outcomes except for figural intelligence and processing capacity. Regarding the two different explanations of the non-decision time mediation proposed by Schubert and colleagues (2020), we found that the mediation effect was strongest for psychometric speed, and (as was already mentioned) not at all found for processing capacity. In this way, our results speak in favor of the hypothesis that the mediation of age differences in intelligence test scores via non-decision times most likely reflects the fact that motor response execution influences the intelligence test scores via speed of hand-writing.

Taken together, our results shed some light on the complex relationship between age, the decision process components reflected in the core diffusion model parameters, and other cognitive abilities. Given the finding that it might partly be motor speed that gives rise to age differences in intelligence test scores, it would be interesting to follow up on these results with a study using, as measure of intelligence, a true power test without any time pressure. Even more interesting seems the still unclear pattern of results for the association between age and drift rates. While our meta-analysis suggested that age effects on drift rates depended on the type of task, in our study of 18 different response time tasks no clear pattern emerged between content domains and task complexities (that also moderated results in the meta-analysis as task difficulty). In addition, in our exploratory analyses, we found evidence for non-linear age trends in the majority of tasks, with an increase in drift rates up to about age 30. Unfortunately, our sample size was far too small to explore the age trends over middle adulthood in greater detail. It thus seemed imperative to study age differences in diffusion model parameters in a much greater sample, in order to gain a clear view of the relation of age and processing speed across the lifespan.

6 Age differences in diffusion model parameters in a large sample (Manuscript 5)[5]

In order to be able to study in depth the associations of age and the diffusion model parameters, especially drift rates, across the lifespan, we re-analyzed a very large dataset of response times and accuracy rates. As an example of a binary decision task, we used the race implicit association test (IAT; Greenwald et al., 1998, 2003; Greenwald & Farnham, 2000). Since the introduction of the race IAT at the end of the 1990s, a great number of people have completed the test at the websites provided by Project Implicit (Xu et al., 2014). In the race IAT, people are shown either words or images, which they have to classify as belonging to one of two categories, for example, “good” or “bad” for the words, and “White person” or “Black person” for the images. The answer categories are mapped to the same response buttons. In this way, across experimental conditions, “good” is in one block paired with “Black person”, but in

[5]von Krause, M., Radev, S.T., & Voss, A. (submitted). Processing speed is high until age 60 - Insights from Bayesian modeling in a one million sample (with a little help of deep learning). *Proceedings of the National Academy of Sciences of the United States of America.*

another block paired with “White person”. The (transformed) difference in mean response times is interpreted as reflecting the strength of implicit associations of the respective categories, and thus an implicit racial bias.

We were not interested in the race IAT as a measure of implicit cognition, but rather as an example of a binary decision task. IAT data have already been analyzed successfully with the diffusion model (Klauer et al., 2007), making the Project Implicit data a promising target for our analysis of age differences in diffusion model parameters in a large sample. We obtained the raw data from Project Implicit – summary statistics and demographics were already available at the Project’s OSF page (https://osf.io/y9hiq/). For our analyses, we used raw data collected between September 2016 and December 2018, adding up to a total of over 1,800,000 people – a sample size we deemed sufficient for fine-grained analyses of age differences.

When obtaining diffusion model parameters for such a large data set, standard estimation methods become computationally infeasible, especially when a Bayesian approach is employed. Thus, we used BayesFlow, a newly developed deep learning method based on invertible neural networks for extremely efficient parameter estimation (Radev et al., 2020). Utilizing the BayesFlow method, we obtained full individual posterior distributions of the three core diffusion parameters for our large sample on a standard laptop within a day. After data cleaning, our sample size was 1,185,898. Ages 10 to 80 were covered in sufficient depth for year-specific analyses, with oftentimes (tens of) thousands of participants for each year of age.

To be able to better compare our results with previous studies measuring processing speed with mean correct RTs (Finkel et al., 2007; Hartshorne & Germine, 2015; Jensen, 2006; Salthouse, 1996, 2010; Zimprich & Martin, 2002), we also analyzed the age relations with mean correct RTs in our sample. Specifically, we computed the across-person means of the individual mean correct RTs, and the individual posterior means of drift rates, boundary separations, and non-decision times, separately for each year of age.

Mean correct RTs showed, on average, decreases from age 10 to about the age of 20. They then exhibited a quasi-linear positive trend that continued until about age 60, after which this age-related tendency (i.e., cross-sectional slow-down) in mean RTs increased further, with the highest mean RTs found around the age of 80. This finding is in line with what was previously reported in the literature (see e.g., Hartshorne & Germine, 2015; Jensen, 2006; Salthouse, 2004).

Boundary separation, that is, decision caution, exhibited an age-related pattern that mirrored the one found for mean RTs, at least until about the age of 60. Decision caution displayed a decreasing trend over the teenage years, was lowest around age 20, and showed, on average, a quasi-linear increase thereafter up until the age of 80, with a steeper increasing trend found after age 60 for the incongruent experimental condition. Non-decision times, that is, the times needed for encoding and motor processes, exhibited a decreasing trend until ages 14 to 16, and a quasi-linear average increase starting thereafter, that continued over the entire age span studied.

Our most interesting results were found for drift rates, that is, processing speed. On average, the drift rates exhibited an increasing trend that lasted until about age 30. From ages 30 to 60, there were little age differences in processing speed as measured by drift rates, with a slow average decline starting at around age 50. From age 60 on, a clear and accelerating slow-down in average drift rates was present in our data, that continued until the age of 80 – the latter trend was more pronounced for the incongruent compared to the congruent experimental condition.

Also of interest was the fact that while mean RTs displayed an increase in across-person variance in old age, neither drift rates nor boundary separation exhibited a corresponding trend, but non-decision times noticeably did.

Taken together, our results help to explain many of the age patterns found in previous diffusion model studies, our meta-analysis (Manuscript 3) and in our 18 task study (Manuscript 4). Previous diffusion model studies most often compared drift rates found in college aged participants with those obtained from old adults, aged 65 or older. When taking the results of our large IAT analysis into account, it seems that the young age group in such studies might have not yet reached their maximum in processing speed, while the older age group might have already started age-related decline after a period of stability over middle adulthood. This might explain why no consistent differences in drift rates were found in these previous studies. Of course, given the cross-sectional nature of our data, such interpretations must remain cautious.

Referring back to Manuscript 4, our results from the large dataset replicate the finding that processing speed peaks around the age of 30 years. It seems that after the age of 60, trends in boundary separations, non-decision times and drift rates jointly contribute to an age-related slow-down, that is also mirrored in mean RTs. In this way, the results we found in the large IAT dataset complement the previous findings presented in this thesis on the relationships of age, decision process components as represented in the three core diffusion model parameters, and (other) cognitive abilities.

The results also shed a new light on our meta-analysis, where we found that differences in drift rates between young and old adults partly depended on the type of task studied. It seems plausible that the shifting point towards an accelerated decline in drift rates, that we found to be roughly at the age of 60 for the IAT, could be earlier or later in the lifespan for different types of task. For example, in lexical decision tasks, where old people might profit from their practice of language over a long period of time (Ratcliff, Gomez, et al., 2004; Ratcliff, Thapar, et al., 2004), processing speed might decline later than in simple perceptual tasks. In this way, the fact that most of the two group studies used simply one category for old adults (because of the low overall sample sizes) might have hidden these differential developmental patters by mapping them to a very simple three-point scale: that old adults generally either have similar, higher, or lower drift rates than young adults in a particular task.

7 Discussion

In this section, I will discuss the five manuscripts that are part of this thesis, uniting them in relation to the overall topic of this work: the use of diffusion model parameters in individual differences research. I will point out some of the limitations of this research, suggest some ideas for future projects, and finally give some concluding remarks.

7.1 Summary and General Discussion

My thesis can be divided in two main parts. In the first part, Manuscript 1, I tested the assumptions underlying the use of the diffusion model parameters as estimates of reliable individual differences. Specifically, I focused on an aspect that had been rarely studied in the diffusion model literature, that is, to what extent the model parameters exhibit stability and change across a longer time period. This question is essential to determine whether the diffusion model should be considered traits, as these are expected to be stable across situations and time. Because the stability across situations had already been studied in various research projects analyzing across-task correlations of the parameters (e.g., Ratcliff et al., 2010; Schmiedek et al., 2007; Schubert et al., 2016), my focus was on the temporal aspect.

We found that the main diffusion model parameters (drift rates/processing speed, boundary separation/decision caution, encoding and motor processes/non-decision times) showed great rank-order stability over time periods of up to two years. In addition, profiles of the relative (standardized) values of the parameters were also very stable for the majority of people. Finally, mean-level change and individual differences in change were easily interpretable as training effects leading to more effective information accumulation and lower decision caution. In this way our results support the assumption that the core diffusion model parameters can be considered trait-like, as they show great temporal stability and interpretable developmental patterns. Together with previous studies that also focused on the trans-situational aspect of stability (Lerche & Voss, 2017b; Ratcliff et al., 2010; Schubert et al., 2016;

Yap et al., 2012), Manuscript 1 thus provided a strong additional argument for the application of the diffusion model and the individual parameter estimates obtained from it in individual differences research. In Manuscripts 2 to 5, I shifted the focus from the question of how the diffusion model parameters should be interpreted towards the more applied question how these parameters can be helpful to conduct better research on individual differences in cognition.

I set out to seek answers to two questions arising out of the literature on individual differences in cognitive parameters: i) Is the structure of processing speed across tasks truly unitary, and how should its relationship to intelligence best be described? ii) What are the exact relationships between age, processing speed and other cognitive abilities? In both cases, previous studies had suffered from multiple shortcomings – they had, for example, either relied on mean RTs as a heuristic measure of processing speed, or had, in the case of diffusion model studies, used small numbers of tasks or tested only small and demographically homogeneous groups of participants. In our studies, we tried to address these limitations.

In Manuscript 2, we analyzed the across-task structure of processing speed and its relationship to intelligence. Utilizing 18 tasks from three different content domains, with half the tasks being simple and fast, and the other half being more complex, we found a distinct pattern of results. Processing speed, measured as drift rates, was best represented by a multi-faceted hierarchical structure, encompassing both a general factor, content-domain specific aspects, and a method factor representing the shared variance of the more complex tasks. This is in contrast to processing speed as measured in correct mean RTs, where we could not find a measurement model with adequate fit to our data. In addition, we found that the content domains of processing speed showed strong positive relations to the respective intelligence domains, while the factors representing general processing speed and the shared variance of the complex tasks predicted about 70% of the variance in general intelligence.

These results clearly spoke in favor of two interpretations: First, processing speed is not unitary, but multi-faceted and partly domain-specific; second, processing speed shows a robust and specific relationship to other cognitive abilities, most importantly general intelligence. The use of the drift rate parameter thus provided unique and novel insights that would not have been attainable had we relied on mean RTs as our estimates of processing speed.

The second main complex of substantial research I tackled in this thesis concerned the relationship between age, diffusion model parameters, and, once more, intelligence. In previous studies, decision caution and non-decision times were quite consistently higher in older people, while the pattern of results on the relation of age and drift rates remained ambiguous. This uncertainty regarding drift rates might have been caused by the fact that most of the studies reported only results based on a very low number of tasks from small samples, typically consisting of two age groups (young adults and old adults). To provide a clear picture, we studied age differences in three steps: i) we quantitatively analyzed the results reported in previous studies in a meta-analysis (Manuscript 3); ii) we studied age differences across 18 tasks within the same sample (Manuscript 4); iii) we provided fine-grained, year-specific age trend analyses based on a single very large sample (Manuscript 5).

Combined, our results underline the notion that boundary separations and non-decision times show higher across-person means with increasing age, even among young adults. For non-decision times, we even found that the lowest values were among teenagers aged 14 to 16 (see Manuscript 5). Conversely, drift rates seem to show increases over large parts of young adulthood (ages 20 to 30; see Manuscripts 4 and 5). Means in drift rates were roughly equal over middle adulthood, with an accelerated decrease in old adulthood in our analyses presented in Manuscript 5.

The task-specificities of the relationship between age and drift rates found in the meta-analysis (Manuscript 3) were only partly mirrored in our 18 task study (Manuscript 4). It must be noted that previous studies (that entered the meta-analysis) compared young adults and old people, often aged 65 and older. On the contrary, in our sample the oldest participants were 62 years old. Yet, we found a verbal task (though not the lexical decision task that formed a category in our meta-analysis) to be the only one to show a positive age trend.[6]

Finally, in Manuscript 4 we also studied which parts of a decision process might be responsible for the mediation of the relationship between age and intelligence via mean RTs reported in the literature (Salthouse, 1996; Zimprich & Martin, 2002). As it turned out, the most likely explanation of the mediation was via non-decision times – Schubert and colleagues (2020) had reported similar results. In our study, we replicated their findings in regard to general (fluid) intelligence, and expanded the results to other outcome measures, namely different intelligence content domains and intelligence process domains (which had not been done before).

We also provided evidence in favor of one of the two possible explanations of the mediation via non-decision times offered by Schubert and colleagues (2020). The differential results we found among the intelligence process domains, with the strongest mediation found for the psychometric speed intelligence tasks, and no mediation via non-decision times found

[6] In this task, participants had to judge whether a word shown on the screen was a noun or an adjective.

for the processing capacity tasks, support one specific interpretation. As the psychometric speed scores are in large part dependent on speed of handwriting, whereas the processing capacity scores are much closer to a power test, one might infer that it is precisely the motoric component inherent in intelligence test scores that at least partly drives the age differences found for them, and subsequently also their mediation via mean RTs. Of course, in the light of the non-linear age trends we found for drift rates in Manuscript 5, the (linear) mediation models estimated in Manuscript 4 also for drift rates should probably be reconsidered.

Bringing together the results reported in all five manuscripts that are part of this thesis, it seems that applying the diffusion model to obtain individual estimates of decision process components is both possible and fruitful. Diffusion model parameter estimates provide reliable, stable measures that show interpretable developmental patterns over a time period of up to two years and might therefore be at least in the temporal respect considered trait-like entities (Manuscript 1). When used to study substantial research questions, the parameters provide novel insights that would be impossible to obtain when relying on raw data. Manuscript 2 demonstrated this with regard to the structure of processing speed and its relationship to intelligence; we found content domain specific aspects of processing speed related to the respective intelligence components, that were not recoverable when analyzing mean RTs.

In Manuscripts 3 to 5, we scrutinized the relationship between age and the decision processes components represented by core diffusion model parameters. Once more, our results, especially regarding differences in processing speed across the lifespan, were in sharp contrast to what was previously inferred based on raw data. These combined findings are also a significant step forward from previous diffusion model analyses, given our strong data, with large numbers of tasks and participants and wide age ranges studied.

Another important keystone of our studies was the use of state-of-the-art parameter estimation methods. In Manuscript 1, we employed hierarchical Bayesian diffusion modeling (Wiecki et al., 2013), while in Manuscript 5, we utilized a novel deep learning approach for efficient Bayesian parameter estimation (Radev et al., 2020). These methods enabled us to reliably assess individual differences in diffusion model parameters, even in a large sample, and were thus an important prerequisite for our analyses.

7.2 Limitations and Ideas for Future Research

The research program described within this thesis has a number of unique features. Most importantly, we obtained robust, reliable and informative results by studying four different types of longitudinal development in diffusion model parameters over a long time period

(Manuscript 1), measuring the diffusion model parameters in 18 diverse tasks and studying their relations to a set of intelligence outcomes (Manuscript 2 and 4), systematically summarizing previous findings in a meta-analysis (Manuscript 3), and utilizing heterogeneous (Manuscripts 1, 2, 4, 5) and large (Manuscript 5) samples. These advantages were vital for obtaining the interesting findings of our studies. However, it must also be noted that this thesis also has some limitations.

First, the manuscripts concerned with the relationships of drift rates, non-decision times, and other cognitive abilities such as general intelligence, might have profited from incorporating a neurophysiological approach. The studies on the neural correlates of diffusion model parameters are plentiful (for overviews, see e.g. Dully et al., 2018; Schubert & Frischkorn, 2020). Yet specifically in the context of examining the structure of processing speed (Manuscript 2) it would have been interesting to note if differentiable patterns in processing speed map to differentiable patterns in brain activation.

Second, for all results on age differences in diffusion model parameters, it is important to note that we report purely cross-sectional data. Therefore, strictly speaking, statements about a longitudinal change are not possible. In order to get a better view of the true developmental patterns underlying the age-related mean differences we found in our studies, it would be vital to follow and test a group of participants over time, ideally for decades. A related aspect is that of cohort effects. We did not differentiate age effects and cohort effects in our analyses. In this way, it might for example be the case that the lower across-person means in drift rates we found for participants aged 60 and older in Manuscript 5 are partly explainable by the fact that these people had less experience in responding to computer tasks, independent of their age. Fortunately, the raw data published by Project Implicit (Xu et al., 2014) were collected between 2002 and 2020, and also include participant IDs. In this way, it should be possible to both study cohort effects (comparing, for example, people aged 60 in 2002 to people of the same age in 2020), and longitudinal developments in parameter values for people who participated several times over the years. Regarding cohort effects, it might also be interesting to study whether there is a Flynn effect (Flynn, 1987) in processing speed, possibly attributable to greater familiarity with computer-based assessments: Over the years of data collection, people might generally exhibit faster processing speed, regardless of age.

Third, in our analysis we did not take into account new developments in the diffusion model literature regarding the introduction of a possible additional model parameter, alpha, that describes the individual degree of heavy-tailedness in the noise distribution underlying the information accumulation process (Voss et al., 2019; Wieschen et al., 2020). If alpha is considerably lower than 2, this indicates a deviation from a standard diffusion process, and can model (random) jumps in the information sampling process, that might signify sudden insights. The literature on this topic is still in its infancy, but it seems worthwhile to study individual differences in this new parameter and its embedding in a nomological network of related constructs to be able to better interpret it.

Fourth, we put our focus strictly on the diffusion model and did not apply other types of evidence accumulation models that have been proposed in the literature, like the linear ballistic accumulator model (LBA; Brown & Heathcote, 2008) or leaky competing accumulator models (LCA; Usher & McClelland, 2001). The diffusion model as proposed by Roger Ratcliff (Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998) is but one member of the family of models trying to translate the underlying processes in simple decision making to a mathematical formulation. The competing models have a number of unique features, for example, the LCA has a stronger focus on mirroring the neural basis of information processing. In our studies, we only used the diffusion model. There were two main reasons for doing so. First and most importantly, the majority of the main model parameters are quite similar among the diffusion model, the LBA, and the LCA. This relates both to the implementation of the parameters and especially to their psychological interpretation. For example, Donkin et al. (2011) found that the diffusion model and the LBA agree on the mappings of the effects of experimental manipulations to the main model parameters (speed of information accumulation, decision caution, non-decision time), concluding that "inferences about psychological processes made from real data are unlikely to depend on the model that is used" (Donkin et al., 2011, p. 61; but see Goldfarb et al., 2014). Given that the diffusion model is the type of evidence accumulation model that has received by far the most attention in the literature and is also likely to continue being the most-researched approach (Voss et al., 2013), it made sense to probe the usefulness of this particular model. Second, as we only analyzed binary decision tasks, we had no need to employ one of the models that can also accommodate choices among multiple response options (Brown & Heathcote, 2008; Usher & McClelland, 2001).

After pointing out some limitations of the research project presented in this dissertation, I will now sketch a few ideas for additional analyses and possible future studies based on our results. Regarding the relation between drift rates and intelligence studied in Manuscript 2, it might be interesting to see whether drift rates show positive relationships to some of the real-life outcomes that intelligence is known to predict, for example, educational success (Sternberg, 2000). While in our 18 task study we did not assess educational background, I followed up on our results linking drift rates and intelligence after I had obtained diffusion model parameter estimates from the large IAT dataset described in Manuscript 5. This dataset also contains numerous additional measures, for example, detailed demographic questionnaires and personality items. I wanted to probe whether drift rates are higher for people with a stronger educational background in the large sample. The highest level of education attained was related to age, so I first regressed the drift rates (of trials from the incongruent condition, but results were similar for congruent trials) on age and age squared, to account for the non-linear relation of age to drift rates. I then analyzed the distributions of drift rates over levels of education. To my knowledge, no similar analyses have been published to this date.

Figure 1 shows the corresponding plot. The points indicate the group-specific means, with bars representing one standard deviation. As can be seen, within-group variance is high across all levels of education. Nevertheless, an increasing trend can be found with higher drift rates for people of a higher level of education, up until the point where people at least attended “some college”. Please note that age and the quadratic effect of age were controlled for in these graphical analyses. When post-hoc dichotomizing the data in people with no college education vs. at least some college education, I found a corrected effect size of d = .307 for the difference in drift rates (in the incongruent condition). The humble effect size and large within-group standard deviations in the residualized analyses underline the scope of individual differences. Yet, it seems that drift rates are, on average, slightly higher among people with a higher education level, underlining their relationship to cognitive abilities such as intelligence.

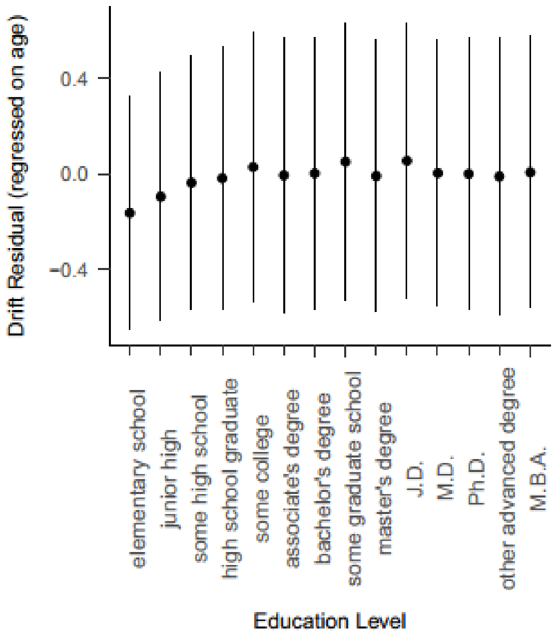

Figure 1. *Mean levels and standard deviations of drift rates (from the incongruent condition and after controlling for age and the quadratic effect of age) for each level of education in the dataset used in Manuscript 5 (N = 1,185,898). For the congruent condition, trends are similar.*

Another interesting line of research continuing on from our results would be to repeat the mediation analyses conducted for Manuscript 4 with participants from an age range that we would expect to show clear linear age trends in drift rates based on Manuscript 5, for example, people aged 50 to 80 – maybe also in combination with both a power test and a speeded task as intelligence outcomes. The precise differences in mean parameter values over the lifespan obtained in the very large dataset allow us to specifically define age ranges of interest. Similarly, the finding that non-decision times were lowest at around the age of 15 opens up an unexplored field of research, namely the developmental patterns of non-decisional processes in adolescence. It would also be intriguing to examine whether it is mostly encoding times or motor response execution times that drive the age differences in non-decision times.

Finally, given our results from the large sample (Manuscript 5), one possible approach for a future study assessing differences among types of response time tasks might be to employ a perceptual task, a memory task, and a lexical decision task (the categories we used in our meta-analysis) in a fairly large, representative sample covering large parts of adulthood (e.g., ages 18 to 80). Such an approach could be conducted with reasonable costs, if the number of trials per person was kept low. The results obtained from such a study might provide better insights in the differential (cross-sectional) temporal patterns between tasks. Based on the results found for the IAT data, one might expect the tasks to show quantitative differences regarding the age ranges where, on the one hand, the maximum in drift rates is observed, and, on the other hand, the trend towards a decline in drift rates becomes clear. The latter might start quite late for vocabulary-based tasks such as the lexical decision task, as high scores in verbal tasks were also found in less-speeded contexts for older adults (Hartshorne & Germine, 2015).

7.3 A measure of dark personality based on the diffusion model?

One possible avenue of extending the use of the diffusion model in individual differences research is to turn away from the interpretation of the parameters purely as cognitive process parameters as an end in itself, but rather to use them to calculate derived measures, for example, of implicit personality. As has already been noted, the diffusion model has successfully been applied to IAT data (Klauer et al., 2007, Manuscripts 1 and 5). The so-called IAT effect, that is, the difference in (adjusted) mean response times between the congruent and incongruent conditions in an IAT was shown to be closely mapped by the difference in drift rates between the conditions (Klauer et al., 2007). In this way, the drift rate difference scores constitute a measure of implicit association, or, in case of a personality IAT, of implicit personality.

Indirect measures such as the IAT try to capture implicit processes and associations and specifically aim at assessing socially aversive attitudes or traits, for example, implicit racial bias (Greenwald et al., 1998). Other examples of such constructs would be the so-called dark personality traits, with the most prominent being the Dark Triad of narcissism, Machiavellianism, and psychopathy (Furnham et al., 2013; Paulhus, 2014; Paulhus & Jones, 2015; Paulhus & Williams, 2002). In recent years, it has been proposed that the variety of dark trait constructs proposed in the literature shares a common core that is characterized by the "tendency to maximize one's individual utility - disregarding, accepting, or malevolently provoking disutility for other - accompanied by beliefs that serve as justifications" (Moshagen et al., 2018, p. 656).

As such traits should by their very definition be socially aversive (given the need for justifying beliefs), people might be inclined to present themselves incorrectly, either because of a conscious use of strategies aiming at making a positive impression, or unconsciously, because of insufficient insight in one's own trait expression on a particular dark trait (Back et al., 2009; Calanchini & Sherman, 2013; Greenwald & Farnham, 2000; Quintus et al., 2020). Thus, the development of an indirect assessment method relying on the use of drift rate difference scores seems a promising avenue for dark personality research to explore a novel type of assessment.

Over the course of two different studies (both *N*s > 300), we developed two different measures of an implicit "dark score". On the one hand, we tested an IAT, using the categories "me" and "other" (see Schmukle et al., 2008, for a similar approach aiming at the Big Five of personality), and adjectives associated with either the positive or negative pole of a hypothesized dark trait continuum (e.g., "spiteful", "good-hearted"). On the other hand, we tested a slightly different assessment method. Here, the binary decision options participants had to choose from were "that's me" and "that's not me" – in this way, there were no longer correct and wrong answers (as in the IAT). The stimuli were adjectives representing either "dark" personality or its opposite, based on a review of the literature on dark traits. As a measure of dark personality, we calculated the mean of drift rates between the answers for the positively- or negatively-coded dark trait stimuli.

We successfully fit the diffusion model to the data from both experimental paradigms tested. Figure 2 shows the exemplary scatterplot of the empirical response time quartiles and response choices for the indirect dark trait ("D") measure using the "that's me / that's not me" answer categories, plotted against the simulated data based on the diffusion model parameters.

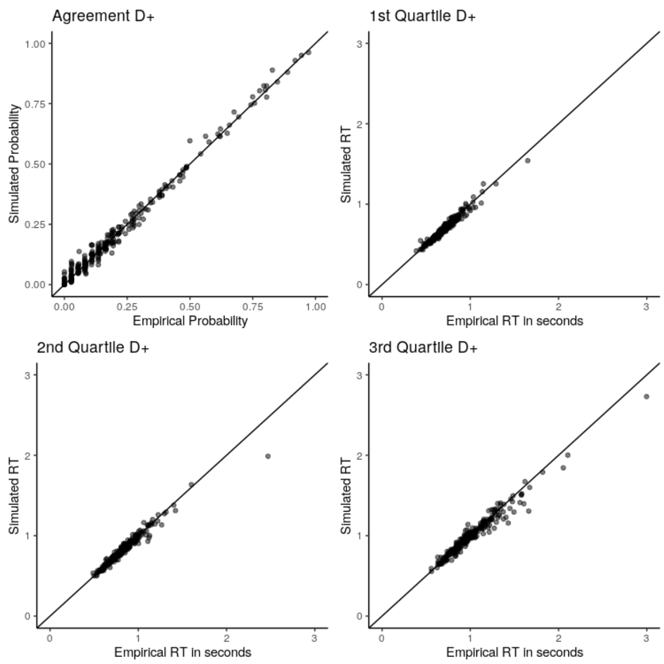

Figure 2. *Empirical response time quartiles and response choice probabilities plotted against corresponding simulated values based on the diffusion model parameter estimates. Participants either agreed ("that's me") or disagreed ("that's not me") to an adjective of the dark trait spectrum (e.g., "hateful"). Based on the data collected in Dark Trait Study 1.*

As an example, I show the answers to stimuli linked to the "dark" or socially aversive pole of "D" in Study 1. As can be seen, the recovered values closely mirror the empirical data, indicating reasonable generative performance of the diffusion model in the tasks employed.

We also obtained questionnaire data measuring several commonly studied dark trait constructs and different types of behavioral outcomes. To keep the results short, the measure of dark personality based on an IAT failed to show any considerable criterion-related correlations. The measure based on the "that's me" / "that's not me" distinction predicted actual behavior (sharing real money with other participants, lowering their payment, and cheating to avoid a tedious task) in a similar magnitude to dark trait questionnaire scales.

Data analysis of these studies is still ongoing and additional studies might be required to determine the usefulness of a measure of dark personality based on diffusion model estimates. In any case, opening the interpretation of parameter estimates and their differences to a context that is no longer based on ability testing, but seeks to obtain content-specific judgments on, for example, one's (dark) personality, seems a promising approach according to our initial results.

7.4 Conclusions

In this thesis, I presented a research program on the use of the diffusion model parameters as measures of individual differences. After studying the temporal patterns of individual parameter estimates, I applied the diffusion model to two different sets of substantive research questions from the field of individual differences in cognition. Employing the diffusion model to disentangle the different process components contributing to the raw data of response times and accuracy rates made it possible to gain novel insights in the across-task structure of processing speed, its relationships to other cognitive parameters, and its relationship to age. These findings could not have been obtained from raw data, and in many cases were in direct contrast to previous results based on mean RTs - the most important new finding probably being that in our large cross-sectional IAT dataset, processing speed was high throughout middle adulthood, although average mean RTs showed a positive age trend already from the beginning of young adulthood. In this way, we could show that individual differences research can profit from taking a model-based perspective on cognition.

As a member of the Research Training Group Statistical Modeling in Psychology (SMiP), I will at this point briefly point out the relation of my studies to the aims and conceptual framework of SMiP. One of the core elements of SMiP is the idea that there is a gap between psychological research focusing on developing statistical methods and substantive research. Novel statistical approaches are often largely ignored in applied studies (Sharpe, 2013) – a fact that might have detrimental consequences for scientific progress, and that SMiP is hoping to help overcome. My research focuses on how diffusion modeling, an elaborate statistical modeling technique, can be joined with individual differences research, and is thus in line with the core features and mission of SMiP.

The model-based study of decision process components to describe individual differences has in the past often adhered to research practices better suited for experimental psychology, for example, in the relatively low sample sizes used and the often-found loyalty to the comparison of parameter means between two groups as the main method of analysis. These same research practices are also assumed to form an important part of the so-called replication crisis still haunting large parts of psychology (Stanley et al., 2018). In this sense, implementing more robust research practices, for example by increasing statistical power, testing the generalizability of findings across a variety of paradigms, openly sharing data and also utilizing shared data for both replication studies and novel research should only bring fruitful results.

By following principles deemed important in individual differences research, for example, using longitudinal studies or improving reliability by employing numerous tasks and large and heterogeneous samples, the diffusion model parameters, originally stemming from a background in cognitive, experimental psychology, could successfully be transferred to a new context. In the end, we could show that experimental psychology can profit from incorporating ideas rooted in individual differences research, while scientists interested in the ways people differ from one another gain a powerful new tool by embracing mathematical modeling approaches. In this way, my thesis hopes to help bridge the gaps between these all-too-often separated fields of psychological research.

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