A meta-analysis of the worst performance rule

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Abstract

The worst performance rule (WPR) describes the phenomenon that individuals' slowest responses in a task are more predictive of their intelligence than their fastest or average responses. Because the WPR supposedly amplifies in heavily *g*-loaded tasks and in samples whose cognitive abilities factor structure is dominated by a strong *g*-factor, it has been suggested that whatever mechanism is giving rise to the positive manifold may not promote peak performance, but may rather limit performance in a wide range of cognitive tasks. The aim of the present meta-analysis was to provide a meta-analytically determined estimate of the strength, consistency, and generalizability of the WPR. Across 19 studies containing 23 datasets with a total of 3,767 participants, there was robust evidence for the WPR. However, the increase in correlations across quantiles of the RT distribution did not follow a linear, but a logarithmic trend, suggesting that those cognitive processes contributing to fast responses in reaction time tasks are less strongly related to cognitive abilities (r = -.18) than other cognitive processes contributing to average (r = -.28) and slow responses (r = -.33). There was no evidence that the strength of the worst performance rule increased with greater mean reaction times, in tests of general intelligence, or in samples with lower or average cognitive abilities. Instead, it was attenuated in less intelligent samples and greater when correlated with speed instead of intelligence or memory tests. Hence, the WPR may not be as characteristic for *g* and may play a smaller role for theoretical accounts of the positive manifold than previously thought.

Keywords: worst performance rule; intelligence; meta-analysis

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Substantial evidence supports the claim that more intelligent individuals show a higher speed of information-processing, as indexed by their consistently shorter reaction times in simple cognitive tasks (Doebler & Scheffler, 2016; Sheppard & Vernon, 2008). This association between mental speed and mental abilities has far-reaching implications regarding the basic cognitive processes underlying general intelligence and has inspired different areas of research trying to identify the genetic, neural, and cognitive mechanisms giving rise to this association (e.g., Kievit et al., 2016; Posthuma, de Geus, & Boomsma, 2001; Schubert, Hagemann, & Frischkorn, 2017; van Ravenzwaaij, Brown, & Wagenmakers, 2011).

One enthralling enigma first discovered by Baumeister and Kellas (1968) in mental speed research on intelligence is the *worst performance rule* (WPR; Larson & Alderton, 1990). The worst performance rule describes the phenomenon that individuals' slowest responses in a task are more predictive of their general intelligence than their fastest or average responses. What is intriguing about this phenomenon is that it is not in line with the assumption of classical test theory, which states that scores deviating strongly from a measure of central tendency contain largely unsystematic error-variance. Under the assumptions of classical test theory, extreme scores in a reaction time distribution should contain substantially more error variance than average reaction times and should therefore be less strongly related to other variables such as cognitive ability tests. Even more intriguingly, the worst performance rule amplifies in tasks with greater *g*-loading and in participants with lower cognitive abilities, whose cognitive abilities factor structure is typically dominated by a strong *g*-factor (Blum & Holling, 2017; Coyle, 2003a; Spearman, 1927). These results suggest that whatever mechanism is giving rise to the positive manifold may not promote peak performance, but may rather limit performance in a wide range of cognitive tasks (see Kovacs & Conway, 2016, for a related idea). In addition, the worst performance rule does not only hold for reaction time tasks, but has also been demonstrated in recall tasks in which the lowest amount of correctly recalled items was most predictive of participants' intelligence (Coyle, 2001; 2003b). However, the current meta-analysis focuses only on reaction time tasks to allow comparability of study results.

Two theoretical accounts of the WPR have been proposed: the attentional control account (Larson & Alderton, 1990; Unsworth, Redick, Lakey, & Young, 2010) and the drift diffusion model account (Ratcliff, Schmiedek, & McKoon, 2008; van Ravenzwaaij et al., 2011). The *attentional control account* presumes that less intelligent individuals are more prone to occasional attentional lapses that disrupt goal maintenance in working memory. Theses attentional lapses result in longer reaction times, because attention first needs to be redirected to the task before a response can be made. Thus, the attentional control account presumes that slow reaction times reflect to some degree individual differences in attentional control. They are therefore most predictive of general intelligence, because domain-general attentional control capabilities contribute to performance on higher-order cognitive tasks such as working memory tasks and intelligence tests (Diamond, 2013; Kane, Conway, Hambrick, & Engle, 2007). Consistent with the attentional control account of the WPR, thought-probed mind wandering during the sustained attention to response task has been shown to partly mediate the association between working memory capacity and slowest reaction times (McVay & Kane, 2012).

The *drift diffusion model account*, on the other hand, is based on the diffusion model, which is a mathematical model of decision making that assumes that evidence accumulation in any binary choice task follows a Wiener diffusion process that can be described by a systematic component, the drift rate, and random noise (Ratcliff, 1978). While other cognitive processes such as encoding and motor reaction times or decision cautiousness also contribute to reaction time distributions, it is the strength and direction of the drift rate that determines the distribution of slower reaction times (Ratcliff, Schmiedek, & McKoon, 2008). Hence, because the drift rate parameter of the diffusion model is related to working memory capacity and intelligence (Frischkorn & Schubert, 2018; Schmiedek, Oberauer, Wilhelm, Süss, & Wittmann, 2007; Schubert, Hagemann, Voss, Schankin, & Bergmann, 2015) and because the drift rate parameter is the most relevant parameter for the proportion of slow extreme values in a reaction time distribution, the drift diffusion model account is able to explain the emergence of the worst performance rule.

It should be noted that the drift diffusion model account of the worst performance rule is often considered as a technical description, but not a fully comprehensive theoretical account of the phenomenon, because any number of cognitive processes may affect the velocity of evidence accumulation reflected in drift rates. In particular, it cannot be ruled out that individual differences in drift rate are affected by individual differences in attentional control, which makes the two accounts of the worst performance rule not mutually exclusive. In fact, both drift rates and trial-to-trial variabilities of drift rates in a related evidence accumulation model were associated with individual differences in attentional lapses (McVay & Kane, 2012). Moreover, individual differences in other cognitive processes, such as the strength and robustness of temporary bindings between stimulus and response representations (Wilhelm & Oberauer, 2006), may also affect the velocity of evidence accumulation. Regrettably, an empirical proof of the drift diffusion model account is still pending, as a former attempt to test the diffusion model explanation of the WPR using preregistration and blinding failed to find any evidence for the WPR, probably due to the low *g*-loading of the applied perceptual decision task (Dutilh et al., 2017).

The amount of theorizing and research fueled by the initial discovery of the worst performance rule demonstrates its relevance for intelligence research, as it seems to be one of the key phenomena any process theory of general intelligence has to account for. The worst performance rule has been conceptually replicated in many studies with different reaction time tasks, different samples and different age groups, e.g. in school children (Fernandez, Fagot, Dirk, & de Ribaupierre, 2014), undergraduate students (e.g., Diasco & Brody, 1992; Fernandez et al., 2014; Kranzler, 1992; Leite, 2009; Schmiedek et al., 2007; Schmitz, Rotter, & Wilhelm, 2018; Unsworth et al., 2010), and age-heterogeneous community samples (e.g., Fernandez et al., 2014; Frischkorn, Schubert, Neubauer, & Hagemann, 2016; Rammsayer & Troche, 2016; Schmitz & Wilhelm, 2016). In addition, it has been suggested that the size of the worst performance effect, i.e. the slope with which the correlation between reaction times and cognitive abilities increases over quantiles of the reaction time distribution, becomes larger with greater task complexity and greater *g*-loading of the cognitive ability measure (Coyle, 2003a; Kranzler, 1992; Rammsayer & Troche, 2016). Together, these results have influenced process models of intelligence and cognitive development that accounted for bottlenecks in information-processing as an important explanandum (Kovacs & Conway, 2016) or considered changes in information-processing consistency as a central catalyst of cognitive development (Coyle, 2017).

However, there are three fundamental problems that challenge the generalizability and universality of the worst performance rule: The failure to replicate the phenomenon in several studies, the lack of a clear statistical test of the worst performance rule, and the great heterogeneity of sample compositions, reaction time tasks, and cognitive ability measures that complicates a systematic evaluation of the moderating effects of task complexity and *g*-loading on the worst performance rule.

1) Replicability of the worst performance rule

Despite the number of studies that found the worst performance rule in a variety of tasks and samples, there are a few studies that failed to find evidence for the enigmatic phenomenon. In an early study on attentional processes in age-related slowing (Salthouse, 1993), participants of different age groups completed computerized digit-digit and digit-symbol tasks and two working memory, two perceptual speed, two motor speed, and three cognitive ability tasks. Slowest reaction times did not predict any variance beyond median response times in any of these four criteria composites.

The second failed conceptual replication attempt was also published by Salthouse (1998), in which an age-heterogeneous community sample completed a battery of either two or five reaction time tasks (digit-digit, digit-symbol, right/left, more/odd, add/subtract) and a broad cognitive ability test battery consisting of matrix reasoning, vocabulary knowledge, perceptual speed, free recall, and block assembly tests. Averaged across all reaction time tasks and cognitive ability tests, the correlation between slowest RTs and intelligence test performance was not larger than the correlation between median RT and intelligence test performance (r_{best} = -0.25 vs. r_{median} = -.41 vs. r_{worst} = -.40).

In a third failed conceptual replication, college students and elderly individuals completed speeded numerosity discrimination, recognition memory, and lexical decision tasks as well as the WAIS-III as a measure of general intelligence (Ratcliff, Thapar, & McKoon, 2010). Overall, the correlations between intelligence and reaction times either slightly decreased with increasing quantiles or followed a shallow U-shaped function, as reflected in the average correlations for best, median, and worst performance for college students (r_{best} = .07, r_{median} = -.08, r_{worst} = -.04), older adults between 60 and 74 years (r_{best} = -.12, r_{median} = -.17, r_{worst} = -.16), and older adults between 75 and 90 years (r_{best} = -.17, r_{median} = -.21, r_{worst} = -.16).

Another failed replication attempt was reported in a student sample, with intelligence assessed with the Intelligence Structure Test and reaction times measured in an *N*-back task with an unequal rate of matches to no-matches (Saville et al., 2016). The correlations between reaction times and intelligence test performance only showed a consistent increase across RT quantiles for the 1-back condition (r_{best} = -.10, r_{median} = -.14; r_{worst} = -.20), while they instead decreased across quantiles for the 0-back condition (r_{best} = -.06, r_{median} = -.06; r_{worst} = .06), and followed a U-shaped function in the 2-back condition (r_{best} = .04, r_{median} = -.12; r_{worst} = .00). Although the data did not corroborate the worst performance rule on a behavioral level, neural data confirmed to the worst performance rule, as correlations between P3 latencies and intelligence test scores increased across quantiles of the P3 latency distribution.

Finally, a recent large-scale preregistered study failed to find any evidence for the worst performance rule in a heterogeneous sample using a perceptual decision making task and working memory capacity as a cognitive ability measure (Dutilh et al., 2017). However, the study also failed to find the well-replicated association between mean reaction times and cognitive abilities (Doebler & Scheffler, 2016; Sheppard & Vernon, 2008). Therefore, it is questionable whether the perceptual decision task, in which participants had to decide whether there were more white or black dots in an array of 10x10 dots, was particularly suited to study the association between mental speed and mental abilities. It is possible that individual differences in reaction times in this task largely reflected individual differences in either very elementary perceptual processing or in the decision when to terminate evidence accumulation. The result that drift rates *were* associated with working memory capacity, while reaction times were not, supports the view that the reaction time measure was contaminated by variance from other processes unrelated to cognitive abilities.

Taken together, while there were more studies that found evidence in favor of the worst performance rule, there were a few studies that failed to replicate the phenomenon. What is most concerning is that there were no obvious differences in study characteristics such as sample composition or task difficulty between those studies that found and those that did not find evidence for the worst performance rule, except for the study by Dutilh et al. (2017). Therefore, it is unclear whether the scale is tipped in favor of studies *finding* the worst performance rule due to publication bias, or because the phenomenon exists, but shows substantial variation across studies.

2) The lack of statistical tests of the worst performance rule

As pointed out by both Frischkorn et al. (2016) and Dutilh et al. (2017), the simplest statistical formulation of the worst performance rule consists of a linear regression of the correlation between intelligence test performance and reaction times ρ_i on quantiles Q_i: $\rho_i = \beta_0 + \beta_1 \cdot Q_i$. A sequential estimation of this regression (i.e., first correlations need to be calculated and then entered into the regression as the criterion variable) results in an underestimation of standard error, because estimation uncertainty of correlation coefficients cannot be accounted for. As a result, virtually any small deviation in correlation coefficients across quantiles of the reaction time distribution will become significant. Therefore, Frischkorn et al. (2016) suggested to instead formulate the worst performance rule as a regression of intelligence test performance g_i on reaction times RT_i moderated by quantiles of the reaction time distribution Q_i, $g_i = \beta_0 + \beta_1 \cdot RT_i \cdot Q_i$, as this approach allows for the simultaneous estimation of the association between reaction times and intelligence test performance and the moderation of this association by quantiles.

However, except for these two publications, none of the studies on the worst performance rule formally tested the worst performance rule as regression. Only one study statistically tested the difference of correlations between slowest and fastest reaction times (Rammsayer & Troche, 2016), and only a few studies calculated regressions of cognitive ability test performance on multiple RT quantiles to test if slowest reaction times predicted any variance in cognitive ability test performance beyond fastest and/or median reaction times (Fernandez et al., 2014; Salthouse, 1993; 1998). The vast majority of studies on the worst performance rule instead only reported the course of correlations between reaction times and cognitive ability test performance across quantiles of the RT distribution and employed no formal test of the worst performance rule. This lack of a clear statistical test is problematic for three reasons: First, the 95 % confidence intervals around correlations of the size typically found in research on mental abilities and mental speed are surprisingly large (Schönbrodt, 2013; also see Table 1). This uncertainty may lead to an overestimation of the significance of correlation differences when inspecting the course of correlations between reaction times and cognitive ability test performance across quantiles.

Table 1

95 % confidence intervals around r given correlation coefficient r and sample size n

	95 % confidence interval around *r*				
	n = 50	*n* = 100	*n* = 250	*n* = 500	*n* = 1000
r = -.20	-.45; .08	-.38; .00	-.32; -.08	-.28; -.11	-.26; -.14
r = -.25	-.49; -.03	-.43; -.06	-.36; -.13	-.33; -.17	-.31; -.19
r = -.30	-.53; .02	-.47; -.11	-.41; -.18	-.38; -.22	-.36; -.24
r = -.35	-.57; -.08	-.51; -.16	-.45; -.24	-.42; -.27	-.40; -.29
r = -.40	-.61; -.14	-.55; -.22	-.50; -.29	-.47; -.32	-.45; -.35

Second, dependent overlapping correlation coefficients r_{x1y} and r_{x2y} can only be compared under consideration of r_{x1x2} (Steiger, 1980). This implies that a difference between correlations of fastest and slowest reaction times with intelligence is more likely to be statistically meaningful if the covariation between fastest and slowest reaction times is large. However, a visual inspection of the course of correlations between reaction times and cognitive ability test performance across quantiles does not convey this crucial information and does therefore not allow inferences regarding the worst performance rule unless correlation differences are either negligible or very large.

Third, even if slowest reaction times are more strongly related to intelligence than fastest reaction times, this only provides necessary, but not sufficient evidence for the worst performance rule. Because the worst performance rule implies that slowest reaction times predict cognitive abilities better than both fastest and median reaction times, the correlation between slowest reaction times and cognitive abilities needs always at least to be compared to both competing correlations.

Taken together, these three issues illustrate why the lack of a univocal statistical test of the worst performance rule in many studies is concerning and why it is unclear whether the often-reported statistical increase in correlations across quantiles contains only anecdotal or strong evidence for the worst performance rule.

3) Moderating effects of task complexity and *g*-loading

Theoretical accounts of the worst performance rule suggest that the worst performance rule becomes more prevalent in more complex reaction time tasks and in cognitive ability tests with a greater *g*-loading (Coyle, 2003a; Ratcliff et al., 2008). However, there are hardly any systematic empirical studies on the role of task complexity and *g*-loading. One notable exception is a study by Rammsayer and Troche (2016), who demonstrated that the worst performance rule only emerged for a highly *g*-saturated measure of intelligence, but not for a low *g*-saturated measure of intelligence. In addition, they found that a manipulation of task complexity, which consisted of varying the number of choice alternatives in a computerized Hick task, moderated the strength of the worst performance rule. Despite their promising results, it is unclear if these effects of *g*-saturation and task complexity can be broadly generalized, as individual studies on the worst performance rule vary too much in sample compositions, task demands, and employed cognitive ability tests to allow the drawing of a clear picture. This heterogeneity and lack of systematic within-subject designs on task complexity also limits any meta-analytically derived estimates of the role of task complexity. Moreover, the lack of a clear statistical test of the worst performance rule (and an associated effect size) makes it difficult to gauge if the phenomenon may be moderated by *g*-saturation and task complexity.

The present meta-analysis

The aim of the present meta-analysis was to address these issues and provide a meta-analytically determined estimate of the strength, consistency, and generalizability of the worst performance rule. In addition, this meta-analysis tested if the strength of the worst performance rule was moderated by sample composition, cognitive ability measure, and task complexity as predicted by theories of the worst performance rule (Coyle, 2003a; Ratcliff et al., 2008). To account for the great heterogeneity in task demands across studies, task complexity was defined by mean reaction times, with larger mean reaction times indicating greater task complexity. It should be noted, however, that mean reaction times can be affected by a number of factors unrelated to task complexity (e.g., the amount of allocated practice trials, the number of experimental trials, presentation times, or stimulus properties) and that any moderating effect of mean reaction times across studies may therefore also be attributed to any number of different experimental factors. If the worst performance rule represents a processing bottleneck underlying general intelligence that affects a variety of cognitive tasks, it should be strongest in complex reaction time tasks, in tests of general intelligence, and in samples with lower average cognitive abilities.

Methods

The meta-analysis was designed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher, Liberati, Tetzlaff, & Altman, 2009).

Eligibility criteria and literature search

Criteria for inclusion in the meta-analysis were as follows: Reaction times were measured in a computerized simple or choice reaction time task. Cognitive abilities were measured with a standardized intelligence test, a subset of a standardized intelligence test battery, a test battery of multiple non-standardized cognitive ability tests, a combination of several standardized intelligence tests or test batteries, or one or more working memory tasks. Correlations between fast, median or mean, and slowest reaction times and a cognitive ability measure were available. No restrictions were made regarding the number of quantiles the reaction time distribution was divided into. The methods and results were in German or English.

To identify studies meeting these criteria, electronic databases (PsycINFO, Social Sciences Citation Index, PubMed, ERIC, ProQuest Dissertations & Theses) were searched using combinations of the following search terms: "intelligence" or "IQ" and "reaction time", "reaction time variability", "reaction time distribution", "mental speed", "processing speed", or "worst performance rule". In addition, studies citing one of the initial papers on the WPR (Baumeister & Kellas, 1968; Larson & Alderton, 1990) or the systematic review by Coyle (2003a) were screened for inclusion in the meta-analysis and searched for further references. After duplicates had been removed and the relevant studies had been selected from these searches, references were screened within each study to find additional reports of interest. Finally, we e-mailed all authors of relevant studies to ask them for any unpublished manuscripts, theses, or preprints on the WPR. Figure 1 summarizes the overall literature search process.

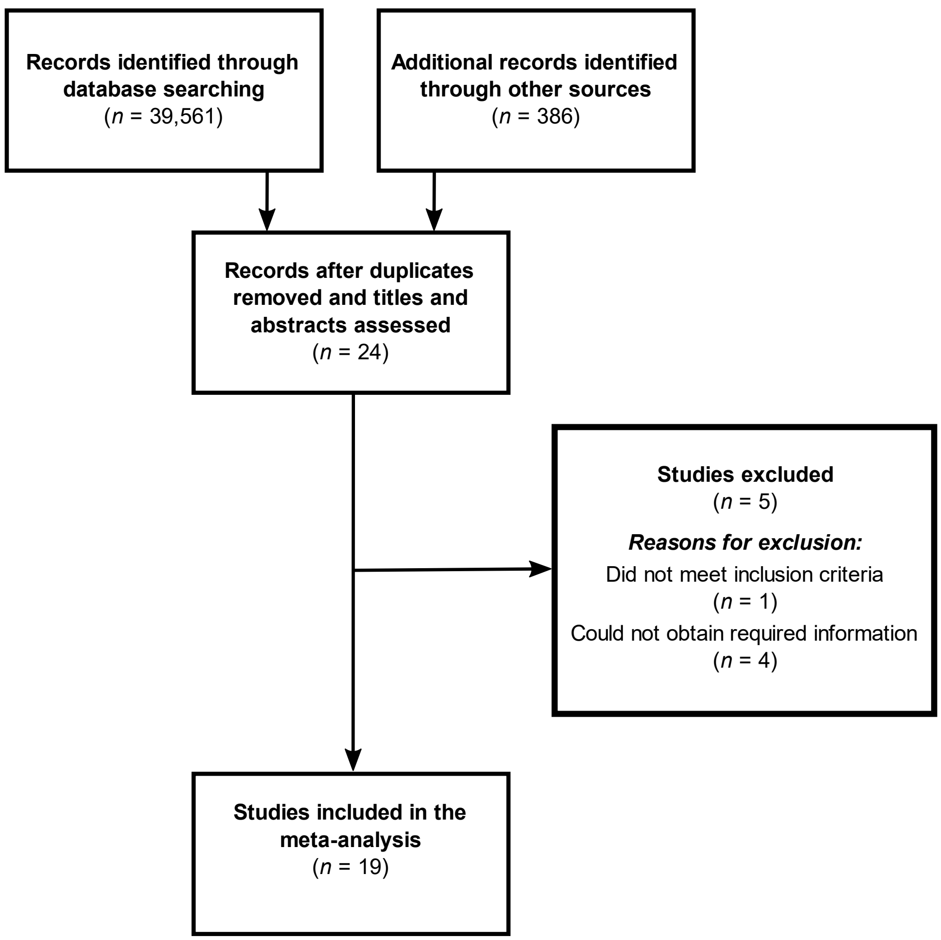

Figure 1. Flow chart for literature search and study inclusion.

After identifying 24 studies containing data on the WPR, each study was closely examined regarding inclusion criteria and the availability of all required information. One study had to be excluded because it did not meet the inclusion criteria: Reaction times were not measured in a simple or choice reaction time task, but as response lag in a self-paced timing task (Madison, Forsman, Blom, Karabanov, & Ullén, 2009).

Subsequently, the authors of the remaining 23 studies were contacted and asked to provide any missing information. To be included in the meta-analysis, the study needed to contain at least one correlation between slowest RTs, one between median or mean RTs, and one between fastest RTs and a cognitive ability measure. Four more studies (Baumeister & Kellas, 1968; Jensen, 1982; Maylor & Rabbitt, 1995; Salthouse, 1993) had to be excluded because this information was not contained in the reports and could also not be provided by the original authors (see Table 2 for details regarding included studies).

Coding procedure

Bibliographical information, correlations between fastest/mean/slowest quantile of the RT distribution and the cognitive ability measure, correlations of fastest/mean/slowest quantile of the RT distribution with each other, sample characteristics (size, age, sex, educational background), properties of the RT task (type of task, number of trials, mean RT, reliability of each RT quantile, standard deviation of RTs in each quantile), properties of the cognitive ability measure (exact tests, cognitive ability construct), and level of analysis (manifest vs. latent) were coded for each study.

Table 2

Details of included studies

Author(s)	Year	Participants	Mean age	RT task(s)	Mean RT	Rel. (fastest)	Rel. (slowest)
Larson & Alderton	1990	Heterogeneous	19.8	Arrows Test	574 (91)		
Diascro & Brody	1992	Students		Visual search	670		
Kranzler	1992	Students	20.3 (1.8)	SRT, CRT, OMO	363 (47)		
Salthouse	1998	Heterogeneous	46.4	Digit-Digit, Digit-Symbol, right/left task, more/odd task, add/subtract task			
Schmiedek et al.	2007	Students	25.8 (3.8)	8 different CRTs	598 (159)		
Leite	2009	Students	18.5 (0.8)	Letter discrimination, brightness discrimination	448 (45)	0.99	0.97
Ratcliff et al.	2010	Students	20.8 (1.7)	Numerosity discrimination, recognition memory, lexical decision	644	1.00	0.98
Ratcliff et al.	2010	Elderly	68.8 (4.1)	Numerosity discrimination, recognition memory, lexical decision	881	1.00	0.97
Ratcliff et al.	2010	Elderly	81.5 (5.0)	Numerosity discrimination, recognition memory, lexical decision	970	0.91	0.92
Unsworth et al.	2010	Students		SART, antisaccade, arrow flankers, Stroop, psychomotor vigilance	330 (32)	0.91	0.99
Weeda	2012	Students		Tau task	443 (84)	0.95	0.95
Fernandez et al.	2014	Children	10.5 (1.1)	SRT, CRT, Stroop	703 (129)	0.96	0.94
Fernandez et al.	2014	Students	21.7 (2.5)	SRT, CRT, Stroop	504 (68)	0.97	0.97
Fernandez et al.	2014	Heterogeneous	69.8 (6.5)	SRT, CRT, Stroop	629 (110)		
Unsworth	2015	Students	19.6 (1.6)	SART, antisaccade, arrow flankers, Stroop, psychomotor vigilance		0.99	0.97
Frischkorn et al.	2016	Heterogeneous	36.6 (15.7)	Sternberg memory scanning	735 (173)		
Rammsayer et al.	2016	Heterogeneous	24.7 (5.6)	Hick	324 (45)	0.86	0.68
Saville et al.	2016	Students	22.0 (3.6)	*n*-back oddball	535 (58)		
Schmitz & Wilhelm	2016	Heterogeneous	25.7 (5.2)	Search task, comparison task, substitution task	935 (158)		
Dutilh et al.	2017	Heterogeneous	24	Speeded perceptual decison making task	926 (215)	0.86	0.86
Wallert et al.	2017	Elderly	77.3 (7.3)	Deary-Liewald reaction time task	367 (89)	0.99	0.99
Löffler	2018	Heterogeneous	30.8 (12.5)	Switching task	931 (176)		
Schmitz et al.	2018	Heterogeneous	22.0 (3.1)	Search task, comparison task, substitution task	877 (114)	0.87	0.85

Table 2 (cont.)

Details of included studies

Author(s)	Year	Participants	Level of analysis	*n* trials	*N*	Cognitive ability measure(s)	*r*(fastest, IQ)	*r*(mean, IQ)	*r*(slowest, IQ)
Larson & Alderton	1990	Heterogeneous	manifest	80	303	*g* (RAPM; ASVAB)	-0.2	-0.28	-0.37
						speed (ASVAB)	-0.1	-0.18	-0.17
						memory (sequential memory, mental counters)	-0.21	-0.31	-0.36
Diascro & Brody	1992	Students	manifest	384	47	*gf* (CFT)	0.06	-0.05	-0.27
Kranzler	1992	Students	manifest	85	97	*g* (MAB)	-0.18	-0.18	-0.30
Salthouse	1998	Heterogeneous	manifest	556	265	*g* (different cognitive tests)	-0.25	-0.41	-0.40
Schmiedek et al.	2007	Students	latent	640	131	*gf* (BIS)	-0.41	-0.54	-0.64
						memory (complex span and updating tasks)	-0.43	-0.55	-0.65
						speed (BIS PS)	-0.41	-0.52	-0.57
Leite	2009	Students	manifest	1812	51	*g* (two subtests of the WAIS-III)	-0.13	-0.19	-0.31
Ratcliff et al.	2010	Students	manifest	4132	45	*g* (WAIS-III)	0.07	-0.08	-0.04
Ratcliff et al.	2010	Elderly	manifest	4132	43	*g* (WAIS-III)	-0.12	-0.17	-0.16
Ratcliff et al.	2010	Elderly	manifest	4132	42	*g* (WAIS-III)	-0.17	-0.21	-0.16
Unsworth et al.	2010	Students	latent	75	151	*gf* (RAPM, verbal analogies, number series)	-0.11	-0.42	-0.4
						memory (complex span tasks)	-0.08	-0.32	-0.36
Weeda	2012	Students	manifest	400	46	*gf* (RAPM)	0.22	0.05	-0.06
Fernandez et al.	2014	Children	manifest	672	198	*gf* (RSPM)	-0.13	-0.26	-0.32
Fernandez et al.	2014	Students	manifest	672	137	*gf* (RSPM)	-0.13	-0.21	-0.24
Fernandez et al.	2014	Heterogeneous	manifest	672	114	*gf* (RSPM)	-0.15	-0.23	-0.26
Unsworth	2015	Students	latent	325	241	*gf* (RAPM, number series, letter sets)	0.01	-0.29	-0.37
Frischkorn et al.	2016	Heterogeneous	manifest	300	121	*gf* (BIS)	-0.33	-0.34	-0.35
Rammsayer et al.	2016	Heterogeneous	manifest	90	245	*g* (BIS, LPS, CFT)	-0.13	-0.22	-0.32
						memory (BIS M)	-0.03	-0.09	-0.13
Saville et al.	2016	Students	manifest	1680	50	*gf* (figural and numeric subtests of the BIS)	-0.04	-0.11	-0.05
Schmitz & Wilhelm	2016	Heterogeneous	latent	80	200	*gf* (BEFKI)	-0.41	-0.46	-0.44
						memory (1-back tasks)	-0.59	-0.69	-0.68
Dutilh et al.	2017	Heterogeneous	manifest	180	916	*memory* (complex span tasks, spatial short-term memory task)	0.07	0.06	0.03
Wallert et al.	2017	Elderly	manifest	107	103	*gf* (two subtests of the WAIS-IV)	-0.19	-0.16	-0.31
Löffler	2018	Heterogeneous	manifest	640	92	*gf* (BIS)	-0.25	-0.27	-0.30
Schmitz et al.	2018	Students	latent	1095	129	*memory* (1-back tasks)	-0.59	-0.68	-0.62

Note. Rel. = estimate of reliability (odd-even correlations or Cronbach's alpha for manifest measures); *n* trials = total number of trials across all RT measures); SRT = single choice reaction task; CRT = choice reaction task; OMO = odd-man out task; SART = sustained attention to response task; RAPM = Raven's Advanced Progressive Matrices; RSPM = Raven's Standard Progressive Matrices; ASVAB = Armed Services Vocational Aptitude Battery; MAB = Multidimensional Aptitude Battery; BIS = Berlin Intelligence Structure Test; BIS PS = processing speed subtests of the BIS, BIS M = memory subtests of the BIS, WAIS = Wechsler Adult Intelligence Scale; BEFKI = Berliner Test zur Erfassung fluider und kristalliner Intelligenz (Berlin test of fluid and crystallized intelligence); *g* = general intelligence; *gf* = fluid intelligence

If correlations between RT quantiles and cognitive abilities were reported for different RT tasks, they were *z*-transformed and subsequently averaged, as were all properties of the RT task (i.e., reliability estimates and SDs per quantile, mean RTs) except for the number of trials, which was summed across all RT tasks. If studies reported correlations between RTs and different cognitive ability measures, all results were included to later analyze the moderating effect of cognitive ability measure. However, if studies reported multiple cognitive ability measures within the same construct domain (e.g., different working memory tasks) that had not been aggregated by the authors, correlations between RTs and cognitive abilities measures were *z*-transformed and subsequently averaged within that specific domain. A few studies contained multiple distinct samples (i.e., different age groups), which were then included as sub-studies in the analyses, resulting in a total of 23 data sets. In two studies, exact correlations were not reported in the report and could also not be provided by the original authors; in this case, correlations were coded by two independent raters based on figures included in the paper and any differences between raters were resolved by consensus. In six studies, correlations of fastest/mean/slowest quantile of the RT distribution with each other were not reported and could also not be obtained from the authors; in these cases, correlations between quantiles were imputed as mean correlations between the specific quantiles across all other data sets, because this information was mandatory for all further statistical tests of the worst performance rule. Data are available in the associated repository at osf.io/fyuh2/ (Schubert, 2018).

Statistical analyses

Mixed-effects meta-analysis was performed with the *metafor* package for *R* (Viechtbauer, 2010). Random effects were included to account for the multilevel structure induced by the inclusion of different samples and measures from one study in the data (Konstantopoulos, 2011; Nakagawa & Santos, 2012). This four-level multilevel model specified that there were multiple estimates of the RT-intelligence correlation for different quantiles of the RT distribution, which were nested in cognitive ability measures and samples, which were nested within studies. In the absence of heterogeneity, the results of a mixed-effects meta-analysis reduce to the results of a fixed-effects meta-analysis.

To investigate if the association between RTs and intelligence varied as a function of quantile of the RT distribution, quantile (fastest vs. mean vs. slowest) was introduced as a moderator of the RT-intelligence relationship as suggested by Frischkorn et al. (2016). The effect of potential moderators of the worst performance effect (i.e., the difference in correlations of slowest and fastest RT quantile with cognitive abilities) was analyzed separately for each moderating variable by introducing an interaction term, Quantile x Moderator, as an additional fixed effect into the mixed-effects meta-analysis. If moderators were categorial variables, it was subsequently tested if the size of the worst performance effect differed across different levels of the moderating variable. If moderators were continuous variables, it was subsequently tested if variations in the moderating variable affected correlations of fastest and slowest RTs with cognitive abilities to a different degree. Analysis code is available in the associated repository at osf.io/fyuh2/ (Schubert, 2018).

Study heterogeneity was evaluated based on the T statistic. In addition, the proportion of between-study variation accounted for by variation in the true effects in comparison to sampling error was evaluated based on the I^2 statistic with cut-off values of 25 %, 50 %, and 70 % indicating low, moderate, and high proportions of between-study variance accounted for by variation in true effects, respectively (Higgins, Thompson, Deeks, & Altman, 2003).

Publication bias was analyzed using funnel plots (Sterne et al., 2011) and based on the regression of correlation coefficients on sample sizes (Macaskill, Walter, & Irwig, 2001). Correlation coefficients were regressed on sample sizes instead of standard errors, because the variance of a correlation coefficient is a function of the correlation coefficient itself. This mathematical property results in an unavoidable association between correlation coefficients and their standard errors, which are therefore not diagnostic regarding the presence or absence of publication bias.

Results

Across all studies included in the meta-analysis, correlations between fastest RTs and intelligence (see Figure 2), $r = -.18$, 95 % CI = [-.27; -.08], were smaller than correlations between mean RTs and intelligence (see Figure 3), $r = -.28$, 95 % CI = [-.38; -.18], which were in turn smaller than correlations between slowest RTs and intelligence (see Figure 4), $r = -.33$, 95 % CI = [-.41; -.24]. See Figures 2-4 for study-specific and summary effect sizes of the three correlations. Study heterogeneity was comparable across all RT quantiles and ranged from T = 0.19 to T = 0.21. A large amount of the variation in observed effects could be accounted for by variation in true effects, $I^2 = 85.22$ % to $I^2 = 87.81$ %. No study was identified as an influential outlier for any of the RT quantiles based on the set of diagnostics derived from linear regression available in *metafor*. There was little evidence for systematic publication bias, all ps > .173. An inspection of funnel plots presented in Figure 5 suggests that small studies tended to underestimate rather than overestimate the correlations of RTs with intelligence. Moreover, the study with the largest sample size (N = 916; Dutilh et al., 2017) provided the most conservative estimate of the correlation between RTs and intelligence across all quantiles.

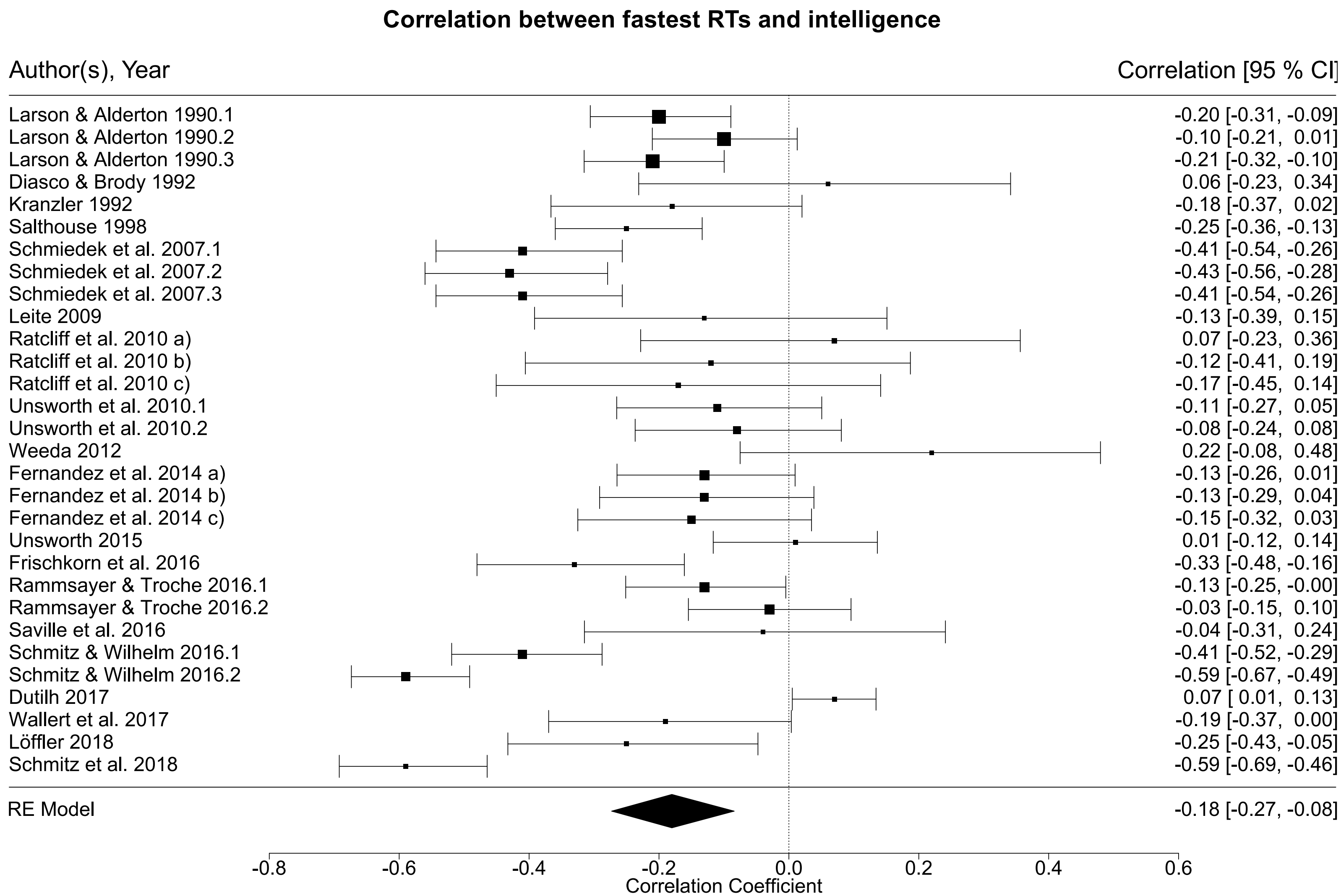

Figure 2. Forest plots for mixed-effects meta-analyses of the association between fastest RTs and intelligence. If there are multiple studies indexed by letters a), b), and c), these indicate different samples reported in a single study. If there are multiple studies indexed by number .1, .2, and .3, these indicate different dependent variables (e.g., intelligence tests and working memory test) measured in the same sample. See Table 2 for details regarding included studies.

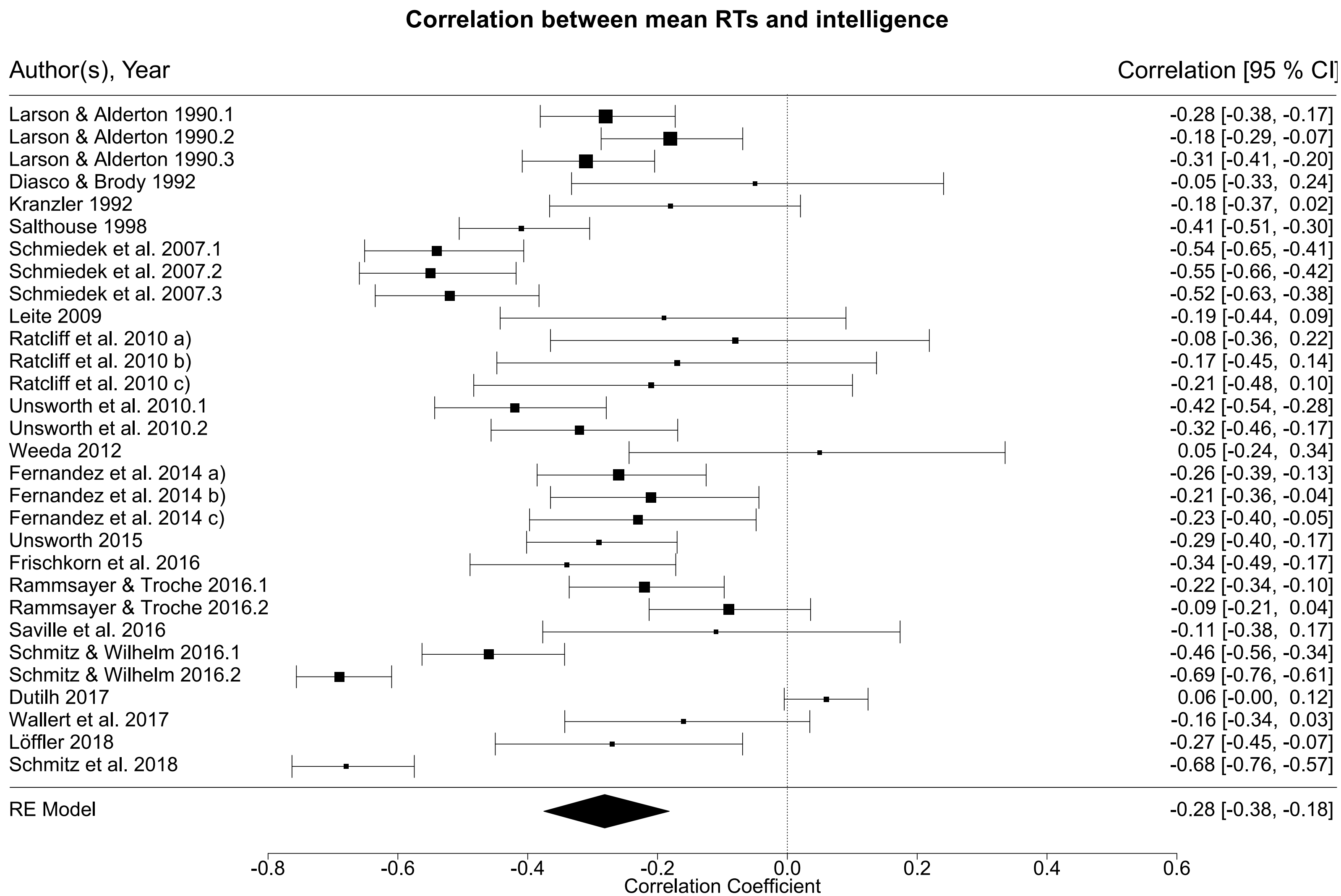

Figure 3. Forest plots for mixed-effects meta-analyses of the association between mean RTs and intelligence. If there are multiple studies indexed by letters a), b), and c), these indicate different samples reported in a single study. If there are multiple studies indexed by number .1, .2, and .3, these indicate different dependent variables (e.g., intelligence tests and working memory test) measured in the same sample. See Table 2 for details regarding included studies.

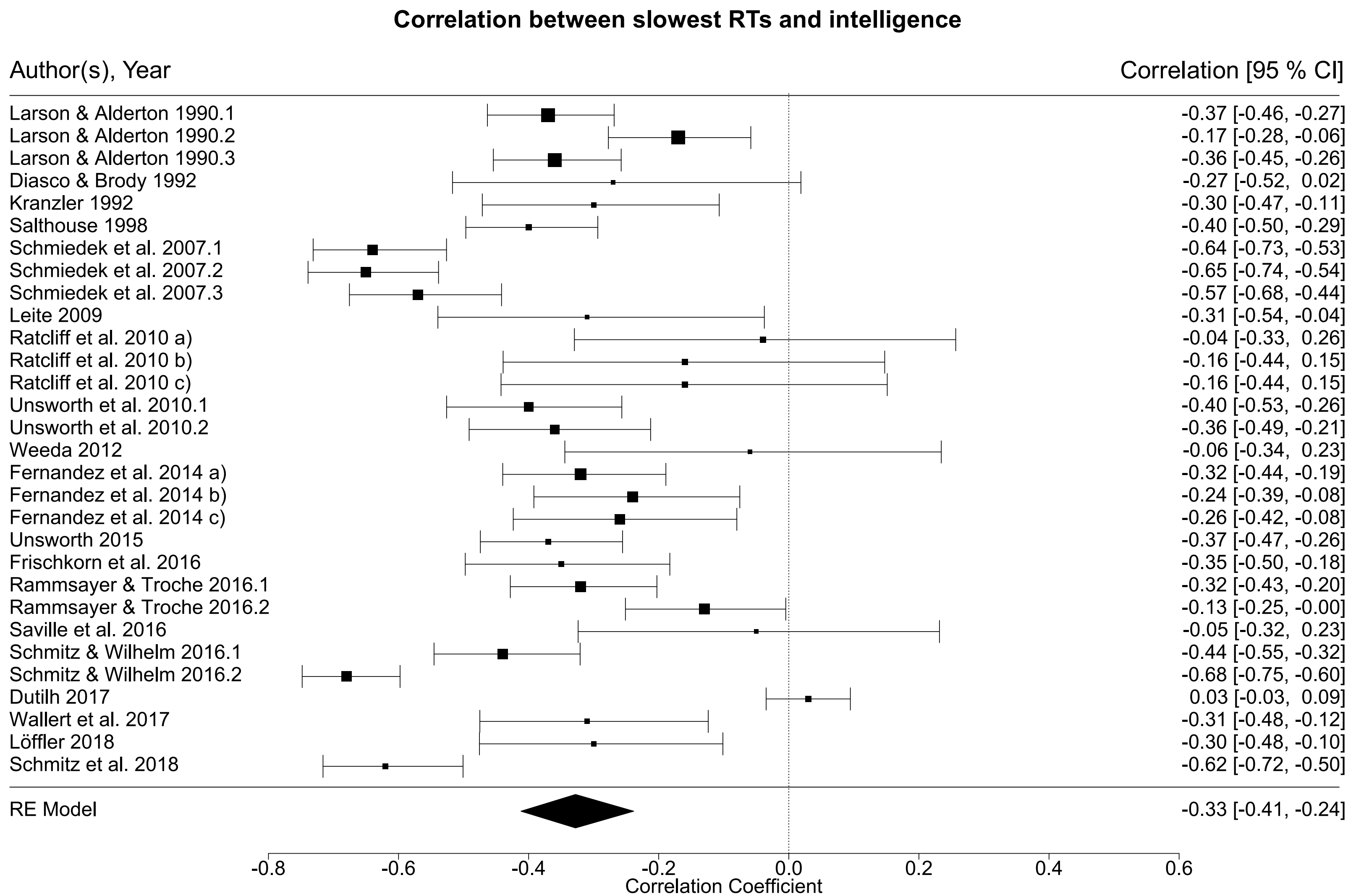

Figure 4. Forest plots for mixed-effects meta-analyses of the association between slowest RTs and intelligence. If there are multiple studies indexed by letters a), b), and c), these indicate different samples reported in a single study. If there are multiple studies indexed by number .1, .2, and .3, these indicate different dependent variables (e.g., intelligence tests and working memory test) measured in the same sample. See Table 2 for details regarding included studies.

To test if correlations between reaction times and intelligence differed significantly across RT quantiles, RT quantile (fastest vs. mean vs. slowest) was introduced as a moderator of the association between mental abilities and mental speed. All pairwise comparisons were significant, suggesting that mean RTs were more strongly related to intelligence than fastest RTs, $\chi^2(1) = 26.01$, $p < .001$, and that slowest RTs were more strongly related to intelligence than fastest RTs, $\chi^2(1) = 42.00$, $p < .001$, and mean RTs, $\chi^2(1) = 11.28$, $p < .001$. There was some variation between studies with regard to correlation differences, $\overline{T} = 0.03$, that was largely accounted for by variation in true effects, $\overline{I^2} = 97.73$ %.

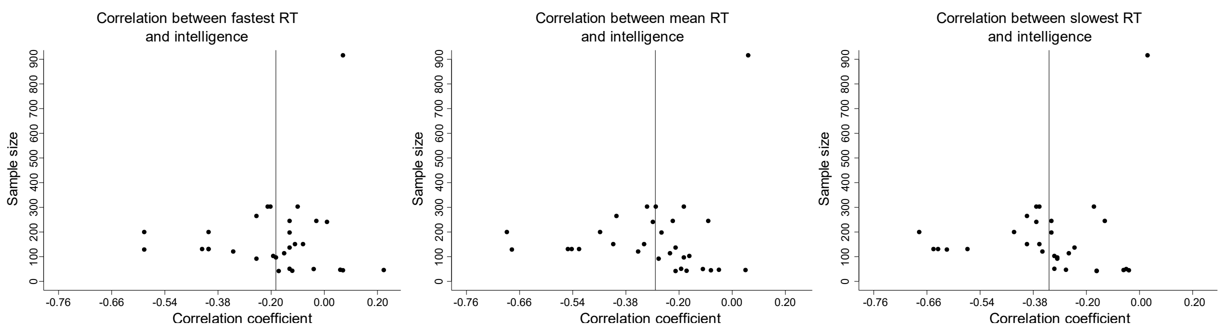

Figure 5. Funnel plots comparing correlation coefficients to sample size. If no publication bias is present, correlation coefficients should get closer to the meta-analytically derived mean correlation (vertical line) with larger sample sizes. Moreover, correlation coefficients should be symmetrical around the vertical line.

Moderators of the worst performance rule

Sample composition, cognitive ability measure, and mean RT in the reaction time task were introduced as moderators of the worst performance rule.

Moderation by sample composition

Because standardized IQ scores were only available for 10 out of 23 data sets, samples were instead coded as "heterogeneous", "students", "elderly", or "children" according to their description in the original studies and in consultation with the original authors where needed. As there was only one study with a children sample, this level of the sample factor was excluded from further analyses. For the remaining 22 studies, sample characteristics (heterogeneous sample vs. student sample vs. elderly sample) moderated the worst performance rule (see Figure 6).

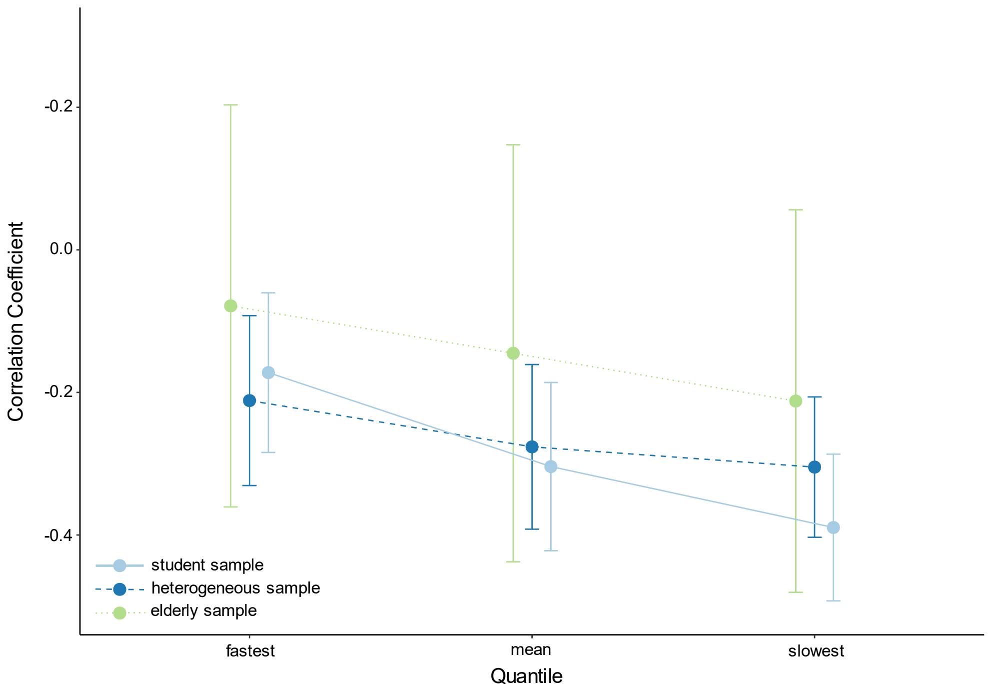

Figure 6. Differences in the worst performance rule between student samples, heterogeneous samples, and elderly samples.

Contrary to theoretical expectations, the worst performance effect (i.e., the difference in correlations of slowest and fastest RT quantile with intelligence) was more pronounced in student samples with supposedly above-average intelligence than in heterogeneous samples with supposedly average intelligence, $\chi^2(1) = 15.72$, $p < .001$. Similarly, the worst performance effect was greater in student samples than in elderly samples with supposedly average or even below-average intelligence due to suspected cognitive dysfunction (see Wallert et al., 2017), $\chi^2(1) = 4.56$, $p = .033$, while there was no difference in the worst performance effect between heterogeneous and elderly samples, $\chi^2(1) = 0.01$, $p = .923$.

Moderation by cognitive ability measure

The cognitive ability measure in each study was categorized either as a measure of a) general intelligence, b) fluid intelligence, c) memory, or d) clerical speed. The worst performance effect (i.e., the difference in correlations of slowest and fastest RT quantile with intelligence) ranged from $\Delta r = .10$ to $\Delta r = .37$ (see Figure 7). The size of the worst performance effect did not differ among general intelligence, fluid intelligence, and memory measures, all χ^2s ≤ 1.95, all ps $\geq .162$. However, the worst performance effect was substantially larger for clerical speed measures than for any other cognitive ability measure, all χ^2s ≥ 14.57, all ps $< .001$, although it should be noted that there were only two studies with clerical speed measures included in the present meta-analysis (Larson & Alderton, 1990; Schmiedek et al., 2007).

To investigate whether the factor cognitive ability measure was confounded with reliability, the number of tests contained within each measure was introduced as a random factor nested within studies. Including this nested factor in the meta-analysis model did not change any of the results regarding the moderating effect of cognitive ability measure.

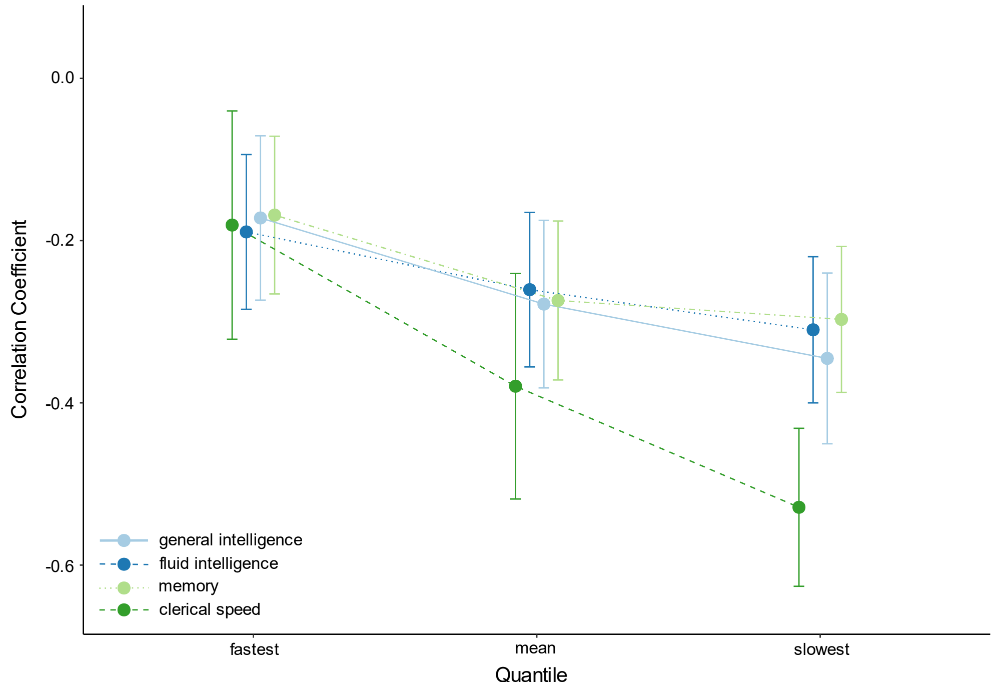

Figure 7. Differences in the worst performance rule between cognitive ability measures.

Moderation by mean reaction time

To investigate the moderating effect of task complexity, mean reaction time in the experimental task was introduced as a moderator to the worst performance rule (see Figure 8). For this moderator analysis, sample composition (children, student, heterogeneous, or elderly sample) was introduced as an additional random factor nested within studies to account for the fact that reaction times are – among other factors – affected by both sample ability and task complexity. Each increase in mean reaction time by 100 ms led to an increase in correlations between fastest RTs and intelligence by b = -.02, p = .138, while the same increase in mean reaction time increased correlations between slowest RTs and intelligence by b = -.03, p = .140. Taken together, there was no evidence that mean reaction time moderated the worst performance effect, $\chi^2(1) = 0.14$, p = .711.

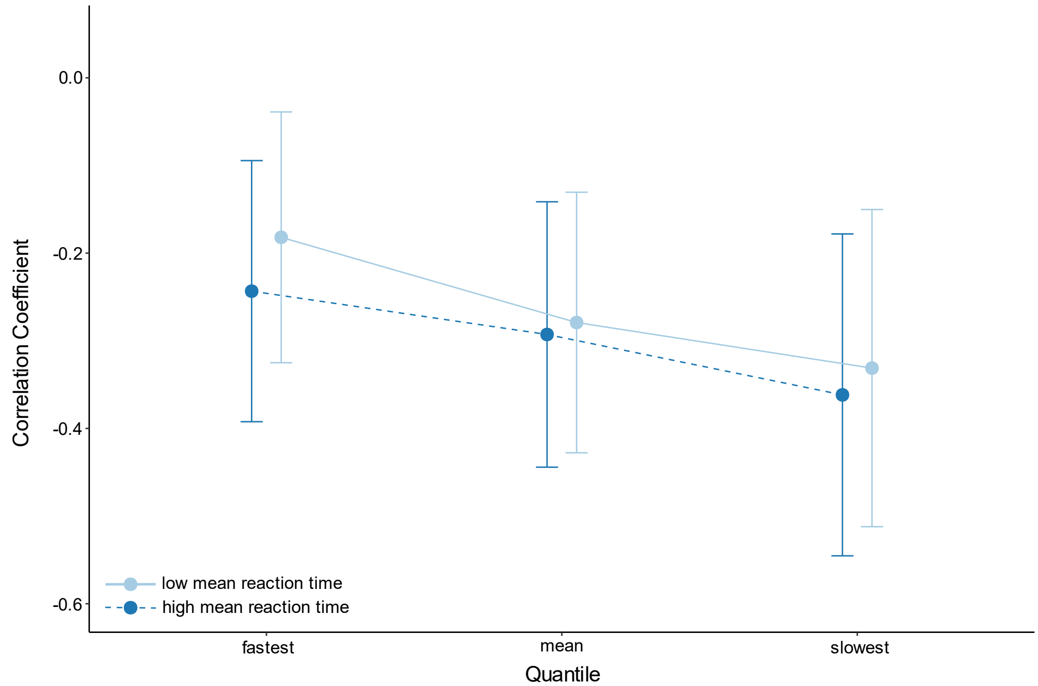

Figure 8. Differences in the worst performance rule between tasks with lower and higher mean reaction times.

Exploring further moderators

In addition, several methodological properties of the studies were included as potential moderators to test if the worst performance rule may be attributed to statistical artifacts. Neither the number of trials in the experimental task, $\chi^2(1) = 0.77$, $p = .382$, nor the analysis level (latent vs. manifest), $\chi^2(1) = 2.42$, $p = .120$, nor the reliability of slowest RTs, $\chi^2(1) = 0.83$, $p = .362$, nor the difference in reliabilities between slowest and fastest RTs, $\chi^2(1) = 1.65$, $p = .199$, nor the difference in variance between slowest and fastest RTs, $\chi^2(1) = 1.67$, $p = .196$, nor the number of RT quantiles, $\chi^2(1) = 0.00$, $p = .973$, nor the size of the correlation of mean RTs with cognitive abilities, $\chi^2(1) = 1.37$, $p = .243$, moderated the worst performance effect.

Discussion

The worst performance rule could be corroborated in a meta-analysis of 19 studies containing 23 data sets with a total of 3,767 participants. The correlation between reaction times and intelligence increased across quantiles of the RT distribution and was substantially larger for slowest than for fastest RTs. Overall, correlations between reaction times and cognitive ability tests ranged from r = -.18 in the fastest quantile to r = -.33 in the slowest quantile and were comparable to correlations previously established in reviews and meta-analyses of the association between mental speed and mental abilities (Doebler & Scheffler, 2016; Sheppard & Vernon, 2018)

Contrary to typical expectations regarding the worst performance rule (e.g., Coyle, 2003a; Dutilh et al., 2017; Frischkorn et al., 2016), the increase in correlations across quantiles did not follow a linear, but a logarithmic trend. Correlations increased most substantially from fastest to mean reaction times, Δr = .10, while there was only a small, but significant increase from mean to slowest reaction times, Δr = .05. This result suggests that the variance in fastest reaction times (i.e., in best performance) was least predictive of intelligence and that the worst performance rule might be better renamed as the “not-best performance rule”. Moreover, it implies that those cognitive processes contributing to fast responses in reaction time tasks are less strongly related to cognitive abilities than other cognitive processes contributing to average and slow responses.

Due to the great heterogeneity in the number and nature of quantiles across studies, it was not possible to conduct a more fine-grained analysis of the trend of correlations across quantiles of the reaction time distribution. Previous research on the shape of the relationship between cognitive abilities and reaction times suggests that correlations increased across quantiles of the reaction time distribution, followed by a drop in correlations for extremely slow values (Larson &

Alderton, 1990; Schmitz et al., 2018). Moreover, the correlation between slowest reaction times and cognitive abilities may have been attenuated due to outliers affecting the reliability of the slowest quantile of the reaction time distribution. However, this seems unlikely as more than 80 percent of the included studies reported some kind of outlier removal and neither the reliability of slowest RTs nor the difference in reliabilities between slowest and fastest RTs moderated the size of the worst performance effect. It may even be possible that aggregation across studies resulted in the logarithmic shape observed in the present meta-analysis. Therefore, future studies on the worst performance rule should aim for a detailed analysis of this trend across the whole reaction time distribution.

If the logarithmic trend of the worst performance rule held in future studies on the shape of the relationship between cognitive abilities and reaction times across the whole reaction time distribution, this would have far-reaching implications for explanatory accounts of the worst performance rule. In particular, these theoretical accounts would have to predict a decelerated increase of the association between reaction times and intelligence across slower quantiles of the reaction time distribution.

The attentional lapses account of the worst performance rule presumes that occasional lapses in attention disrupt goal maintenance in working memory and that slowest reaction times reflect lapses in attentional control due to the additional processing time required by the redirection of attention to the task stimulus (Larson & Alderton, 1990; Unsworth et al., 2010). These attentional lapses are supposed to primarily affect the right tail of the reaction time distribution and Unsworth et al. (2010) even suggested that “the slowest RTs […] provide an index of lapses of attention” (p. 114). Hence, it may be argued that the attentional lapses account would predict that slowest reaction times should correlate most strongly with intelligence, and that this correlation should be substantially greater than the correlation of other parts of the reaction time distribution with intelligence. Such a prediction would be hard to reconcile with the results from the present meta-analysis. However, because the theoretical account itself makes no specific predictions regarding the shape of the worst performance rule across the whole reaction time distribution (Larson & Alderton, 1990; Unsworth et al., 2010), it cannot be decided unequivocally whether it is supported or contradicted by these results. Therefore, it would be informative to specify alternative versions of the attentional lapses account making different predictions regarding the shape of the worst performance rule and test which of these alternatives predicts the empirical shape of the worst performance rule across the reaction time distribution most accurately. Such a comparison using computational modeling would help to clarify if disruptions of attentional control affected only the right tail or also the bulk of the reaction time distribution. Moreover, it would shed light on the question if intelligence-related failures in information-processing were more likely to reflect complete lapses of attention, gradual variations in attentional control, or a mixture of both (see Adam, Mance, Fukuda, & Vogel, 2015, for a comparison of the two attentional control accounts in visual working memory).

For the drift diffusion model account of the worst performance rule, on the other hand, the implications are more straightforward, as it would not be challenged by a negatively accelerated trend of the worst performance rule across quantiles of the reaction time distribution. In their simulation study, Ratcliff et al. (2008) demonstrated that the shape of the relationship between cognitive abilities and reaction times across quantiles depended on the trial-to-trial variability of two diffusion model parameters, boundary separation and non-decision time. Although certain specifications of trial-to-trial variability in these parameters may predict a logarithmic trend of the worst performance rule, it may be questioned whether the drift diffusion model account qualifies as a theoretical explanation of the worst performance rule if it can account for *any* trend of the relationship between cognitive abilities and reaction times across quantiles.

There was little evidence for publication bias in the included studies. Funnel plots suggested that small studies *underestimated* rather than *overestimated* the correlations between reaction times and cognitive abilities. Together with the great heterogeneity in study results, these properties of funnel plots suggest that the asymmetry in funnel plots may be caused by true heterogeneity or by some unidentified confound between sample size and study characteristics that affects the correlation between reaction times and intelligence (Sterne et al., 2011). Although there was little evidence that publication bias led to a systematic overestimation of the worst performance rule, it would be interesting to derive an estimate of the worst performance rule unaffected by reporting biases. This could be achieved by reanalyzing a selected number of representative, large-sample studies on the relationship between reaction times and intelligence that did not primarily investigate the worst performance rule themselves. Given the recent rise of open science in psychology, such a re-analysis of freely available data sets will be a promising avenue for collaborative meta research in the future.

Moderating effects of mean reaction time, cognitive ability measure, and sample composition

There was no evidence that the worst performance rule became more prevalent in more complex reaction time tasks and in cognitive ability tests with a greater *g*-loading (Coyle, 2003a; Ratcliff et al., 2008). This result contradicts an experimental study by Rammsayer and Troche (2016), in which both the cognitive ability measure and task complexity were experimentally manipulated and found to affect the worst performance rule. In particular, the present meta-analysis was not in line with their result that the worst performance rule was less pronounced when memory tasks were used as a cognitive ability measure. The main difference between their study and the studies included in the meta-analysis is that Rammsayer and Troche (2016) used memory subtests of the BIS as a measure of memory, whereas other studies included in the meta-analysis employed *N*-back or complex span tasks. Although it may be argued that the memory subtests of the BIS measure a different construct than typical working memory tasks, factor analyses have demonstrated that highly similar bindings tasks show equally high loadings on a latent factor of working memory capacity as updating, *n*-back, and complex span tasks (Wilhelm, Hildebrandt, & Oberauer, 2013).

Another difference between their study and the present meta-analysis is that Rammsayer and Troche (2016) manipulated task complexity in an experimentally controlled manner by systematically increasing the information needed to be processed in a Hick task, whereas task complexity was defined by mean RTs in the meta-analysis. Because other cognitive processes than increased information processing demands may lead to an increase in mean reaction times (Ratcliff, 1978; Schubert et al., 2015), the lack of a meta-analytically derived moderation of the worst performance rule by mean reaction times may also reflect interacting effects of other cognitive processes such as encoding demands or speed/accuracy-tradeoffs. To allow a better evaluation of the moderation effects of tasks complexity, more within-subject designs similar to Rammsayer and Troche (2016) would be required.

The meta-analysis also failed to find any evidence for the hypothesis that the worst performance rule is more pronounced in individuals with lower cognitive abilities than in individuals with higher cognitive abilities (Coyle, 2003a). Instead, there was a trend towards the opposite, namely that the worst performance rule was slightly larger in above-average student samples than in heterogeneous samples. Because there were insufficient studies on the worst performance rule in samples with below-average intelligence, it can only be speculated if this trend may reverse in the lower end of the ability spectrum. However, this notion was not supported by the only study that investigated the worst performance rule in a sample with below-average intelligence: In elderly with abnormal cognitive decline, the difference in correlations between fastest and slowest reaction times of $\Delta r = .12$ was comparable to the average trend in this meta-analysis (Wallert, Ekman, Westman, & Madison, 2017).

Taken together, these results suggest that the worst performance rule may not be as characteristic for *g* and may play a smaller role for the explanation of the positive manifold than previously thought. Specifically, the worst performance rule was most pronounced in clerical speed tests and in student samples with supposedly above-average intelligence, which show a lower *g*-saturation than broad test batteries of general intelligence and samples with low or average intelligence (Blum & Holling, 2017; Carroll, 1993; Spearman, 1927). If the worst performance rule was particularly characteristic for *g*, however, it should have been most pronounced in general intelligence tests and samples with below or average intelligence (Coyle, 2003a; Ratcliff et al., 2008). Hence, it may be argued that comprehensive process models of the positive manifold should not consider the worst performance rule as a phenomenon particular informative with regard to *g* or as a cornerstone for their explanatory models. This does not diminish the relevance of the worst performance rule, however: Even if the worst performance rule is not stronger for general intelligence tests than other dimensions of intelligence, it still emerged for any kind of cognitive ability measure and therefore needs to be explained.

Limitations

One limitation of the present meta-analysis is that the moderating variable "task complexity" was defined based on mean reaction times in the experimental tasks. Unlike psychometric tests, experimental tasks are not standardized, which is why task properties that affect mean reaction times often vary across different studies (Hedge, Powell, & Summer, 2018). Among others, the amount of allocated practice trials, the number of experimental trials, presentation times, and stimulus properties may affect both cognitive processing and mean reaction times. Moreover, an increase in reaction times does not necessarily reflect increased processing demands, but may also reflect a shift in speed/accuracy-trade-offs or greater motor demands (Ratcliff, 1978; Schubert et al., 2015). In addition to an increase in reaction times, greater task complexity is also defined by a greater number of more difficult mental operations. Because the complexity of mental operations is hardly comparable across vastly different experimental tasks, it was not feasible to categorize experimental tasks according to process characteristics. Nevertheless, the measure of task complexity used in the present meta-analysis should only be regarded as a very limited approximation to true task complexities.

Similarly, it would have been more desirable to introduce standardized intelligence test scores as a continuous moderator variable instead of categorizing samples according to their composition. The implicit assumption that student samples were of higher intelligence than heterogeneous or elderly samples may not hold for all studies, although standardized IQ scores were greater in student samples (M_{IQ} = 114) than in heterogeneous samples (M_{IQ} = 99), but not in elderly samples (M_{IQ} = 113) if they were reported. However, calculating standardized IQ scores was not feasible for the majority of studies that used abbreviated, speeded, or otherwise altered cognitive ability tests that deviated from manual instructions. Moreover, published norms were often not applicable for the studied age groups, prohibiting even an approximation of intelligence test scores. Nevertheless, when standardized IQ scores were introduced as a moderating variable for those ten data sets in which they were reported, the data corroborated the results based on sample categorization: The correlation between slowest RTs and intelligence increased by $b = .003$, $p < .001$, for each additional IQ point, while the correlation between fastest RTs and intelligence increased only by $b = -.002$, $p < .001$, $\chi^2(1) = 13.69$, $p < .001$.

Finally, the reverse literature search may have been more prone to introduce publication bias in the present meta-analysis. However, there was no evidence that the worst performance rule was amplified by reporting biases. Therefore, the inclusion of studies discovered in reverse literature search is likely to have increased the precision of the population estimate without introducing systematic biases.

Conclusion

There was robust evidence for the worst performance rule: The association between intelligence and reaction times increased from fastest over median to slowest quantiles of the reaction time distribution. This increase in correlations across quantiles did not follow a linear, but a logarithmic trend, suggesting that the variance in fastest reaction times (i.e., in best performance) was least predictive of intelligence test performance. The shape of the worst performance rule is relevant to explanatory accounts of the worst performance rule, because these theoretical accounts would have to predict a decelerated increase of the association between reaction times and intelligence across slower quantiles of the reaction time distribution. There was no evidence that the strength of the worst performance rule increased in tasks with greater mean reaction times, in tests of general intelligence, or in samples with lower or average cognitive abilities. Instead, it was attenuated in less intelligent samples. Hence, the worst performance rule may not be as characteristic for *g* and may play a smaller role for the explanation of the positive manifold than previously thought.

References

Adam, K. C. S., Mance, I., Fukuda, K., & Vogel, E. K. (2015). The contribution of attentional lapses to individual differences in visual working memory capacity. Journal of Cognitive Neuroscience, 27, 1601–1616. doi:10.1162/jocn_a_00811

Baumeister, A. A., & Kellas, G. (1968). Reaction Time and Mental Retardation. In Norman R. Ellis (Ed.), *International Review of Research in Mental Retardation, 3,* 163–193. doi: 10.1016/S0074-7750(08)60011-7

Blum, D., & Holling, H. (2017). Spearman's law of diminishing returns. A meta-analysis. *Intelligence*, *65*, 60–66. doi:10.1016/j.intell.2017.07.004

Carroll, J.B. (1993). *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge, England: Cambridge University Press.

Coyle, T. R. (2001). IQ is related to the worst performance rule in a memory task involving children. *Intelligence*, *29*, 117 – 129.

Coyle, T. R. (2003a). A review of the worst performance rule: Evidence, theory, and alternative hypotheses. *Intelligence*, *31*, 567–587. doi:10.1016/S0160-2896(03)00054-0

Coyle, T. R. (2003b). IQ, the worst performance rule, and Spearman's law: A reanalysis and extension. *Intelligence, 31*, 473 – 489.

Coyle, T. (2017). A Differential–Developmental Model (DDM): Mental Speed, Attention Lapses, and General Intelligence (g). *Journal of Intelligence*, *5*, 25. doi:10.3390/jintelligence5020025

Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*, 135–168. doi:10.1146/annurev-psych-113011-143750

*Diascro, M. N., & Brody, N. (1993). Serial versus parallel processing in visual search tasks and IQ. *Personality and Individual Differences, 14*, 243–245. doi:10.1016/0191-8869(93)90195-9

Doebler, P., & Scheffler, B. (2016). The relationship of choice reaction time variability and intelligence: A meta-analysis. *Learning and Individual Differences*, *52*, 157–166. doi:10.1016/j.lindif.2015.02.009

*Dutilh, G., Vandekerckhove, J., Ly, A., Matzke, D., Pedroni, A., Frey, R., (…), Wagenmakers, E.-J. (2017). A test of the diffusion model explanation for the worst performance rule using preregistration and blinding. *Attention, Perception, & Psychophysics*, *79*, 713–725. doi:10.3758/s13414-017-1304-y

*Fernandez, S., Fagot, D., Dirk, J., & de Ribaupierre, A. (2014). Generalization of the worst performance rule across the lifespan. *Intelligence*, *42*, 31–43. doi:10.1016/j.intell.2013.10.001

Frischkorn, G. T., & Schubert, A.-L. (2018). Cognitive Models in Intelligence Research: Advantages and Recommendations for Their Application. *Journal of Intelligence, 6*, 34. doi:10.3390/jintelligence6030034

*Frischkorn, G. T., Schubert, A.-L., Neubauer, A. B., & Hagemann, D. (2016). The Worst Performance Rule as Moderation: New Methods for Worst Performance Analysis. *Journal of Intelligence*, *4*, 9. doi:10.3390/jintelligence4030009

Hedge, C., Powell, G., & Sumner, P. (2018). The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. *Behavior Research Methods*, *50*, 1166–1186. doi:10.3758/s13428-017-0935-1

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ*, *327*, 557–560. doi:10.1136/bmj.327.7414.557

Jensen, A. R. (1982). Reaction time and psychometric "g". In Eysenck, H. J. (Ed.), *A model for intelligence*. New York: Plenum.

Kane, M. J., Conway, A. R. A., Hambrick, D. Z., & Engle, R. W. (2007). Variation in working memory as variation in executive attention and control. In A. Conway, C. Jarrold, M. J. Kane,

A. Miyake, & J. N. Towse (Eds.), *Variation in working memory*. New York, NY: Oxford University Press.

Kievit, R. A., Davis, S. W., Griffiths, J., Correia, M. M., Cam-CAN, & Henson, R. N. (2016). A watershed model of individual differences in fluid intelligence. *Neuropsychologia*, *91*, 186–198. doi:10.1016/j.neuropsychologia.2016.08.008

Konstantopoulos, S. (2011). Fixed effects and variance components estimation in three-level meta-analysis. *Research Synthesis Methods*, *2*(1), 61–76. doi:10.1002/jrsm.35

Kovacs, K., & Conway, A. R. A. (2016). Process Overlap Theory: A Unified Account of the General Factor of Intelligence. *Psychological Inquiry*, *27*, 151–177. doi:10.1080/1047840X.2016.1153946

*Kranzler, J. H. (1992). A test of Larson and Alderton’s (1990) worst performance rule of reaction time variability. *Personality and Individual Differences*, *13*, 255–261. doi:10.1016/0191-8869(92)90099-B

*Larson, G.E., & Alderton, D. L. (1990). Reaction time variability and intelligence: A “worst performance” analysis of individual differences. *Intelligence*, *14*, 309–325. doi:10.1016/0160-2896(90)90021-K

*Leite, F. P. (2009). Should IQ, perceptual speed, or both be used to explain response time? *The American Journal of Psychology*, *122*, 517-526.

*Löffler, C. (2018). *Exekutive Aufmerksamkeit als Erklärungsansatz der Worst Performance Rule* [Executive attention as an explanation of the worst performance rule] (Unpublished master’s thesis). Heidelberg University, Heidelberg, Germany.

Macaskill, P., Walter, S. D., & Irwig, L. (2001). A comparison of methods to detect publication bias in meta-analysis. *Statistics in Medicine*, *20*, 641–654. doi:10.1002/sim.698

Madison, G., Forsman, L., Blom, Ö., Karabanov, A., & Ullén, F. (2009). Correlations between intelligence and components of serial timing variability. *Intelligence, 37*, 68–75. doi:10.1016/j.intell.2008.07.006

Maylor, E. A., & Rabbitt, P. M. A. (1995). Investigating Individual Differences in a Serial Choice Reaction Time Task: Use of Auditory Feedback and Analysis of Responses Surrounding Errors. *Journal of Motor Behavior, 27*, 325–332. doi:10.1080/00222895.1995.9941721

McVay, J. C., & Kane, M. J. (2012). Drifting from Slow to "D'oh!" Working Memory Capacity and Mind Wandering Predict Extreme Reaction Times and Executive-Control Errors. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*, 525–549. doi:10.1037/a0025896

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Medicine*, *6*(7), e1000097. doi:10.1371/journal.pmed.1000097

Nakagawa, S., & Santos, E. S. A. (2012). Methodological issues and advances in biological meta-analysis. *Evolutionary Ecology*, *26*, 1253–1274. doi:10.1007/s10682-012-9555-5

Posthuma, D., Geus, E. J. de, & Boomsma, D. I. (2001). Perceptual speed and IQ are associated through common genetic factors. *Behavior Genetics*, *31,* 593–602.

*Rammsayer, T. H., & Troche, S. J. (2016). Validity of the Worst Performance Rule as a Function of Task Complexity and Psychometric g: On the Crucial Role of g Saturation. *Journal of Intelligence*, *4*,5. doi:10.3390/jintelligence4010005

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59–108. doi:10.1037/0033-295X.85.2.59

Ratcliff, R., Schmiedek, F., & McKoon, G. (2008). A diffusion model explanation of the worst performance rule for reaction time and IQ. *Intelligence, 36*, 10–17. doi:10.1016/j.intell.2006.12.002

*Ratcliff, R., Thapar, A., & McKoon, G.. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology*, *60*, 127–157. doi:10.1016/j.cogpsych.2009.09.001

Salthouse, T. A. (1993). Attentional Blocks Are Not Responsible for Age-Related Slowing. *Journal of Gerontology*, *48*, 263-270. doi:10.1093/geronj/48.6.P263

*Salthouse, T. A. (1998). Relation of successive quantiles of reaction time distributions to cognitive variables and adult age. *Intelligence*, *26*, 153–166. doi:10.1016/S0160-2896(99)80059-2

*Saville, C. W. N., Beckles, K. D. O., MacLeod, C. A., Feige, B., Biscaldi, M., Beauducel, A., & Klein, C. (2016). A neural analogue of the worst performance rule: Insights from single-trial event-related potentials. *Intelligence, 55*, 95–103. doi:10.1016/j.intell.2015.12.005

*Schmiedek, F., Oberauer, K., Wilhelm, O., Süss, H.-M., & Wittmann, W. W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General*, *136*, 414–429. doi:10.1037/0096-3445.136.3.414

*Schmitz, F., & Wilhelm, O. (2016). Modeling Mental Speed: Decomposing Response Time Distributions in Elementary Cognitive Tasks and Correlations with Working Memory Capacity and Fluid Intelligence. *Journal of Intelligence*, *4*, 13. doi:10.3390/jintelligence4040013

*Schmitz, F., Rotter, D., & Wilhelm, O. (2018). Scoring Alternatives for Mental Speed Tests: Measurement Issues and Validity for Working Memory Capacity and the Attentional Blink Effect. *Journal of Intelligence*, *6*, 47. doi:10.3390/jintelligence6040047

Schönbrodt, F. D. & Perugini, M. (2013). At what sample size do correlations stabilize? *Journal of Research in Personality*, *47*, 609–612. doi:10.1016/j.jrp.2013.05.009

[dataset] Schubert, A.-L. (2018, November 12). A meta-analysis of the worst performance rule. Retrieved from osf.io/fyuh2

Schubert, A.-L., Hagemann, D., & Frischkorn, G. T. (2017). Is general intelligence little more than the speed of higher-order processing? *Journal of Experimental Psychology: General, 146,* 1498–1512. doi:10.1037/xge0000325

Schubert, A.-L., Hagemann, D., Voss, A., Schankin, A., & Bergmann, K. (2015). Decomposing the relationship between mental speed and mental abilities. *Intelligence, 51*, 28–46. doi:10.1016/j.intell.2015.05.002

Sheppard, L. D., & Vernon, P. A. (2008). Intelligence and speed of information-processing: A review of 50 years of research. *Personality and Individual Differences*, *44*, 535–551. doi:10.1016/j.paid.2007.09.015

Spearman, C. (1927). *The abilities of man*. New York: MacMillan.

Steiger, J. H. (1980). Tests for comparing elements of a correlation matrix. *Psychological Bulletin*, *87,* 245–251. doi:10.1037/0033-2909.87.2.245

Sterne, J. A. C., Sutton, A. J., Ioannidis, J. P. A., Terrin, N., Jones, D. R., Lau, J., (…), Higgins, J. P. T. (2011). Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ, 343.* doi:10.1136/bmj.d4002

*Unsworth, N. (2015). Consistency of attentional control as an important cognitive trait: A latent variable analysis. *Intelligence*, *49*, 110–128. doi:10.1016/j.intell.2015.01.005

*Unsworth, N., Redick, T. S., Lakey, C. E., & Young, D. L.. (2010). Lapses in sustained attention and their relation to executive control and fluid abilities: An individual differences investigation. *Intelligence*, *38*, 111–122. doi:10.1016/j.intell.2009.08.002

van Ravenzwaaij, D., Brown, S., & Wagenmakers, E.-J. (2011). An integrated perspective on the relation between response speed and intelligence. *Cognition*, *119*, 381–393. doi:10.1016/j.cognition.2011.02.002

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*, 1–48.

*Wallert, J., Ekman, U., Westman, E., & Madison, G.. (2017). The worst performance rule with elderly in abnormal cognitive decline. *Intelligence*, *64*, 9–17. doi:10.1016/j.intell.2017.06.003

*Weeda, W. (2012). *New methods for the analysis of trial-to-trial variability in neuroimaging studies* (Doctoral dissertation, University of Amsterdam, Amsterdam, Netherlands). Retrieved from http://hdl.handle.net/11245/1.370355

Wilhelm, O., Hildebrandt, A., & Oberauer, K. (2013). What is working memory capacity, and how can we measure it? *Frontiers in Psychology*, *4*, 433. doi:10.3389/fpsyg.2013.00433

Wilhelm, O., & Oberauer, K. (2006). Why are reasoning ability and working memory capacity related to mental speed? An investigation of stimulus-response compatibility in choice reaction time tasks. *European Journal of Cognitive Psychology, 18*, 18-50. doi:10.1080/09541440500215921