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A Meta-Analysis of the Relation between RAN and Mathematics

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Abstract

Several studies have shown that rapid automatized naming (RAN) is a significant predictor of mathematics, but the nature of their relationship remains elusive. Thus, the purpose of this meta-analysis was to estimate the size of their relationship and determine the conditions under which they correlate. We used a random-effects model analysis of data from 38 studies (33 unique samples, 151 correlations, 7,135 participants) to examine the size of the RAN–mathematics relationship and the role of different moderators (i.e., math measure and variable, type of RAN task, math age, study design, and sample characteristics). The results showed a significant correlation between RAN and mathematics (r = .37; 95% confidence interval [CI] .33–.42) as well as a large heterogeneity of individual correlations. The results also revealed that RAN produced stronger correlations with arithmetic calculation tasks than with general achievement tests; stronger correlations with single-digit calculation tasks than multi-digit calculation tasks; and stronger correlations with math fluency tasks than math accuracy tasks. The effect of these moderators suggests that part of the reason why RAN predicts mathematics is that they both require quick access to and retrieval of phonological representations from long-term memory. Our findings also suggest that RAN objects or colors can be used as early predictors of mathematical skill, especially of arithmetic fluency.

Keywords: Rapid automatized naming (RAN), mathematics, arithmetic, meta-analysis

Educational Impact and Implications Statement

RAN and mathematics are significantly related and RAN can be used as a predictor of later mathematical skills, especially of arithmetic fluency. Equally strong correlations between non-alphanumeric RAN, alphanumeric RAN, and mathematics suggest that the relationship between RAN and mathematics is related to both conceptual and phonological processing factors. Non-alphanumeric RAN can be used as a predictor of mathematics performance even before children go to school and become familiar with letters and digits.

A Meta-Analysis of the Effects of RAN on Mathematics

Rapid automatized naming (RAN), defined as the ability to rapidly name familiar visual stimuli, such as letters, digits, colors, and objects, has been established as a strong concurrent and longitudinal predictor of reading in different languages (e.g., Compton, 2003; de Jong & van der Leij, 1999; Georgiou, Torppa, Manolitsis, Parrila, & Lyytinen, 2012; Juul, Poulsen, & Elbro, 2014; Landerl & Wimmer, 2008; Lervåg, Bråten, & Hulme, 2009; Liao, Georgiou, & Parrila, 2008; Parrila, Kirby, & McQuarrie, 2004; Savage & Frederickson, 2005) and a core deficit in dyslexia (e.g., de Jong & van der Leij, 2002; Eklund, Torppa, & Lyytinen, 2013; Kirby, Parrila, & Pfeiffer, 2003; Korhonen, 1995; Wimmer, Mayringer, & Landerl, 1998). Four independent meta-analyses have estimated the correlation between RAN and reading to be between .38 and .51 (see Araújo, Reis, Petersson, & Faísca, 2015; Scarborough, 1998; Song, Georgiou, Su, & Shu, 2016; Swanson, Trainin, Necoechea, & Hammill, 2003).

More recently, however, researchers have used RAN as a predictor of another important academic skill: mathematics. Despite the steady increase in the number of these studies, the findings are mixed and the conclusions indefinite. On the one hand, some studies have shown that RAN is an important predictor of mathematical skills and that the correlations between rapid naming and mathematics might be as high as those reported for reading (e.g., Berg, 2008; Koponen et al., 2016; Swanson, 2006b; Swanson, Jerman, & Zheng, 2008). Substantial correlations between RAN and mathematics have been reported in both cross-sectional (e.g., Cirino, 2011; Koponen, Aunola, Ahonen, & Nurmi, 2007) and longitudinal studies (e.g., Geary, 2011; Georgiou, Tziraki, Manolitsis, & Fella, 2013; Koponen et al., 2016). Such correlations have also been reported in various samples, such as typically developing children (e.g., Koponen et al., 2016; Niklas & Schneider, 2013), children at familial risk for dyslexia (e.g., de Jong, Maassen, & van der Leij, 2014; Koponen, Salmi, Eklund, & Aro, 2013), and children with mathematical difficulties (Mazzocco & Grimm, 2013). On the other hand, there are studies reporting either non-significant or weak correlations between RAN and mathematics (e.g., Niklas & Schneider, 2013) or high variance in the correlations (Hart, Petril, Thompson, & Plomin, 2009). The contradictory findings might be related to the fact that math skill is multifactorial by nature (with several subskills) and thus RAN does not correlate equally well with all mathematical skills. It is also possible that there are some other moderating variables that influence the size of the relationship between RAN and mathematics. In order to develop a more comprehensive picture of the relationship between RAN and mathematics, this meta-analysis examines the size of the relationship between RAN and different mathematics skills as well as the role of different moderators in the RAN–math relationship.

Examining the relationship between RAN and mathematics has important practical and theoretical implications. From a practical point of view, generating new information on the relationship between RAN and mathematics is important because it will enhance our understanding of the early predictors of mathematics development and the possible sources of difficulties in mathematics disabilities. If RAN proves to be a significant correlate of mathematics, then RAN tasks could be used as predictors of mathematics performance and early markers of future mathematical difficulties. Previous studies suggest that RAN, measured in children as young as 5 or 6 years old, can predict mathematics skill at school age (e.g., Georgiou et al., 2013; Koponen et al., 2013, 2016). Some of the previous studies suggest also that RAN make a unique contribution to arithmetic fluency in grades 2 and 3 above and beyond the contribution of verbal short-term memory, working memory, and phonological awareness (Koponen et al., 2013, 2016). However, some researchers have questioned the role of RAN in mathematics (e.g., Georgiou et al., 2013; Willburger et al., 2008). For example, Georgiou et al. (2013) found that processing speed (including numerical items) and visual memory explained most of RAN's predictive variance in calculation fluency. Due to the contradictory findings of previous studies, a meta-analysis could shed light on the RAN–mathematics relationship and on the role of different moderating variables.

From a theoretical point of view, examining the RAN–mathematics relationship allows us to test some interesting hypotheses regarding the nature of RAN and the underlying cognitive processes in mathematics. In reading research, scholars have argued that RAN is an index of the speed of access to and retrieval of phonological representations from long-term memory (e.g., Bowey, McGuigan, & Ruschena, 2005; Torgesen, Wagner, Rashotte, Burgess, & Hecht, 1997). Empirical findings from behavioral studies have also suggested that besides reading, mathematics and arithmetical calculation also require quick retrieval of phonological representations from long-term memory (de Smedt, Taylor, Archibald, & Ansari, 2010), because arithmetic facts are also supposedly stored as phonological forms in long-term memory (de Smedt et al., 2010; Simmons & Singleton, 2008). In line with such findings, evidence from neuroimaging studies on RAN (e.g., Cummine, Szepesvari, Choinard, Hanif, & Georgiou, 2014; Misra, Katzir, Wolf, & Poldrack, 2004) and mathematics (e.g., Dehaene, Piazza, Pinel, & Cohen, 2003; Wei, Chen, Zhang, & Zhou, 2014) indicate that both skills are associated with regions of the left tempo-parietal cortex, such as the left angular gyrus. This region is activated during phonological decoding (e.g., Price & McCrory, 2005). Quick access to arithmetical facts is important because it facilitates the calculation process and enables the learner to release her working memory capacity for problem solving. Finding a predictor for arithmetical calculation fluency at school age could provide a possibility for early identification of risk for dysfluency difficulties and thus for early support.

However, given that mathematics consists of a wide set of different subskills and that retrieval of arithmetic facts from memory is not a core requirement in all mathematical tasks, RAN should not correlate equally well with all mathematical outcomes. In addition to the distinction between general mathematical achievement and arithmetic calculation, other aspects of the math outcome may also influence the RAN–mathematics relationship. As is the case with reading tasks (Araújo et al., 2015), RAN (which is a speeded measure) may correlate more strongly with the speed of mathematics performance, i.e., tasks in which the score is either the response time or the number of items completed within a specified time limit. Moreover, the type of arithmetic problems might influence the association between RAN and mathematics. Answers to single-digit calculation problems (e.g., 3 + 5; 5 × 2) are usually retrieved from memory. This is obviously not the case in multi-digit calculation problems (e.g., 325 + 196), which require knowledge of place value and mastery of arithmetic procedures in addition to retrieving/calculating partial answers. According to this proposal, if RAN is an index of the speed of lexical access (e.g., Norton & Wolf, 2012), it should correlate more strongly with single-digit calculation problems than with multi-digit calculation problems that require several mental operations on top of retrieval, such as calculating partial answers and composing them in order to find the final answers. The type of RAN tasks may also influence the RAN–mathematics relationship. Araújo et al. (2015) and Scarborough (1998) showed that alphanumeric RAN (digits and letters) is more strongly related to reading than non-alphanumeric RAN (objects and colors). Once formal reading instruction begins, alphanumeric stimuli are explicitly taught and practiced, in contrast to the names of colors and objects that are learned more implicitly during language development. Obviously, the same argument holds for mathematics, and thus a stronger relationship would be expected between alphanumeric RAN and mathematics than between non-alphanumeric RAN and mathematics. However, there might also be some domain-specific features in the relationship between RAN and mathematics, and thus the findings not necessary be the same for those found for reading. A recent study conducted by Donker, Kroesbergen, Slot, Van Viersen, and De Bree (2016) found that children with mathematical difficulties were impaired only in non-alphanumeric RAN, while children with reading or comorbid difficulties were impaired in both alphanumeric and non-alphanumeric RAN. Donker et al. (2016) suggested that non-alphanumeric RAN requires additional conceptual processing, as opposed to alphanumeric RAN, which requires more phonological processing. Furthermore, children with mathematical disabilities may have difficulty with the conceptual processing of quantities represented by the digits, but not with access to number words per se.

This proposal is closely related to the discussion of the underlying deficit in mathematical learning difficulties. According to the access deficit hypothesis, the origin of mathematical disability lies in problems accessing magnitude representations from symbolic information (numbers) (Roussell & Noel, 2007). If this is true, then RAN should be more strongly related to mathematics when RAN stimuli are numbers rather than letters, colors, or objects. However, another approach suggests that the core deficit of mathematical disabilities is in magnitude processing, which can be seen both in non-symbolic and symbolic magnitude processing (Butterworth, 2005. According to this view, an equally important division of the RAN tasks could be grouping them into numeric (digits, dice) and non-numeric (letters, colors, and objects) tasks. The assumption that the RAN–mathematics relationship is restricted to the use of a numeric stimulus in RAN tasks has received support in previous studies (Landerl, Fussenegger, Moll, & Willburger, 2009; Willburger et al., 2008). However, it is also possible that the association between RAN and mathematics might not be specific to numbers, but could instead reflect an inherent ability to learn and retrieve arbitrary visual–verbal associations (Manis, Seidenberg, & Doi, 1999). If this is true, then equally strong correlations should be observed between numeric (quantities, digits) and non-numeric RAN (letters, colors, and objects) tasks with mathematics.

A third moderator of the RAN–mathematics relationship may be the age when mathematics was first assessed. Between grades 2 and 3, arithmetic calculation skills generally progress from effortful counting strategies to more automatic retrieval strategies (Jordan, 2003; Nunes & Bryant, 1996). Thus, in age-appropriate development of arithmetic skills, children usually start using fact retrieval as their main strategy for solving mathematical problems between the ages of 9 and 10 (Lemair & Siegler, 1995; Nunes & Bryant, 1996). Consequently, after the age of 9, when arithmetic calculation skill has reached an automatic level, RAN should be more strongly related to arithmetic, compared to the developmental phase when counting-based strategies (e.g., the counting-on strategy) are more common.

Finally, factors such as study design and participant characteristics should be taken into account when examining the RAN–mathematics relation. In general, correlations between two measures obtained at the same measurement point (as in concurrent studies) are stronger than correlations between two measures assessed at different time points (as in longitudinal studies). Previous studies in reading have shown that RAN is more strongly related to reading among low-performing children (e.g., McBride-Chang & Manis, 1996; Savage & Frederickson, 2005; Scarborough, 1998). To our knowledge, no previous studies have examined whether the RAN–mathematics relationship is stronger among children with math disabilities. In light of the findings of previous reading studies, it would be interesting to assess whether RAN is also more strongly associated with math among low-performing children. We could assume a higher prevalence of retrieval difficulties among atypical samples and overlapping dysfluency problems in naming and calculation.

The Present Study

The current study aims to answer the following six research questions:

Research question 1. To what extent is RAN related to mathematics? Because of the contradictory findings of previous studies, we did not formulate a specific hypothesis.

Research question 2. Is the RAN–mathematics relationship affected by the nature of the mathematics measure (achievement tests vs. arithmetic; multi-digit vs. single-digit calculations) or task requirements (fluency vs. accuracy)? Because fluent calculation relies on rapid retrieval of the answers (arithmetic facts) from long-term memory, we hypothesized that RAN tasks would be more strongly related to arithmetic calculation than to general math achievement; more strongly related to single-digit calculation than to multi-digit calculation; and more strongly related to math fluency than to math accuracy.

Research question 3. Is the RAN–mathematics relationship affected by the type of RAN task? More specifically, does numeric RAN (numbers and/or quantities) correlate more strongly with mathematics than non-numeric RAN (colors, objects, letters)? Furthermore, does alphanumeric RAN (digits and letters) correlate more strongly with mathematics than non-alphanumeric RAN? Based on the findings of previous studies that showed children with dyscalculia have a specific deficit in RAN quantities (e.g., Landerl et al., 2009; Willburger et al., 2008), we hypothesized that numeric RAN would be more strongly related to math than non-numeric RAN. Because the findings of previous studies on the role of alphanumeric and non-alphanumeric RAN in mathematics are mixed, we did not formulate a specific hypothesis.

Research question 4. Is the RAN–mathematics relationship affected by the age when math tasks are assessed? We hypothesized that RAN would be more strongly related to mathematics after the age of 9 (around the time when arithmetic calculation skill becomes automatic) than in younger ages.

Research question 5. Is the RAN–mathematics relationship affected by the study design (cross-sectional vs. longitudinal)? Given that correlations tend to be higher in skills assessed concurrently than when there is a time distance between measurements, we hypothesized that RAN would correlate more strongly with mathematics in concurrent studies than in longitudinal studies.

Research question 6. Is the RAN–mathematics relationship affected by the sample characteristics (a sample including high prevalence of children with learning disabilities or low-performing children vs. a normal sample)? As RAN is more strongly related to reading among poor or at-risk readers (e.g., Meyer et al., 1998; Savage & Frederickson, 2005; Scarborough, 1998), we hypothesized that RAN would be more strongly associated with math among low-performing children. This is based on the assumption that dysfluent calculation, which often means retrieval difficulties, is at least partly related to co-occurring naming difficulties. However, a strong hypothesis cannot be proposed because the studies with atypical samples consist of quite heterogeneous populations with different kinds of difficulties and not only children with mathematical difficulties. Moreover, previous math literature does not provide information regarding whether the relationship between RAN and math would vary among poor-, average-, and well-performing children.

Method

Data Collection

The inclusion, search, and coding procedures are detailed in Figure 1. For the target constructs examined in this study (RAN and mathematics), we established the operational criteria to determine the indicators of each construct. A task was considered a measure of RAN if quick serial naming of an array of objects, colors, letters, digits, or quantities was required. In turn, to be considered a measure of math achievement, the test should require mathematical skills other than just arithmetic calculation (e.g., knowledge of the number system, fractions, or geometry). Arithmetic calculation included only tasks that required solving different arithmetic operations (addition, subtraction, multiplication, and division). Arithmetic calculation was further divided into single-digit (e.g., 3 + 4; 6 – 2; 5 × 4) and multi-digit calculation (32 + 41, 76 − 12, 14 × 24) tasks. Mathematical accuracy included measures based on the accuracy of mathematical problem solving or calculation. To be considered a measure of math fluency, the task should require children to solve as many arithmetic or other math problems as possible within a specified time limit.

Inclusionary Criteria and Screening Process

The search followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement protocol (Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group, 2009), and three methods were used to identify relevant studies. First, we searched electronic databases and e-journal services (ERIC, Medline, PubMed, PsychArticles, PsychInfo, ProQuest Educational and Psychology Journals, Science Direct, Scopus, and Google Scholar) for publications in English by using the keywords “rapid serial naming*”, “naming speed*”, “rapid automatized naming*”, and “RAN*” combined with “mathematics*” and “arithmetic*” in the subject or title. Second, we searched online dissertations and theses via databases (ERIC, ProQuest Dissertations & Theses Global, and Google Scholar) with the same keywords. No restrictions were imposed regarding the publication year. The search covered studies published before July 2016. Third, we checked the reference lists of the collected reports for relevant studies. We contacted authors who had published an article with RAN and math measures but had not provided correlations via e-mail and kindly asked them to send us the correlations.

In addition, we used the following eight inclusionary criteria:

(a) The RAN tasks required serial naming instead of isolated naming;

(b) Original empirical data were based on direct assessment (not teacher/parent rating scales or surveys);

(c) Correlations were reported at the level of naming sub-tasks (studies including RAN composite scores consisting of several subskills were excluded);

(d) RAN was used as a predictor of a mathematics outcome or both constructs (RAN and mathematics) were measured concurrently (studies in which mathematics performance was assessed prior to RAN were excluded);

(e) Math was measured at school age or the calculation was measured at kindergarten (early number skills were not included);

(f) When analyzing the moderator effect of mathematics age, studies reporting RAN–math correlations among samples consisting of several age groups in the same sample (three or more age groups) were excluded if all age groups were not younger or older than 9 years;

(g) When multiple measures were used to assess one construct, all qualified correlations were included in the dataset. In the analyses, dependencies between correlations from a single study or a single data set were taken into account; and

(h) All studies that provided effect sizes (*d*) and regression coefficients (R^2, beta) as an estimate of the RAN–math relationship were also included after they had been converted into the Pearson product-moment correlation coefficient effect sizes *r* (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

After these criteria were used, 33 unique samples with 151 outcomes were found (min = 1, max = 40) with sample sizes ranging from 29 to 628 (see Table 2).

Coding Procedures

After the qualified studies had been selected, we coded relevant information from the studies. This information included the following variables of descriptive data: (a) number of participants; (b) mean ages of the participants at the time RAN and math were measured; (c) design: longitudinal versus cross-sectional; (d) sample characteristics: typical or atypical; (e) the type of measure used for each construct and the outcome variable (e.g., accuracy or fluency); and (f) the year of publication. In the published studies, some measures were coded so that a negative correlation indicated a positive relationship between RAN and mathematical performance. In these cases, the effect size measures were recoded such that a positive correlation always indicated a positive relationship. The first author, together with an expert in math research, double-coded the moderator variables. The agreement rate between the coders varied between 89% and 94%. Differences between the coders were mostly due to limited information provided in the studies regarding the sample characteristics and tasks. Differences in the scoring by the raters were resolved after discussions with the first author.

Moderators

We coded two types of moderators: procedural and sample characteristics. Procedural moderators included the math domain assessed (general math achievement vs. arithmetic and single-digit vs. multi-digit calculation), outcome variable in arithmetic (fluency vs. accuracy), RAN stimulus (non-numeric vs. numeric and non-alphanumeric vs. alphanumeric), and study design (cross-sectional vs. longitudinal). Sample moderators included the mathematical age of the children as a continuous variable and the sample type (two categories: an atypical sample that consisted of a high prevalence of low achievers or children with learning disabilities vs. a typical sample, i.e., a population-based sample or a sample with high prevalence of high achievers).

Effect Size Calculations

Effect sizes (*d*) and regression coefficients (R^2, beta) were first transformed into the Pearson product-moment correlation coefficient effect sizes *r* (Borenstein et al., 2009; Cohen, 1988). Next, the *r* effect sizes were transformed into Fisher's *z* values to be used in a meta-analysis, and the variance was calculated with Cox's (2008) formula 1/(n – 3).

Meta-analytic Integration

Summative results and graphics (funnel plot, symmetry tests, violin plots, and forest plot) were produced in R (R Project, 2015). The metafor (Viechtbauer, 2010) package was used for funnel plot symmetry tests and forest plot construction. The Fisher *z* values were averaged by the studies individually and then transformed back into Pearson's correlation coefficients. The estimation method was the random-effects model with the restricted maximum likelihood (REML) method. The funnel plot asymmetry was tested with a trim fill test and a regression test in which the predictor was the standard error (Sterne & Egger, 2005; Sterne et al., 2011). We used the vioplot package (Adler, 2005) for the violin plot production (Hintze & Nelson, 1998).

A random-effects meta-analysis and a meta-regression analysis for the moderators were performed in R (R Project, 2015). We used the robumeta application package (Fisher & Tipton, 2015) and the robust variance estimation (RVE) method (Hedges, Tipton, & Johnson, 2010; Tanner-Smith & Tipton, 2014) because there were several correlations from a single study and thus the data points were not independent. We adopted a dependent effects meta-regression (D-MR) approach. The correlation coefficients were clustered into unique samples; that is, the number of studies represented the number of unique study samples. The weight of each study was the square of the standard error (Lipsey & Wilson, 2001). The heterogeneity was estimated from τ^2 and I^2 statistics (Higgins & Thompson, 2002). τ^2 was interpreted as between-study variance in study-average effect sizes. I^2 assessed the percentage of the total variance attributable to true heterogeneity. The efficient weights were analyzed with a sensitivity approach (effects of various ρ values (0–1) on the results). Because the results were not sensitive to the ρ values used, the results were reported for ρ = .80. Finally, small sample adjustments were used in the analysis (Tipton, 2015). The moderator effects were analyzed as within-study and between-study partition effects (i.e., the partition was done by using group.center and group.mean robumeta functions). Partitioned moderators were entered into the analysis separately in order to maximize the number of studies and correlation coefficients in the calculations.

The funnel plot and forest plot graphics and the overall testing of asymmetry were kept at the level of unique samples; i.e., the data was the sample average of coefficients. The violin plot was used for the illustrations of distribution of all correlation coefficients (Figure 4). The average RAN–mathematics result presented in the forest plot (metafor) is the same as the average RAN–mathematics result in Table 2 (robumeta), but they were obtained via different random effects meta-analytic approaches.

Results

The literature search yielded 306 reports. We then narrowed down the literature to 92 potentially relevant reports (after duplicates were removed and the titles screened). Further screening of the abstracts resulted in 53 candidate reports. After the full texts were read, 38 reports with 33 unique samples were included in the meta-analysis. Figure 2 provides a funnel plot graph of the unique samples in which the correlation coefficients were averaged within the unique samples. The regression test for funnel plot asymmetry showed that the standard error was not a statistically significant predictor ($z = 1.67$, $p = .095$). The trim and fill analysis revealed that there was an estimated number of five missing studies on the left side of the funnel plot. The probability that there were no missing studies on the left side of the funnel plot was statistically significant ($p = .016$). The unique sample-averaged coefficients (Fisher's *z*) varied from .17 to .77, as is observable from the random-effect model forest plot graph presented in Figure 3. In sum, there was large variation among the correlation coefficients and substantive heterogeneity ($Q(32) = 136.51$, $p < .001$).

The summarized results are presented in Table 2 (Question1). The mean random-effects model RAN–math weighted Fisher's *z* coefficient equaled .38 ($p < .001$, 95% CI [.33,

.43), and after being back-transformed to Pearson *r*, equaled .37 (95% CI [.32, .41]). The violin plot of Fisher's *z* coefficients presented in Figure 4 indicates that the distribution is clearly positively skewed.

Next, we examined the role of the different moderators. In the within-study and between-study meta-regression analyses, variations in the moderator effects were taken into account. The results showed that after the between-study partition estimation, the achievement versus arithmetic task (i.e., domain of math assessed 1) was a significant moderator ($\beta = .12$, $p < .05$). Arithmetic math measurements were associated with higher correlation coefficients. At the within-study partition level, the type of calculation performed (single-digit vs. multi-digit calculations) was a significant moderator ($\beta = .14$, $p < .01$). The correlations were higher for the single-digit calculations. The math outcome measure (fluency vs. accuracy) was also a significant moderator associated with the between-study variation ($\beta = –.13$, $p < .05$). Fluency math outcomes produced higher correlations than math accuracy outcomes. Numeric RAN tasks also produced significantly larger correlations with math outcomes than non-numeric RAN ($\beta = .04$, $p < .01$); however, the statistically significant *p* (despite the low beta) might be an artifact (type I error) associated with the estimation methods (see Tipton, 2015). The type of RAN stimulus (alphanumeric vs. non-alphanumeric), the design of the study (cross-sectional vs. longitudinal), age when math was assessed (at or below 9 years vs. above 9 years), and type of sample (population-based sample or sample with high prevalence of high achievers vs. high prevalence of low achievers or children with learning disabilities) were not significant moderators.

Discussion

The number of studies using RAN as a predictor of mathematics performance has steadily increased over the last decade (e.g., Berg, 2008; Cirino, 2011; Geary, 2011; Georgiou et al., 2013; Hecht et al., 2001; Koponen et al., 2007, 2013; Swanson et al., 2008).

However, the nature of the RAN–mathematics relationship remains elusive. The current meta-analysis aimed first to examine the size of the RAN–mathematics relationship. We found a positive and significant relationship (r = .37) between RAN and mathematics and the effect size was large (Cohen, 1988). Interestingly, the average size of the RAN–mathematics relationship is close to that reported in previous meta-analyses of RAN and reading (Araújo et al., 2015; Scarborough, 1998; Song et al., 2016; Swanson et al., 2003).

However, the size of the RAN–mathematics relationship appears to be influenced by different moderators. First, the math domain used in previous studies was related to the strength of the RAN–mathematics relationship. As expected, RAN was a stronger correlate of math when math was operationalized with an arithmetic calculation task than when math was operationalized with general math achievement tests. More specifically, arithmetic tasks (e.g., Woodcock-Johnson math fluency) require responding to simple addition, subtraction, and multiplication problems or finding partial and total answers in multi-digit calculations. Retrieving the names of numbers, operation symbols (e.g., +, −), and answers from long-term memory are central processes in arithmetical calculation, which tap the same capacities as RAN. In contrast, math achievement tests (e.g., the Wechsler Individual Achievement Test [WIAT] numerical operations) involve a wider set of mathematical subskills, including problems that cannot be simply solved with the retrieval of an answer from long-term memory. Consequently, compared to RAN, these tasks require a number of different processes, which results in lower correlations between them.

In previous arithmetic calculation studies, single-digit calculations produced significantly stronger correlations than multi-digit calculations. This finding is in line with those of previous studies conducted by Koponen and colleagues (Koponen et al., 2007, 2013, 2016), which showed that RAN was related with reading and single-digit calculation fluency, but not with multi-digit calculation (Koponen et al., 2007). Although single-digit calculation is needed to obtain intermediate answers in multi-digit calculation, understanding place value, the ability to retrieve procedural knowledge, the use of algorithms, and monitoring multistep processes are required in multi-digit calculation. In other words, multi-digit calculation includes retrieving factual, procedural, and conceptual knowledge, whereas RAN and fluent single-digit calculation rely more on retrieving factual knowledge, such as names of numbers or objects.

The type of math outcome also explained a significant amount of variance in the RAN–mathematics relationship. Fluency outcomes produced stronger correlations with RAN than accuracy outcomes. This is similar to the finding reported for the RAN–reading relationship (Araújo et al., 2015; Song et al., 2016). These moderator effects support the view that RAN reflects, to some extent, the efficiency of access to and retrieval of phonological representations from long-term memory, which are needed in fluent calculation (de Smedt & Boets, 2010; Koponen et al., 2013).

The distinction between alphanumeric and non-alphanumeric RAN tasks failed to explain the significant variance in the RAN–mathematics relationship. This might partly be due to the different types of processes involved in RAN and in basic reading and arithmetic skills. More specifically, some researchers have argued that RAN letters and digits activate the same neural networks that are involved in phonological and orthographic processing in reading (e.g., Cummine et al., 2014, 2015; Misra et al., 2004). In contrast, RAN objects also engage networks that are involved in semantic processing (e.g., Cummine et al., 2014; Humphreys, Price, & Riddoch, 1999). Since reading is usually assessed with word recognition and decoding tasks and not with comprehension tasks that would require semantic processing, alphanumeric RAN proves to be more reliable in predicting reading over non-alphanumeric RAN. In math, many tasks involve access to magnitude, and the use of magnitude information is beneficial in solving mathematical problems. Magnitude processing is also helpful in arithmetic calculation. For example, knowing that 6 is 1 more than 5 and being able to retrieve the answer for 5 + 5, which equals 10, can help an individual derive the answer for 5 + 6. Thus, in mathematics, parallel access to phonological and semantic information may boost the association between non-alphanumeric RAN and mathematics and explain why an equally strong correlation was found between non-alphanumeric and alphanumeric RAN tasks with math in the present meta-analysis. This suggestion is in line with the findings of a recent study conducted by Donker et al. (2016), in which non-alphanumeric RAN correlated with mathematics but alphanumeric RAN did not in a sample of children with math learning disabilities. Donker et al. suggested that non-alphanumeric RAN requires additional conceptual processing compared to the mere phonological processing that is required in alphanumeric RAN. Children with difficulties in math may have difficulties in conceptual processing over and above the difficulties in accessing and retrieving the digit names.

Using numeric stimuli (numbers or quantities) versus non-numeric stimuli (letters, objects, or colors) had a very small effect on the RAN–math relationship and explained only the within-studies (not between) variation. This suggests that the RAN–math relationship cannot be explained by the use of numeric stimuli alone, but is related to the naming process itself. Thus, the findings from the present meta-analysis are only partially in line with the findings of Willburger et al. (2008) and Landerl et al. (2009), who showed that children with dyscalculia exhibited a unique deficit in the rapid naming of quantities, whereas a more general deficit in the rapid naming of objects, letters, digits, and quantities was evident in the dyslexia group and the comorbid dyslexia/dyscalculia group.

Math age or sample characteristics (high prevalence of children with difficulties or low-achieving children vs. a normal sample) did not account for the large variation among the correlations. The non-significant moderator effects of age were unexpected because fact retrieval ability underlies the RAN–mathematics relation, and in math, fact retrieval is less automatized in younger children. There can be several reasons for this finding, one of which is the confounding effect within moderators. More studies and correlations are needed in order to examine the interactions between the moderators. The non-significant moderator effect of sample type (typical vs. atypical) was not expected either. A possible explanation may be that the "atypical sample" grouping covered quite heterogeneous populations with different kinds of difficulties and not solely children with mathematical or language-based difficulties. Along these lines, a theoretically important but unexplored question is whether the RAN–mathematics relationship is similar or different among poor- and well-performing children. The findings of the present study did not provide any evidence that there are differences among these groups. However, as stated above, in the present study it was not possible to compare correlations in children with difficulties in math and/or naming to those of typically achieving children. Finally, it was expected that RAN would correlate more strongly with mathematics in concurrent studies than in longitudinal studies. Although there was a trend showing that concurrent correlations are higher than longitudinal correlations, the difference was not significant.

Limitations

Some limitations of the present study are worth mentioning. The search procedure may have left out some relevant reports. For example, only published studies, theses, and dissertations were included, which is known to cause some publication bias, meaning that studies with large and/or statistically significant effects, relative to reports with small or null effects, are more likely to be published (Polanin, Tanner-Smith, & Hennessy, 2015). However, publication bias in general may be less important when looking at correlational studies when the effect sizes are purely descriptive and not related to the outcome of the study (e.g., intervention effect). Heterogeneity among the RAN–mathematics correlations was anticipated, but it was larger than expected. In this study, we used independent and correlated correlation coefficients to develop a general understanding regarding the RAN–math association. This means that the independence of observation assumption was purposefully violated in the overall association calculation. However, we used the robust variance estimation method in the moderator analysis that used correlated data. Due to the low number of unique samples, only one partitioned moderator was analyzed at a time and it was not possible to analyze interactions between moderator factors. Some moderator effects might be confounded (e.g., math achievement was mostly assessed with accuracy-based measurements). In addition, much of the variance in the RAN–mathematics correlations was left unexplained. A possible reason for this could be that there are interactions between some of the moderators that were not taken into account. For example, math age could matter only if arithmetic fluency (not math accuracy) was used as an outcome measure. Finally, we used Fisher's *z* values in the calculations, which may bias the results upward (cf., Schmidt & Hunter, 2015). Also, we followed the meta-regression approach for correlated data in which the moderators were dummy coded; however, there is still relatively little research on the method itself and its biases (Hedges et al., 2010; Tipton, 2015). Forthcoming research may better understand the heterogeneity of the RAN–mathematics relationship and moderator associations within a meta-analytic structural equation modeling framework (Cheung, 2008, 2015a, 2015b). More studies are also needed in order to analyze possible interaction effects between the different moderators.

Conclusions and Implications

To date, we have learned about RAN through the studies examining its value as a predictor of reading (e.g., Araújo et al., 2015). The current study revealed that RAN is also a strong correlate of mathematics (particularly of math fluency). A practical implication of this finding is that RAN could be used as an early predictor of mathematics development and perhaps even as a risk factor of future mathematics difficulties, particularly of arithmetic dysfluency (e.g., Koponen, Aro, Räsänen, & Ahonen, 2007; Koponen et al., 2006; Waber et al., 2000). This should be taken into account when assessing school readiness, monitoring skill development, and planning for educational support. In addition, given that no significant differences were found in the size of the correlations between the different types of RAN tasks and mathematics, researchers may rely on non-alphanumeric RAN as a predictor of mathematics performance even before children go to school and become familiar with letters and digits.

From a theoretical point of view, the effects of the moderators (arithmetic vs. math achievement, single-digit vs. multi-digit, and fluency vs. accuracy in math) support the view that the RAN–mathematics relationship can at least partially be explained by shared underlying processing requirements, i.e., rapid access from visual stimuli to phonological representation stored in long-term memory. Previous studies suggested that this kind of process is important in fluent calculation (de Smedt & Boets, 2010; Koponen et al., 2013). Equally strong correlations between non-alphanumeric RAN, alphanumeric RAN, and mathematics suggest that the relationship between RAN and mathematics is related to both conceptual and phonological processing factors.

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Table 1

Description of the Studies Presenting RAN-math Correlations

Author	Year	*n*	*r* math	Sample type	Design	Age	Math measure	Math variable	RAN stimulus
Ackerman	2001	101	.43	LD and controls	Cross-sectional	116.4	Multi-digit calc.	A	L+ D+. D& L
Berg	2008	90	.44	Normal	Cross-sectional	121.5	Multi-digit calc.	A	D
van Bergen	2014	196	.48	LD and controls	Longitudinal	107.1	Multi-digit calc.	F	C
Chan	2010	168	.43	LD and controls	Cross-sectional	110.4	Multi-digit calc.	A	D
							Single-digit calc.	F	
Cirino	2011	285	.41–.47	Normal	Cross-sectional	73.4	Single-digit calc.	F	D
									L
									O
Foster	2015	208	.31–.34	Normal	Longitudinal	67.4–74.4	Math achievement	A	O
Fuchs	2005	272	.24–.29	LA and controls	Cross-sectional		Math achievement	F	D
							Multi-digit calc.	A	
							Single-digit calc.	F	
de Jong	1999	166	.28–.31	Normal	Longitudinal	100.4	Single-digit calc.	F	O
Geary	2011	177	.16–.47	Normal	Longitudinal	74.0–134.0	Math achievement	A	D
									L
Georgiou	2013	72	.40	Normal	Longitudinal	83.1	Multi-digit calc.	F	O + C
Hannula	2010	139	.25	Normal	Longitudinal	102	Multi-digit calc.	A	O + C

Hart	2009	628	.11–.43	Twin	Longitudinal	102.5–118.7	Multi-digit calc.	A	L+ D
							Single-digit calc.	F	
Kleemans	2012	160	.17–.39	LD and controls	Longitudinal	85.1	Single-digit calc.	F	O
Koponen	2006	29	.64	LD	Cross-sectional	123.6	Single-digit calc.	F	O + C
Koponen	2007	207	.13–.37	Normal	Longitudinal	129	Single-digit calc.	F	O
							Multi-digit calc.	A	
Koponen	2013	362	.28–.42	LD and controls	Longitudinal	108.0–118.0	Multi-digit calc.	F	C
Koponen	2016	378	.27–.36	Normal	Longitudinal	115.0–127.0	Multi-digit calc.	F	O
									O
Krajewski	2009	130	.33–.44	Normal	Longitudinal	91.0–103.0	Math achievement	A	Dots & D
Landerl	2010	439	.32	LD and controls	Cross-sectional	111	Multi-digit calc.	F	L+D+O
Lepola	2005	139	.15–.25	Normal	Longitudinal	104	Multi-digit calc.	A	O + C
							Single-digit calc.	A	
Moll	2014	89	.26–.49	LD and controls	Cross-sectional	NA	Single-digit calc.	F	L
							Multi-digit calc.	A	D
Niklas	2013a,b	608	.07–.27	Normal	Cross-sectional	77.0–87.0	Math achievement	A	O
Swanson	2004	353	.63	LA and controls	Cross-sectional	107.9	Multi-digit calc.	A & F	L+ D
Swanson	2006a	127	.50–.59	HA and normal	Cross-sectional	88.4	Multi-digit calc.	A	L
								F	D
Swanson	2006b	320	.52	LA and controls	Longitudinal	120.1	Multi-digit calc.	A & F	L+ D
Swanson	2007	353	.38–.64	Normal	Cross-sectional	NA	Multi-digit calc.	A	D

							Multi-digit calc.	F	L
Swanson	2008	205	.64–.65	Normal	Cross-sectional	91.8	Multi-digit calc.	F	D
									L
Swanson et al.	2008	353	.43–.60	LA and controls	Longitudinal	132.7	Multi-digit calc. (verbal)	F	L+ D
Träff	2013	134	.37–.48	LA and controls	Cross-sectional	142	Single-digit calc.	F	C
								A	
van Daal	2012	82	.46–.61	LD and	Cross-sectional	167	Single-digit calc.	F	O
				controls					C
									D
									L
									L+ D
van der Sluis	2007	127	.38–.45	Normal	Cross-sectional	128	Multi-digit calc.	F	Q
									D
									L
									C
Waber	2000	188	.16–.33	LD	Cross-sectional	114	Math achievement	A	D
									L
									C
									O
Wocadlo	2007	63	.35	At- risk group	Cross-sectional	97	Math achievement	A	L+ D

Note. HA=high achieving; LA= Low achieving; LD= Learning difficulties; A =Accuracy; F=Fluency; Co= Comprehension; D=Digits; C=Colors, O= Objects; L=Letters; Q=quantities.

Table 2

Number of Correlations, Meta-regression Estimate based on Fisher's z, Standard error, T-test results, 95% Confidence Interval (CI), Heterogeneity Statistics of the Relationship Between RAN-math and Procedural and Sample Moderators

			n(k)	*Estimate*	*StdErr*	*t-value*	*df*	*p*	*95% CI*	τ^2	I^2
Null model											
	Intercept		33(151)	.38	.03	15.19	31.25	<.001	[.33,.43]	.02	81.25
Procedural moderators											
	Domain of math assessed										
1			33(148)	.01	.05	0.28	1.00[2]	.828	[-.66, .69]	.02	81.29
		Center	34(151)	.12	.05	2.51	8.41	.035	[.04, .23]	.02	78.99
		Mean									
	Domain of math assessed										
2			27(92)	.14	.03	5.11	5.87	.002	[.08, .21]	.02	79.02
		Center	27(98)	-.05	.07	-0.74	17.01	.469	[-.19,.09]	.02	80.32
		Mean									
	Math outcome										
		Center	33(146)	-.07	.05	-1.40	8.84	.194	[-.19, .04]	.02	80.30
		Mean	33(151)	-.13	.05	-2.34	21.68	.029	[-.24, -.01]	.02	79.64
	RAN stimulus 1										
		Center	27(115)	.04	.01	3.59	6.79	.009	[.01, .07]	.02	82.19
		Mean	27(124)	.14	.08	1.78	8.36	.111	[-.04, .32]	.02	81.48
	RAN stimulus 2										
		Center	31(145)	.01	.07	0.10	3.96[2]	.924	[-.19, .21]	.02	82.18
		Mean	31(146)	.09	.06	1.51	23.97	.144	[-.03, .21]	.02	81.13
	Design										
		Center[1]	-	-	-	-	-	-	-	-	-
		Mean	34(152)	-.08	.04	-1.83	26.16	.079	[-.17, .01]	.02	81.20

Continues

	n(k)	*Estimate*	*StdErr*	*t-value*	*df*	*p*	*95% CI*	τ^2	I^2
Sample moderators									
Age of math assessed									
Center	30(136)	-.00	.04	-0.05	2.92[2]	.963	[-.14, .13]	.02	79.30
Mean	30(136)	.04	.05	0.81	22.29	.428	[-.07, .16]	.02	79.87
Type of sample									
Center	33(151)	.02	.12	0.14	1.00[2]	.913	[-1.5, 1.53]	.02	81.28
Mean	33(151)	.02	.05	0.45	28.63	.656	[-.08, .12]	.02	81.68

Note. *n(k):* number of samples (number of coefficients). *Estimate*: Robumeta correlated data meta-regression estimate, small-sample adjustment, ρ=0.80. *StdErr*: standard error. *CI*: confidence interval. Domain of math assessed 1: 0=achievement, 1=arithmetic, Domain of math assessed 2: 0=multi-digit, 1=single digit. Math outcome: 0=fluency, 1=accuracy. RAN stimulus 1: 0=nonnumeric, 1=numeric. RAN stimulus 2: 0=non-alphanumeric, 1=alphanumeric. Design: 0=cross-sectional, 1=longitudinal. Age of math assessed: 0=at or below 9 years, 1= above 9 years. Type of sample: 0=typical sample, 1=atypical sample. Center: within-study centered estimation. Mean: between-study centered estimation. [1] Estimation was not possible. [2] The result should be viewed with some caution due to low degrees of freedom value; df<4.

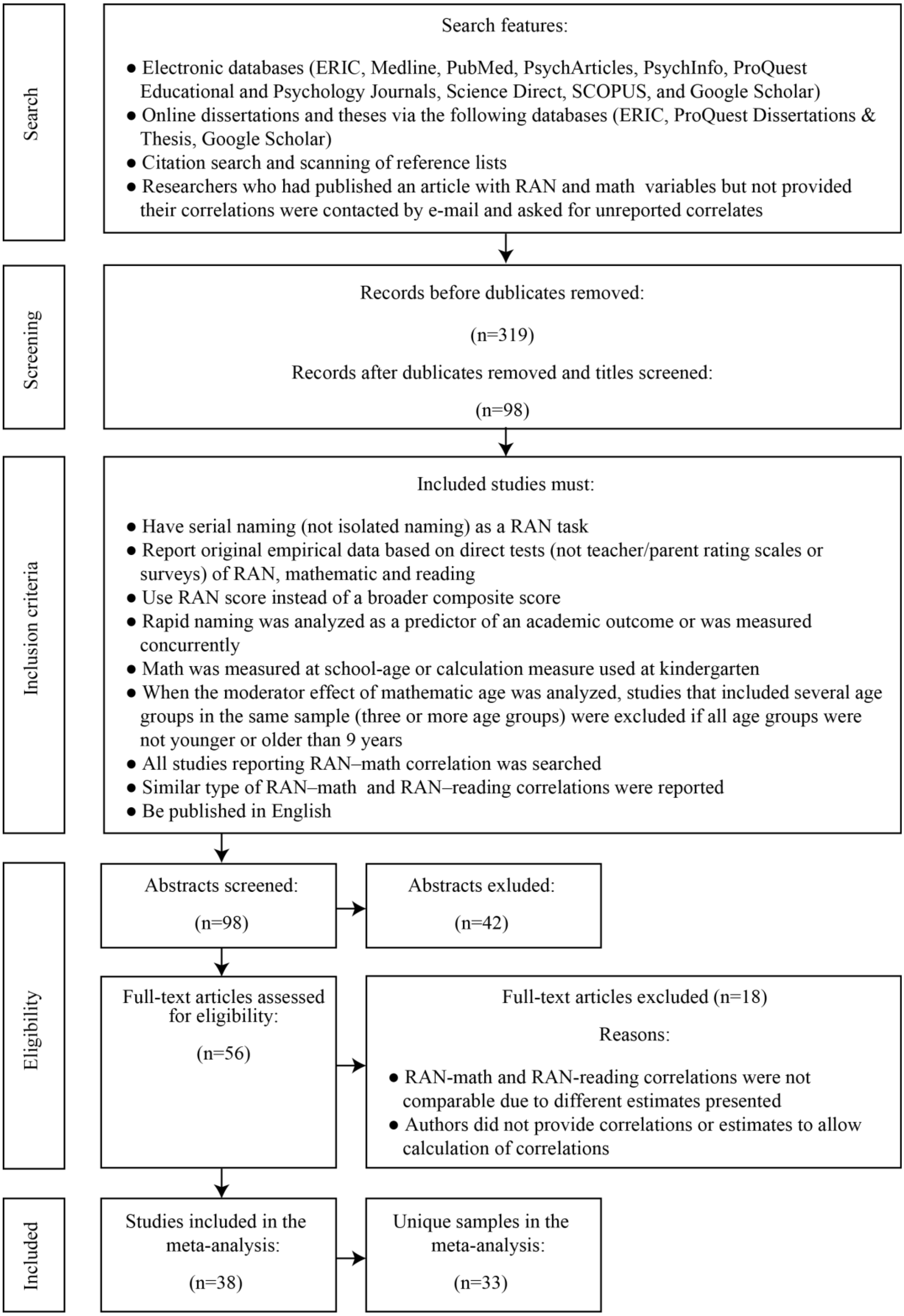

Figure 1. Flow diagram for the search for and inclusion of studies.

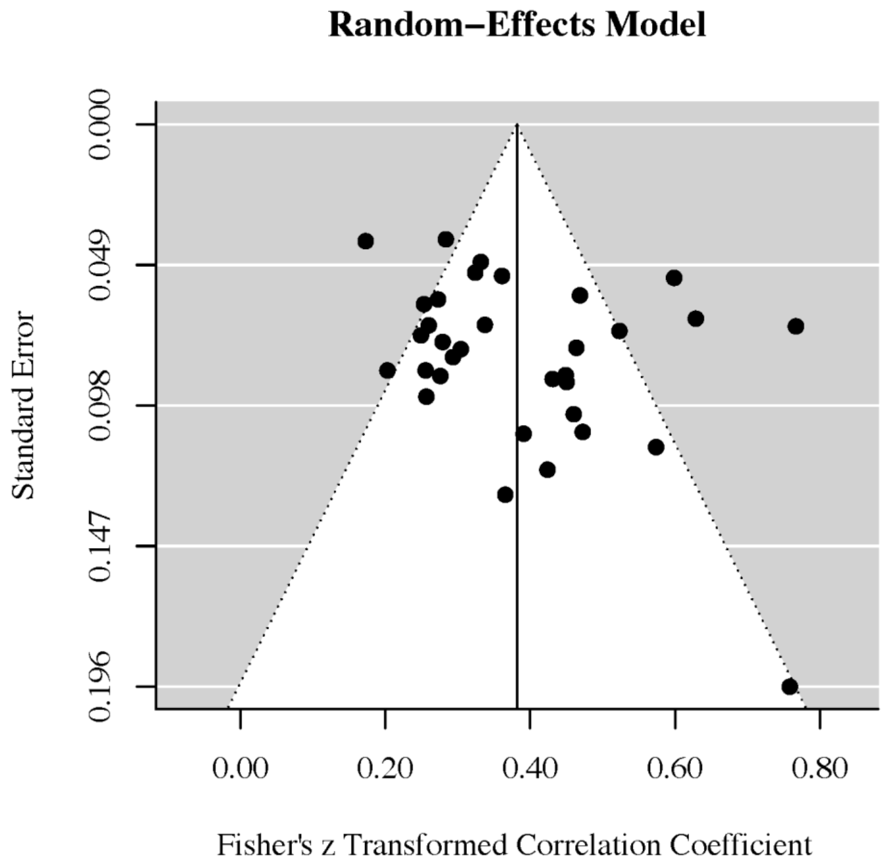

Figure 2. A funnel plot graph of the averaged and Fisher's *z* transformed RAN–Math correlation coefficients in the unique samples (N=33).

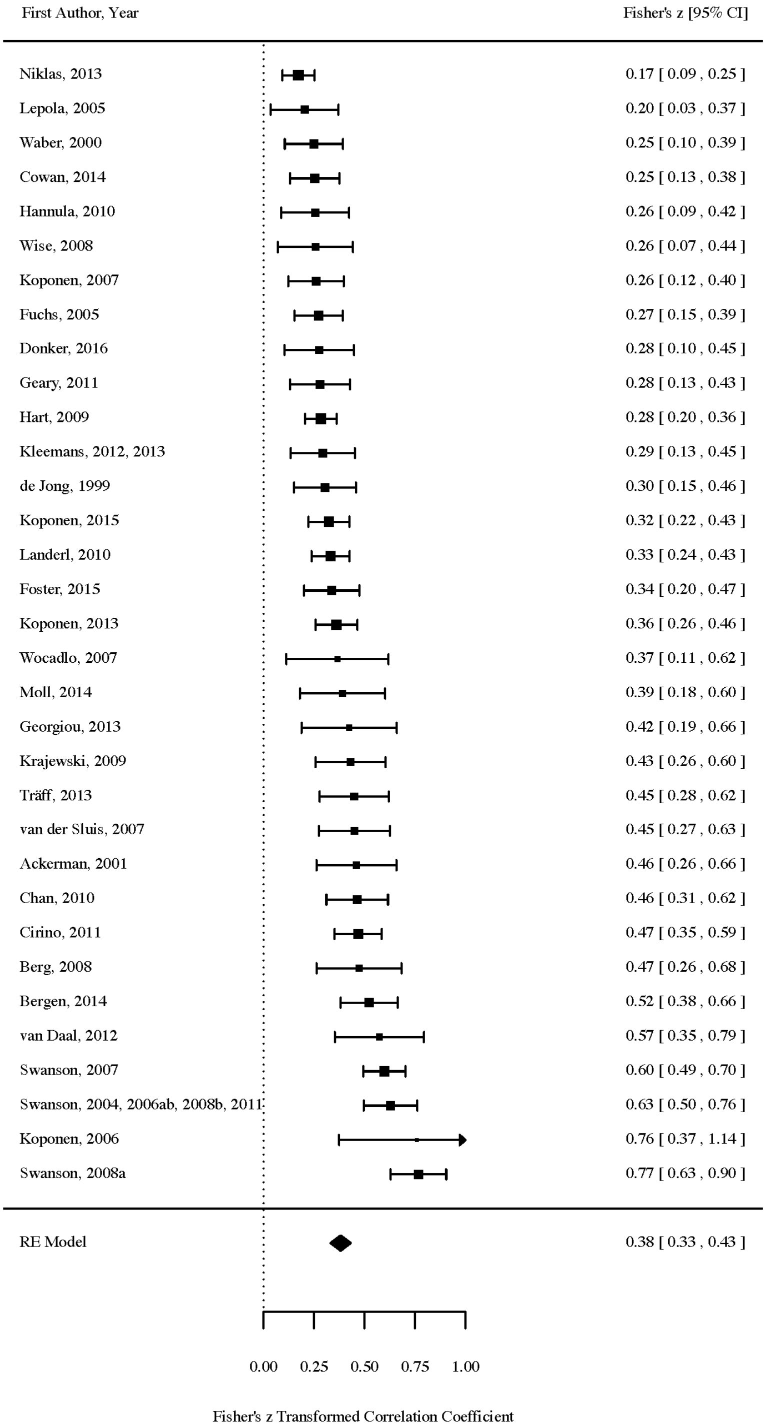

Figure 3. Overall random-effect model meta-analysis average of Fisher's *z* transformed correlation coefficient of RAN–Math correlation coefficients (displayed by ◆) in the unique samples (N=33) and coefficient with 95% confidence interval for each study. Coefficients represent average values of each unique sample.

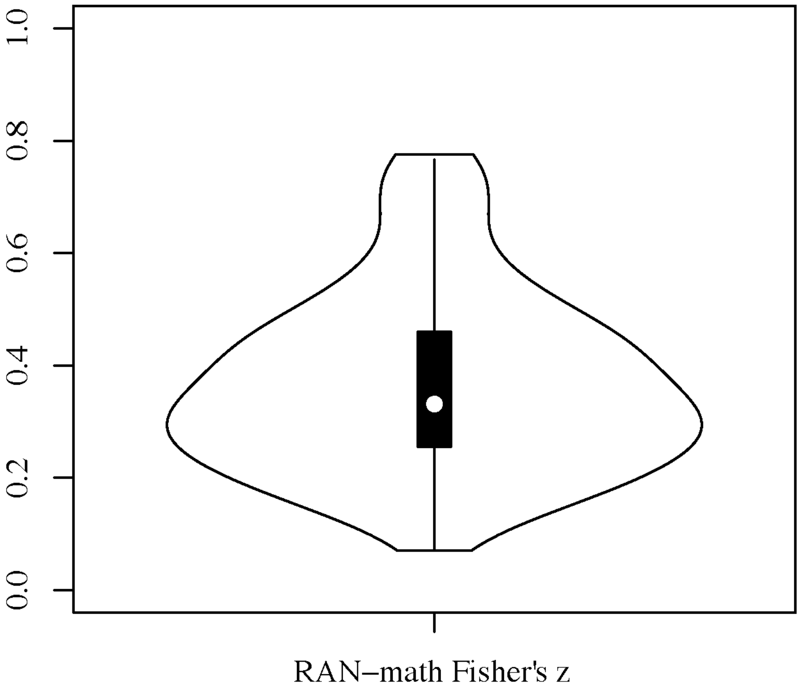

Figure 4. Violin plot of Fisher's *z* transformed correlation coefficients between RAN and Math (N=151)

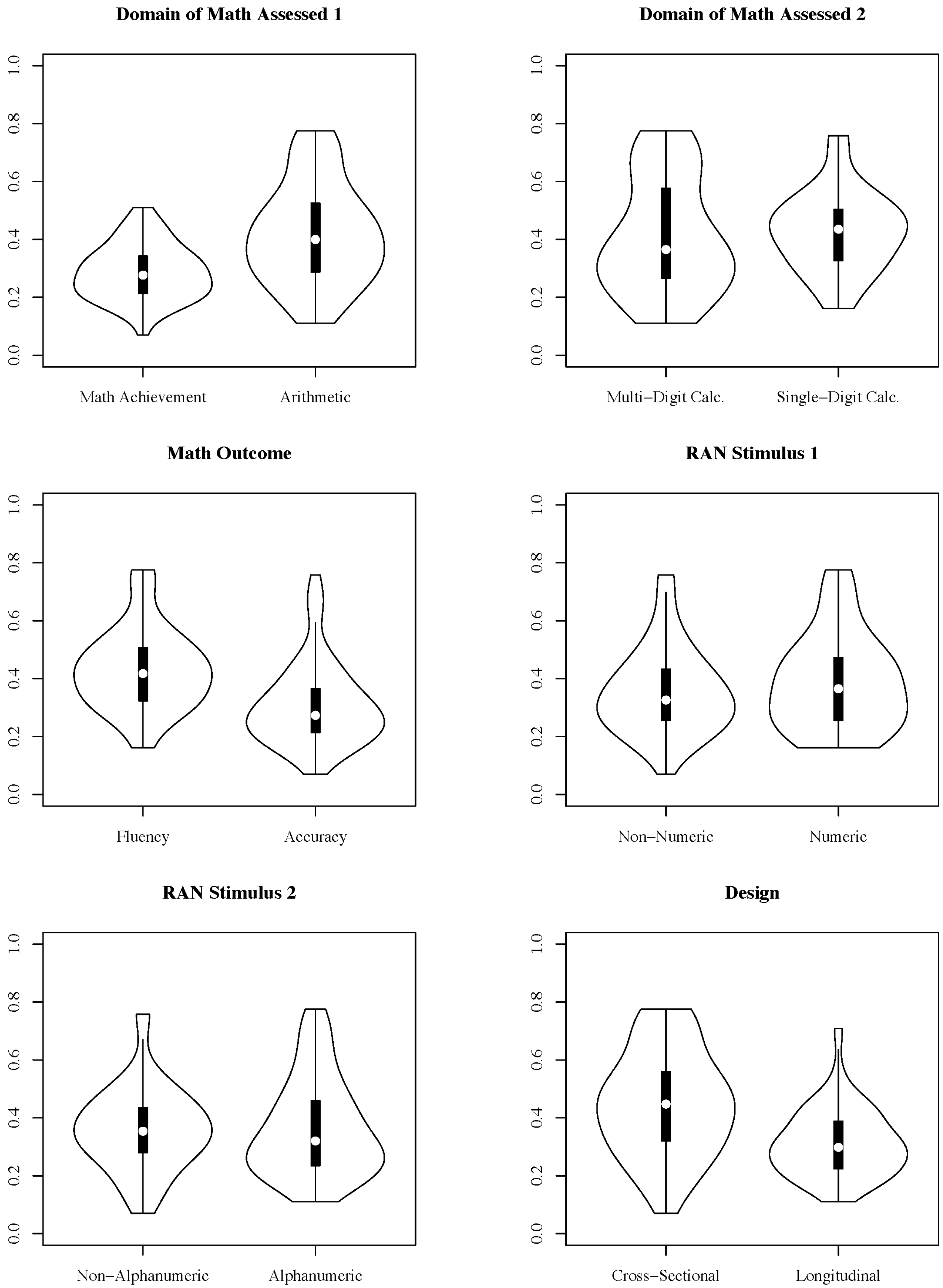

Figure 5. Violin plot of Fisher's *z* transformed correlation coefficients for procedural moderators

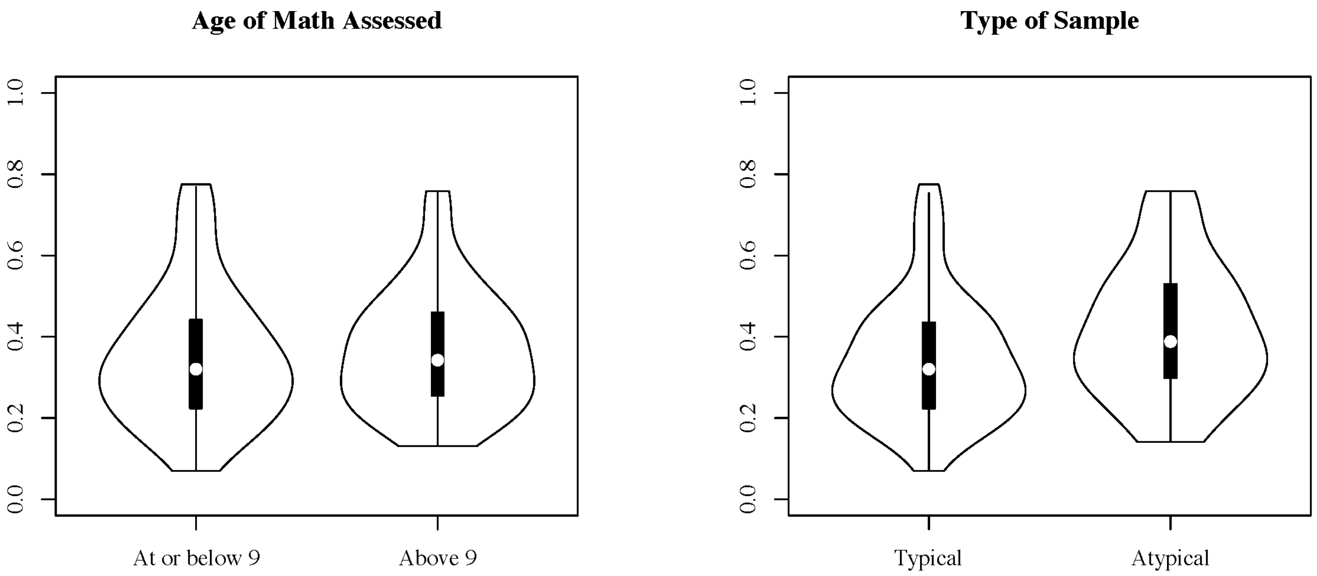

Figure 6. Violin plot of Fisher's *z* transformed correlation coefficients for sample moderators