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Educational Research Review

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Review

Effectiveness of learning strategy instruction on academic performance: A meta-analysis

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ARTICLE INFO

Article history:

Received 10 April 2013

Revised 11 November 2013

Accepted 12 November 2013

Available online 21 November 2013

Keywords:

Self-regulated learning

Metacognition

Learning strategies

Academic performance

Meta-analysis

ABSTRACT

In this meta-analysis the results of studies on learning strategy instruction focused on improving self-regulated learning were brought together to determine which specific strategies were the most effective in increasing academic performance. The meta-analysis included 58 studies in primary and secondary education on interventions aimed at improving cognitive, metacognitive, and management strategy skills, as well as motivational aspects and metacognitive knowledge. A total of 95 interventions and 180 effect sizes demonstrated substantial effects in the domains of writing (Hedges' $g = 1.25$), science (.73), mathematics (.66) and comprehensive reading (.36). These domains differed in terms of which strategies were the most effective in improving academic performance. However, metacognitive knowledge instruction appeared to be valuable in all of them. Furthermore, it was found that the effects were higher when self-developed tests were used than in the case of intervention-independent tests. Finally, no differential effects were observed for students with different ability levels. To conclude, the authors have listed some implications of their analysis for the educational practice and made some suggestions for further research.

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Contents

1. Introduction	2
1.1. Self-regulated learning and metacognition	2
1.2. Learning strategies	2
1.2.1. Cognitive strategies	3
1.2.2. Metacognitive Strategies	3
1.2.3. Management strategies	3
1.3. Motivation and metacognitive knowledge	3
1.3.1. Motivational aspects	3
1.3.2. Metacognitive knowledge	4
1.4. Instructing learning strategies: findings from earlier meta-analyses	4
1.4.1. Effective strategies	4
1.4.2. Student characteristics	4
1.4.3. Outcome variables and measures	5
1.5. The current study	5

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2.	Method	5
2.1.	Literature search and eligibility criteria	5
2.2.	Coding	6
2.2.1.	Learning strategies	6
2.2.2.	Student characteristics	7
2.2.3.	Outcome measures	7
2.3.	Meta-analysis	7
2.3.1.	Random and mixed effects models	7
2.3.2.	Calculating the effect size and regression coefficient	7
2.3.3.	Method of analysis	8
3.	Results	8
3.1.	Descriptives	8
3.2.	Effective strategies	8
3.3.	Student characteristics	12
3.4.	Outcome measures and effectiveness	13
3.5.	Publication bias	13
4.	Conclusion and discussion	14
4.1.	Effective strategies	14
4.2.	Student characteristics	15
4.3.	Outcome measures	16
4.4.	Publication bias	16
4.5.	Practical recommendations	16
4.6.	Limitations	17
Appendix A.	Strategies – categories and examples	18
Appendix B.	Key characteristics of the studies included in the meta-analysis	19
References		24
References: Articles included in the Meta-Analysis		24

1. Introduction

1.1. Self-regulated learning and metacognition

Self-regulated learners are students who are capable of supporting their own learning processes by applying domain-appropriate learning strategies (e.g., [Boekaerts, 1997](#); [Zimmerman, 1990, 1994](#)). Self-regulated learning can be described as: “an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate and control their cognition, motivation and behavior, guided and constrained by their goals and the contextual features in the environment” ([Pintrich, 2000, p. 453](#)). In short: students who are able to self-regulate their learning are active, responsible learners who act purposefully (i.e. use learning strategies) to achieve their academic goals. To this end, they need meta-cognitive knowledge; knowledge and awareness about their own cognition ([Flavell, 1976, 1979](#)).

The term ‘metacognition’ is not new in this field, and it is sometimes used interchangeably with self-regulation ([Dinsmore, Alexander, & Loughlin, 2008](#)). This is because self-regulation includes the regulation of cognition, which relates to (cognitive) strategies and metacognition. Whereas metacognition is more narrowly defined and refers only to knowledge regarding cognition ([Dinsmore et al., 2008](#)), self-regulated learning is broader in a sense, as it comprises both the knowledge and control of not only cognition, but also of motivation.

Students have to acquire knowledge, as it is required to apply learning strategies. Furthermore, in order to become effective self-regulated learners, they have to practice the actual application of this knowledge. However, becoming a self-regulated learner is not an end in itself; it is a means to another end, namely to improve academic performance, as it is demonstrated that self-regulated learners usually do well in education (e.g., [Zimmerman, 1990](#)). Research ([Dignath, Büttner, & Langfeldt, 2008](#); [Hattie, Biggs, & Purdie, 1996](#)) has suggested a causal relationship between strategy use and performance: using the proper learning strategies improves academic performance. As not all students spontaneously master the use of learning strategies and certainly not in the most effective way, students require additional instruction of learning strategies.

1.2. Learning strategies

Learning strategies are defined as “processes (or sequences of processes) that, when matched to the requirements of tasks, facilitate performance” ([Pressley, Goodchild, Fleet, & Zajchowski, 1989, p.303](#)). Learning strategies have been repeatedly demonstrated to be positively correlated with academic performance ([Alexander, Graham, & Harris, 1998](#); [Hattie et al., 1996](#); [Weinstein, Husman, & Dierking, 2000](#)). They structure the processing of information by facilitating particular activities, such as the planning of learning tasks, goal setting, monitoring the progress toward these goals, making

adjustments if needed, and evaluating the learning process and the outcomes (Boekaerts, 1997). The literature has provided a large number of strategies, ranging from very basic re-reading approaches to more complex methods of synthesizing knowledge or drawing conceptual frameworks. These strategies can be categorized in many ways according to various taxonomies and classifications (e.g. Mayer, 2008; Pressley, 2002; Weinstein & Mayer, 1986). In this study the following categories have been defined: cognitive, metacognitive and management strategies.

1.2.1. Cognitive strategies

Cognitive strategies are used to increase the understanding of a certain domain. They refer directly to the use of the information learned and are therefore domain- or even task-specific. Three main subcategories of cognitive strategies can be distinguished: rehearsal, elaboration and organization strategies (Pintrich, Smith, Garcia, & McKeachie, 1991). Rehearsal strategies are used to select and encode information in a verbatim manner. Here the focus is on repeating material in order to facilitate learning or remembering, for example when learning vocabulary or idiom. Elaboration strategies help students store information into their long-term memory by building internal connections between the items to be learned and already existing knowledge. Summarizing and paraphrasing are examples of this type of strategy, which is mostly used in reading. In mathematics an example of the rehearsal strategy is finding similarities between new problems and the ones solved earlier, using comparable calculations. Lastly, organization strategies help students select appropriate information by drawing graphs or pictures and establishing connections among the different elements to create meaningful units of information (Weinstein et al., 2000).

1.2.2. Metacognitive Strategies

Metacognitive strategies regulate students' cognition by activating relevant cognitive approaches. As metacognitive strategies are linked to cognitive domains, they always involve a particular degree of learning content and can be considered as higher order strategies. Three subcategories related to the three phases of the learning process can be distinguished: planning, monitoring and evaluation (Schraw & Dennison, 1994). Planning strategies are deployed at the start of a learning episode and include subprocesses such as goal setting and allocating resources. Examples of these strategies are making a plan, deciding upon the amount of time to spend on an activity, and choosing what to do first. Monitoring strategies are used for checking one's comprehension. These strategies can be considered as continuous assessments of one's learning and/or strategy use. Examples include self-questioning and changing the approach to a specific learning task if necessary, for instance, re-reading a passage if its' meaning is not properly understood. After the learning process, evaluation strategies can be used in the analysis of one's performance and the effectiveness of the learning methods. In writing, for example, reviewing a text is a strategy that might help improve the written text, while in mathematics it is important to check whether the answers found make sense in the context of the original problem.

1.2.3. Management strategies

Management strategies are strategies to manage the aspects in the context which directly influence the learning process. This type of strategy is related to the theoretical framework proposed by Pintrich (2000), which explicitly refers to the contextual features that influence learning. Management strategies can be classified into three main subcategories: management of effort, management of peers and others (e.g., teachers) and management of the environment. Effort-management refers to strategies which reflect the commitment to completing one's study goals, in spite of difficulties or distractions (Pintrich et al., 1991). It is a form of actively motivating oneself to persist in studying. The second subcategory, management of peers (or others), includes strategies deducted from theories that reflect a socio-constructive view of learning, in which peers work together to construct knowledge. Asking fellow students to assist in learning, working together on tasks, as well as forms of reciprocal teaching can be very effective in enhancing one's learning and understanding (e.g., Palincsar & Brown, 1984). Finally, management of the environment relates to strategies which help in using the environment to optimize the possibilities for learning, e.g., by using the library or dictionaries and finding a quiet place to study.

1.3. Motivation and metacognitive knowledge

Apart from focusing on the strategies mentioned above, learning strategy trainings frequently address two related topics, namely motivation and knowledge. These elements could be considered as a crucial condition for learning strategies if the aim is specifically to enhance one's self-regulated learning. As learning strategies are controllable and have to be implemented consciously by an individual (Bjorklund, Dukes, & Brown, 2009), students need to have sufficient knowledge regarding these strategies as well as the motivation to apply them. Therefore, in completing the overview of learning strategies for self-regulated learning, motivational aspects and metacognition are considered as well.

1.3.1. Motivational aspects

Motivation is a multi-facetted construct which can help students engage in learning in various ways. With respect to academic performance, there are several aspects that might influence a student's approach to a task, for instance self-efficacy beliefs, which refer to one's perception of one's ability to accomplish a task and one's confidence in one's skills to perform this task (Pintrich et al., 1991). Furthermore, task-value beliefs concern the extent to which students perceive academic tasks as interesting and important. Finally, goal orientation relates to the reasons why students perform a task, which can be either

intrinsic (e.g., curiosity) or extrinsic (e.g., rewards) (Pintrich et al., 1991). All these motivational aspects play a role in students' decisions whether to engage in or refrain from strategy use (e.g., Garner, 1990; Hadwin & Winne, 1996).

1.3.2. Metacognitive knowledge

In summarizing conditions for effective strategy trainings, Hattie et al. (1996) pointed to the relevance of contextual as well as strategic knowledge about learning tasks. Furthermore, Dignath et al. (2008) found metacognitive knowledge, or reflection, to be an important element in strategy trainings. It is therefore a component commonly used in trainings, and considered as a relevant factor in the interpretation of effects. Furthermore, it comprises declarative, procedural and conditional elements: knowledge of how, when and why to use which learning strategies (Schraw & Dennison, 1994).

1.4. Instructing learning strategies: findings from earlier meta-analyses

Over the years, the number of learning strategy interventions conducted has become considerable. All of them have made a relevant contribution to the growing insight into the effectiveness of learning strategy instruction and strategy application. From the nineties on, important meta-analyses have been conducted in order to synthesize the findings available so far. The first meta-analysis was conducted by Hattie et al. (1996). This analysis included 51 studies, resulting in an overall effect size on student performance of Cohen's $d = .57$ ($SE = .04$). The authors reported the highest effects for the direct teaching of cognitive skills. These effects were mostly produced by interventions aimed at the near transfer of a specific task-related skill. Multiple-component interventions, in which various strategies were addressed, revealed lower impacts. Regarding student characteristics, it was reported that in general low ability students seemed unable to profit from these interventions. However, in this and other studies several issues remained unaddressed. For example, in the analysis of Hattie et al. (1996) the trainings took place outside the regular school context and were focused on multiple independent variables aimed at increasing various kinds of performance stretching beyond achievements in the learning of content. Furthermore, in many analyses the mean effects were computed based on student performance, study skills and affect as a whole. And if a separate effect for performance was specified, it was not reported whether it was statistically significant or not.

Dignath and colleagues (Dignath & Büttner, 2008; Dignath et al., 2008) conducted two follow-up meta-analyses. They synthesized information from studies from 1992 to 2006 and simultaneously tested the effects of a number of study characteristics on academic performance via stepwise backwards metaregression (Dignath & Büttner, 2008). They reported overall effect sizes on performance of Cohen's $d = 0.61$ (0.05) for primary schools and 0.54 (0.11) for secondary schools. For both school types, the effect sizes were found to be higher when metacognitive reflection was included in the trainings. With respect to the effects of other strategies on academic achievement, the results were mixed. Taking a closer look at which learning strategies were the most effective in primary education, Dignath et al. (2008) – using ANOVA – reported the highest effects for interventions which combined the instruction of different types of strategies. The authors argued that the trainings should include both metacognitive and motivational strategies. In secondary education the highest effects were indicated for interventions focused on motivation and/or metacognitive reflection. Furthermore, it was observed that group work had a negative effect in primary education but a positive impact in secondary education. Regarding school subject, contradictory results were found. In primary school, interventions in mathematics were more effective than those in reading or writing, whereas in secondary school the opposite was true. The authors did not address students' ability, as only studies conducted in the regular education segment were included in the literature review.

Again, additional questions arose. For example, the effects largely varied between interventions in mathematics and those in reading and writing (which were combined in these analyses). Furthermore, instructing all types of strategies would be overwhelming for the students, so where to focus on as a teacher? And finally, earlier meta-analyses did not clarify the nature of the tests used in the studies analyzed, for example whether they were independent assessments or tests specifically developed for the study, a difference which might have influenced the effect sizes reported. In sum, although the previous meta-analyses provided insight into the potential effectiveness of strategy instruction, their results also gave rise to new questions, especially with respect to the application of the research findings in practice. Three issues are of interest here: which specific strategies are effective, which students profit from strategy instruction and what influence do the types of test instruments have on the effect sizes found?

1.4.1. Effective strategies

Probably the most relevant question is which specific strategies are the most effective in improving student learning. Earlier meta-analyses have investigated the effectiveness of a broad spectrum of strategy trainings, including cognitive, meta-cognitive, and motivational learning strategies (the latter we call motivational aspects). However, in planning and implementing interventions in the curriculum, it is useful to know quite specifically which concrete strategies (included in the various broad categories) should be taught to make students' learning more effective. And as earlier meta-analyses have found differences among the various subjects in this respect, another question arises, namely how the effectiveness of strategies is influenced by the subject-domains in which these strategies are implemented.

1.4.2. Student characteristics

There has been an ongoing debate about the age at which learners are capable of self-regulating their learning. Some researchers claim that children are not yet capable to engage in metacognitive activity because it requires a particular level

of cognition, accurate knowledge of academic tasks and learning, and the ability to monitor oneself. And, as argued by some, these are elements which are not yet fully developed at such a young age (e.g., Paris & Newman, 1990). Others see metacognitive activity and self-regulated learning initiatives in children already as early as in Kindergarten (e.g., Whitebread et al., 2009). These different viewpoints are partly dependent on the researchers' theoretical backgrounds and what they consider to be metacognition and self-regulated learning. There is general consensus, however, on the view that both concepts develop as children mature (e.g., Veenman & Spaans, 2005).

The debate about the prerequisites for students to engage in strategy use is not only limited to their age. Other variables, such as background and capability, and the way in which these elements influence the effect of learning strategies, also play a role. For example, according to Hattie et al. (1996), low achievers seem unable to benefit from most types of interventions. However, considering that new models of self-regulated learning and strategy instruction have emerged since these authors' meta-analysis was conducted, it seems interesting to re-assess the effects of these types of student characteristics.

1.4.3. Outcome variables and measures

Another issue not addressed thoroughly in earlier meta-analyses relates to the outcome measures used in the original studies to determine the effectiveness of the interventions. Most studies only use self-developed measures to evaluate student performance. This situation could cause effect size inflation, as researchers may direct student performance toward the test used at the end of the intervention. The question then arises whether these effects would also have been found when intervention independent tests had been used. This issue was addressed in a meta-analysis of student performance performed by Haller, Child, and Walberg (1988), who reported that there was no difference between the effects found via self-developed versus intervention independent tests, although it was not clear on which analysis this conclusion was based. In a study on the effects of metacognitive instruction interventions on comprehensive reading, Chiu (1998) also examined whether the type of measurement instrument matters. He found that the effects were higher when the test was nonstandardized (Cohen's $d = .61$) than when it was standardized (Cohen's $d = .24$).

The results of the meta-analyses by Hattie et al. (1996) and Dignath et al. (2008) may have been influenced by the fact that they did not correct for the type of test instrument used in the primary studies. Considering the common use of self-developed tests in strategy interventions, it would therefore be interesting to research whether the training effect outcomes indicated by these instruments actually differ from those yielded by independent achievement assessments and how this difference might have influenced the interpretation of the results.

1.5. The current study

This article addresses a number of research questions, using a meta-analytical approach. The first one is: Which strategies instructed are the most effective in improving academic performance? In answering this question, we include three types of strategies: cognitive, metacognitive and management strategies (and their respective substrategies), while also considering the effects of motivational aspects and metacognitive knowledge. In doing so we elaborate on earlier findings, taking a closer look at these broad categories to investigate which concrete substrategies are the most effective. Furthermore, we distinguish among subject domains to look for differential effects. Secondly, our focus is on student characteristics, which forms the basis for our second research question: Do the effects of the strategies instructed differ for different types of students? Next, we address the possible influence of the measurement instruments used to evaluate the strategies' effectiveness. We expect the highest effect sizes for studies based on self-developed tests. To check this hypothesis, we formulate our third research question: does the type of measurement instrument used in the interventions influence the effect sizes reported? Finally, we assess whether publication bias affects our results. Several sources of evidence have shown that studies which present relatively high effect sizes have in general more chance of being published than accounts of lower effect sizes (Ahn, Ames, & Myers, 2012; Borenstein, Hedges, Higgins, & Rothstein, 2009). This bias is reflected in a meta-analysis. In our research, however, we checked for publication bias using a statistical method. via statistical means insight can be gained into the extent and effects of possible publication bias. This emphasis brings us to our last research question: To what degree are results influenced by publication bias?

2. Method

In order to be able to conduct our analysis, first the relevant literature had to be located and coded. Before explaining our methods of analysis we will describe how we selected the literature and specify the content in which we are interested.

2.1. Literature search and eligibility criteria

We conducted our literature search on the basis of a series of steps by which we eventually narrowed down the studies found to our final sample. The first step was a literature search using the internet databases *ERIC* and *PsychInfo*. We chose a limited time span; from January 1st 2000 to January 1st 2012. We decided to take the year 2000 as starting point, as in that year the Handbook of Self-Regulation by Boekaerts, Pintrich, and Zeidner (2000) was published, which marked a new era of research in this field. The search terms we used were 'metacognit*' and 'self-reg*' which had to be part of the title of the

articles. Another option would have been to enter all possible learning strategies as search terms. However, we did not know all of the terms used for the learning strategies by all of the authors of the articles. Rather than potentially overlooking articles by choosing search terms which were too specific, we decided to enter the aforementioned broad terms because they sufficiently reflected the educational context in which strategy instruction generally takes place. Subsequently, we used further search criteria to narrow down our literature to the topic of learning strategies. As advanced search options we limited ourselves to articles written in English and published in peer-reviewed journals in the field of (research in) education. This first search resulted in a total of over 1000 articles.

In the second step of our selection procedure, this number was decreased by more than half because many studies found were conducted outside the school context and did not include academic performance (e.g., studies on self-regulation in psychiatric patients). The third step was the application of the following main selection criterion: interventions in which learning strategies are instructed or trained using outcome measures which include academic performance. So, we included only empirical studies of learning strategies instructed with the aim of improving academic achievement. This approach meant that we selected articles in which 'academic achievement' (operationalized as performance in one or more school subject-domains) was the dependent variable. Correlational studies were excluded as these do not prove causality. After this step the total number of studies was significantly decreased.

So far, our choices in capturing our scope of interest had been based on rather broad criteria. In our last step we therefore used the following eligibility criteria to complete our selection procedure: the studies had to have a control group, as for study designs without a control group it is not clear whether the results of the experimental group can be ascribed to the intervention or to natural developments. Furthermore, studies which only provided posttest scores were only included if it was indicated that the groups had been comparable before the actual intervention had started.

To ensure that the Cohen's *d* effect size was approximately normally distributed, the samples used in the studies had to include at least ten students per group (Hedges & Olkin 1985). Studies based on smaller groups were therefore excluded from our meta-analysis. For studies which did not provide sufficient descriptions of the exact type(s) of intervention(s), it was not possible to identify and code the learning strategies. So we also excluded these publications from our analysis.

Next, with regard to the school-subject domains, only the core academic subjects were included. This criterion meant that music, arts and physical education were excluded. Although learning strategies are also applied in these domains, the research conducted here is more rare compared to that focused on subjects with more cognitive content. In practice, the majority of the studies focused on comprehensive reading, writing texts, mathematics and science. Studies on the remaining subjects were clustered under the heading 'other' in our analysis. To be able to generalize our results, the participants in the studies had to be primary school or secondary students up to and including the twelfth grade, in line with the American and most European School Systems. Furthermore, they had to be representative of the complete school community. Therefore, we also included studies containing samples of children with learning difficulties or disabilities in our sample.

Ideally, it was our objective to perform a meta-analysis of studies in which the effect of the interventions on academic achievement had been examined via tests independent of the intervention. Such tests are for example standardized achievement tests. However, because in practice so many studies use self-developed tests for estimating intervention effects, we decided to include them as well. Finally, the publications had to provide sufficient quantitative measures to calculate an effect size. Those which did not were excluded from the meta-analysis. After applying all of these criteria, the original sample was reduced to 58 studies.

2.2. Coding

Following Lipsey and Wilson (2000), we developed a coding scheme containing both statistical and theoretical components. This scheme was tested and refined until the authors reached agreement on the topics and corresponding categories. Next, two of the authors coded five articles together and further discussed the outcomes until full agreement was obtained. Finally, the same two authors coded ten articles independently, after which the interrater reliability was determined. This reliability was calculated based on the percentage of agreement reached, which was 96%. Next, the remaining articles were divided between the same two authors to be coded independently. If necessary, particular issues or concerns were additionally discussed. The coding scheme was based on the following components: the learning strategies instructed, student characteristics and the measurement instrument used.

2.2.1. Learning strategies

For all learning strategies, we coded whether they were (1) or were not (0) included in the intervention. In coding the strategies, the same classification as described earlier was followed. For the sake of comparability we chose not to label the strategies on a micro-level (e.g., activating the prior knowledge of a topic on which a text in a comprehensive reading lesson is based) but to classify them on a higher level (in this case elaboration). Appendix A provides an overview of our categorization with examples of each type of strategy used in the studies included in our meta-analysis.

Strategies can be described on several levels. All the aforementioned categories have been broadly defined and are domain-independent. A strategy such as 'planning' can be referred to in general terms as 'making a plan' to structure, for instance, the order in which homework is conducted and the amount of time available for each assignment. On this level the description of strategy use applies to all domain and learning tasks. On a lower level, however, the execution of strategies differs among domains. For example, in mathematics planning might include extracting the right numbers and calculations

needed to solve the problem, whereas in reading it might refer to predicting what the story will be about and estimating the time needed to read the text.

Aligned to the strategies we also included whether or not the motivational aspects were part of the intervention. Finally, as some studies were more focused on stimulating students' metacognitive knowledge than on teaching of specific strategies, a category of metacognitive knowledge was added, with as subcategories personal metacognitive knowledge (e.g., feedback specifically targeted at the student's work, including metacognitive hints) and general metacognitive knowledge (e.g., an introduction into when, why and how to use learning strategies).

2.2.2. Student characteristics

As we wanted to be able to differentiate among student populations, we also divided the students into categories, using the following labels: (1) regular population (students who were representative of the student population in the country in which the study was conducted), (2) children from a low socioeconomic status and background (low SES), (3) students with learning disabilities and special needs, and (4) gifted and high SES students (although we realized that students who are gifted do not necessarily come from high SES families and vice versa; due to the low number of studies on either one of these categories we decided to combine them).

2.2.3. Outcome measures

With regard to the outcome measures, we only coded performance tests used to determine academic achievement. If multiple tests were used to determine performance we coded all of them, whereas, for example, questionnaires to measure student motivation were not coded because we were only interested in effects on academic performance. With respect to these outcomes, we coded the domain in which the performance was measured and the nature of the instrument; self-developed (designed by the researchers who also evaluated the performance in the intervention), or independent of the intervention/standardized (e.g., tests used in comparable studies, or more general tests such as national exams).

2.3. Meta-analysis

To calculate the effect sizes, we used the software package Comprehensive Meta Analysis, developed by BioStat (see www.meta-analysis.com). Here we had to decide which data we needed and how we wanted to analyze them. Before presenting our results we will give a brief explanation of the choices made in the analysis of our data.

2.3.1. Random and mixed effects models

We ran our first analysis using a random model which assumes random effects among the studies. Because the studies differed in terms of participants and interventions, it was likely that the effect sizes also differed (Borenstein et al., 2009). Our goal was to estimate the mean of the distribution of these effects (i.e., the influence of the populations in the studies on the effects of the learning strategies, of which we had a sample). This was done by assigning weights to the studies, based on the variances within the samples (as opposed to their size). In the next step, when focusing on the different categories or subgroups, we used mixed effects models. This approach allows for random between-study effects and a fixed moderator effect (Borenstein et al., 2009), that is, variability in the effect size distribution attributed to systematic between-study differences (e.g., type of intervention), which could be modeled, and subject-level sampling error plus an additional random component (Lipsey & Wilson, 2000).

2.3.2. Calculating the effect size and regression coefficient

The effect size used in this analysis was Hedges' g : the corrected standardized mean difference between two groups, based on the pooled, weighted standard deviation (Ellis, 2010, p. 13). We chose this effect size to account for the different sample sizes in the studies included in our meta-analysis. The following formula is used to calculate Hedges' g : $g = \sqrt{[(n_1 + n_2 - 2/n_1 + n_2)d]}$ where d represents Cohen's d (the standardized mean difference, that is, the difference between two means divided by the pooled standard deviation). If the primary studies only reported an overall sample size but did not provide clear divisions into treatment groups, the total sample size was equally divided over the number of groups included in the studies. To prevent outliers which would influence our results in an unrepresentative way, we adjusted them by Winsorizing (Lipsey & Wilson, 2000). Outliers were recorded to the general, unweighted mean of the effect sizes (.89) plus or minus two times the standard deviations (.87).

Many studies included multiple effect sizes. However, we only calculated those with our variables of interest, namely academic outcome variables. These outcomes were frequently assessed using multiple tests. In our descriptive data analyses these assessments led to multiple effect sizes within one study (for example, the study of Bruce and Robinson (2001) reported four effect sizes as index effects on students' reading ability). Using the CMA software these effect sizes are averaged to obtain one representative effect size per study.

In some studies multiple experimental groups were compared to one control group. In these cases the statistical dependence of data comes into play (Lipsey & Wilson, 2000). If this dependency is not accounted for, the weight assigned to the experimental groups would be too high. To correct for this problem, the number of students in the control group was divided by the number of experimental groups. For example, if a study examined the effects of two experimental groups and

compared the results to a control group of 60 students, we used the same mean and standard deviation of the control group test scores but filled in 30 as sample size. This correction resulted in a higher variance and thus a lower study weight.

2.3.3. Method of analysis

The CMA software makes it possible to perform meta-analyses and examine the influence of a single moderator on the summary effect. This moderator can be either a variable measured on an interval scale (such as age), or a categorical variable with multiple categories (for example ethnicity). In the case of a categorical variable, CMA executes an analysis of variance, adapted to meta-analytical data. CMA also has the option to check for possible publication bias.

For additional analyses, we used the statistical package 'Hierarchical Linear Modeling' (HLM), version 6, of [Raudenbush, Bryk, and Congdon \(2004\)](#) because of its option to perform meta-regressions with multiple predictors. A meta-regression is a regression-analysis in which the predictors, or moderators, are at the level of the intervention while the dependent variable is the effect size in the intervention. This analysis method was used to simultaneously test the effects of multiple learning strategies on the summary effect.

In the studies of our sample the effects of an intervention on academic performance were often measured via multiple tests. CMA automatically calculates the mean of these outcomes into one representative effect size. However, when correcting for effects related to the measurement instrument we wanted to use all effect size measures separately. To this end we applied HLM, which made it possible to correct for the effects related to the measurement instrument while regressing the multiple predictors of the effect size.

To be able to load all effect sizes separately into HLM, we had to adjust their weights because otherwise interventions containing multiple tests would be given a larger weight than those based on only one test. To adjust these weights, we divided them by the number of tests through which the effectiveness of the intervention was measured.

3. Results

3.1. Descriptives

A total of 58 articles including 95 strategy-interventions met our eligibility criteria and were included in our analysis. The majority of the interventions took place in the context of mathematics ($n = 44$), followed by (comprehensive) reading, writing and science ($n = 23$, $n = 16$, and $n = 9$, respectively). In total, 180 effect sizes were coded, which indicates that many interventions had been evaluated using multiple tests. [Table 1](#) presents a summary of the study characteristics. A table with the key characteristics of each individual study can be found in [Appendix B](#).

The middle column of the table shows the frequency of the characteristics as included in our analyses. The strategies most frequently addressed in the interventions were metacognitive approaches with a focus on 'planning' and 'monitoring'. With regard to cognitive strategies, elaboration was by far the most frequently trained substrategy. Management strategies were addressed somewhat less while motivational aspects were referred to the least. In addition to the metacognitive strategies, metacognitive knowledge was also addressed explicitly in about half of the trainings. This knowledge mostly dealt with the 'when' and 'why' of using learning strategies and was in some cases specifically tailored to the individual students. [Allen and Hancock \(2008\)](#), for example, provided students with information on their 'cognitive profiles' and how they related to their reading comprehension. Their students were given instruction on how to use their strengths to compensate for their weaknesses. In this case, students were individually provided with personal metacognitive knowledge.

Most studies were conducted in schools with regular students, followed by interventions for students with special needs. The instruments used to measure the effects of the strategy instructions were for the most part self-developed and aligned to the interventions. Nevertheless, a few studies used existing tests to measure the effectiveness of the interventions, such as the Test of Science Knowledge ([Michalsky, Mevarech, & Haibi, 2009](#)), a domain-specific test designed by the National Science Committee, and the Graded Word Reading Test (in the study of [Wright & Jacobs, 2003](#)), widely used in the United Kingdom. Even in these studies, however, the measures were completed by additionally assessing the students via a self-developed test.

The column on the right presents the mean effect sizes (Hedges' g). These are the effects of strategy interventions in a certain domain, aimed at a certain type of students or including a specific substrategy. To calculate these effects, all interventions that met the criterion were analyzed together. The table gives us an indication of the overall effectiveness of learning strategy interventions aimed at improving academic performance. The mean weighted effect size of Hedges' $g = .66$ ($SE = .05$, with a confidence interval of Hedges' g from $.56$ to $.76$: a significant effect) further strengthens the finding that interventions are in general effective. In the following analyses the effectiveness of learning strategies is investigated in more detail.

3.2. Effective strategies

We first tested the effects of each learning strategy on student performance separately in a meta-regression model with the measurement instrument as covariate. This covariate was included to account for the differences in effect sizes caused by the measurement instruments. [Table 2](#) shows the results.

Table 1
Characteristics of the intervention.

Variable	<i>n</i> Interventions	Effect size
<i>Strategies</i>		
<i>Cognitive strategies</i>		
Rehearsal	10	1.39
Elaboration	50	.75
Organization	32	.81
<i>Metacognitive strategies</i>		
Planning	68	.80
Monitoring	81	.71
Evaluation	54	.75
<i>Management strategies</i>		
Effort	15	.77
Peers	21	.83
Environment	6	.59
<i>Motivational aspects</i>		
Self-efficacy	13	.72
Task value	6	1.84
Goal orientation	6	.46
<i>Metacognitive knowledge</i>		
General	35	.97
Personal	13	.94
<i>Student characteristics</i>		
Regular	67	.61
Low SES and ethnic minority	7	.72
Special needs	14	.89
Gifted and high SES	7	.72
<i>Measurement instruments</i>		
Self-developed	122 effect sizes	.78
Intervention independent	50 effect sizes	.45
Unknown	8 effect sizes	
<i>School subject</i>		
Reading	23	.36
Writing	16	1.25
Mathematics	44	.66
Science	9	.73
Other	3	.23

Table 2
Effect of each learning strategy on student performance: meta-regression results.

	<i>B</i> (<i>SE</i>)
Cognitive strategy rehearsal	.42 (.15)**
Cognitive strategy elaboration	.14 (.09)
Cognitive strategy organization	.09 (.09)
Metacognitive strategy planning	.20 (.09)*
Metacognitive strategy monitoring	.07 (.12)
Metacognitive strategy evaluation	.06 (.08)
Management strategy effort	.02 (.13)
Management strategy environment	−.03 (.15)
Management strategy peers/others	.03 (.10)
Motivational aspect self-efficacy	−.10 (.13)
Motivational aspect task value	.94 (.21)**
Motivational aspect goal orientation	−.35 (.16)*
Metacognitive knowledge (personal)	.04 (.12)
Metacognitive knowledge (general)	.31 (.08)**

Notes: ** $p < .01$; * $p < .05$. Reference category of the learning strategies: 'strategy not in intervention'.

In presenting the regression coefficients we show the differences between the interventions which did and did not include the strategy under study; the effects presented are those found when the strategy was addressed compared to the interventions which did not include the strategy. So, for example, interventions in which the strategy 'planning' was included were compared with other learning strategy interventions, to test its effect. Planning shows a regression coefficient of .20, which means that the effect size of interventions including planning (whether or not in combination with other strategies) is .20 higher than of those focused on other strategies. The analyses show significant positive effects of the inclusion of

general metacognitive knowledge, the learning strategies planning and rehearsal, and the motivational aspect task value. Table 2 further indicates that the inclusion of the motivational aspect task value has the largest positive influence on the effectiveness of the intervention. Lastly, the coefficients indicate that the inclusion of 'goal orientation' has a negative influence on the intervention's effectiveness. Again, this finding does not mean that interventions focused on goal orientation have negative effects on student performance: goal orientation has a positive influence on performance, yet this influence is significantly lower than the influence of any of the other strategies.

Next, the effects of the significant learning strategies on student performance were analyzed simultaneously. Again, the measurement instrument served as a covariate in the meta-regression. Table 3 shows the results of this analysis.

The results show that the effect of the cognitive strategy 'rehearsal' is no longer significant, whereas the impacts of general metacognitive knowledge, planning and task value still are. This finding indicates that interventions which include 'general metacognitive knowledge', 'planning' or 'task value' enhance student performance the most effectively. The effect of the inclusion of goal orientation in the interventions remained negative. For both motivational aspects, however, the results are based on only a few studies which included these items, which is why this result should be interpreted with care. Together, the significant strategies accounted for 36.1% of the variance in effect size.

In order to verify our findings, we also ran a regression analysis with backwards elimination. Although this analysis was not suitable for taking a closer look at the different domains (because for this purpose we would have needed more interventions in the separate domains), we could use it to obtain an overall picture of the effective strategies. To this end, we included all strategies in the model and eliminated the least significant ones until a model with only significant strategies remained. The strategies in this final model generally matched the ones we had found in the previous analysis (general metacognitive knowledge and task value). However, planning was no longer significant, whereas elaboration now belonged to the significant strategies.

In the next step, we distinguished among the different subject domains, as they might differ in terms of the effectiveness of the strategies used. Figs. 1–4 show all effect sizes found in the primary studies per subject domain, as displayed in forest plots.

Table 3
Meta-regression of multiple learning strategies related to student performance.

	B (SE)
Intercept	.29 (.08)**
Measurement instrument self-developed	.20 (.08)*
Cognitive strategy rehearsal	.01 (.16)
Metacognitive knowledge general	.25 (.08)**
Metacognitive strategy planning and prediction	.17 (.08)*
Motivational aspect task value	.81 (.23)**
Motivational aspect goal orientation	-.33 (.14)*

Notes: ** $p < .01$; * $p < .05$. Reference categories of the measurement instruments and the learning strategies: 'intervention independent test' and 'strategy not in intervention', respectively.

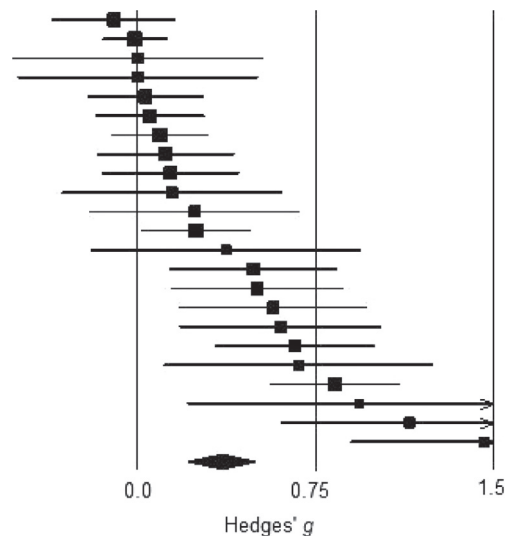


Fig. 1. Forest plot for comprehensive reading studies. Forest plot of average effect size and 95%-confidence interval of each of the comprehensive reading interventions (represented by a square) and summary effect (represented by a diamond).

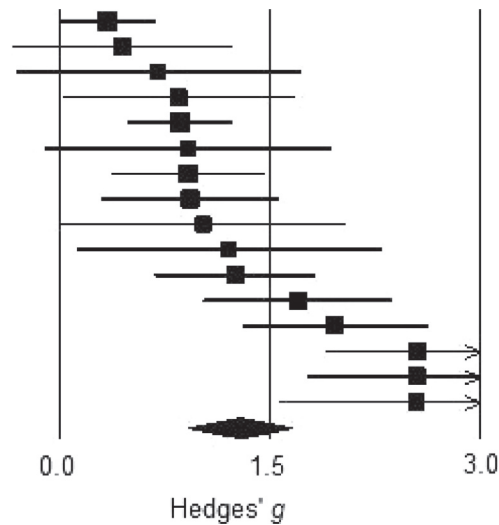


Fig. 2. Forest plot for writing studies. Forest plot of average effect size and 95%-confidence interval of each of the writing interventions (represented by a square) and summary effect (represented by a diamond).

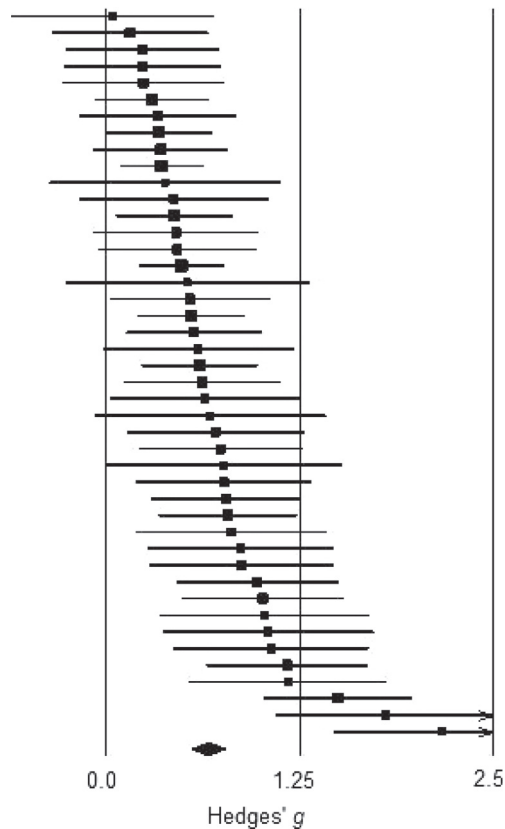


Fig. 3. Forest plot for mathematics studies. Forest plot of average effect size and 95%-confidence interval of each of the mathematics interventions (represented by a square) and summary effect (represented by a diamond).

The forest plots show only four studies in the domain of comprehensive reading with effect sizes below or around zero; all other interventions have positive and sometimes quite high effect sizes. The strategy interventions yielded the highest effects within the domain of writing, although the differences are large here. Within the separate domains we looked again at the effectiveness of specific substrategies. Table 4 reports the contribution of substrategies instructed in the various domains to student performance. Again the measurement instrument was used as a covariate to correct for possible influences.

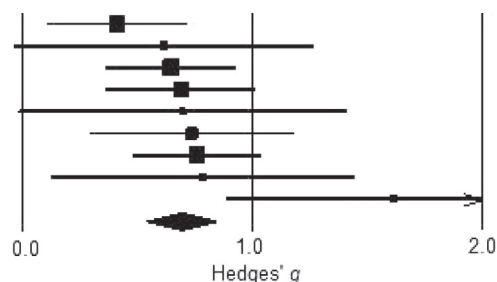


Fig. 4. Forest plot for science studies. Forest plot of average effect size and 95%-confidence interval of each of the science interventions (represented by a square) and summary effect (represented by a diamond).

Table 4

Effectiveness of learning strategies: regression coefficients.

Main strategy	Sub strategy	Reading		Writing		Math		Science	
		n	B (SE)	n	B (SE)	n	B (SE)	n	B (SE)
Cognitive strategies	Rehearsal	2	.08 (.21)	7	.37 (.30)	1	-.22 (.33)		
	Elaboration	19	-.48 (.15)**	8	.47 (.29)	18	.21 (.10)*	4	.16 (.19)
	Organization	11	-.07 (.11)	14	-.42 (.45)	4	.11 (.20)	1	-.02 (.25)
Metacognitive strategies	Planning	14	.15 (.11)	13	.38 (.38)	32	.08 (.12)	7	.08 (.18)
	Monitoring	22	-.29 (.23)	12	.46 (.32)	36	.20 (.14)	8	-.07 (.38)
	Evaluation	12	-.05 (.11)	11	.60 (.30)*	21	-.03 (.11)	8	.02 (.25)
Management strategies	Effort	3	.07 (.16)	7	-.17 (.31)	5	-.28 (.15)		
	Environment	3	.04 (.13)	1	.72 (.54)	2	-.25 (.22)		
	Peers	6	-.27 (.09)**	9	.45 (.30)	5	.16 (.17)		
Motivational aspects	Self-efficacy	3	.10 (.17)	3	.08 (.39)	7	-.27 (.14)		
	Task value	0		6	.43 (.30)	0			
	Goal orientation	0		2	-.72 (.58)	3	-.21 (.19)		
Metacognitive knowledge	Personal	2	-.17 (.13)	2	-.43 (.47)	6	.16 (.15)	3	.25 (.22)
	General	8	.27 (.12)*	9	.78 (.26)**	14	.03 (.11)	3	.15 (.15)

Notes: ** $p < .01$; * $p < .05$. Cells are empty when there are no interventions with or without the strategy under study.

In reading, (general) metacognitive knowledge significantly improved student performance. However, the substrategies elaboration and management of peers yielded lower levels of effectiveness. So with respect to interventions in the domain of reading, the inclusion of metacognitive knowledge was beneficial, whereas a focus on elaboration and management of peers (i.e., collaboration) appeared to be less so. Interventions based on the substrategies planning and effort management had slightly favorable results, yet compared to other strategies their effects were non-significant. Also rehearsal, management of the environment and self-efficacy showed (non-significant, yet) positive effects. However, these were based on only a small number of interventions, so again this result should be interpreted with caution. Although in writing the effects were more salient than in other domains, only evaluation or (general) metacognitive knowledge clearly proved to be more beneficial than other strategies. Here no significant negative effects were found. In mathematics elaboration was the only substrategy which improved student performance significantly more than other methods. It may therefore be worth incorporating in any intervention within this domain.

In reading and mathematics, only one type of substrategy showed significant positive results, while in science no significant effects were found at all. In the domain of writing however, two substrategies appeared more effective than other ones. We analyzed these substrategies together to test the effectiveness of this combination. In writing the combination of (general) metacognitive knowledge and evaluation was $B = .75 (.24)$ and $.57 (.26)$, respectively ($p < .05$), indicating that interventions which included both strategies were the most effective here.

3.3. Student characteristics

With respect to our second research question about student characteristics, we investigated whether the effectiveness of the strategy interventions depended on the type of students. Table 5 shows the average effect sizes of the interventions for the different categories of the 'student characteristics' predictor. The meta-analysis of variance revealed no significant between-groups differences; the effect sizes show that the learning strategy interventions were highly effective for all types of students.

With the aid of meta-regression, we examined the between-groups differences more thoroughly. In this way, we could compare two groups with each other instead of analyzing the between-groups differences as a total. Furthermore, with this analysis the possible effects of the type of measurement instrument were controlled for as the instrument was included as a covariate. The last column of Table 5 shows the results. Although it appears that special needs students benefited more from the interventions, we did not find significant differences ($B = .23$, $p = .58$).

Table 5
Mean effect size for student characteristics and meta-regression.

	Mean Hedges's <i>g</i> (SE)	Regression <i>B</i> (SE)
Intercept		.40 (.07)**
Instrument self-developed		.33 (.09)**
Average/regular	.61 (.06)**	
Low SES	.72 (.18)**	.06 (.15)
Special needs	.89 (.14)**	.23 (.12)
High SES/gifted	.72 (.18)**	.16 (.17)

Notes: ** $p < .01$; * $p < .05$. The reference categories for measurement instrument and characteristics are intervention dependent test and regular students, respectively.

There was no relationship between the effects of the interventions on student performance and the students' age (in grades). A meta-regression with grade as predictor and measurement instrument as covariate revealed a coefficient of only $B = -.01$ ($SE = .02$; $p = .55$) for grade.

3.4. Outcome measures and effectiveness

Our third research question concerned the instruments used to measure the outcomes of the interventions. We found an average effect size of Hedges *g* .78 for the self-developed tests and of .45 for the intervention independent tests. This difference was significant ($p < .01$).

There were also some differences among the domains. In reading, the number of intervention-independent tests was quite high; in 70% of the interventions a standardized measure was used. To math and writing the opposite applied: in only 10% and 11% of the interventions respectively, an independent test was used to calculate the effects. For science the amount was slightly higher, with 29% of intervention-independent tests. Earlier we had also found lower effects for interventions in the domain of comprehensive reading, which led us to believe that these results were related to the use of intervention-independent tests. To test this premise, we therefore analyzed the effect of the measurement instrument for each subject domain separately. Table 6 shows the results.

It appeared, however, that comprehensive reading was the only subject in which intervention-independent tests resulted in a significant lower effect than self-developed tests. For writing, math and science, the difference in effect size between the two types of tests was not significant.

3.5. Publication bias

The last element we were interested in concerned a problematic issue associated with meta-analysis: publication bias. Several lines of evidence have shown that studies reporting on relatively high effect sizes have more chance of being published than studies describing lower effect sizes (Borenstein et al., 2009). If this had also been the case in this field of research, the bias would have been reflected in our meta-analysis. To test whether bias had indeed occurred, we applied Duval and Tweedie's *Trim and Fill* method (Borenstein et al., 2009; Duval & Tweedie, 2000). We used a random effects model to estimate if there were any interventions missing in the meta-analysis. Following the trim and fill method, extreme effect sizes of interventions on the right hand of a funnel are trimmed to obtain a symmetric funnel plot. In this way a new, unbiased estimate of the summary effect size is calculated. Next, the funnel plot is filled again with the trimmed effect sizes of the interventions and their counterparts on the left hand of the funnel plot (the lacking interventions). Then, a pooled estimate of the summary effect size is calculated. Fig. 5 shows the funnel plot of the relationship between standard error and the effect sizes of the interventions in the current meta-analysis. The interventions with a small sample size have in general a larger standard error and appear at the bottom of the figure. The larger interventions are positioned higher up. Applying this approach to our meta-analysis, we obtained Fig. 5.

The figure shows that the interventions are quite neatly spread. According to the trim and fill method, there were no studies missing, suggesting that there was no publication bias. We conducted these analyses for all separate subject domains and found that only in the case of science publication bias had occurred. Still, inclusion of the missing studies would have resulted in effects in the same direction.

Table 6
Effects for separate measurement instruments.

	Self-developed Hedges's <i>g</i>	Intervention independent Hedges's <i>g</i>
Total	.78	.45**
Reading	.82	.22**
Writing	1.31	1.07
Mathematics	.61	.84
Science	.63	.88

Notes: ** $p < .01$; * $p < .05$.

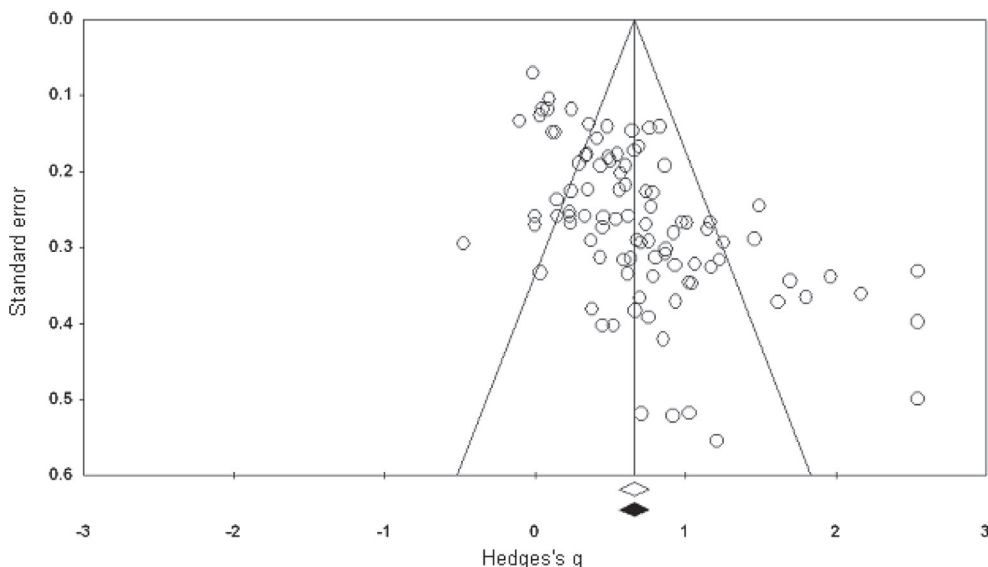


Fig. 5. Funnel plot of standard error by effect size for all interventions. Note: The observed interventions are represented by an open circle; imputed interventions would have been represented by a filled circle. The open diamond at the bottom represents our mean effect size, the filled diamond represents the mean effect size based on the total number of interventions (imputed interventions included).

4. Conclusion and discussion

This meta-analysis addressed the question which learning strategies are the most effective in enhancing the academic performance of students in primary and secondary education. To establish the effects of these strategies, we relied on research studies which describe interventions in which learning strategies are instructed, assuming that the instruction of these strategies would result in their adoption by the students. A search for literature published in a period of more than a decade yielded a total of 58 studies, including 95 interventions of strategy instruction, which comprised 180 effect sizes. The studies' average mean effect size of Hedges' $g = .66$ (S.E. = 0.05) again demonstrated that students' academic performance can indeed be improved by the instruction of learning strategies.

Three types of learning strategies were included in this meta-analysis: cognitive, metacognitive, and management strategies, and their related motivational aspects and metacognitive knowledge. Of the interventions assessed, metacognitive strategies were the most commonly used, with a focus on planning and monitoring. With regard to cognitive strategies, elaboration was by far the most frequently trained approach. Management strategies were used to a somewhat lesser extent while motivational aspects were addressed the least. These results differ from the findings of Dignath et al. (2008), who found many more motivational strategies (included in our category 'motivational aspects'). This difference might be due to a different focus; whereas we concentrated on improving academic performance through the use of learning strategies, Dignath et al. (2008) emphasized the improvement of self-regulated learning, involving metacognition, cognition and motivation. The meta-analysis of Hattie et al. (1996) particularly dealt with the thrust of the programs. The results of this analysis are more in line with our findings, as the majority of these studies focused on study skills, whereas aspects such as motivation and attribution received much less attention.

In the interventions in our analysis, performance was almost always improved by a combination of strategies. Furthermore, certain subject domains appeared to be more suitable for strategy instruction than other course fields: in writing the highest effects were found, regardless of the exact content of the intervention (i.e., the strategies taught). We have no definite explanation for this finding. However, in writing education there is generally less explicit focus on (strategy) instruction, which implies that any increase in the emphasis on this approach may already have an effect. Dignath and Büttner (2008) established the highest effect sizes in mathematics, but this finding might have been the result of the fact that they considered reading and writing as one domain, whereas we addressed them as separate subjects because the performance tasks associated with them require different approaches. In the domain of comprehensive reading, a mean weighted effect size of .36 was found, a considerably lower result than the effect size reported by Chiu (1998), which was .67. However, due to the different approaches used in analyzing the studies included in these meta-analyses, these findings cannot be compared on a one to one basis.

4.1. Effective strategies

Although we identified many different strategies that contributed to performance, we were unable to present a broad spectrum of significant findings. This does not mean that strategies are ineffective, on the contrary, *all* of them clearly

proved to be effective. A few aspects do stand out however. First of all, the metacognitive knowledge component adds to academic performance. By including this component in the intervention, students are not only taught which strategies to use and how to apply them (declarative knowledge) but also when and why to use them (procedural and conditional knowledge). This type of informed strategy instruction leads to a significantly larger degree of metacognitive engagement and is therefore more effective than a plain instruction of the application of learning strategies. This conclusion supports earlier findings from [Dignath and Büttner \(2008\)](#), who observed higher results each time metacognitive reflection, as they referred to it, was included in the training. Secondly, planning and task value have generally appeared to be effective, which is possibly a reflection of the role played by motivation in these types of interventions. Although [Hattie et al. \(1996\)](#) reported interventions with a focus on motivation to be less successful than other interventions, this finding was based on only one study. In general, in the context of self-regulated learning, the need to engage students in strategy use or learning by motivating them is widely acknowledged (see for example [Weinstein, Acee, & Jung, 2011](#)). Double-checking these strategies by regression analysis with backwards elimination also revealed elaboration as a significant strategy, whereas planning no longer appeared to be significant. Although our regular regression analysis provided more information on the strategies' domain-specific effects, which is why it was given preference in addressing the research questions, leaving out the finding that elaboration is generally also a very effective strategy would have been an omission.

In our analysis some strategies were given a negative *B*-value, for example goal orientation. This means that although the strategy is helpful, it is clearly less so compared to other strategies. However, because the results for goal orientation were based on only a few studies, this rating should be interpreted with care. It would be interesting to see if future meta-analyses which include a larger number of studies focused on goal orientation also yield this result. A second explanation for negative outcomes, also when more studies were included – as was the case for elaboration or working with peers in the domain of comprehensive reading – could be related to the complexity of the strategy. Perhaps these strategies are perceived as more complicated, and perhaps the more complex strategies may be more difficult to train. It may require time before students know how to use these approaches properly and before their effects on performance outcomes become really visible. In this case, the training of complex strategies may have produced lower effects than that of less multifaceted approaches. And although some of them were negatively valued, they may actually be helpful in the long run. In this respect, a closer investigation of the intervention effects in the longer term would provide more insight. Our first recommendation for future research would therefore be to compare the short-term to the long-term outcomes, especially for the more complex or higher order strategies.

4.2. Student characteristics

Our next question concerned the types of students which would profit from the strategy trainings. We distinguished four categories: (1) regular/average, applying to the student population generally representative of the particular country, (2) children from low SES backgrounds, (3) children with learning disabilities and special needs, and (4) gifted children and children from higher SES backgrounds. Student characteristics were coded and placed into these categories. [Graham, Harris, and Mason \(2005\)](#), for example, trained struggling writers (category 2), and in the study of [Lublinter and Smetana \(2005\)](#) over half of the students were provided with free or lower-priced breakfast and lunch programs, a proxy for low SES. Strategy use was effective for all groups; here no significant differences were found. In this respect our results differ from those obtained by [Hattie et al. \(1996\)](#), who found that low-ability students were unable to profit from the majority of interventions and that the medium-ability level students, comparable to our 'regular students' group, benefited the most, as did the underachievers. The fact that our findings point in the opposite direction might be explained by the belief held by many researchers that strategies in particular can be a way to fulfill the special needs of low-achieving students (see, e.g., [Graham & Harris, 2003](#)). Furthermore, the difference in findings may be the result of the improvement of the training programs over the course of the years. However, it would be interesting to compare these programs to see if there are indeed differences in terms of improvement, and to determine how other programs could be enhanced.

Our analyses showed that students in both primary and secondary education profit from strategy instruction and that grade level is related to the training outcomes. Although [Dignath and Büttner \(2008\)](#) exclusively focused on trainings for the regular student category, they also consider the students' age. They established that the trainings were more effective in primary education (overall mean effect size of .61) than in secondary education (overall mean effect size of .54). Although the difference reported in our study was non-significant, there might be a trend that students in primary education profit more than those in secondary education, an outcome also in line with other earlier findings ([Hattie et al., 1996](#)). This result may be explained by the fact that younger children have not yet developed counterproductive learning habits and are therefore better capable of learning particular tasks, including strategies, than older children, who have already been influenced more by their experiences (at school). Another possibility is that motivation plays a role and that younger students are still more open to events, such as education interventions. We did not investigate this assumption but it might be interesting for future research, as motivation is also associated with improved self-regulated learning. In addition, although both age and student characteristics revealed no significant differences, it would be worthwhile to investigate if there is any interaction between these two variables. Unfortunately, we were not able to conduct this type of analysis.

4.3. Outcome measures

Apart from looking at the results in different time frames, it is also important to consider the ways in which they are measured, which brings us to our third research question. We expected the students' scores to be higher for self-developed tests, regardless of the strategies trained or the type of students. We indeed observed higher effects for self-developed tests (Hedges' $g = .78$) than for intervention independent tests (Hedges' $g = .45$). We assumed that these self-developed tests included near-transfer tasks (see also [Hattie et al., 1996](#)) as opposed to more general performance measures. Achieving well in these tasks is considered favorable as it indicates that the use of learning strategies has improved the performance. Yet, in this context the transferability of the results could be questioned. Of course, positive effects of self-developed tests indicate the effectiveness of trained learning strategies. Furthermore, it could be argued that self-developed tests are necessary to detect effects that would be overlooked if independent tests were used, as the former might be more sensitive to changes occurring as a result of the learning strategies instructed. However, using self-developed tests might also tempt trainers to direct the student performance toward the test used at the end of the intervention. In the case of intervention-independent tests this chance is reduced. Whereas in our analysis the independent tests produced an average effect size of .45, a quite substantial effect, the effects of the self-developed tests were higher. Of course, an even more promising result would have been if the intervention independent tests had yielded these higher results. In general, independent tests provide more information about the effects of strategies on learning or on possibilities of transfer. Furthermore, interventions can be compared more easily if their effects are measured in the same way.

However, many of the investigated studies used self-developed tests, and the research based on intervention independent tests was frequently combined with additional self-developed measures. Next, there were differences among the domains. Especially in the interventions in writing, self-developed outcome measures were used. For example, [García-Sánchez and Fidalgo-Redondo \(2006\)](#) judged the structure, coherence and overall quality of texts written by students on the basis of an elaborated list of criteria, whereas [Graham et al. \(2005\)](#) used traditional holistic rating scales. Both are examples of well-defined, extensive evaluation measures. However, standardized tests generally seemed to be lacking in this domain, which caused differences in the rating scales. In the other domains more standardized tests were available, although these were not always used to evaluate student performance. We did find some examples, for instance the TSK (a domain-specific test designed by the National Science Committee of the IME (2004) to examine students' knowledge of subjects in the science curriculum), used in the study of [Michalsky et al. \(2009\)](#) or the 'average mathematics grade', the general measure used by [Camahalan \(2006\)](#). Intervention-independent tests were the most often used in comprehensive reading. Examples are the Oregon State Assessment used in the study of [Allen and Hancock \(2008\)](#) and the Graded Word Reading Test applied by [Wright and Jacobs \(2003\)](#). When accounting for the measurement instruments applied, we found significantly higher results for the self-developed tests used in the comprehensive reading domain. To find an explanation for this difference in transferability it would be interesting to further investigate the learning strategy interventions within this domain.

4.4. Publication bias

Our last question regarded possible publication bias. In meta-analysis a complete coverage of all relevant literature is by definition unlikely, despite thorough and systematic searches. For example, non-published work is frequently left out, which means that the results of these studies are not accounted for in the final meta-analyses. To be more specific, effects estimated in published work tend to be somewhat higher than those gathered in unpublished studies, which means that if the latter were also included, the meta-analyses' outcomes would be different. However, since this pitfall has been acknowledged, methods have been developed to identify the effects of these missing studies. We used the *Trim & Fill* method ([Borenstein et al., 2009](#); [Duval & Tweedie, 2000](#)) to see how our results might have been affected. We concluded that there was some bias in the domain of science, whereas overall it was low. The effects we presented seem to be representative of the outcomes which would have been obtained if more studies had been included.

4.5. Practical recommendations

Summarizing our findings, we conclude that strategy instruction is beneficial for students. Furthermore, our results have provided us with practical suggestions for future trainings. Which strategies should be instructed depends on the context, i.e. the subject domain, in which the interventions take place. For strategies to be effective in comprehensive reading, trainings should incorporate metacognitive knowledge. Students should be taught when, why and how to use strategies and learn to master a number of them so they have a flexible set of instruments at their disposal. A good example of how this objective can be realized is having teachers model different strategies and explain their rationale to the students (e.g., [Mason, 2004](#); [Wright & Jacobs, 2003](#)). This kind of metacognitive knowledge can also be tailored to the students individually by providing them with information about their personal learning style and strengths and weaknesses, and teach them how they can purposefully use this knowledge to improve themselves (e.g., [Allen & Hancock, 2008](#); [Dresel & Haugwitz, 2008](#)).

Metacognitive knowledge is also important in writing. Here trainings could particularly focus on the metacognitive strategy "evaluation". Evaluating writing is a step away from reviewing texts, which means editing one's own texts or those of others to meet the criteria of an assignment or to make a story more coherent. In this way performance is improved. In many

interventions in writing this strategy has been applied (see for instance the studies of Glaser and Burnstein (2007), Reynolds and Perin (2009) and Torrance, Fidalgo, and García (2007)).

In mathematics, elaboration proved to be very effective. This substrategy entails attaching meaning to new information by connecting the old to the new material. For instance, in the study on problem solving by Tajika, Nakatsu, Nozaki, Neumann, and Maruno (2007), students were encouraged to explain to themselves why they chose particular solution steps when solving a problem. The authors referred to this approach as self-explanation by inference, which means generating new pieces of knowledge not explicitly included in the problem-solving step approach related to the specific problem. Another method we frequently came across was connecting new material to previously learned information by finding similarities among the tasks which help solve new problems (e.g., Kramarski & Hirsch, 2003; Kramarski, Mevarech, & Arami, 2002).

4.6. Limitations

The interpretation of our study's results is subject to several limitations. First of all, there was quite some fluctuation in the degree to which the different strategies were addressed in the studies analyzed. In other words, some strategies were used in a large number of studies while others were conducted in only a few of them. Therefore, the results should be interpreted with caution, given that part of them is based on only a limited amount of studies. For example, metacognitive strategies were quite common whereas other (sub)strategies were found much less frequently, making the evidence of their impact less strong.

A second limitation refers to the degree of differentiation among the findings. Our analyses included the characteristics and grade levels of a broad range of students. Based on these data, we were able to identify effects for different types of students. However, although we concluded that there were no significant differences among the groups, there are indications that students with learning disabilities profit the most from learning strategy trainings. What we do not know, however, is whether these trainings can be compared with the trainings for regular students, in other words, whether the same strategies are instructed in different ways to regular and disabled students. What would be interesting is to first differentiate among student groups and then conduct the analyses again, to see which strategies in which domain are the most effective for which type of student. Unfortunately, the number of studies included in our analyses was too limited to attain this level of differentiation. A more extensive study sample would be required to be able to distinguish among types of students and to sufficiently balance the results.

The most important limitation, however, relates to the type of studies included in our analysis. Although referring to strategies, we in fact analyzed studies of interventions in which strategies were trained. We included only these intervention studies based on the view that in this way causality could be proven, assuming that the strategies instructed would actually be used by the students after the instruction had ended, so that the effects estimated would reflect the effects of strategy use. However, we cannot be entirely sure that this assumption was always met. Furthermore, there were differences among the interventions. Some were obvious, such as the strategies addressed, but there were also other factors which might have moderated their effectiveness, for example the trainer of the intervention (a teacher, a researcher, an assistant or a computer program) or the intensity of the training (the number and length of the sessions). We did not consider these issues because reliable information was not consistently available across the studies. However, these factors might have partly explained the effects found, and if so, the strategies' actual influence may diverge somewhat from the results reported in our study. Therefore, it is important to keep in mind that when referring to effective learning strategies, we in fact refer to the effectiveness of the *interventions* focused on the instruction of these strategies. We assume that these trainings are conducted properly, that the strategies addressed are indeed the approaches used by the students after the training and that they were instrumental in improving student performance. Of course, as we rely on the accounts of primary studies, we can never be totally sure that all aforementioned assumptions have been met.

Moreover, one drawback of the relatively small number of studies we gathered is that it was statistically impossible to calculate singular or additional effects of the individual strategies, as almost all studies involved more than one trained strategy. To be able to draw any reliable conclusions in this respect, the input for the meta-analysis would have to be far larger than the current set was. Our results can only claim that, for example, trainings including the substrategy 'planning' (either with or without another strategy), seems to be more beneficial for performance than trainings without this strategy. Nevertheless, we did manage to account for this drawback to some degree: we assumed that both groups of training (the one including a certain strategy and the one not including this strategy) were on average comparable with respect to other strategies included as we could rely on a substantial number of studies. Furthermore, the strategies that proved significant in our study were brought together in an additional analysis to test the effects of all these strategies at once. This analysis showed similar results, which indicates that our initial significant findings were not related to other strategies in the training.

In addition to the limitations of our own research, meta-analysis in general is associated with two problems in particular, namely publication bias and the difficulty of deciding which studies are and which are not suitable for comparison (a balance has to be found between the use of a large sample which includes all relevant studies and the risk of comparing apples with oranges). As researchers we are aware of these risks and we have tried to take them into account in our study. It would, however, not be reasonable to assume that meta-analysis provides perfect solutions and definite, clear-cut answers to each and every research problem.

Yet, in our case, what resulted from our approach is a meta-analysis in which we investigated the effectiveness of learning strategies. More specifically, we tried to provide an answer to the questions which learning strategies improve academic performance, and whether the results yielded vary per student group or outcome measure. What justifies our decision to

use meta-analysis, which combines the results of a number of studies carefully selected on the basis of both content-related and methodological criteria, is that this approach has provided information and insights which could not have been obtained by any individual study. And although some questions remain, this analysis has presented a first outline of effective strategies. This information is valuable in that it contributes to both the body of knowledge of learning strategies and to the educational practice, where it can be used in the realization of effective strategies in different contexts to improve student performance.

Appendix A. Strategies – categories and examples

Strategy	Example	Study
<i>Cognitive</i>		
Rehearsal	Playing flash-card games to remember new words.	Bruce and Robinson (2001)
Elaboration	Summarizing passages, reducing the number of words to $\frac{1}{4}$ of the original text.	Boulware-Gooden, Carreker, Thornhill, and Malatesha (2007)
Organization	Using graphic organizers to structure writing ideas.	Harris, Graham, & Mason, 2006
<i>Metacognitive</i>		
Planning	Making judgments about use of cognitive abilities and predicting the number of pages to be read in a specific time period.	Allen and Hancock (2008)
Monitoring	Children were asked if they had a clear understanding of what they were doing, if the task made sense, if they needed to make any changes.	Pennequin, Sorel, Nanty, and Fontaine (2010)
Evaluating	Students had to answer questions on the computer screen during and after the solution process (e.g. ‘What is the difference between the expression X and the expression that you found?’).	Kramarski and Gutman (2006)
<i>Management</i>		
Effort	Emphasizing the role of effort in learning, making the positive effects of instruction concrete and visible and promoting an “I can do” attitude.	Tracy, Reid, and Graham (2009)
Peer	Explicitly encouraging students to seek assistance from their peers, parents, teachers and tutors.	Camahalan (2006)
Environment	Using a worksheet with tips on how to organize a workplace, regulate study time and breaks, deal with distractions etc.	Stoeger and Ziegler (2008)
<i>Motivational aspects</i>		
Self-efficacy	An explicit focus on statements such as ‘I feel capable of writing a good text’. Students also learned to make positive causal attributions (I made a big effort and I got a good result).	García-Sánchez and Fidalgo-Redondo (2006)
Task value	The first training session aimed to motivate students by focusing on the communicative function and importance of writing.	Torrance et al. (2007)
Goal orientation	One of the students’ goals was to become aware of their positive and negative “attitudes toward mathematics”. The children were supported in developing a constructive and positive attitude toward the subject.	Perels, Dignath, and Schmitz (2009)
<i>Metacognitive knowledge</i>		
Personal metacognitive knowledge	Students and teachers evaluated students’ prior knowledge with two open-ended questions (i.e., “What can I already do well?” and “What do I still have trouble with?”), thus evaluating personal strengths and weaknesses.	Dresel and Haugwitz (2008)
General metacognitive knowledge	Modeling was combined with feedback about when, where and why specific strategies were useful in conjunction with checking procedures to establish whether or not a strategy was effective.	Wright and Jacobs (2003)

Appendix B. Key characteristics of the studies included in the meta-analysis

Authors	Subject	<i>n</i>	Students' grade	Student characteristics	Metacognitive knowledge	Cognitive and metacognitive strategies	Motivation and Management strategies	Type Instrument (<i>n</i> tests)	Effect size
Aleven and Koedinger (2002)	Math	24	10	Regular	None	Planning, monitoring	None	Self (1)	0,52
Allen and Hancock (2008)	Reading	113	5	Low SES	None	Monitoring	None	Self (1)	0,64
					General	Planning, monitoring, control	None	Indep (2)	0,15
					General	Planning, monitoring, control, rehearsal, elaboration	None	Indep (2)	0,24
Blank (2000)	Other	125	7	Regular	None	Monitoring	None	Self (1)	-0,48
Boulware-Gooden et al. (2007)	Reading	112	3	Regular	None	Planning, control, elaboration, organization	None	Indep (2)	0,50
Bruce and Robinson (2001)	Reading	46	5,5	Special needs	None	Planning, monitoring, rehearsal, elaboration	Self-efficacy	Indep (2)	0,37
Brunstein and Glaser (2011) Camahalan (2006)	Writing	117	4	Regular	General	None	None	Indep (1)	0,86
	Math	60	5	Special needs	Personal	Planning, monitoring, control, rehearsal	Self-efficacy, resources, peers	Both (2)	0,54
Cantrell, Almasi, and Carter (2010)	Reading	47	6	Special needs	None	Monitoring, elaboration, organisation	Resources, peers	Indep (2)	0,25
Cantrell et al. (2010)	Reading	47	9	Special needs	None	Monitoring, elaboration, organisation	Resources, peers	Indep (2)	0,09
Dejonckheere, Van de Keere, and Tallir (2011)	Science	117	4,5	Regular	General	Planning, control	None	Self (1)	0,70
Dresel and Haugwitz (2008)	Math	151	6	Regular	None	Control	Self-efficacy	Self (1)	0,23
					Personal	Planning, monitoring, control	Self-efficacy	Self (1)	0,77
Erktin (2004)	Math	45	6	Gifted	None	Planning, monitoring, control, elaboration	None	Self (1)	0,87
García-Sánchez and Fidalgo-Redondo (2006)	Writing	121	5,5	Special needs	General	Planning, monitoring, control, rehearsal, elaboration, organisation	Task value, effort, peers	Self (3)	2,55
					General	Planning, monitoring, control, rehearsal, elaboration	Self-efficacy, effort, resrouces, peers	Self (3)	1,96
Glaser and Burnstein (2007)	Writing	46	4	Regular	None	Planning, monitoring, control, elaboration,	None	Both (4)	1,70

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Appendix B (continued)

Authors	Subject	<i>n</i>	Students' grade	Student characteristics	Metacognitive knowledge	Cognitive and metacognitive strategies	Motivation and Management strategies	Type Instrument (<i>n</i> tests)	Effect size
Graham et al. (2005)	Writing	30	3	Special needs	None	organisation Elaboration, organisation	None Task value, effort, peers	Both (4) Self (4)	0,93 0,92
					None	Planning, monitoring, control, rehearsal, organisation			
Guterman (2003)	Reading	109	4	Low SES	General	Planning, monitoring, control, rehearsal, organisation	Task value, effort, peers	Self (4)	1,03
					None	Planning, monitoring, control, elaboration			
Harris et al. (2006)	Writing	45	2	Special needs	None	Planning, monitoring, control, rehearsal, organisation	Task value, effort, peers	Self (4)	0,71
					General	Planning, monitoring, control, rehearsal, organisation			
Hauptman and Cohen (2011)	Math	80	10	Regular	None	Planning, monitoring, control	None	Indep (1)	0,35
					None	Planning, monitoring, control			
Huff and Nietfeld (2009)	Reading	73	5	Regular	None	Monitoring, elaboration	None	Indep (1)	0,00
					General	Monitoring, elaboration			
Jacobse and Harskamp (2009)	Math	73	5	Regular	None	Planning, monitoring, control	None	Self (1)	0,76
Kaniel, Licht, and Peled (2000)	Reading	79	5	Gifted	General	Monitoring, control, elaboration	Resources	Indep (1)	0,66
Kapa (2007)	Math	79	8	Regular	None	Planning, monitoring, control	None	Self (2)	1,01
					None	Planning, monitoring			
Kapa (2001)	Math	72	8	Regular	None	Control	None	Self (2)	0,74
					None	Planning, monitoring, control			
Kim and Pedersen (2011)	Science	72	6	Regular	None	Planning, monitoring	None	Self (1)	0,44
					None	Control			
Kramarski and Dudai (2009)	Math	24	9	Regular	None	Planning, monitoring, control	None	Self (2)	0,41
					General	Monitoring			
Kramarski and Dudai (2009)	Math	24	9	Regular	General	Monitoring	None	Both (2)	0,24
					General	Monitoring			

Appendix B (continued)

Authors	Subject	<i>n</i>	Students' grade	Student characteristics	Metacognitive knowledge	Cognitive and metacognitive strategies	Motivation and Management strategies	Type Instrument (<i>n</i> tests)	Effect size
Kramarski and Gutman (2006)	Math	24	9	Regular	Personal	Monitoring, control	None	Self (2)	1,17
Kramarski and Hirsch (2003)	Math	24	8	Regular	None	Planning, monitoring, elaboration	None	Unknown (1)	0,80
					None	Planning, monitoring, elaboration	None	Unknown (1)	0,43
Kramarski and Mevarech (2003)	Math	24	8	Regular	General	Planning, monitoring, elaboration	None	Self (2)	0,55
					General	Planning, monitoring, elaboration	None	Self (2)	0,34
Kramarski and Mizrachi (2006)	Math	24	7	Regular	General	Planning, monitoring, elaboration	Peers	Self (2)	1,80
					General	Planning, monitoring, elaboration	Peers	Self (2)	1,06
Kramarski and Ritkof (2002)	Math	22	9	Regular	General	Planning, monitoring, elaboration	Peers	Self (2)	0,71
Kramarski and Zoldan (2008)	Math	22	9	Regular	General	Monitoring, control	None	Self (4)	0,67
					General	Planning, monitoring, elaboration	None	Self (4)	0,38
					General	Planning, monitoring, control, elaboration	None	Self (4)	0,76
Kramarski et al. (2002)	Math	22	7	Regular	None	Planning, monitoring, elaboration	None	Self (2)	1,02
					None	Planning, monitoring, elaboration	None	Self (2)	1,17
Kramarski, Mevarech, and Lieberman (2001)	Math	22	7	Regular	General	Planning, monitoring, elaboration	None	Self (2)	1,49
					General	Planning, monitoring, elaboration	None	Self (2)	0,56
Lubliner and Smetana (2005)	Reading	77	5	Low SES	General	Monitoring, control, elaboration	Peers	Self (2)	0,60
Mason (2004)	Reading	32	5	Special needs	General	Planning, monitoring, control, elaboration, organisation	None	Self (8)	0,94
Mevarech and Kramarski (2004)	Math	94	8	Regular	None	Planning, monitoring, elaboration	None	Self (1)	0,15
					None	Planning, monitoring, elaboration	None	Self (1)	0,62

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Appendix B (continued)

Authors	Subject	<i>n</i>	Students' grade	Student characteristics	Metacognitive knowledge	Cognitive and metacognitive strategies	Motivation and Management strategies	Type Instrument (<i>n</i> tests)	Effect size
Meyer, Abrami, Wade, Aslan, and Deault (2010)	Other	296	5	Regular	None	Planning, monitoring, control, organisation	Goal orientation, peers	Indep (4)	0,08
Michalsky et al. (2009)	Science	108	4	Regular	Personal	Planning, monitoring, control, elaboration	None	Both (2)	0,79
					Personal	Planning, monitoring, control, elaboration	None	Both (2)	0,62
					Personal	Planning, monitoring, control, elaboration	None	Both (2)	1,62
Molenaar, Chiu, and Slegers (2011)	Writing	110	5	Regular	None	Planning, monitoring, control, elaboration, organisation	Goal orientation, peers	Self (1)	0,45
					None	Planning, monitoring, control, elaboration, organisation	Goal orientation, peers	Self (1)	0,85
Mourad (2009)	Writing	97	7	Special needs	Both	Planning, monitoring, rehearsal, elaboration, organisation	Self-efficacy	Self (1)	2,55
Pennequin et al. (2010)	Math	97	3	Regular	Personal	Planning, monitoring, control, elaboration, organisation	None	Indep (1)	2,17
Perels et al. (2009)	Math	220	6	Regular	Both	Planning, monitoring, control	Self-efficacy, goal orientation	Self (1)	0,45
Perels, Gurtler, and Schmitz (2005)	Math	220	8	Gifted	None	Planning, control, organisation	Self-efficacy, effort	Self (1)	0,23
					None	Planning, control	Self-efficacy, effort	Self (1)	0,33
Peters and Kitsantas (2010a)	Science	170	8	Regular	None	Organisation	None	Self (1)	0,46
Peters and Kitsantas (2010b)	Science	68	8	Regular	None	Monitoring, control	None	Both (2)	0,69
Reynolds and Perin (2009)	Writing	68	7	Low SES	General	Monitoring, ebaloration, organisation	None	Both (2)	0,74
						Control, elaboration, organisation	None	Self (3)	1,26
Sanz de Acedo Lizarraga, Sanz de Acedo Baquedano, and Oliver (2010)	Other	68	11	Low SES	General	Planning, organisatie	None	Self (3)	0,92
					General	Planning, monitoring, control, elaboration, organisation	None	Self (1)	1,22

Appendix B (continued)

Authors	Subject	<i>n</i>	Students' grade	Student characteristics	Metacognitive knowledge	Cognitive and metacognitive strategies	Motivation and Management strategies	Type Instrument (<i>n</i> tests)	Effect size
Souvignier and Mokhlesgerami (2006)	Reading	65	5	Regular	None	Planning, monitoring, control, elaboration, organisation	Self-efficacy, effort	Indep (1)	0,14
		65			None	Planning, monitoring, control, elaboration, organisation	None	Indep (1)	-0,10
		43			None	Monitoring, elaboration, organisation	None	Indep (1)	0,12
		40			None	Planning, monitoring, control, elaboration, organisation	Self-efficacy, effort	Indep (1)	0,49
		198			None	Planning, monitoring, control, elaboration, organisation	None	Indep (1)	0,57
Stoeger and Ziegler (2008)	Math	198	4	Regular	Personal	Planning, monitoring, control	Self-efficacy, goal orientation effort, resources	Self (1)	0,36
Stoeger and Ziegler (2010)	Math	188	4	Regular	General	Planning, control	Goal orientation, effort	Self (1)	0,48
Tajika et al. (2007)	Math	188	6	Regular	None	elaboration	Effort	Self (1)	1,04
Talebi (2009)	Math	43	6	Regular	None	Monitoring	None	Self (1)	0,04
	Reading	43	11	Gifted	General	Planning, monitoring	None	Both (2)	1,15
Teong (2003)	Math	43	6	Special needs	General	Planning, monitoring	None	Both (2)	1,46
					None	Monitoring, control, organisation	None	Self (1)	0,60
Torrance et al. (2007)	Writing	50	6	Regular	General	Planning, monitoring, control, organisation	Task value, peers	Self (3)	2,55
Tracy et al. (2009)	Writing	50	3	Regular	Personal	Planning, monitoring, organisation	Self-efficacy, effort	Self (2)	0,34
					None	Monitoring, elaboration, organisation	Peers	Indep (1)	0,05
Van Keer and Vanderlinde (2010)	Reading	59	3	Regular	None	Monitoring, elaboration, organisation	Peers	Indep (1)	0,05
			6		None	Monitoring, elaboration, organisation	Peers	Indep (1)	0,03
Vaughn, Klingner, and Swanson (2011)	Reading	59	7,5	Regular	Personal	Planning, monitoring, control, elaboration	Peers	Indep (3)	-0,01
Wright and Jacobs (2003) Zion, Michalsky, and Mevarech (2005)	Reading	59	3,5	Special needs	Personal	Planning, monitoring	None	Indep (3)	0,68
	Science	53	10	Regular	General	Planning, monitoring, control	None	Self (2)	0,65
					General	Planning, monitoring, control	None	Self (2)	0,76

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