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Solving multiplication and division problems: latent variable modeling of students' solution strategies and performance

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Solving multiplication and division problems

Latent variable modeling of students' solution strategies
and performance

Fagginger Auer, Marije F.

Solving multiplication and division problems:

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Solving multiplication and division problems

Latent variable modeling of students' solution strategies
and performance

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General introduction

This dissertation concerns the mathematical strategies and performance of students and what factors affect these different aspects of problem solving. Before delving into the research on this point, I would like to invite you to take a moment to solve the multiplication and division problem presented below:

$$23 \times 56$$

$$544 \div 34$$

Were you successful in obtaining the answers? For the multiplication problem, you should have found the answer 1288, and for the division problem the answer 16. And how did you go about obtaining the answers? Did you diligently take up paper and pencil and perform the algorithms you were taught in primary school, or did you perhaps take a less formal approach? Given that you are reading a dissertation, you probably enjoyed quite some years of education or even have a PhD, which means that according to Goodnow (1976), you are especially likely to solve mathematical problems using a mental approach without any external aids.

In taking such an approach, you would not be alone. The line of research that gave rise to this dissertation, comes from the observation of simultaneously declining performance in multiplication and division at the end of Dutch primary school and increasing amounts of problems that are answered without any calculations that are written down (Fagginger Auer, Hickendorff, & Van Putten, 2013; Hickendorff, Heiser, Van Putten, & Verhelst, 2009; Van Putten, 2005). In this dissertation, factors that affect students' solution strategy use and performance are therefore investigated, as well as the statistical techniques that may be used to conduct such an investigation. This introduction provides a framework for this research by discussing solution strategies from a cognitive psychology point of view, and the

place of strategies in developments in mathematics education. The introduction is concluded with an outline of how the different chapters of this dissertation each contribute to the larger theme.

1.1 Solution strategies in cognitive psychology

Learning and problem solving are characterized by the use of a variety of strategies at every developmental stage (Siegler, 2007). This is already evident in children as young as infants: for example, some infants who are in their first weeks of independent walking use a stepping strategy, while others use a twisting strategy, and still others a falling strategy (Snapp-Childs & Corbetta, 2009). First graders who are asked to spell words use strategies as varied as retrieval, sounding out, drawing analogies, relying on rules, and visual checking (Rittle-Johnson & Siegler, 1999). Older children who solve transitive reasoning problems differ in their use of deductive and visual solution strategies (Sijtsma & Verweij, 1999). Solution strategies of children and adults have been a topic of continued investigation for cognitive tasks concerning diverse topics, such as mental rotation and transformation (e.g., Arendasy, Sommer, Hergovich, & Feldhammer, 2011), counting (e.g., Blöte, Van Otterloo, Stevenson, & Veenman, 2004), class inclusion (e.g., Siegler & Svetina, 2006), analogical reasoning (e.g., Tunteler, Pronk, & Resing, 2008), and digital gaming (e.g., Ott & Pozzi, 2012).

A popular topic in solution strategy research is strategy use for arithmetic problems. Many studies have been conducted on elementary addition, subtraction, multiplication and division (e.g. Barrouillet & Lépine, 2005; Barrouillet, Mignon, & Thevenot, 2008; Beishuizen, 1993; Bjorklund, Hubertz, & Reubens, 2004; Campbell & Fugelsang, 2001; Campbell & Xue, 2001; Carr & Davis, 2001; Davis & Carr, 2002; Geary, Hoard, Byrd-Craven, & DeSoto, 2004; Imbo & Vandierendonck, 2007; Laski et al., 2013; Mulligan & Mitchelmore, 1997; Van der Ven, Boom, Kroesbergen, & Leseman, 2012), which concern operations in the number domain up to 100 that are taught in the lower grades of primary school. However, while this elementary arithmetic is the subject of a rich body of literature that has identified the strategies that are used and described their characteristics, there is less research on strategy use by higher grade students on more complex arithmetic problems (though there is some; e.g., Hickendorff, 2013; Van Putten, Van den Brom-Snijders, & Beishuizen, 2005; Selter, 2001; Torbeyns, Ghesquière, & Verschaffel, 2009). This more advanced arithmetic is called multidigit arithmetic, as it involves larger numbers and decimal

numbers.

When solving mathematical problems, especially more complex multidigit problems, there is an array of possible solution strategies. Lemaire and Siegler (1995) proposed a general framework for charting the strategy use for a given domain, consisting of four aspects of strategic competence. The first aspect of the framework is the strategy repertoire, or in other words, which strategies are used. The second aspect concerns the frequency with which each of the strategies in that repertoire is chosen for use. The third aspect is strategy efficiency, which describes the performance of each strategy. The fourth aspect is the adaptivity of the choices that are made between strategies, which can be judged based on task, subject and context variables. Combining these different factors, Verschaffel, Luwel, Torbeyns, and Van Dooren (2009) defined the choice for a strategy as adaptive when the chosen strategy is most appropriate for a particular problem for a particular individual, in a particular sociocultural context.

An important aspect of adaptivity is the degree to which choices between strategies are adapted to the relative performance of those strategies. This performance entails both accuracy and speed, which can be considered simultaneously by defining the best performing strategy as the one that results in the correct solution the fastest (Luwel, Onghena, Torbeyns, Schillemans, & Verschaffel, 2009; Torbeyns, De Smedt, Ghesquière, & Verschaffel, 2009; Kerkman & Siegler, 1997). Performance depends on both the person using the strategy and on the problem the strategy is applied to. In the Adaptive Strategy Choice Model (ASCM; Siegler & Shipley, 1995), a strategy is selected for a problem using individual strategy accuracy and speed information for both problems in general and problems with the specific features of the problem at hand. Another important aspect of adaptivity is the degree to which strategy choices are adapted to the context in which they are made (Verschaffel et al., 2009). Both the direct task context (e.g., demands on working memory, time restrictions, or the characteristics of preceding items) and the sociocultural context can be considered. Examples of influential aspects of the sociocultural context are whether mental strategies are valued over using external aids, whether speed or accuracy is more important, whether using conventional procedures or original approaches is preferred, and whether asking for help in problem solving is desirable (Ellis, 1997).

1.2 Solution strategies in mathematics education

An essential element of the context for mathematical solution strategies is of course the educational system. The educational systems for mathematics underwent quite some changes in the second half of the twentieth century in many Western countries, among which the Netherlands, where the research for this dissertation took place (see descriptions by Klein, 2003, and the Royal Netherlands Academy of Arts and Sciences, 2009). Already prior to this period, there was discontent with mathematics education and its outcomes, but no real changes occurred until the U.S.S.R. launched the first space satellite Sputnik in 1957. This caused a shock in the Western world and an international conference was held in Royaumont in 1959, with the aim of reforming education to advance economical and technological development. Here, a radically different approach to mathematics education was envisioned with the name of 'New Math', which de-emphasized algorithms in light of the uprise of computers and calculators, and focused on set theory and logic instead.

New Math was adopted in various European countries and in the U.S., and mathematics education followed its own course of development after that in each country. For example, in the U.S. (Klein, 2003), New Math's scant attention for basic skills and applications and its sometimes overly formal and abstract nature led to criticisms, and by the early 1970s, New Math programs were discontinued there. During the 1980s, progressivist changes to the curriculum were proposed in the U.S., that revolved around student-centered, discovery-based learning through 'real world' problem solving. Increased attention was prescribed for topics such as cooperative work, mental computation and use of calculators, whereas direct teacher instruction, algorithms (long division in particular) and paper-and-pencil computations were to receive decreased attention (National Council of Teachers of Mathematics, 1989). In the 1990s, these changes were implemented throughout the country, but they also met with resistance from parents and mathematicians, resulting in so-called 'math wars'.

In the Netherlands (Royal Netherlands Academy of Arts and Sciences, 2009), a committee was set to work in 1961 to translate the ideas of New Math into changes of the curriculum, which resulted in publications on a new curriculum in the late 1970s. Though New Math was the starting point for the committee, the end result was something quite different: basic skills remained important (though algorithms to a lesser extent), and clever strategies, estimation, measurement, and geometry were added to the curriculum (Freudenthal, 1973). This new curriculum was labeled 'realistic mathematics', because contexts familiar to students were used

that should make mathematics meaningful. Five core principles were established for realistic mathematics (Treffers, 1987b): students construct their own knowledge, making students' own strategies the starting point; models are used to advance from informal to more formal approaches; students reflect on their own approaches; students learn from their own and others' approaches through interaction; and students are stimulated find connections between what they have learned. By 2002, there were only realistic mathematics textbooks on the market for primary schools. Following a talk that heavily criticized realistic mathematics at a mathematics education conference in 2007 (Van de Craats, 2008), a national debate started.

1.2.1 Strategy use and performance

As can be seen from this short history description, solution strategies were an important aspect of the reforms of mathematics education. Algorithms were de-emphasized in the light of technological advances, while attention for students' problem solving strategies increased. In realistic mathematics, the informal strategies that students invent themselves are used as the building blocks for formalization. Problems do not have a single standardized approach; instead, the multitude of possible strategies is emphasized through interaction, and students have to make choices between strategies when they solve a problem. This makes the adaptivity of strategy choices highly important: selecting the best performing strategy is vital to performance.

That students do not always choose the optimal strategy from the array at their disposal is illustrated by Dutch students' strategy choices for multidigit multiplication and division problems. These are problems with larger or decimal numbers (e.g., 23×56 or $31.2 \div 1.2$), that were typically solved with algorithms in traditional mathematics education. Given the challenging nature of the numbers in these problems, often a variety of informal strategies can be applied (e.g., Fagginger Auer & Scheltens, 2012), and realistic mathematics also introduced new standardized approaches (Treffers, 1987a). Whereas in the traditional algorithms numbers are broken up into digits that can be handled without an appreciation of their magnitude in the whole number, in these new approaches numbers are considered as a whole. The different approaches have therefore been labeled digit-based and whole-number-based respectively (Van den Heuvel-Panhuizen, Robitzsch, Treffers, & Köller, 2009; see Table 1.1 for examples). For multiplication, the digit-based algorithm is usually learned after the whole-number-based approach, but for quite some time this was not the case for division (Buijs, 2008; J. Janssen, Van der Schoot,

Table 1.1: Examples of written work for different multiplication and division strategies for the problems 23×56 and $544 \div 34$.

	digit-based algorithm	whole-number- based algorithm	non-algorithmic written	no written work
23×56	56	56	$1120 + 3 \times 56$	1288
	<u>23</u> ×	<u>23</u> ×	$1120 + 168$	
	168	18	1288	
	<u>1120</u> +	150		
	1288	120		
		<u>1000</u> + 1288		
$544 \div 34$	$34/544 \backslash 16$	$544 : 34 =$	$10 \times 34 = 340$	16
	<u>34</u>	<u>340</u> - $10 \times$	$15 \times 34 = 510$	
	204	204	$16 \times 34 = 544$	
	<u>204</u>	<u>102</u> - $3 \times$		
	0	102		
		<u>102</u> - $3 \times$ + 0 $16 \times$		

& Hemker, 2005). The newest editions of some textbooks do include digit-based division.

The development of students’ strategy use in a context of changing mathematics education can be followed through national large-scale assessments, of which five have taken place in the Netherlands since the late 1980s (Wijnstra, 1988; Bokhove, Van der Schoot, & Eggen, 1996; J. Janssen, Van der Schoot, Hemker, & Verhelst, 1999; J. Janssen et al., 2005; Scheltens, Hemker, & Vermeulen, 2013). Students write down their calculations in the assessment booklets, and from this written work strategy use can be inferred (Fagginger Auer, Hickendorff, & Van Putten, 2015). Analyses of strategy use (Fagginger Auer et al., 2013; Hickendorff et al., 2009) showed that from 1997 to 2004, the use of digit-based algorithms for multidigit multiplication and division decreased considerably, as might be expected given the changes in the curriculum (see Figure 1.1 for strategy use in the assessments of 1997, 2004 and 2011; Table 1.1 provides an example of each of the strategies). However, use of the whole-number-based algorithms and more informal written approaches did not increase accordingly; instead, there was a large increase in the number of problems that were solved without any calculations that were written down. From 2004 to 2011 strategy use remained largely stable, with high levels of answering

without written work. Follow-up research indicated that this answering without any written work should be interpreted as mental calculation (Hickendorff, Van Putten, Verhelst, & Heiser, 2010).

The accuracy of mental strategies was found to be much lower than that of written strategies (see percentage correct rates in Figure 1.1). The increasing choices for an inaccurate strategy rather than for the much more accurate alternatives suggest that the important educational goal of adaptivity is not attained for a substantial part of the students. Especially lower ability students and boys appear at risk in this respect (Hickendorff et al., 2009). The changing strategy choices also appear to have had considerable consequences for performance: the overall performance level for the domain of multidigit multiplication and division decreased sharply from 1997 to 2004 (J. Janssen et al., 2005), and remained at that lower level in 2011 (Scheltens et al., 2013).

This also raises the question of how instruction affects students' performance. As illustrated by the endings of the paragraphs on the history of mathematics reforms in the U.S. and the Netherlands, this is a topic that inspires (sometimes heated) debate. An important contribution to the discussion can be made by empirical investigations that evaluate the actual effects that the prescribed curriculum and different instructional practices have on performance. The existing research on the effects of the curriculum (usually operationalized as the mathematics textbook that is used) finds those effects to be very limited, though studies often lack proper experimental design (Royal Netherlands Academy of Arts and Sciences, 2009; Slavin & Lake, 2008). However, there are considerable effects of teachers' actual instructional behaviors (e.g., positive effects of cooperative learning methods and programs targeting teachers' skills in classroom management, motivation, and effective time use; Slavin & Lake, 2008).

1.3 Contents of this dissertation

This dissertation is an investigation of factors that affect students' mathematical strategy use and performance. Both instruction (in daily practice and special interventions) and students' and teachers' characteristics are considered. This investigation is carried out in the context of multidigit multiplication and division at the end of Dutch primary school. This context has special theoretical and practical relevance: theoretical because it is an interesting case of developments in strategy use in reform mathematics; and practical because it constitutes a direct problem in

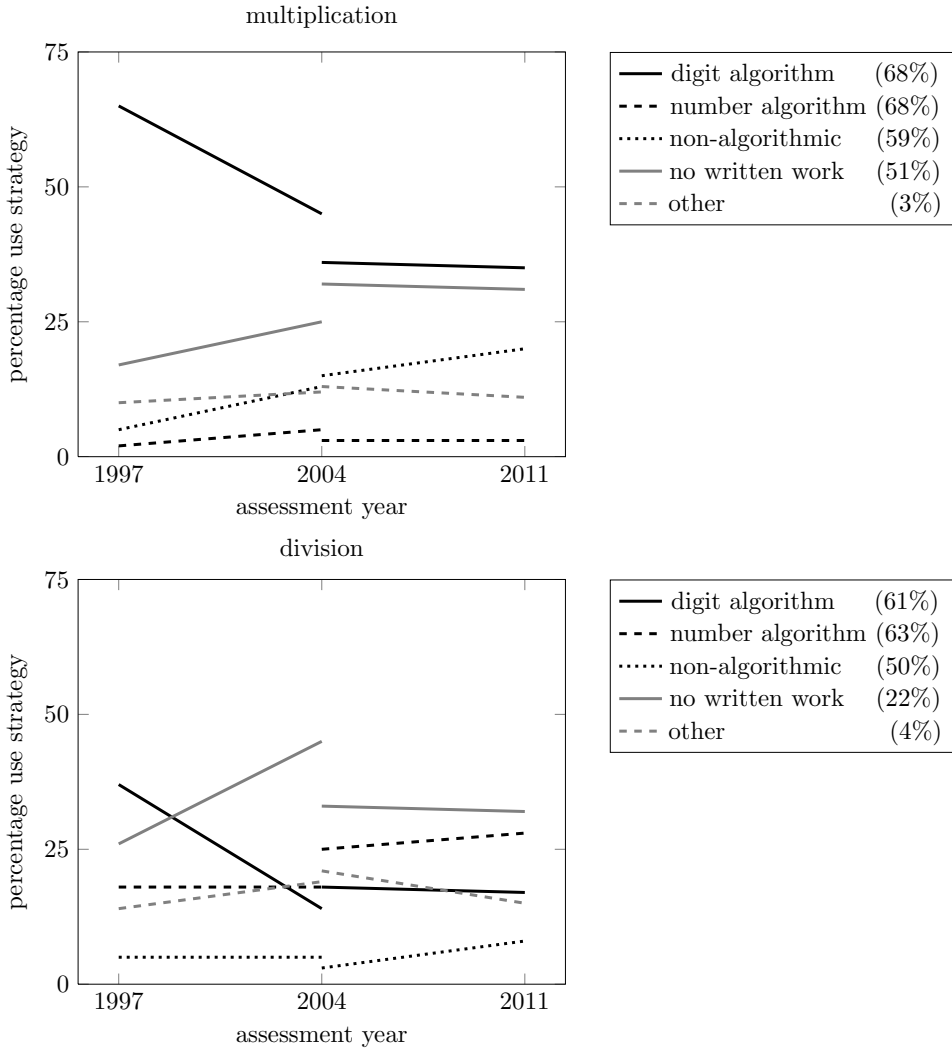


Figure 1.1: Use of the different multiplication and division strategies on the assessments in 1997, 2004 and 2011 (percentage correct per strategy in 2011 is given between brackets). The lines are broken because the items that are compared for 1997 and 2004 are different from those compared for 2004 and 2011.

students' mathematical performance that needs to be addressed. Two approaches to investigating relations with strategy use and performance are taken: secondary analyses of large-scale assessment data and experiments in primary schools.

The first approach is taken in Chapter 2 and Chapter 3, which contain secondary analyses of data from the most recent Dutch large-scale assessment of mathematical ability at the end of primary school. Many of the students participating in this assessment solved several multidigit multiplication and division problems, and the accuracy and strategy use for each of these solutions was coded based on students' written work. The students' teachers filled out a questionnaire on their mathematics instruction: both on general aspects of this instruction and on multiplication and division instruction more specifically. These teacher reports, and student characteristics, were related to students' strategy use (Chapter 2) and to their performance (Chapter 3).

Investigating these relations posed several statistical challenges: how to deal with the large number of items from the teacher questionnaire; the multilevel structure of the data (item responses within students, who are within classes); the nominal measurement level of the strategies; and the incomplete assessment design, in which students do not complete all items but only systematically varying subsets of items. These issues are addressed with latent variable models. In Chapter 2, a first application of multilevel latent class analysis (MLCA) to large-scale assessment data is demonstrated, and several issues in applying this technique are discussed. In Chapter 3, a new combination of LASSO penalization and explanatory item response theory (IRT) is introduced to deal with the large number of teacher variables.

The second approach to investigating the relation between instruction and strategy use and performance is taken in Chapter 4 and Chapter 5, which describe experiments in primary schools. Whereas analyses of large-scale assessments only allow for the investigation of correlational relations, experiments enable causal inference. The experiments in both chapters focus on mental versus written strategy use, given the large performance difference between the two, and consider the effects of student characteristics.

In Chapter 4, it is investigated whether instructing students to write down their calculations actually improves their performance. In a choice/no-choice experiment (Siegler & Lemaire, 1997), students first solved a set of division problems with free strategy choice as usual, but this choice phase of the experiment was followed by a no-choice phase, in which students were required to write down calculations for

another version of the set of division problems, and to not do so for a third version. This experimental set-up allowed for an unbiased assessment of the differences in accuracy and speed between mental and written strategies, and for an investigation of the adaptivity of students' strategy choices. In Chapter 5, it is evaluated what the effects on spontaneous strategy choices and performance are of a training program that features instruction in writing down calculations, using a pretest-posttest design with a control training condition and a no training condition.

Finally, in Chapter 6, a particular aspect of the comparability of results from the first approach in Chapters 2 and 3 and the second approach in Chapters 4 and 5 is considered. It is investigated to which extent strategy and performance results can be generalized from tasks that only concern one mathematical operation (typical in experiments) to tasks in which multiple operations are mixed together (typical in assessments and educational practice). This generalization could be hindered by task switching costs and strategy perseveration, and the occurrence of these phenomena is investigated with an experimental comparison of a single-task and a mixed-task condition.

Multilevel latent class analysis for large-scale educational assessment data: Exploring the relation between the curriculum and students' mathematical strategies

Abstract

A first application of multilevel latent class analysis (MLCA) to educational large-scale assessment data is demonstrated. This statistical technique addresses several of the challenges that assessment data offers. Importantly, MLCA allows modeling of the often ignored teacher effects and of the joint influence of teacher and student variables. Using data from the 2011 assessment of Dutch primary schools' mathematics, this study explores the relation between the curriculum as reported by 107 teachers and the strategy choices of their 1619 students, while controlling for student characteristics. Considerable teacher effects are demonstrated, as well as significant relations between the intended as well as enacted curriculum and students' strategy use. Implications of these results for both more theoretical and practical educational research are discussed, as are several issues in applying MLCA and possibilities for applying MLCA to different types of educational data.

2.1 Introduction

Latent class analysis (LCA) is a powerful tool for classifying individuals into groups based on their responses on a set of nominal variables (Hagenaars & McCutcheon,

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2002; McCutcheon, 1987). LC models have a categorical latent (unobserved) variable, and every class or category of this latent variable has class-specific probabilities of responses in the categories of the different observed response variables. As such, each latent class has a specific typical response pattern where some responses have a higher and others have a lower probability, and different response profiles of individuals may be discerned based on this. For example, for a test covering language, mathematics and science, one latent class of students may have a high probability of correct responses for mathematics and science items but a lower probability for language items, while for an other latent class the probability of a correct response is high for language items and lower for mathematics and science items. These two classes then reflect different performance profiles.

Relatively recently, the technique of LCA has been extended to accommodate an additional hierarchical level (Vermunt, 2003): not only the nesting of variables within individuals is included in the model, but also the nesting of individuals in some higher level group (e.g., students within school classes). This multilevel LCA (MLCA) is beginning to be applied more and more in various areas, such as psychiatry (Derks, Boks, & Vermunt, 2012), political science (Morselli & Passini, 2012), and education (Hsieh & Yang, 2012; Mutz & Daniel, 2011; Vermunt, 2003). In the current investigation, we describe a first application of MLCA to educational large-scale assessment data.

2.1.1 MLCA for educational large-scale assessment data

MLCA can address several of the challenges of large-scale assessment data. A first challenge that many large-scale assessments offer is that they employ so-called incomplete designs: the complete item set is too large to be administered in full to students, and is therefore decomposed into smaller subsets. Relating these subsets to each other is difficult using traditional techniques, but is possible using a latent variable to which all items are related (Embretson & Reise, 2000; Hickendorff et al., 2009), such as the latent class variable in LCA. No imputation of missing responses on the items that were not administered is necessary, as the likelihood function of the analysis is only based on cases' observed responses (Vermunt & Magidson, 2005). A second challenge is the complexity of modeling cognitive phenomena that are not measured on an interval but on a nominal level (such as solution strategy use, item correctness or error types). Nominal response variables are naturally accommodated by (M)LCA.

The third challenge that MLCA addresses is the inherent multilevel structure of

educational data (items nested within students, who are nested within teachers and schools). Previous applications of LCA (and also of other techniques) to students' responses on cognitive tests have generally ignored the teacher (or school) level in their modeling (e.g., Geiser, Lehman, & Eid, 2010; Hickendorff et al., 2009, 2010; Lee Webb, Cohen, & Schwanenflugel, 2008; Yang, Shaftel, Glasnapp, & Poggio, 2005). Yet, the context of learning is vital to its outcomes. Zumbo et al. (2015) recently proposed an ecological model of item responding where responses are influenced by contextual variables at various levels: characteristics of the test, of the individual, of the teacher and school, of the family and ecology outside of school, and of the larger community. Based on this model, the authors demonstrate ecologically moderated differential item functioning (DIF) where different factors in this broader context play a role.

The consideration of a broader context fits in very well with MLCA, as its multilevel aspect makes it especially suited for the incorporation of contextual factors in models of students' item responses. Predictors at different hierarchical levels can be included in the model, a feature that is naturally called for in modeling the effects of both student and teacher characteristics on students' item solving.

In the current investigation, we therefore demonstrate the use of MLCA for educational large-scale assessment data, by applying it to data from the most recent large-scale assessment of Dutch sixth graders' mathematics. We investigate the relation between the curriculum on the one hand and students' use of solution strategies on the other (while controlling for student characteristics), and describe the technique of MLCA and some of the challenges in its application in more detail.

2.1.2 Curriculum effects on students' mathematical achievement and strategies

Recent reviews of research on the effects of mathematics teaching have concluded that the influence of the intended curriculum (as it is formally laid down in curriculum guides and textbooks; Remillard, 2005) on achievement is very small, while changes in the enacted curriculum of daily teaching practices have a much larger influence (Slavin & Lake, 2008). These findings are based mainly on small experiments, and can be supplemented using large-scale assessment data, which does not allow for causal inference but does offer much larger samples and representative descriptions of the natural variation in daily teaching practices (Slavin, 2008).

Previous research has indicated that this variation in instruction has substantial effects on students' achievement growth (Nye, Konstantopoulos, & Hedges,

2004; Rowan, Correnti, & Miller, 2002). In identifying the factors that determine teachers' influence on students' mathematical achievement, a line of research called 'education production function research' has focused on the effects of available resources. Generally, routinely collected information on teachers' resources (such as their education level) has failed to show consistent, sizable effects (e.g., Jepsen, 2005; Nye et al., 2004; Wenglinsky, 2002), while more in-depth teacher resource measurements (such as knowledge for mathematical teaching) show more consistent positive effects (Hill, Rowan, & Ball, 2005; Wayne & Youngs, 2003). The more process-focused line of 'process-product research' has most notably found positive effects of active teaching, which involves teachers' direct instruction of students in formats such as lecturing, leading discussions, and interaction during individual work (as described by Hill et al., 2005, and Rowan et al., 2002), as contrasted with frequent independent work of students and working on nonacademic subjects. Also, positive effects have been found of reform-oriented classroom practice, which involves activities such as exploring possible methods to solve a mathematical problem (Cohen & Hill, 2000).

These results all concern curriculum effects on students' mathematical *achievement*, but the mathematical *strategies* of students that are the focus of this investigation are also of great interest. The various reforms in mathematics education that have taken place in a number of countries in the past decades (Kilpatrick, Swafford, & Findell, 2001) share a view on strategy use that moves away from product-focused algorithmic approaches towards process-focused approaches with more space for students' own strategic explorations (Gravemeijer, 1997). Investigating which instructional practices elicit particular patterns of strategy choices may shed light on how reforms actually affect students' behavior. On a more theoretical level, the literature on children's choices between and performance with mathematical strategies has so far focused on the effects of children's individual characteristics and of the nature of the mathematical problems that are offered (e.g., Hickendorff et al., 2010; Imbo & Vandierendonck, 2008; Lemaire & Lecacheur, 2011; Lemaire & Siegler, 1995), and may therefore be extended by also exploring the effects of instruction.

2.1.3 Multidigit multiplication and division strategies in the Netherlands

An illustration of the connection between mathematics reforms and changes in strategy choices is provided by previous research on multidigit multiplication and

Table 2.1: Examples of the digit-based algorithms, whole-number-based algorithms, and non-algorithmic strategies applied to the multiplication problem 23×56 and the division problem $544 \div 34$.

strategy	multiplication	division
digit-based algorithm	56 $\underline{23} \times$ 168 $\underline{1120} +$ 1288	$34/544 \setminus 16$ $\underline{34}$ 204 $\underline{204}$ 0
whole-number-based algorithm	56 $\underline{23} \times$ 18 150 120 $\underline{1000} +$ 1288	$544 : 34 =$ $\underline{340} - 10 \times$ 204 $\underline{102} - 3 \times$ 102 $\underline{102} - 3 \times +$ $0 \quad 16 \times$
non-algorithmic written strategies	$1120 + 3 \times 56$ $1120 + 168$ 1288	$10 \times 34 = 340$ $13 \times 34 = 442$ $16 \times 34 = 544$

division strategies in the Dutch situation (Hickendorff, 2011; J. Janssen et al., 2005). Multidigit multiplication and division go beyond simple multiplication table facts (such as 5×6 or $72 \div 8$) and require operations on larger numbers or decimal numbers (such as 56×23 or $544 \div 16$). The Dutch mathematics education reform introduced new algorithmic 'whole-number-based' approaches for these multidigit operations, where every step towards obtaining the solution requires students to understand the magnitude of the numbers they are working with (Treffers, 1987a). This approach deviates from the more traditional 'digit-based' algorithms, where the numbers are broken up into digits that can be handled without an appreciation of their magnitude in the whole number (see Table 2.1 for examples of both algorithms). In general, Dutch children's learning trajectory consists of first learning the whole-number-based multiplication and division algorithms, and later switching to the digit-based algorithm for multiplication (and in some schools, also for division; Buijs, 2008).

Using data from large-scale assessments, it was demonstrated that with growing adoption of reform-based mathematics textbooks in Dutch elementary schools, many primary school students abandoned the digit-based algorithms for multidigit

multiplication and division and switched to answering without writing down any calculations (mental calculation; Hickendorff et al., 2010) instead. These mental calculation strategies were found to be much less accurate than written strategies (digit-based or other) (Hickendorff, 2011; Hickendorff et al., 2009), and were used more by boys, students with low mathematical proficiency, and lower SES students.

2.1.4 The present study

In the present study, MLCA is used to investigate the relation between both the intended and enacted curriculum and the use of solution strategies for multidigit multiplication and division items by 1619 Dutch sixth graders (11-12-year-olds). The intended curriculum is operationalized as the mathematics textbook and the enacted curriculum as the self-reports on mathematics teaching practices of the students' 107 teachers. The data are from the most recent (2011) large-scale national assessment of the mathematical abilities of Dutch students at the end of primary school (Scheltens et al., 2013).

Hypotheses

Based on previous research on Dutch students' multiplication and division strategy use by Hickendorff (2011), we expect to find a considerable group of students who mostly answer without written calculations (with relatively many boys, students with low mathematical proficiency, and lower SES students), one group where students mostly use the digit-based algorithm, and one group where students mostly use the whole-number-based algorithm or non-algorithmic approaches. Hickendorff (2011) considered multiplication and division in isolation, but we consider them simultaneously and can therefore analyze the relation between individual differences in strategy use on multiplication and division items. For example, there may be a group of students who prefer the digit-based algorithm for multiplication and the whole-number-based algorithm for division, matching the most common end points of the respective learning trajectories.

The lack of research on the effects of the curriculum on strategy use makes it hard to make strong predictions in that area, but a tentative generalization of curriculum effects on achievement suggests that the effects of the enacted curriculum might be greater than those of the intended curriculum - though this could be countered by the fact that the mathematics textbooks which form the intended curriculum are an important direct source of strategy instruction. As for the particular

effects of the enacted curriculum, the previously discussed achievement literature described positive effects of direct instruction rather than independent work, so these activities might affect choices for more accurate (written) or less accurate (mental) strategies. Differentiated instruction might also have such effects, especially because of the association between ability and strategy choices. Furthermore, we expect effects of teachers' strategy instruction in algorithms, mental calculation, and strategy flexibility, because of the apparent direct connection to students' strategy use.

Issues in applying MLCA

The application of MLCA with predictors which is the focus of the present study comes with several practical issues that require attention. The first is the specification of the multilevel effect in the model. The common parametric approach specifies a normal distribution for group (in our case, teacher) deviations from the overall parameter value, but this distributional assumption is strong and the interpretation of such group effects is abstract. The nonparametric approach proposed by Vermunt (2003) instead creates a latent class variable for the groups (in addition to the latent class variable for the individuals), requiring less strong distributional assumptions, making computations less intensive, and allowing for easier substantive interpretation. Therefore, we will use the nonparametric approach.

The second issue is the inclusion of predictors in the model, as discussed by Bolck, Croon, and Hagenaars (2004). In the so-called one-step approach, the measurement part of the model (the part of the model without predictors) and the structural part (the predictor part) are estimated simultaneously. While this leads to unbiased effect estimates, the number of models that needs to be fitted and compared can quickly become unfeasible (all combinations of lower level and higher level latent class structures, combined with all predictor structures). In addition, the structural part of the model may influence the measurement part: individuals' class membership may be different with and without predictors. These problems do not occur in the three-step approach, where the measurement model without any predictors is fitted first, then individual class membership predictions are computed, and finally these class membership predictions are treated as observed variables in an analysis with the predictors. However, this approach treats class membership as deterministic and leads to systematic underestimation of the effects of the predictors. This can be corrected by taking into account the misclassification in the second step during the final third step (Asparouhov & Muthén, 2014). Therefore,

we will use this corrected three-step approach.

The third issue is the selection of the best model. This is usually done based on information criteria that consider model fit and complexity simultaneously, such as the popular Akaike and Bayesian Information Criterion (AIC and BIC). However, these criteria penalize model complexity differently and therefore often identify different models as optimal (Burnham & Anderson, 2004). The issue is further complicated with the introduction of a multilevel effect, because the BIC penalization depends on sample size, and it is then unclear whether to use the number of individuals or groups for that (Jones, 2011). Lukočienė and Vermunt (2010) investigated this issue and demonstrate optimal performance of the group-based BIC, and underestimation of complexity by the individual-based BIC and overestimation by the AIC. In our analyses, model selection with all three criteria is compared.

2.2 Method

2.2.1 Sample

For our data from the most recent large-scale assessment of the mathematical abilities of Dutch students, 107 schools from the entire country were selected according to a random sampling procedure stratified by socioeconomic status. From a total of 2548 participating sixth graders (11-12-year-olds) in those schools, 1619 students from the classes of 107 teachers (one teacher per school, between 5 and 25 students per school in most cases) solved multidigit multiplication and division problems (because of the incomplete assessment design, not all students solved this type of problems). Of the 1619 children, 49 percent were boys and 51 percent were girls. Fifty percent of the children had a relatively higher general scholastic ability level, as they were to go to secondary school types after summer that would prepare them for higher education, while the other 50 percent were to go to vocational types of secondary education. In terms of SES, most children (88 percent) had at least one parent who completed at least two years of secondary school, while 12 percent did not.

Different mathematics textbooks were used on which the children's mathematics instruction was based. These textbooks are part of a textbook series that is used for mathematics instruction throughout the various grades of primary school, and are therefore not (solely) determined by the sixth grade teacher. All textbooks in our sample could be considered reform-based, but they differ in instruction elements such as lesson structure, differentiation, and assessment. Textbooks from six

Table 2.2: The content of the thirteen multidigit multiplication problems and eight multidigit division problems in the assessment, and the strategy use frequency on each item.

	problem	context	strategy use (percent)						
			DA	WA	NA	NW	U	O	<i>N</i>
M01	$9 \times 48 = 432$	yes	39	4	24	30	2	2	368
M02	$23 \times 56 = 1288$	yes	45	6	21	17	5	6	358
M03	$209 \times 76 = 15884$	no	49	5	24	12	7	3	344
<i>M04</i>	<i>$35 \times 29 = 1015$</i>	yes	40	4	28	23	3	2	353
<i>M05</i>	<i>$35 \times 29 = 1015$</i>	no	43	4	23	24	3	3	352
M06	$24 \times 37.50 = 900$	no	39	2	31	18	6	5	352
<i>M07</i>	<i>$9.8 \times 7.2 = 70.56$</i>	no	40	3	17	27	10	3	352
<i>M08</i>	<i>$8 \times 194 = 1552$</i>	yes	43	3	25	27	2	1	355
M09	$6 \times 192 = 1152$	no	33	2	33	23	4	5	352
M10	$1.5 \times 1.80 = 2.70$	yes	1	0	13	79	3	4	353
M11	$0.18 \times 750 = 135$	no	41	2	16	27	12	2	356
M12	$6 \times 14.95 = 89.70$	yes	32	1	29	34	2	2	359
<i>M13</i>	<i>$3340 \times 5.50 = 18370$</i>	yes	41	3	23	18	10	5	359
<i>D01</i>	<i>$544 \div 34 = 16$</i>	yes	18	32	5	27	10	7	368
<i>D02</i>	<i>$31.2 \div 1.2 = 26$</i>	no	9	10	6	50	18	7	369
D03	$11585 \div 14 = 827.5$	yes	17	30	4	32	10	7	345
D04	$1470 \div 12 = 122.50$	yes	19	25	11	31	12	3	350
<i>D05</i>	<i>$1575 \div 14 = 112.50$</i>	no	17	30	16	22	12	3	355
<i>D06</i>	<i>$47.25 \div 7 = 6.75$</i>	yes	17	25	10	33	10	5	352
<i>D07</i>	<i>$6496 \div 14 = 464$</i>	yes	16	24	5	36	12	7	354
D08	$2500 \div 40 = 62$	yes	12	15	11	45	6	11	359
total multiplication			37	3	24	28	5	3	4613
total division			16	24	9	35	11	6	2852

Note: Parallel versions of problems not yet released for publication are in italics. DA=digit-based algorithm, WA=whole-number-based algorithm, NA=non-algorithmic written, NW=no written work, U=unanswered, O=other

different methods were used in our sample: Pluspunt (PP; used by 37% percent of the teachers in our sample); Wereld in Getallen (WiG; 30%); Rekenrijk (RR; 14%); Alles Telt (AT; 11%); Wis en Reken (6%); and Talrijk (2%).

2.2.2 Materials

Multiplication and division problems

The assessment contained thirteen multidigit multiplication and eight division problems, of which students solved systematically varying subsets of three or six problems according to an incomplete design (see Hickendorff et al., 2009, for more details on such designs). The problems are given in Table 2.2, including whether the problem to be solved was provided in a realistic context (such as determining how many bundles of 40 tulips can be made from 2500 tulips). Students were allowed to write down their calculations in the ample blank space in their test booklets, and these calculations were coded for strategy use. Six categories were discerned: the aforementioned digit-based and whole-number-based algorithms, written work without an algorithmic notation (such as only writing down intermediate steps), no written work, unanswered problems, and other (unclear) solutions (see Table 2.1 for examples). The coding was carried out by the first and third author and three undergraduate students, and interrater agreement was high (Cohen's κ 's (J. Cohen, 1960) of .90 for the multiplication and .89 for the division coding on average, based on 112 multiplication and 112 division solutions categorized by all).

Teacher survey about classroom practice

The teachers of the participating students filled out a survey about their mathematics teaching practices. The 14 questions in the survey that concerned multiplication, division, and mental calculation strategy instruction were used to create four scores (by taking the mean of the standardized responses to the questions), as were the 10 questions that concerned instruction formats, and the 10 questions that concerned instruction differentiation. The Appendix gives the questions that were used to create each score.

2.2.3 Multilevel latent class analysis

We estimated latent classes of students reflecting particular strategy choice profiles using MLCA, which classifies respondents in latent classes that are each characterized by a particular pattern of response probabilities for a set of problems (Goodman, 1974; Hagenaars & McCutcheon, 2002). For our case, let Y_{ijk} denote the strategy choice of student i of teacher j for item k . A particular strategy choice on item k is denoted by s_k . The latent class variable is denoted by X_{ij} , a particular latent class by t , and the number of latent classes by T . The full vector of strategy

choices of a student is denoted by $\mathbf{Y}_{ij}$ and a possible strategy choice pattern by $\mathbf{s}$. This makes the model:

$$P(\mathbf{Y}_{ij} = \mathbf{s}) = \sum_{t=1}^T P(X_{ij} = t) \prod_{k=1}^K P(Y_{ijk} = s_k | X_{ij} = t). \quad (2.1)$$

In this model, the general probability of a particular pattern of strategy choices, $P(\mathbf{Y}_{ij} = \mathbf{s})$, is decomposed into T class-dependent probabilities, $\prod_{k=1}^K P(Y_{ijk} = s_k | X_{ij} = t)$. These class-dependent probabilities are each weighted by the probability of being in that latent class, $P(X_{ij} = t)$. The interpretation of the nature of the latent classes is based on the class-dependent probabilities of strategy choices on each of the problems, $P(Y_{ijk} = s_k | X_{ij} = t)$. The model is extended with a multilevel component by adding a latent teacher class variable, on which students' probability of being in each latent student class ($P(X_{ij} = t)$) is dependent. Predictors at the teacher and student level that influence class probabilities can also be added, as described by Vermunt (2003, 2005). For such a multilevel model with one teacher-level predictor Z_{1j} and one student-level predictor Z_{2ij} , let W_j denote the latent teacher class that that teacher j is in, with m denoting a particular teacher class. The model then becomes:

$$P(X_{ij} = t | W_j = m) = \frac{\exp(\gamma_{tm} + \gamma_{1t}Z_{1j} + \gamma_{2t}Z_{2ij})}{\sum_{r=1}^T \exp(\gamma_{rm} + \gamma_{1r}Z_{1j} + \gamma_{2r}Z_{2ij})}. \quad (2.2)$$

See Henry and Muthén (2010) for graphical representations of this type of models.

The MLCA was conducted with version 5.0 of the Latent GOLD program (Vermunt & Magidson, 2013). All thirteen multiplication and eight division strategy choice variables were entered as observed response variables and a teacher identifier variable as the grouping variable for the multilevel effect. Models with latent structures with up to eight latent student classes and eleven latent teacher classes were fitted, and the model with the optimal structure was selected using the AIC and BICs. Using the three-step approach (Bakk, Tekle, & Vermunt, 2013), this measurement model was then fixed and curriculum and student predictors were added to the model in groups, because of the high number of predictors. The successive models were compared using information criteria and the best model was investigated in more detail by evaluating the statistical significance of each of the predictors with a Wald test. The practical significance of the predictors was

evaluated based on the magnitude of the changes in the probability of class memberships associated with different levels of the predictors. Effect coding was used for all predictors.

2.3 Results

2.3.1 The latent class measurement model

For the LC measurement models fitted on the strategy data, both the AIC and BICs (see Table 2.3) show that adding a multilevel structure greatly improves model fit, signifying a considerable within-teacher dependency of observations. While the AIC identifies a very complex model as optimal (ten latent teacher classes and six latent student classes), the BICs are in near agreement on a more simple model (four latent teacher classes and three or four latent student classes). Of these simpler models, the model with four student classes has a much clearer interpretation and is also favored by the group-based BIC that is optimal according to Lukočiienė and Vermunt (2010). This model has an entropy R^2 of .87 for the latent student classes and .82 for the teacher classes, which both indicate a high level of classification certainty (Dias & Vermunt, 2006).

We also estimated measurement models with a parametric rather than a non-parametric teacher effect (see the bottom part of Table 2.3). The parametric model with the lowest group-based BIC also had four student classes, and the class-specific probabilities of these classes were very similar to those of the classes in the non-parametric model (indicating very similar nature of the classes), but the classes differed considerably in size in the two approaches (by 13, 4, 25, and 15 percentage points respectively). Latent teacher classes cannot be compared as there are none in the parametric approach, which also prevents later easy substantive interpretation of the multilevel effect. The fit of the best parametric model was not better than that of the best non-parametric model according to the information criteria, and the entropy R^2 for the student classes of the parametric model was lower (.80).

Latent student classes

Overall, students solved multiplication problems most often with the digit-based algorithm, while solutions without written work were most frequent for division (see Table 2.2 for frequencies for each strategy). The class-dependent probabilities of choosing each strategy in each of the four latent student classes are given in Table

Table 2.3: Fit statistics for the non-parametric and parametric multilevel latent class models.

latent classes		BIC				
teachers	students	LL	parameters	AIC	individual	group
1 (no multi-level effect)	2	-9801	209	20020	21146	20587
	3	-9388	314	19403	21096	20242
	4	-9165	419	19169	21427	20289
	5	-8964	524	18976	21800	20376
2	2	-9717	211	19856	20993	20419
	3	-9253	317	19141	20849	19988
	4	-8912	423	18670	20950	19800
	5	-8713	529	18484	21335	19898
3	2	-9707	213	19839	20987	20408
	3	-9207	320	19054	20779	19910
	4	-8819	427	18491	20792	19632
	5	-8614	534	18295	21173	19723
4	2	-9705	215	19840	20999	20415
	3	-9178	323	19002	20743	19865
	4	-8790	431	18441	20764	19593
	5	-8585	539	18248	21153	19688
5	2	-9705	217	19844	21013	21965
	3	-9220	326	19092	20849	19963
	4	-8866	435	18257	21189	19711
	5	-8584	544	18234	21167	19689
parametric	2	-9708	210	19836	20968	20397
	3	-9205	316	19042	20745	19887
	4	-8861	422	18566	20841	19694
	5	-8661	528	18377	21223	19789

Note: The lowest BICs are bold. The lowest AIC was for 10 teacher and 6 student classes.

Table 2.4: The mean probabilities of choosing each of the six strategies for the multiplication and division problems for each latent class.

strategy	strategy probability (proportion students in class)							
	NW class (.31)		MA class (.29)		NA class (.21)		DA class (.20)	
	×	÷	×	÷	×	÷	×	÷
DA	.06	.01	.71	.01	.04	.03	.68	.70
WA	.01	.02	.02	.54	.14	.37	.02	.01
NA	.25	.03	.15	.10	.68	.21	.16	.03
NW	.52	.65	.10	.24	.08	.22	.10	.17
U	.13	.23	.02	.06	.03	.08	.03	.03
O	.04	.05	.02	.05	.04	.10	.02	.06

Note: The highest probability per operation within a class is in boldface. MA=mixed algorithm, see Table 2.2 for other abbreviations.

2.4, which shows that every latent student class is dominated by high probabilities of choosing one or two strategies.

The largest student class (with a class probability of .31, i.e., containing 31 percent of students) is characterized by a high probability of answering without written work for every item, and also a considerable probability of leaving problems unanswered (especially division problems). Because of this, we label this class the 'no written work class'. The second largest student class (probability of .29) is characterized by a high probability of solving multiplication problems with the digit-based algorithm and a high probability of solving division problems with the number-based algorithm (the 'mixed algorithm class'). The third largest student class (probability of .21) is characterized by a high probability of solving multiplication problems with non-algorithmic written strategies and a mixture of the number algorithm, non-algorithmic written strategies and no written work for the division problems (the 'non-algorithmic written class'). The smallest student class (probability of .20) is characterized by a high probability of solving both multiplication and division problems with digit-based algorithms (the 'digit-based algorithm class'.)

Latent teacher classes

The latent student class probabilities (or sizes) from Table 2.4 are the mean for all the teachers. Within the four latent teacher classes, the student class probabilities differ greatly. As can be seen in Table 2.5, the probability of the digit algorithm

Table 2.5: The latent student class probabilities in each of the four latent teacher classes.

latent teacher class	latent student class probability			
	NW	MA	NA	DA
1 ($P = .39$)	.27	.61	.11	.00
2 ($P = .30$)	.38	.08	.51	.02
3 ($P = .19$)	.23	.00	.03	.74
4 ($P = .12$)	.34	.22	.09	.36
total	.31	.29	.21	.20

Note: The highest latent student class probability within a latent teacher class is in boldface. See Table 2.2 and 2.4 for abbreviations.

class varies most over teacher classes (between .00 and .74), followed by that of the mixed algorithm class (between .00 and .61), and that of the non-algorithmic written class (between .03 and .51). The probability of the no written work class varies relatively little over teacher classes (between .23 and .38). The largest teacher class (size of .39) is characterized by a high probability of the mixed algorithm class, the second largest teacher class (.30) by a high probability of the non-algorithmic written strategy class, the third largest teacher class (.19) by a high probability of the digit-based algorithm class, and the smallest teacher class (.12) by substantial probabilities for all classes except the non-algorithmic written class.

These insightful results on the magnitude and nature of teachers' effects illustrate one of the advantages of the nonparametric specification of the multilevel effect.

2.3.2 Adding predictors to the latent class model

Next, the structural part was added to the model: predictors for students' probability of being in a particular latent strategy class. First the relation between the intended and enacted curriculum(textbook and instruction) was investigated, using a MANOVA with textbook as the between-group independent variable and the twelve teachers' instruction scores as the dependent variables. No significant relation was found, $Wilks' \lambda = .57$, $F(48, 322) = 1.05$, $p = .39$. Next, student characteristics and intended and enacted curriculum predictors were added to the model in a stepwise fashion. As can be seen in Table 2.6, according to both BICs model fit is best with only the student characteristics as predictors, whereas the AIC identifies the more complex model with all predictors as optimal. The group-

Table 2.6: Fit statistics for the latent class models with successively added predictors.

predictors added to the model		LL	pars	AIC	BIC	
					individual	group
none		-1651	15	3333	3414	3373
student char.	gender, ability, SES	-1569	24	3186	3315	3250
intended curr.	textbook	-1550	36	3172	3366	3268
enacted curr.	strategy instruction	-1517	48	3129	3388	3257
	instruction formats	-1500	60	3120	3443	3280
	instruction diff.	-1479	72	3103	3491	3295

Note: The lowest information criteria are in boldface.

based BIC is nearly as low for the model with the textbook and strategy instruction predictors added as for the model with only student predictors (3257 vs. 3250). Since curriculum effects were our primary interest, we chose to proceed with this more extensive model.

The statistical significance of the covariates in this model was evaluated with Wald tests, and the magnitude of the effects is illustrated by comparisons of the probabilities of membership of the latent student classes for individuals at the different levels of the predictors (see Table 2.7). These probabilities were calculated with all of the other selected predictors in the model set at their mean. For the interval-level instruction variables, probabilities are compared for students of teachers who score one standard deviation above the mean of that variable and students of teachers who score one standard deviation below the mean. Probabilities for the different levels of a predictor that differ by .10 or more are discussed.

Student characteristics

Student gender had a significant effect on class probabilities, $W^2 = 107.1$, $p < .001$, with the probability of being in the no written work class being .33 higher for boys than for girls. The probability of being in the mixed algorithm class was .17 higher for girls than for boys. Students’ general scholastic ability also had a significant effect, $W^2 = 53.0$, $p < .001$, with the probability of being in the no written work class being .25 higher for students with a lower compared to a higher ability, and the probability of being in the non-algorithmic class .12 lower. SES also had a significant effect, $W^2 = 8.4$, $p = .04$, but class probability differences between children with a different SES were all smaller than .10.

Table 2.7: Students' probabilities of membership of the four latent student classes for different levels of the student characteristics and the intended and enacted curriculum predictors.

predictor	compared to	difference in probability of class membership [95% confidence interval]			
		no written work	mixed algorithm	non-algorithmic	digit algorithm
gender ability SES	boys				
	lower	+33 [+31, +34]	-17 [-17, -16]	-09 [-09, -08]	-07 [-08, -07]
	higher	+25 [+23, +26]	-09 [-09, -09]	-12 [-13, -11]	-04 [-05, -04]
textbook	low	+06 [+03, +09]	-04 [-05, -03]	+03 [+02, +05]	-05 [-07, -04]
	PP	+04 [+02, +06]	-05 [-06, -05]	+14 [+13, +14]	-13 [-14, -12]
	total	+06 [+04, +07]	+09 [+09, +10]	-08 [-07, -09]	-08 [-08, -07]
AT	WiG	+06 [+03, +09]	+09 [+07, +11]	+01 [+00, +02]	-16 [-17, -16]
	RR	+03 [+01, +05]	-16 [-16, -16]	+13 [+12, +14]	-01 [-02, +00]
	total	-05 [-08, -02]	-14 [-15, -13]	+04 [+02, +06]	+14 [+11, +16]
digit × digit ÷ mental more	+1SD	-08 [-12, -05]	+25 [+18, +27]	-14 [-14, -12]	-02 [-03, -01]
	-1SD	+03 [+00, +07]	-18 [-18, -17]	-12 [-14, -11]	+26 [+24, +29]
	+1SD	-05 [-09, -02]	+18 [+18, +18]	+02 [+00, +04]	-15 [-17, -13]
	-1SD	+18 [+13, +22]	-35 [-36, -33]	+09 [+08, +10]	+08 [+05, +10]

Note: Probabilities for different levels of a predictor that differ by .10 or more are in boldface.

Intended curriculum

Mathematics textbook had a significant effect, $W^2 = 123.6$, $p < .001$. Students being instructed from the Pluspunt (PP) textbook had a probability for the non-algorithmic class that is .14 higher than that of the total, and a .13 lower probability for the digit-based algorithm class. Students with the Rekenrijk (RR) textbook had a .16 lower probability for the digit algorithm class. Students with the Alles Telt (AT) textbook had a .16 lower probability of being in the mixed algorithm class and a .13 higher probability of being in the non-algorithmic written class. Students with other textbooks had .14 lower probability of being in the mixed algorithm class and a .14 higher probability of being in the digit algorithm class.

Enacted curriculum

All strategy instruction scores had significant effects. When comparing students whose teacher scored one standard deviation above the mean in their focus on the digit-based algorithm for multiplication to students whose teacher scored one standard deviation below the mean (and who were thus more focused on the whole-number-based algorithm for multiplication), their probability of being in the mixed algorithm class was .25 higher, while their probability of being in the non-algorithmic written class was .14 lower, $W^2 = 36.6$, $p < .001$. Students whose teacher scored above rather than below the mean for digit-based division had a .26 higher probability of being in the digit algorithm class, and a .18 and .12 lower probability of being in the mixed algorithm and non-algorithmic written class respectively, $W^2 = 100.9$, $p < .001$. Students whose teacher scored above rather than below the mean in their attention to various aspects of mental calculation had a .18 higher probability of being in the mixed algorithm class and a .15 lower probability of being in the digit algorithm class, $W^2 = 49.0$, $p < .001$. Students whose teachers scored above rather than below the mean for the use of multiple strategies per operation type, had a .35 lower probability of being in the mixed algorithm class and a .18 higher probability of being in the no written work class, $W^2 = 54.0$, $p < .001$.

2.4 Discussion

The present study demonstrated a first application of MLCA to educational large-scale assessment data. We argued that this technique is especially suitable for the challenges of this type of data and for evaluating contextual effects on problem

solving (Zumbo et al., 2015). We demonstrated the added value of adequately modeling the multilevel structure inherent to educational data: though teacher effects are often ignored by researchers, we found them to be considerable. Model fit was much better with than without a multilevel structure for the teacher level, and latent teacher groups were found with large differences in students' probability of having a certain strategy choice profile. Ignoring teacher effects therefore seems to result in the omission of a crucial part of the model, and thereby in an incomplete representation of reality. The present study also demonstrated the relevance of the possibility of including predictors at different hierarchical levels in the model by simultaneously controlling for student characteristics and investigating curriculum effects, which led to interesting results relevant to both educational practice and theory.

2.4.1 Substantive conclusions

The results with regard to strategy choice profiles (or latent classes) that were found were largely in line with our hypotheses: there were profiles dominated by answering without written work, by the digit-based algorithm, by non-algorithmic approaches and the whole-number-based algorithm, and by both algorithms depending on the operation (multiplication or division). Students' probability of being in each of these classes was found to depend strongly on the teacher, because it varied considerably between latent teacher groups. The range was largest for the algorithmic classes and smallest for the no written work class. Therefore, teachers appear to have large effects on students' strategy use, but these effects unfortunately seem smallest for the inaccurate mental strategies without written work.

Intended and enacted curriculum predictors were added, controlling for student characteristics. Consistent with previous research findings, boys and students who were going to a lower secondary school level were more likely to answer without written work. The intended curriculum and enacted curriculum were not significantly related to each other, and were both found to be related to strategy choices, despite the suggestion from the literature of limited effects of the intended curriculum. As for the intended curriculum, the textbooks mostly appeared to be related to students' probability of using the different algorithmic and non-algorithmic written strategies.

As for the enacted curriculum, its relation to strategy use appeared somewhat stronger than that of the intended curriculum. Teaching digit-based algorithms was associated with an accordingly higher use of these strategies, while teaching

whole-number-based algorithms appeared to have the unexpected side-effect of a higher use of non-algorithmic written strategies. Devoting more attention to mental strategies was associated with higher probability of the mixed algorithm class and lower probability of the digit-based algorithm class. Teaching more than one strategy per operation was associated with lower probability of the mixed algorithm class and higher probability of the no written work class. Instruction formats did not have significant effects on strategy use, thereby not confirming our expectations regarding the effects of direct instruction versus independent work. Instruction differentiation also did not have a significant effect.

2.4.2 Limitations

A limitation of the present study could be the sample size, which is both relevant for the estimation of the complex MLCA models and the generalizability of the results. As for the sample size required for the estimation of MLCA models (or LCA models more generally), there are no general rules of thumb. Our sample of 1619 students with 107 teachers seems to be of a similar order of magnitude as those in the examples used by Vermunt (2003) in his introduction of MLCA, where applications were featured with 886 employees in 41 teams, 2156 students in 97 schools, and 3584 respondents in 32 countries. A more precise estimate for a specific situation can be made using Monte Carlo simulations, where factors such as the number and type of problems, the separation of the classes and their relative sizes (approximately equal or not) and the amount of missing data play a role (Muthén & Muthén, 2002; Nylund, Asparouhov, & Muthén, 2007). Nylund et al. (2007) found particular problems with information criteria when a small sample ($N = 200$) was combined with unequal class sizes, as small classes then contain very few subjects. This is not the case in our sample.

Another limitation is the correlational nature of the large-scale assessment data. We of course had no influence on the intended or enacted curriculum, and therefore the causal nature of the found relations between curriculum and strategy use is uncertain and requires further (experimental) investigation. The present study does provide a starting point for such follow-up research. It should also be noted that the intended and enacted curriculum do not reflect (direct) effects of the teachers in our sample to the same extent, as the enacted curriculum is in the hands of the teacher, whereas the intended curriculum (the textbook) is determined on a school level.

2.4.3 Implications

The results suggest several implications (though the limited sample size should be noted). They suggest that models for strategy choices such as the Adaptive Strategy Choice Model (ASCM; Lemaire & Siegler, 1995) may need to be extended to include factors beyond the student and the problem (in line with suggestions by Verschaffel et al., 2009), and the same goes for other investigations of mathematical strategy use that have overlooked instructional factors so far (e.g., Hickendorff et al., 2010; Imbo & Vandierendonck, 2008; Lemaire & Lecacheur, 2011). The results also suggest that the investigations of curriculum effects on achievement may so far have omitted an important mediator: curriculum affects strategy use, and there are strong performance differences between strategies (Hickendorff, 2011; Hickendorff et al., 2009), so the curriculum may (in part) affect achievement through its effect on strategy use.

For educational reforms, our results suggest that although positive effects on achievement have been found of instructional practices congruent with reform ideas (Cohen & Hill, 2000), reform-oriented instruction may also have unexpected side-effects: teaching that is more oriented towards the whole-number-based algorithms introduced by the Dutch mathematics education reform, is not only associated with more use of those algorithms, but also with more use of non-algorithmic strategies that have previously been shown to be less accurate than algorithms (Hickendorff et al., 2009). Finally, our finding that the effects of teachers and the curriculum on the proportion of students who mainly use mental strategies were small suggests that it might be challenging to reduce students' use of mental strategies through means of regular instruction, and that perhaps special interventions are necessary to promote their use of more accurate written strategies.

2.4.4 Conclusion

We would like to conclude by noting that our application of MLCA is relevant to applications of this technique to educational data more generally, and that several generalizations can be thought of: applications to other domains (e.g., strategies in spelling or reading), other types of nominal response data (e.g., error types), and also educational data from other sources than large-scale assessments (e.g., educational intervention studies with a large enough sample). With this article, we hope to have increased the attractiveness and accessibility of MLCA for educational researchers.

Using LASSO penalization for explanatory IRT: An application on instructional covariates for mathematical achievement in a large-scale assessment

Abstract

A new combination of statistical techniques is introduced: LASSO penalization for explanatory IRT models. This was made possible by recently released software for LASSO penalization of GLMMs, as IRT models can be conceptualized as GLMMs. LASSO penalized IRT shows special promise for the simultaneous consideration of high numbers of covariates for students' achievement in large-scale educational assessments. This is illustrated with an application of the technique on Dutch mathematical large-scale assessment data from 1619 students, with covariates from a questionnaire filled out by 107 teachers. The various steps in applying the technique are explicated, and educationally relevant results are discussed.

3.1 Introduction

Data with very high numbers of covariates can be analyzed using regularization methods that place a penalty on the regression parameters to improve prediction accuracy and interpretation, making this type of regression known as penalized regression. A popular form of penalized regression is LASSO (least absolute shrinkage and selection operator), where more and more regression parameters become zero as the penalty increases, thereby functioning as a covariate selection tool (Tibshirani,

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1996). LASSO has so far been applied in many (generalized) linear models, but has only recently been extended to generalized linear mixed models (GLMMs), allowing for the modeling of correlated observations (Groll & Tutz, 2014; Schelldorfer, Meier, & Bühlmann, 2014).

In the present study, we utilize this GLMM extension of LASSO to introduce penalized regression for explanatory item response theory (IRT) models, making use of the possibility of conducting IRT analyses with general GLMM software demonstrated by De Boeck and Wilson (2004). This first use of LASSO penalized explanatory IRT is demonstrated with an application to a large-scale educational dataset, a type of data for which this technique promises to be especially useful as it allows for the simultaneous consideration of high numbers of potentially relevant covariates while optimally modeling achievement.

3.1.1 Explanatory IRT with LASSO penalization for large-scale assessment data

In large-scale educational assessments, achievement in an educational domain is assessed for a large representative sample of students to enable evaluation of the outcomes of an educational system (often that of a country), and to make comparisons to past outcomes or to outcomes of other educational systems. The analysis of achievement data from assessments usually requires the linking of different subsets of a total item set. These can be both subsets of the large complete item set within an assessment and item sets of successive assessments, and can be done using IRT (e.g., Mullis, Martin, Foy, & Akora, 2012; Mullis, Martin, Foy, & Drucker, 2012; OECD, 2013; Scheltens et al., 2013). IRT models achievement by placing persons and items on a common latent scale, and the probability of a correct response depends on the distance between the ability θ_p of a person p and the difficulty β_i of an item i in a logistic function: $P(y_{pi} = 1|\theta_p) = \frac{\exp(\theta_p - \beta_i)}{1 + \exp(\theta_p - \beta_i)}$. This basic IRT model is the Rasch model (Rasch, 1960), which can be extended in multiple ways.

One extension is to make it an explanatory model rather than just a measurement model, by including explaining factors for items' difficulty and persons' ability (De Boeck & Wilson, 2004). These explanatory variables can be labeled in various ways (e.g., as predictors), but we will refer to them as covariates. Whereas in a Rasch model a separate difficulty parameter is estimated for each item, in an item explanatory model (e.g., the linear logistic test model (LLTM); G. H. Fischer, 1973) item covariates that differ across items but not persons (such as number of operations required in a math item) are used to model item difficulty. Similarly,

person covariates that vary across persons but not items (such as gender) can be used to explain ability level, and finally, person-by-item covariates that vary across both persons and items (such as solution strategy use) are also possible. IRT can therefore be used not only to optimally model achievement in large-scale assessments, but also to gain more insight into the factors that affect achievement (e.g., see Hickendorff et al., 2009).

Collection of data on such factors is a part of many assessments, as these assessments include questionnaires on topics such as children’s background and attitudes, teachers’ characteristics and instructional practices, and the conditions in schools (Mullis, Martin, Foy, & Akora, 2012; Mullis, Martin, Foy, & Drucker, 2012; OECD, 2013; Scheltens et al., 2013). These many different factors contribute to achievement jointly, and should be considered simultaneously so that effects are evaluated while controlling for other covariates, and so that the importance of different covariates relative to each other can be determined. However, analyses with very high numbers of covariates can be challenging, especially with models that are already complex models such as explanatory IRT models.

Penalized regression

A common way to deal with the challenge of high numbers of covariates is through so-called penalized regression. As described by Tibshirani (1996), normal regression with ordinary least squares (OLS) estimates can be improved in terms of prediction accuracy and interpretation by penalizing regression coefficients by shrinking them or setting some of them to zero. This can be done in various ways. One way is subset selection, in which a model with a subset of the covariates is selected (through forward or backward selection). Though the reduced number of covariates in this situation facilitates interpretation, small changes in the data can lead to the selection of very different models, creating the risk of chance capitalization and compromising prediction accuracy. A second way, ridge regression, is more stable as regression coefficients are shrunk in a continuous process, but is also more complex in terms of interpretation as none of the coefficients become zero. Tibshirani (1996) proposed a third way, LASSO regression, which seeks to combine stability and interpretability by shrinking some regression coefficients and setting others to zero.

Both in LASSO and ridge regression, the sum of a specific function of the regression parameters has to be smaller than or equal to a tuning parameter t . With ridge regression, this is the sum of the squared coefficients, $\sum_j \beta_j^2 \leq t$, and

with LASSO regression, the sum of the absolute coefficients, $\sum_j |\beta_j| \leq t$. With this restriction, the sum of the squared differences between the observed and predicted y 's, $\sum_{i=1}^N (y_i - \sum_j \beta_j x_{ij})^2$, is minimized. Incorporating the restriction explicitly in the latter equation, this can be alternatively formulated as $\sum_{i=1}^N (y_i - \sum_j \beta_j x_{ij})^2 + \lambda \sum_j \beta_j^2$ or $\sum_{i=1}^N (y_i - \sum_j \beta_j x_{ij})^2 + \lambda \sum_j |\beta_j|$. This whole equation is minimized, which in the case of a λ of 0 results in ordinary regression, but with increasing values of λ in a higher and higher penalization for the sum of the coefficients (until finally all penalized coefficients are zero). The different restrictions on the regression coefficients in ridge and LASSO result in shrunken coefficients in both cases, but generally, only with LASSO coefficients are set to zero (Tibshirani, 1996).

Recently, software has become available that allows for LASSO (but as far as we know, not ridge) penalization for GLMMs (Groll & Tutz, 2014; Schelldorfer et al., 2014). Schelldorfer et al. (2014) implemented GLMM LASSO in an R package entitled `glmmixedLASSO`, and demonstrated the efficiency and accuracy of their algorithm using various simulations with both relatively low (e.g., 10 and 50) and very high numbers of covariates (e.g., 500 and 1500) in logistic and Poisson models. They note that the mixed aspect of GLMMs causes a problem for LASSO, as the shrinkage of regression coefficients can severely bias the estimation of the variance components. They address this issue with a two-stage approach: first the LASSO is used as a variable selection tool, and then in a second step an unpenalized model with the selected variables is fitted using a maximum likelihood method, to ensure accurate estimation of the variance components.

The availability of LASSO for GLMMs makes LASSO penalization for explanatory IRT models possible. IRT models were not developed as a special case of GLMMs but in a separate line of research, with specialized IRT software such as BILOG, PARSCALE and TESTFACT (Embretson & Reise, 2000). However, more recently, De Boeck and Wilson (2004) have described how to formulate IRT models as GLMMs and how to estimate them using general purpose GLMM software, enabling a wider application of this class of models. Therefore, LASSO penalization for explanatory IRT models is now possible, and it can be used for the simultaneous consideration of high numbers of covariates for achievement in large-scale assessment data. In the present study, we apply this new combination of techniques for this purpose. We use it to investigate the effects of various factors on mathematical achievement in a large-scale assessment: children's and teachers' characteristics, as-

pects of teachers' instruction, and the solution strategies that children use to obtain item answers. The existing literature on the effects of these factors on achievement will now be succinctly described.

3.1.2 Covariates for mathematical achievement

Children's characteristics and achievement

Various characteristics of children have been found to be related to mathematical achievement. As for other achievement measures, children with a lower socioeconomic status (SES) generally perform less well in mathematics than children with a higher SES (e.g., Sirin, 2005). Children's general intelligence and mathematical achievement are also positively related (e.g., Primi, Eugénia Ferrão, & Almeida, 2010). While stereotypes still suggest that girls perform less well in mathematics than boys, no general gender differences in mathematical achievement for children are indicated (e.g., J. S. Hyde, Lindberg, Linn, Ellis, & Williams, 2008), though in some countries such differences do exist (e.g., the Netherlands; Scheltens et al., 2013).

Effects of teachers on student achievement

There is large amount of research on the effects that teachers and their instruction methods can have on achievement, in which many different aspects of the teaching process are considered. One obvious indicator of instruction is the formal curriculum provided by the mathematics textbook that is used. However, as noted by Remillard (2005), a distinction must be made between this formal curriculum and what actually takes place in the classroom (i.e., the intended versus the enacted curriculum). A review of the existing research on effective programs in mathematics by Slavin and Lake (2008) demonstrated very limited effects of textbooks, but much stronger effects of programs that targeted the instructional processes in which teachers and children interact in the classroom. Positive effects were found of interventions that concerned classroom management, keeping children engaged, promoting cooperation among children, and supplementary tutoring. In another review, the Royal Netherlands Academy of Arts and Sciences (2009) similarly concludes that there is little support for meaningful effects of the formal curriculum and more for effects of the actual teaching process.

However, these reviews for an important part concern studies with small samples, which could bias results as small studies with null or negative results may be

likely to remain unpublished and therefore not included in reviews (Slavin, 2008). Large-scale assessment data can, though correlational rather than experimental, supplement these findings with its very large and representative samples. This has been done for the investigation of the relation between teacher behaviors and children's achievement in what is called the process-product literature. Studies of this kind have indeed shown that certain teaching practices affect children's achievement, and have for example found a consistent positive effect of time spent on active academic instruction rather than other activities (Hill et al., 2005). The related notion of opportunity to learn (Carroll, 1963) posits that the assessed achievement in a domain depends on the time students have spent in learning about that domain relative to the time they need to learn it. The process-product literature can be contrasted with the educational production function literature, where not processes but the resources of children, teachers and schools are related to student outcomes. These can be resources such as children's SES and teachers' education or their years of teaching experience. Generally, the results on the effects of such factors have been mixed, indicating modest effects at best (Wenglinsky, 2002).

Considering these various findings, the literature seems to suggest that effects of teachers on children's mathematics achievement are more in the actual process of how teachers interact with children, than in general characteristics of the teacher or of the curriculum. This is in line with findings about children's achievement in general, for which a large synthesis of thousands of studies by Hattie (2003) shows that teachers have the largest effects on children's achievement through the teaching behaviors of providing feedback and direct instruction, and through instructional quality.

Solution strategies and achievement

Children's solution strategies for mathematical items are also highly relevant to achievement. These strategies vary from formal algorithms with a fixed notation (such as long division), to informal approaches with a customized notation, to approaches that only comprise mental calculation in the head (see Table 3.1 for examples). Increased attention for children's own strategic explorations (rather than for a prescribed set of algorithmic strategies) is an important part of the reform in mathematics education that has taken place in various countries over the past decades (Gravemeijer, 1997; Kilpatrick et al., 2001; Verschaffel, Luwel, Torbeyns, & Van Dooren, 2007). As such, solution strategies are a crucial part of the instructional process, and they have received ample research attention (e.g., Barrouillet et

Table 3.1: Examples for the multiplication and division strategy categories.

	$\times$	$\div$
digit-based algorithm	$\begin{array}{r} 56 \\ 23 \times \\ 168 \\ \hline 1120 + \\ 1288 \end{array}$	$\begin{array}{r} 34/544 \backslash 16 \\ \underline{34} \\ 204 \\ \underline{204} \\ 0 \end{array}$
whole-number-based algorithm	$\begin{array}{r} 56 \\ 23 \times \\ 18 \\ 150 \\ 120 \\ \hline 1000 + \\ 1288 \end{array}$	$\begin{array}{r} 544 : 34 = \\ \underline{340} - 10 \times \\ 204 \\ \underline{102} - 3 \times \\ 102 \\ \hline \underline{102} - 3 \times + \\ 0 \quad 16 \times \end{array}$
non-algorithmic strategies	$\begin{array}{l} 1120 + 3 \times 56 \\ 1120 + 168 \\ 1288 \end{array}$	$\begin{array}{l} 10 \times 34 = 340 \\ 13 \times 34 = 442 \\ 16 \times 34 = 544 \end{array}$
no written work	1288	544

al., 2008; Siegler & Lemaire, 1997; Torbeyns, Verschaffel, & Ghesquière, 2005).

In the present study, we therefore also devote attention to teachers' specific strategy instruction and to children's strategy use. We focus on strategies for answering multidigit multiplication and division items (items with larger or with decimal numbers, such as 23×56 or $31.2 \div 1.2$), as strategies in this domain have been shown to be highly relevant to achievement for the students in our sample (Dutch sixth graders). In particular, Hickendorff et al. (2009) and Hickendorff (2011) demonstrated a large accuracy advantage for multiplication and division strategies that involved writing down calculations compared to strategies that did not, and within these more accurate written strategies, a higher accuracy of the traditional digit-based multiplication algorithm than of other written approaches for multiplication. The accuracy advantage of written over non-written strategies was larger for children with a lower mathematical ability than for children with a higher ability, and girls wrote down calculations more often than boys.

3.1.3 Present study

In the present study, we consider these various types of covariates in our demonstration of the new combination of the techniques of LASSO penalization and explanatory IRT. We apply the LASSO penalized IRT to a large-scale educational dataset from the most recent (2011) national assessment of the mathematical ability of children at the end of primary school (sixth graders) in the Netherlands, for which no links between instruction and achievement have been investigated yet (Scheltens et al., 2013). Data on item responses, gender, ability and SES were collected for the children, and data on teacher characteristics and instructional practices were collected from the children's teachers.

Hypotheses

Based on our previous discussion of instructional effects on achievement, we expect that covariates that concern instructional practices during mathematics lessons are more strongly related to achievement than teacher characteristics or the mathematics textbook that is used. Several particular instructional practices covered in our covariates can be expected to have a positive relation to achievement. One is that of time spent on group instruction and not other activities, given the positive effect of active academic instruction from the process-product literature (Hill et al., 2005). Another is the frequency of practices that engage children in instruction (such as asking the class questions and letting children write out calculations on the blackboard), given the positive effects of keeping children engaged found in the review of effective programs in mathematics (Slavin & Lake, 2008). Another is practices that involve extra attention for weaker students, through extra support at or outside of school (and perhaps differentiation of instruction more broadly), given the positive effects of supplementary tutoring (Slavin & Lake, 2008).

For strategies, we expect to find written strategies to be associated with higher achievement than mental strategies, and possibly best achievement with the traditional digit-based algorithm (Hickendorff, 2011; Hickendorff et al., 2009). Accordingly, instructional practices focused on mental strategies may be negatively related to achievement, while practices that focus on the digit-based algorithm, or more generally, a single standardized approach rather than multiple approaches, may be positively related to achievement. Since previous research indicates interactions between strategy use and accuracy and children's characteristics (e.g., smaller accuracy difference between written and mental strategies for stronger students; Hickendorff et al., 2009), these interactions were also included in the analyses.

3.2 Method

3.2.1 Sample

Schools were selected for participation in the 2011 mathematics assessment according to a random sampling procedure stratified by socioeconomic status, resulting in a total number of 2548 participating sixth graders (11-12-year-olds) from 107 schools. The children were presented subsets of a large set of mathematical items on a variety of topics, and subsets containing multidigit multiplication and division items were presented to 1619 of the children. These children were in the classes of 107 teachers (one teacher per school), which means that an average of 15 children per teacher participated. Of the 1619 children, 49 percent were boys and 51 percent were girls. Fifty percent of the children had a relatively higher general scholastic ability level, as they were to go to secondary school types after summer that would prepare them for higher education, while the other 50 percent were to go to pre-vocational secondary education. In terms of SES, most children (88 percent) had at least one parent who completed at least two years of medium or higher-level secondary school (SES not low), while 12 percent did not (SES low).

3.2.2 Materials

Multiplication and division items

The assessment contained thirteen multidigit multiplication items and eight multidigit division items in total. These items were administered to children according to an incomplete design (see Hickendorff et al., 2009, for more details on such designs): children were presented systematically varying subsets of either three or six of these items. Table 3.2 provides information on the content of the items: the numbers with which the multiplication or division operation had to be performed and whether these numbers were presented in a realistic context describing a problem situation (such as determining how many bundles of 40 tulips can be made from 2500 tulips) or not. The items were presented in booklets in which children could also write down their calculations and solutions. The children were not given any other paper to write on and were explicitly instructed that if they wanted to write down calculations, they could use the (ample) blank space next to the items in the booklet.

Following the assessment, these calculations were coded for strategy use. For this, five different categories were distinguished. The first two categories are for

algorithmic solutions: the more traditional digit-based algorithm and the newer whole-number-based algorithm. The third category consists of written work without an algorithmic notation, such as writing down only intermediate steps. Table 3.1 gives examples for multiplication and division strategies in these three categories. The two remaining categories are solutions with no written calculations, and a small other category, consisting mostly of unanswered items.

The strategy coding was carried out by three undergraduate students and the first and third author. Parts of the material (112 multiplication and 112 division solutions) were coded by all coders to determine the interrater reliability. Cohen's κ (J. Cohen, 1960) was found to be .90 for the multiplication and .89 for the division coding on average, which indicates high levels of interrater agreement.

Teacher questionnaire about classroom practice

The teachers of the participating children filled out a questionnaire about their mathematics teaching. A total of 39 questions were selected from this questionnaire (see the Appendix) that were either relevant to the mathematics lessons in general (teacher characteristics, mathematics textbook used, and general instructional practices during the mathematics lessons), or that specifically concerned multiplication, division, or mental strategies (the latter because of the aforementioned large achievement difference between strategies with and without written down calculations). Questions that were excluded specifically concerned mathematical domains other than multiplication or division (e.g., addition or percentages) or concerned attitudes or opinions rather than concrete characteristics or instructional practices (e.g., opinion on class size rather than actual class size). Dummy variables were made for questions with nominal response categories and scores were standardized for the other questions (missing values were imputed with the variable mode, because multiple imputation was not feasible given the complex LASSO IRT analyses).

3.2.3 Statistical analysis

The R package `glmmixedLASSO` (Schelldorfer et al., 2014) was used to conduct the LASSO penalized explanatory IRT analysis. As described by De Boeck and Wilson (2004), the explanatory IRT model was specified by using a binomial model with the solution accuracy (incorrect or correct) as the dependent variable, and a random person intercept for the latent ability variable and fixed item effects for the

Table 3.2: The content of the thirteen multidigit multiplication items and eight multidigit division items in the assessment and the percentage of correct solutions.

item	context	N	%
$9 \times 48 = 432$	yes	368	76
$8 \times 194 = 1552$	yes	355	72
$6 \times 192 = 1152$	no	352	70
$35 \times 29 = 1015$	yes	353	69
$6 \times 14.95 = 89.70$	yes	359	66
$1.5 \times 1.80 = 2.70$	yes	353	65
$35 \times 29 = 1015$	no	352	64
$23 \times 56 = 1288$	yes	358	58
$209 \times 76 = 15884$	no	344	54
$24 \times 37.50 = 900$	no	352	47
$0.18 \times 750 = 135$	no	356	36
$9.8 \times 7.2 = 70.56$	no	352	26
$3340 \times 5.50 = 18370$	yes	359	21
total multiplication		4613	56
$544 \div 34 = 16$	yes	368	56
$47.25 \div 7 = 6.75$	yes	352	47
$1575 \div 14 = 112.50$	no	355	41
$1470 \div 12 = 122.50$	yes	350	40
$2500 \div 40 = 62$	yes	359	32
$31.2 \div 1.2 = 26$	no	369	30
$6496 \div 14 = 464$	yes	354	29
$11585 \div 14 = 827.5$	yes	345	26
total division		2852	38

Note: The items in italics are slightly modified parallel versions of items that have not yet been released for publication by Cito because they may be used in subsequent assessments.

item easiness parameters. The person covariates that were added were children's gender (boy or girl), general scholastic ability level (lower or higher) and SES (not low or low), and the questions from the teacher questionnaire. The person-by-item covariate that was added was that for strategy use on the item (with dummy variables for the aforementioned multiplication and division strategy categories). In addition, interactions between strategy use and the three student characteristics (gender, ability and SES) were added. The penalization was not imposed on all covariates: the fixed item effects were specified as unpenalized, so the IRT part of the model remained intact regardless of the degree of penalization. The children's characteristics (gender, general scholastic ability level and SES) were also unpenalized, so that these were always controlled for in evaluating the effects of the instruction and strategies.

The final element of the model to be specified is the degree of penalization, which is determined by λ (as discussed in the introduction). We did this using the approach taken by Schelldorfer et al. (2014), the authors of the `glmmixedLASSO` package: we used the Bayesian Information Criterion (BIC) to select the model that provided the best balance between model parsimony and fit to the data. The BIC is calculated by taking the log-likelihood (LL) of the observed data under the model and imposing a penalty for the number of parameters (k) in the model, weighed by the logarithm of the number of cases (N) (individuals, in our case): $-2LL + \log(N) \times k$ (and asymptotically, the BIC is equivalent to k -fold cross-validation with some optimal k ; Shao, 1997). The lower the BIC, the better the trade-off between model fit and complexity, so the model with the lowest BIC was selected.

As recommended by Schelldorfer et al. (2014), we then reran the model with the selected covariates with the R package `lme4` (Bates & Maechler, 2010), for an unbiased estimation of the random effects. In this model, a random intercept was also added for the teachers to account for the nesting of children within teachers (see Doran, Bates, Bliese, & Dowling, 2007), which is not yet possible in `glmmixedLASSO`. This model was used for final interpretation of the covariate effects.

Expressed mathematically, the explanatory model for the probability of a correct response with J person covariates j (which can be both at the child and teacher level) for child p with teacher t (denoted Z_{ptj} with regression parameter ζ_j), H person-by-item covariates h for child p of teacher t and item i (denoted W_{ptih} with regression parameter δ_{ih}), and I item dummy variables X_i with easiness parameter β_i , is then:

Table 3.3: Use and (observed and estimated) accuracy of the multiplication and division strategies.

	observed				estimated $P(\text{correct})$		
	use (%)		correct (%)		$\times$	$\div$	
	$\times$	$\div$	$\times$	$\div$		boys	girls
digit-based algorithm	37	16	68	61	.76	.61	.63
number-based algorithm	3	24	68	63	.75	.65	.64
non-algorithmic strategies	24	10	59	50	.62	.51	.45
no written work	28	35	51	22	.50	.22	.16
other	8	15	2	2	.05	.05	.07

$$P(y_{pti} = 1 | Z_{pt1} \dots Z_{ptJ}, W_{pti1} \dots W_{ptiH}, X_1 \dots X_I) = \frac{\exp(\eta)}{1 + \exp(\eta)} \quad (3.1)$$

with

$$\eta = \sum_{j=1}^J \zeta_j Z_{ptj} + \sum_{h=1}^H \delta_{ih} W_{ptih} + \sum_{i=1}^I \beta_i X_i + \epsilon_p + \epsilon_t \quad (3.2)$$

3.3 Results

3.3.1 Descriptives

Overall, 56 percent of the multiplication items was solved correctly (varying between 21 percent correct for the item 3340×5.50 and 76 percent for 9×48), and 39 percent of the division items (varying between 26 percent correct for $11585 \div 14$ and 56 percent for $544 \div 34$) (see Table 3.2). Multiplication items were most often solved using the digit-based algorithm, which was also (together with the whole-number-based algorithm) the most accurate strategy with 68 percent of correct solutions (see Table 3.3 for strategy descriptives). Solutions without written work were also frequent (and relatively inaccurate, with 51 percent correct solutions), as were non-algorithmic written strategies (59 percent correct). Division items were most often solved without written work, an approach that was very inaccurate (22 percent correct). Application of the whole-number-based algorithm was also frequent, followed by application of the digit-based algorithm, and both these strategies were relatively accurate (63 and 61 percent correct respectively).

3.3.2 Covariate selection using penalized regression

The LASSO IRT model with penalization on the teacher and strategy covariates was estimated with different settings of λ . All penalized coefficients were shrunk to zero for $\lambda \geq 240$, so models with all (integer) λ s from 0 (no penalization) to 240 (all penalized covariates dropped from the model) were estimated. Figure 3.1 shows the shrinking of penalized regression coefficients over this range, with each line representing one coefficient. The optimal amount of penalization indicated by the BICs (also see Figure 3.1) was found to be at $\lambda = 35$. The 18 penalized covariates with non-zero regression coefficients at this λ are the questions from the teacher questionnaire marked with asterisks in the Appendix and the multiplication and division solution strategy use, and the interaction between division strategy use and student gender.

3.3.3 Effects in the final model

The results of running an explanatory IRT model with the unpenalized and the selected covariates are given in Table 3.4 (the selected questions from the teacher questionnaires are numbered as in the Appendix). Of the unpenalized covariates, performance was found to be significantly related to children's general scholastic ability: higher ability children had a significantly higher probability of a correct response ($P = .58$) than lower ability children ($P = .33$), $z = 13.1$, $p < .001$. Gender did not have a significant effect, $z = 1.1$, $p = .29$, nor did SES, $z = -1.6$, $p = .10$.

Of the selected teacher covariates, the strongest positive effect was of the amount of time spent on group instruction in mathematics lessons ($P = .40$ for 1 SD below the mean and $P = .50$ for 1 SD above the mean). The strongest negative effect was of the amount of support at home ($P = .49$ for 1 SD below the mean and $P = .41$ for 1 SD above the mean).

There were strong effects of the employed solution strategy on the probability of a correct response, both for multiplication and division (see Table 3.3 for the estimated probability per strategy). The accuracy of the whole-number-based algorithms was comparable to that of the digit-based algorithms, while non-algorithmic strategies, strategies without any written work and other strategies (mostly leaving items unanswered) were less accurate (with the smallest accuracy difference for non-algorithmic strategies and the largest for other strategies). There was also an interaction between division strategy use and student gender: most notably, the

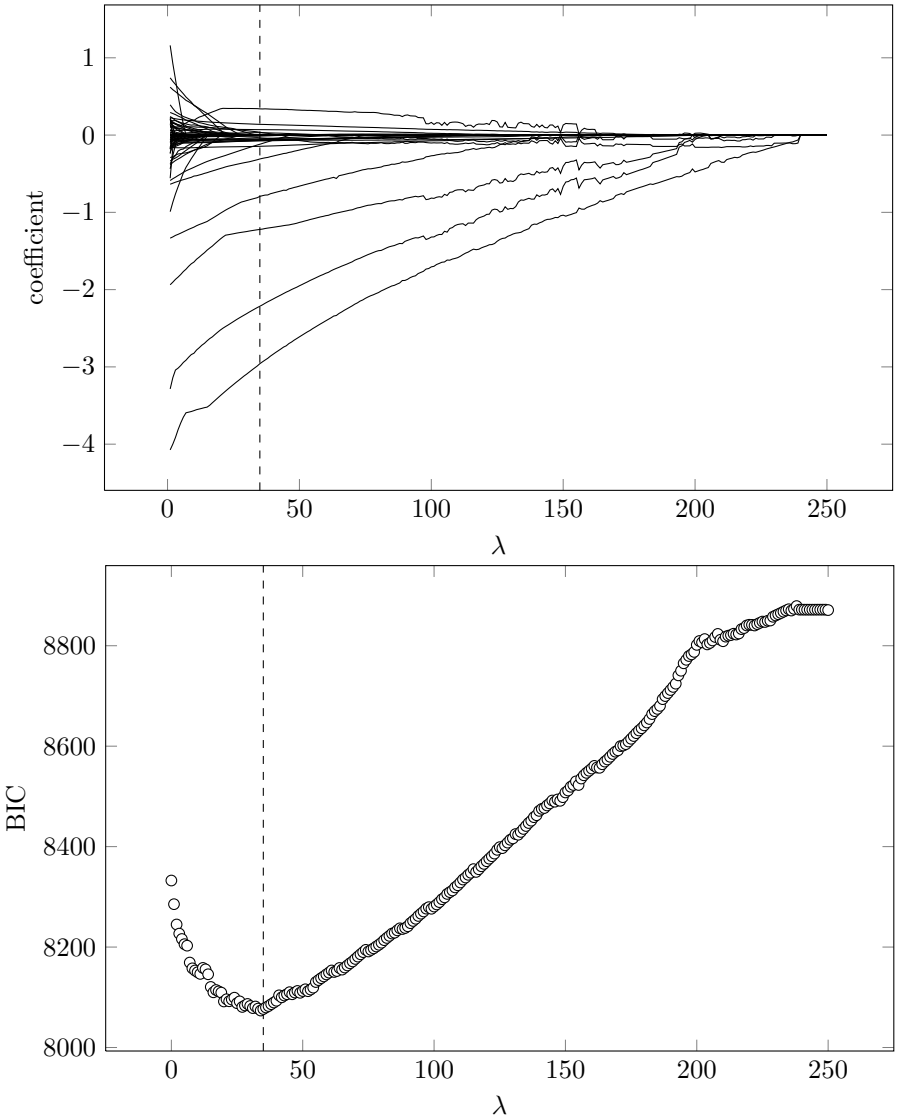


Figure 3.1: Penalized regression coefficients and BICs for the different settings of λ in the LASSO penalized IRT model (dashed vertical line at optimal $\lambda = 35$).

Table 3.4: Effects of the student characteristics and selected teacher covariates.

covariate		levels		estimate (S.E.)
		reference	target	
student char.	gender	boy	girl	0.10 (0.09)
	ability	lower	higher	1.05 (0.08)
	SES	not low	low	-0.20 (0.12)
teacher char.	1. age			0.04 (0.06)
	2. gender	male	female	-0.16 (0.10)
	5. years grade 6			-0.10 (0.05)
general instr.	12. time group instr.			0.18 (0.06)
	13. time indiv. instr.			-0.08 (0.05)
	15. ask class questions			0.01 (0.05)
	16. blackboard solutions			-0.05 (0.05)
	18. discuss errors			-0.01 (0.05)
instr. differ.	19. lesson diff.			-0.09 (0.05)
	22. support at home			-0.17 (0.06)
	23. external support			-0.09 (0.05)
strategy instr.	25. division alg.			0.05 (0.05)
	30. strat. multidigit $\div$	one	multiple	-0.11 (0.10)
	32. ment. mul. div.			-0.07 (0.07)
	35. ment. smart strat.			-0.12 (0.08)
strategy use	multiplication	digit.	number.	-0.03 (0.24)
			non-alg.	-0.63 (0.11)
			no writ.	-1.14 (0.11)
			other	-4.07 (0.27)
	division	digit.	number.	0.19 (0.21)
			non-alg.	-0.40 (0.26)
			no writ.	-1.69 (0.18)
			other	-3.43 (0.33)
	gender $\times$ division	digit.	number.	-0.14 (0.21)
			non-alg.	-0.34 (0.31)
			no writ.	-0.51 (0.21)
			other	0.33 (0.41)

difference in accuracy between the digit-based algorithm and strategies without any written work was larger for girls ($P = .63$ vs. $P = .16$) than for boys ($P = .61$ vs. $P = .22$).

3.4 Discussion

In the present study, we introduced LASSO penalization for explanatory IRT models. This was made possible by recently released software that allows for LASSO penalization of GLMMs (Groll & Tutz, 2014; Schelldorfer et al., 2014), as IRT models can be conceptualized as GLMMs (De Boeck & Wilson, 2004). We argued that this new combination of techniques is especially useful for simultaneous consideration of the effects of the high numbers of covariates for students' achievement that are collected in large-scale educational assessments. This was illustrated with an application of LASSO penalized explanatory IRT to data from the most recent national large-scale assessment of mathematics at the end of primary school in the Netherlands. The various steps involved in applying the technique were explicated and educationally relevant results were discussed.

3.4.1 Substantive conclusions

A first result that was found is that the LASSO did not select formal curriculum covariates as important covariates for students' achievement: at the optimal degree of penalization, the coefficients for the textbook covariate were shrunk to zero. This is in accordance with findings of Slavin and Lake (2008) and the Royal Netherlands Academy of Arts and Sciences (2009) of very limited effects of the formal curriculum. A positive effect of the amount of time the teacher spends on group instruction was found, concordant with the positive effect of time spent on active academic instruction rather than other activities in the process-product literature (Hill et al., 2005). Though we expected practices that involve extra attention for weaker students to be beneficial because of the positive effects of supplementary tutoring (Royal Netherlands Academy of Arts and Sciences, 2009; Slavin & Lake, 2008), the amount of support that students received at home according to their teachers was negatively related to achievement. This could suggest that home support affects achievement negatively, but could also indicate that weaker students receive more home support. However, the teacher reported on the amount of home support only at the class level, and a proper investigation of this effect should be conducted with support measures at the student level.

Children's use of mathematical strategies was also found to play an important role. Strategies with written work were found to be much more accurate than those without written work, as was also found by Hickendorff et al. (2009) and Hickendorff (2011). Within written strategies, these authors found an accuracy advantage of the

digit-based algorithm over other written approaches, and we refined this finding by dividing the other written approaches into the whole-number-based-algorithm and non-algorithmic written strategies. This showed the accuracy of the whole-number-based algorithms to be comparable to that of the digit-based-algorithms, while the non-algorithmic approaches were less accurate. An interaction between gender and division strategy use was also found: strategies without written work were found to be relatively more inaccurate for girls than for boys. Fortunately, girls appear to use strategies without written work less frequently than boys (Fagginger Auer, Hickendorff, Van Putten, Béguin, & Heiser, in press; Hickendorff et al., 2009). It should be noted, however, that the accuracy estimations of the strategies could be biased by the ability of the students using the strategies and the difficulty of the items the strategies are applied to (bias by selection effects; Siegler & Lemaire, 1997), though a statistical correction for such bias is carried out with the inclusion of student ability and item easiness parameters in the model.

3.4.2 Limitations and future directions

The present study also has several limitations, some of which provide directions for future investigation and development.

Mediation student and teacher effects by strategies

A first limitation is substantive in nature. We investigated the effects of student and teacher covariates on student achievement, but some effects may have been obscured because they occurred through strategy use. For example, we found no significant effect of gender per se, but boys do make more use of the inaccurate strategy of answering without any written work (Fagginger Auer et al., in press). As for teacher effects, the sociocultural context is an important determinant of strategy use (Verschaffel et al., 2009), and teacher covariates are significantly related to students' strategy use (Fagginger Auer et al., in press). Given the large differences in students' achievement with different strategies, this means that teacher covariates can exert effects on achievement through strategy use, and these effects may go undetected when strategy use is also in the model. Though hard to incorporate in our current LASSO penalized explanatory IRT analysis, a more thorough investigation of this chain of effects could be done with a mediation analysis. However, it should also be noted that the impact of this issue may be limited, as teachers appear to exert relatively little influence over the strategy that has the largest negative con-

sequences for achievement - answering without any written work (Fagginger Auer et al., in press).

LASSO for correlated covariates

A second limitation is that when LASSO is used for covariates that are (highly) correlated, the selection of covariates can be to some extent random: when there is a near perfect correlation between two covariates, selection of either covariate results in nearly equal prediction of the dependent variable. This limitation is true for LASSO in general and not particular to our LASSO penalized explanatory IRT. However, in their successful simulation tests of the `glmmixedLASSO` procedure, Schelldorfer et al. (2014) included correlations among the covariates of up to .20, and the vast majority (90 percent) of correlations among our teacher covariates fell within that range. Less than one percent of the correlations was large ($\geq .50$), none of which concerned covariates that were found to be significant. Therefore, our results should not be affected too much by correlations among the covariates.

More random effects

A third limitation is that only one random effect could be specified for the LASSO penalization. While this is enough for a basic IRT model, in an educational context (with students nested in classes in schools) a random effect for the teacher or school level is also called for. In addition, in some contexts it makes more sense to model the item effects as random than as fixed - for example when items can be considered random draws from a domain, such as the items in this study from the domain of multidigit multiplication and division (De Boeck, 2008). A larger number of possible random effects (e.g., as in the package `lme4`; Bates & Maechler, 2010) would therefore be an important improvement for LASSO penalized explanatory IRT.

Cross-validation

A fourth limitation is the way in which the optimal degree of LASSO penalization was determined. We did this using the BIC (as in Schelldorfer et al., 2014), but a more common approach is to use cross-validation (e.g., it is a standard option the R package `penalized`; Goeman, 2010). With cross-validation, overfitting is prevented through fitting the model on one part of the data, and evaluating the prediction error of the model on another part of the data (Colby & Bair, 2013). Implement-

ing cross-validation in LASSO GLMM packages would provide an important tool for selecting the amount of penalization in LASSO penalized IRT. One problem with implementing this, however, is that the LASSO penalized IRT is already very computationally intensive with the estimation of just one model for each value of λ , but this should be resolved with ongoing improvements in computational power. Another problem is that cross-validation for GLMMs is not straightforward, but several approaches have been proposed to deal with this issue (Colby & Bair, 2013).

Other IRT models

A final limitation is that not all IRT models can be specified as GLMMs (De Boeck & Wilson, 2004), and therefore that our currently outlined procedure for LASSO penalized explanatory IRT does not apply to all types of IRT models. For example, models that cannot be specified as univariate GLMMs are the popular two-parameter (2PL) model (with item discrimination parameters) and models for polytomous response data. However, there is still ample flexibility within the current Rasch (1PL) framework, as any combination of person, item, and person-by-item covariates that is of interest can be made (e.g., we did not include item covariates, but LLTM-like models that include many potential sources of item difficulty are possible). Therefore, with our current demonstration of LASSO penalized explanatory IRT, we aimed to introduce a new combination of techniques that is versatile and that can lead to insightful results regarding the factors that influence achievement.

3.A Teacher survey questions

(when the same response options apply to multiple questions, those options are given under the last question they apply to for brevity; and the questions selected with the LASSO are marked with asterisks)

3.A.1 Teacher characteristics

1. *What is your age? (*...years*)
2. *What is your gender? (*male / female*)
3. From which teacher education did you graduate? (*PABO (after 1985) / PA, weekschool or kindergarten training (before 1985) / other*)
4. In which grade do you have most teaching experience? (*sixth grade / other grade*)

5. *At the end of this school year, how many successive years have you been teaching in the sixth grade? (*... years*)
6. Have you received extra training in the past five years? (*yes / no*)
7. If so, in what areas have you received extra training? (*optimizing the learning opportunities of students with different backgrounds / evaluating the level of progress of a class / school self evaluation / subject-specific / other*)

3.A.2 Textbook

8. Which textbook do you use (predominantly) for mathematics instruction? (*Pluspunt / Wereld in Getallen / Rekenrijk / Alles Telt / other*)

3.A.3 General instruction

9. How many students are in your class? (*... students*)
10. How much time do you spend on mathematics lessons in an average week? (*... hours*)
11. How many minutes do you spend on multiplication and division in your mathematics lessons in a week? (*<30 minutes / 30-60 minutes / 60-90 minutes / 90-120 minutes / >120 minutes*)
12. *How many minutes do you on average spend on group instruction in a mathematics lesson?
13. *How many minutes do you on average spend on individual instruction in a mathematics lesson?
14. How many minutes do your students on average spend on individual work in a mathematics lesson? (*<10 minutes / 10-20 minutes / 20-30 minutes / 30-40 minutes / >40 minutes*)
15. *How often do you ask the class questions during instruction?
16. *How often do you let students write out calculations on the blackboard?
17. How often do you ask students how they found an answer they gave?
18. *How often do you discuss frequent errors with the class? (*less than once a month / once a month / twice a month / once every two weeks / at least once a week*)

3.A.4 Instruction differentiation

19. *To what extent do you differentiate in your mathematics teaching by level or pace? (*generally no differentiation / differentiation in practice materials but not instruction / differentiation in instruction and materials for different groups / individual instruction and selection of materials*)

20. How much extra learning time do weak students get compared to average students?
(... minutes per week)
21. Are there possibilities for extra individual support in mathematics for students in your school from a remedial teacher or a mathematics specialist? (*no / yes, a remedial teacher / yes, by a care coordinator or mathematics specialist / yes, a remedial teacher and a care coordinator or mathematics specialist*)
22. *How intensive is the support of students at home, by parents or caretakers? (*no support / little support / medium support / frequent support / permanent support*)
23. *How many students receive external support, for example in homework classes?
(... students)

3.A.5 Strategy instruction

24. Which multiplication algorithm reflects the practice in your class most closely?
25. *Which division algorithm reflects the practice in your class most closely?
(*whole-number-based / both / digit-based*)
26. How often do you devote attention to mental calculation and estimation in your mathematics lessons? (... times a week)
27. Do your students use a single or multiple strategies for mental multiplication?
28. Do your students use a single or multiple strategies for mental division?
29. Do your students use a single or multiple strategies for multidigit multiplication?
30. *Do your students use a single or multiple strategies for multidigit division? (*one strategy / multiple strategies*)
31. How much time do you devote to mental calculation and estimation per week?
(... minutes)
32. *How often do you devote attention to basic skills in multiplication and division in mental calculation and estimation?
33. How often do you devote attention to roughly estimating the solution of a problem?
34. How often do you devote attention to applying approximations, estimations and rounding off? (*never / less than once a month / once a month / twice a month / at least once a week*)
35. *How often do you devote attention to finding and using smart number-dependent strategies in mental calculation and estimation?
36. How often do you devote attention to letting students use multiple solution strategies for a single problem type in mental calculation and estimation? (*never / less than once a month / once a month / twice a month / at least once a week*)

37. Are calculators or computer software used during mathematics lessons? (*only calculators / both calculators and computer software / only computer software / neither*)
38. Do you instruct your students in the multiplication function of the calculator? (*yes / no*)
39. Do you instruct your students in the division function of the calculator? (*yes / no*)

Solution strategies and adaptivity in multidigit division in a choice/no-choice experiment: Student and instructional factors

Abstract

Adaptive expertise in choosing when to apply which solution strategy is a central element of current day mathematics, but may not be attainable for all students in all mathematics domains. In the domain of multidigit division, the adaptivity of choices between mental and written strategies appears to be problematic. These solution strategies were investigated with a sample of 162 sixth graders in a choice/no-choice experiment. Children chose freely when to apply which strategy in the choice condition, but not in the no-choice conditions for mental and written calculation, so strategy performance could be assessed unbiasedly. Mental strategies were found to be less accurate but faster than written ones, and lower ability students made counter-adaptive choices between the two strategies. No teacher effects on strategy use were found. Implications for research on individual differences in adaptivity and the feasibility of adaptive expertise for lower ability students are discussed.

4.1 Introduction

Learning and problem solving are characterized by the use of a variety of strategies at every developmental stage (Siegler, 2007). Children's and adults' strategy use has been investigated for cognitive tasks concerning diverse topics such as class inclusion (Siegler & Svetina, 2006), analogical reasoning (Tunteler et al., 2008), and digital gaming (Ott & Pozzi, 2012). A well-studied area of investigation in

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We would like to thank the schools and students for their participation in the experiment.

solution strategy research is strategy use for arithmetic problems. Many studies have been conducted on strategies in elementary addition, subtraction, multiplication and division (e.g., Barrouillet & Lépine, 2005; Imbo & Vandierendonck, 2007; Mulligan & Mitchelmore, 1997; Van der Ven et al., 2012), which concern operations in the number domain up to 100 that are taught in the lower grades of primary school. However, there is a notable scarcity of research on strategy use of higher grade students on more complex arithmetic problems (though not an absence; see for example Van Putten et al., 2005; Selter, 2001; Torbeyns, Ghesquière, & Verschaffel, 2009). This more advanced arithmetic is called multidigit arithmetic, as it involves larger numbers and decimal numbers. Multidigit arithmetic is particularly interesting with regard to strategy use, as the higher complexity of the problems allows for the use of a wider range of strategies.

4.1.1 Solution strategies and adaptivity

To chart strategy use for a given domain, Lemaire and Siegler (1995) proposed a general framework consisting of four aspects of strategic competence: strategy repertoire (which strategies are used); frequency (how often each strategy in that repertoire is chosen for use); efficiency (performance with use of each strategy); and adaptivity (the appropriateness of a choice for a strategy given its relative performance). While the first three aspects of the framework are quite straightforward, the aspect of adaptivity has been conceptualized in various ways by different researchers. Verschaffel et al. (2009) reviewed the existing literature on this topic and identified three factors that play central roles in the different conceptualizations.

First there is the role of task variables, which concern the adaptation of strategy choices to problem characteristics. For example, for a problem such as $62 - 29$ the adaptive strategy choice could be defined as compensation (Blöte, Van der Burg, & Klein, 2001): the problem can be greatly simplified by rounding the subtrahend 29 to 30, and then compensating for this after the subtraction ($62 - 30 + 1$). Second there is the role of subject variables, which concern the adaptation of strategy choices to strategies' relative performance for a particular individual (for a particular problem), such as in the Adaptive Strategy Choice Model (ASCM; Siegler & Shipley, 1995). Third there is the role of context variables, which can be both in the direct context of the task (such as time restrictions) and in the broader socio-cultural context (such as the value placed on accuracy versus speed). Verschaffel et al. (2009) combine all three factors (calling for more research attention for context variables especially) in defining a strategy choice as adaptive when it is most

appropriate for a particular problem for a particular individual, in a particular sociocultural context.

A second issue in determining adaptivity is that often there is not one unequivocal best performing strategy, as the most accurate strategy is not always also the fastest. This can be addressed by combining speed and accuracy in a definition of the best performing strategy as the one that leads to the correct solution the fastest (e.g., Luwel, Onghena, et al., 2009; Torbeyns, De Smedt, et al., 2009; Kerkman & Siegler, 1997). Yet, even with this definition, researchers tend to consider accuracy and speed separately in their statistical analyses in practice (with the exception of Torbeyns et al., 2005).

4.1.2 Adaptive expertise in mathematics education

Debates of its exact definition aside, adaptivity has become more and more important in the educational practice of primary school mathematics. Reforms in mathematics education have taken place in various countries over the past decades (Kilpatrick et al., 2001) and they have reshaped the didactics for multidigit arithmetic from prescribing a fixed algorithmic strategy per problem type to building on students' own strategic explorations (Gravemeijer, 1997). For students, this means that performing well now requires more than perfecting the execution of a limited set of algorithmic strategies, because choosing the best performing strategy for solving a problem is also necessary. Adaptive expertise has become a central element of education: students should have an array of strategies at their disposal, that they can use efficiently, flexibly and creatively when they solve problems (Verschaffel et al., 2009). Investigations differ in their findings of whether such adaptivity is attainable for everyone: some have found evidence of a general adaptivity of strategy choices (e.g., Siegler & Lemaire, 1997; Torbeyns et al., 2005), while others found it only for students with a high mathematical ability (e.g., Hickendorff et al., 2010; Torbeyns, Verschaffel, & Ghesquière, 2006), and some not at all (e.g., Torbeyns, De Smedt, et al., 2009).

In addition to providing more space for informal strategies, the reforms introduced new standardized approaches for the more complex multidigit problems. With traditional algorithms the large numbers in such problems are considered one or two digits at a time, without an appreciation of the magnitude of those digits in the whole number being necessary, while new approaches place more focus on the whole number (as such, the former approaches have been labeled 'digit-based' and the latter 'whole-number-based'; Van den Heuvel-Panhuizen et al., 2009). Espe-

Table 4.1: Examples of applications of the different strategies on $850 \div 25$.

digit-based algorithm	whole-number- based algorithm	repeated addition or subtraction		simplifying strategies
25/850\34	850 : 25 =	4 ×	100	850 ÷ 25
<u>75</u>	<u>250</u> - 10 ×			= 3400 ÷ 100
100	600	32 ×	800	= 34
<u>100</u>	<u>500</u> - 20 ×	<u>2×</u>	<u>50</u>	
0	100	34×	850	
	<u>100</u> - <u>4</u> ×			
	0 34 ×			

cially for multidigit division, digit-based algorithms (e.g., long division) have been de-emphasized or even abandoned in favor of whole-number-based approaches (e.g., partial quotients; Buijs, 2008; Scheltens et al., 2013). Table 4.1 provides examples of digit-based and whole-number-based approaches for division: while they both consist of standardized steps with a schematic notation, the digit-based algorithm breaks the dividend up into digits (e.g., in Table 1, the 85 part of 850 is considered separately when subtracting 75, and the rest of the dividend is only considered in a later step), whereas the whole-number-based algorithm considers the dividend as a whole (e.g., 250 is subtracted from 850).

However, dismissing a digit-based algorithm does not necessarily mean that a whole-number-based algorithm will be used instead; an increase in the use of more informal, non-algorithmic strategies is also possible, even though they may be less suited for challenging problems. For example, the decrease in the use of the digit-based division algorithm in Dutch national assessments from 1997 to 2004 was paired by an almost equal increase in answering problems without writing down any calculations (Van Putten, 2005), which should be interpreted as mental calculation (Hickendorff et al., 2010). This switch from written to mental calculation turned out to be very unfortunate, as the probability for a student to solve a division problem accurately was drastically lower with mental than with written calculation (Hickendorff et al., 2009), and the overall performance level on multidigit division decreased sharply from 1997 to 2004 (J. Janssen et al., 2005). This trend over time of an increasing percentage of students choosing an inaccurate strategy suggests that the reform goal of adaptive expertise may not be feasible for some domains of mathematics.

4.1.3 The present study

The present study therefore constitutes an in-depth experimental investigation of adaptivity in this domain of mathematics that was particularly affected by the reforms: multidigit division. An experimental approach is necessary, because performance estimates of strategies may be biased by so-called selection effects (Siegler & Lemaire, 1997): for example, though mental strategies produce a low percentage of correct solutions for multidigit division problems, this performance estimate may be biased because of the mathematical ability level of the students who choose to use this strategy or because of the difficulty of the problems it is applied to. If mental calculation were used equally by all types of students on all types of problems, then a different estimation of its performance could very well result. Hickendorff et al. (2010) experimentally compared a condition in which students freely chose when to write down calculations and one in which they had to write down calculations for every problem, and found that written calculation was at least as accurate or more accurate than mental calculation, especially for weak students. Mental calculation, however, was only observed in this study when spontaneously chosen and therefore performance estimates were biased by selection effects. In addition, only accuracy and not solution times were measured, so the role of speed in strategy choices and adaptivity remained unclear.

The present study addresses these two issues by experimentally investigating students' spontaneous strategy choices for multidigit division and both their accuracy and speed with required written and required mental calculation. The participants are sixth graders, because the radical changes in performance and strategy use were demonstrated for this age group in the aforementioned large-scale assessment. The aim of the present study is to systematically chart the four aspects of strategic competence of Lemaire and Siegler (1995) - repertoire, frequency, efficiency and adaptivity - with special attention to adaptivity, because of its high relevance to mathematics education and to multidigit division specifically. This was done using the choice/no-choice paradigm introduced by Siegler and Lemaire (1997) to allow for the unbiased assessment of strategy performance characteristics, that has since been applied in numerous solution strategy investigations (e.g., Imbo & Vandierendonck, 2007; Lemaire & Lecacheur, 2002; Torbeyns et al., 2005).

This design consists first of a choice phase in which participants freely choose between strategies in solving a set of problems. This phase provides information on strategy repertoire and the frequency with which strategies in that repertoire are chosen. The choice phase is followed by a no-choice (NC) phase, with a separate

NC-condition for each strategy under investigation, in which participants have to solve (parallel versions of) the problems from the choice phase with that strategy. This provides strategy efficiency estimates unbiased by selection effects, as every participant has to solve each problem with each strategy. Adaptivity can be judged based on the two phases combined: it can be evaluated whether the strategies that the participant chose in the choice phase were the most accurate and fastest in the no-choice phase for him or her.

Hypotheses

There were several hypotheses regarding the four aspects of students' strategic competence in multidigit division. As for strategy repertoire and frequency, previous research indicates that a majority of the students predominantly use written calculation for multidigit division, sometimes with mental calculation for particular problems, while around one third predominantly uses mental calculation (Hickendorff et al., 2009). Girls may use more written calculation than boys, as girls use more algorithmic strategies, while boys tend to use more intuitive, less formal strategies (Carr & Jessup, 1997; Davis & Carr, 2002; Hickendorff et al., 2009). As for strategy efficiency, mental calculation was expected to be less accurate than written calculation (see section 1.2). The fact that mental calculation is used frequently despite its apparent inaccuracy, suggests that it may offer advantages in terms of speed.

As for adaptivity, it was expected that counter-adaptive choices with regard to accuracy would be made for mental rather than written calculation, given the apparent role of increased mental calculation in the Dutch performance decline. Considering the previously described differences in adaptivity for different levels of mathematical ability, this counter-adaptivity may occur particularly in lower ability students. Adaptivity with regard to the sociocultural context was expected, given the large influence on strategy choices that the sociocultural context exerts by defining what choices are appropriate, as described in a review on this topic by Ellis (1997). Among other factors, Ellis (1997) describes cultural values regarding the use of mental strategies and the originality of employed strategies as influential. In the present study, these values (and values regarding the digit-based versus the whole-number-based algorithm) were measured in the students' teachers, and we expected students' strategy choices to be related to these cultural values of the teacher.

Table 4.2: The three versions of the eight problems in the division problem set.

problem							
1	2	3	4	5	6	7	8
$47 \div 2$	$93 \div 4$	$810 \div 30$	$850 \div 25$	$136 \div 32$	$308 \div 14$	$216 \div 6$	$861 \div 7$
$87 \div 2$	$77 \div 4$	$510 \div 30$	$675 \div 25$	$175 \div 28$	$414 \div 18$	$231 \div 7$	$732 \div 6$
$67 \div 2$	$85 \div 4$	$720 \div 30$	$925 \div 25$	$189 \div 36$	$336 \div 16$	$306 \div 9$	$976 \div 8$

4.2 Method

4.2.1 Sample

A sample of 162 sixth graders (11-12-year-olds) from 25 different primary schools participated, of whom 81 were boys (50 percent) and 81 were girls (50 percent). Seventy-two of these students had a mathematical ability score below the national median (44 percent) and the remaining 90 a score above the median (56 percent), as measured by standardized national tests that are administered at most Dutch primary schools (J. Janssen, Verhelst, Engelen, & Scheltens, 2010).

4.2.2 Materials

Division problems

Three comparable versions of a set of eight multidigit division problems were constructed (see Table 4.2). The characteristics of the dividends and divisors were varied systematically: there were two problems with a two-digit dividend and one-digit divisor (e.g., $93 \div 4$); two problems with a relatively easy combination of a three-digit dividend and two-digit divisor (e.g., $850 \div 25$); two problems with a more challenging combination of a three-digit dividend and two-digit divisor (e.g., $308 \div 14$); and two problems with a three-digit dividend and a one-digit divisor (e.g., $861 \div 7$).

Teacher questionnaire

A questionnaire for the students’ teachers was constructed to assess the values regarding arithmetic in the sociocultural context formed by the teacher (see Table 4.3). Two questions in the questionnaire concerned teachers’ values regarding the type of division algorithm (digit-based or whole-number-based). The rest of the questionnaire focused on two values described as influential by Ellis (1997): men-

Table 4.3: The questions from the values questionnaire for the students’ teachers.

Whole-number-based or digit-based algorithm
Which division algorithm best reflects the practice in your class? <i>whole-number-based - both - digit-based</i>
To what extent do you as a teacher prefer a division algorithm? <i>strong preference whole-number-based - digit-based (5-point scale)</i>
Mental versus written calculation
What is important to you when your students solve multidigit problems? <i>that they try that with mental calculation - written calculation (5-point scale)</i>
How important is the skill of writing down calculations to you? <i>not important - very important (5-point scale)</i>
How often do your students write down their calculations? <i>very infrequently - infrequently - sometimes - regularly - often</i>
How important is advising students to write down calculations to you?
How important is instructing students in writing down calculations to you? <i>very unimportant - very important (5-point scale)</i>
Original strategy use
How important is teaching students multiple solution strategies to you?
How important is letting students choose their own solution strategies to you? <i>very unimportant - very important (5-point scale)</i>
How often do you devote attention to convenient solution strategies?
How often do you devote attention to multiple strategies per problem type? <i>< 1/month - 1×/month - 2×/month - 1×/two weeks - ≥ 1/week</i>

Note: Response options are in italics under the question(s) they apply to.

tal (as opposed to written) calculation (five questions) and originality of strategies (four questions). The three scales were found to have adequate reliability (Cronbach’s alphas of .75, .75 and .65 for the algorithm, mental calculation and originality scales respectively). Validity was not separately investigated, but previous research indicates that teachers’ self-reports of instructional practice converge with classroom observations of independent observers and that teachers feel that self-report measures can capture how they teach (Mayer, 1999; Martinez, Borko, & Stecher, 2012).

4.2.3 Procedure

Students were tested individually in a quiet room. They solved the three different versions of the same set of multidigit division problems according to a choice/no-

choice design (Siegler & Lemaire, 1997). The students solved the first set of problems in the choice condition, in which they were free to choose whether they wanted to write down calculations or not. The second and the third problem set were offered in two NC-conditions: one in which the entire set had to be solved without writing down any calculations (the NC mental calculation condition), and one in which calculations had to be written down for every problem in the set (the NC written calculation condition). Both the order in which the different versions of the problem set were presented and the order of the NC-conditions were counterbalanced.

The solution time for each problem was recorded by the experimenter using a stopwatch. Student's strategy use on the division problems was inferred from their written work, and when no calculations were written down for a problem, students were interviewed on their solution strategy. Five different strategy categories were discerned (both within mental and written calculation; see Table 4.1 for examples): the digit-based algorithm; the whole-number-based algorithm (both algorithms were discussed in section 1.2); non-algorithmic strategies that involve repeated addition (or subtraction) of multiples of the divisor; strategies that involve a simplification of the problem (such as the compensation strategy discussed in section 1.1); and remaining solution strategies (unclear strategies, misconceptions such as multiplying rather than dividing, and guessing).

The students' teachers filled out the questionnaire on the day that the experimenter was present at the school for testing, and also solved one of the sets of eight division problems so that their free strategy use and performance could be assessed.

4.2.4 Statistical analysis

Binary logistic mixed models (e.g., Molenberghs & Verbeke, 2006) were used for analyzing the accuracy scores for each problem (correct or incorrect), strategy choices on each problem (mental or written calculation), and students' overall strategy choices in the choice condition (at least once or never mental calculation). Linear mixed models were used for analyzing the proportion of correct solutions with each version of the problem set, and the time students took to obtain the solution to each problem. This solution time was log-transformed to normalize its strongly skewed distribution (as in Klein Entink, Fox, & Van der Linden, 2009).

For analyses at the problem level, random effects were added for the students and the schools, to account for the dependencies of problem solving within students and within schools. For analyses at the student level, only random school effects

were added. All mixed model analyses were carried out using the **SAS** procedure **GLIMMIX** (Schabenberger, 2005). Ninety-five percent confidence intervals (95% CIs) are reported for the regression coefficient estimates (which equal the log of the odds ratio (OR) in the logistic models) and differences in estimated means for an indication of the magnitude of the effects. In addition, the standardized versions of these mean differences (SMDs) are reported as effect sizes for the linear models (where values of 0.2, 0.5 and 0.8 can be considered to reflect small, medium and large effects respectively; J. Cohen, 1988), and ORs for the logistic models (where values of 1.5, 3.5 and 9.0 can be considered small, medium and large respectively; J. Cohen, 1988).

4.3 Results

The difficulty of the three versions of the problem set (aggregated over all conditions) was comparable: students did not differ significantly in their proportion of correct solutions for the first ($M = .62$) and second version ($M = .62$) of the problem set, $z = -0.37$, $p = .71$, 95% CI [-0.04, 0.03], SMD = -0.01 , or for the first and third version ($M = .59$), $z = -1.84$, $p = .07$, 95% CI [-0.07, -0.01], SMD = -0.07 , (and given the intermediate difficulty of the second version, also not for the second and third version).

4.3.1 Strategy repertoire and frequency

Table 4.4 provides information on students' strategy repertoire and the frequency of use of strategies in that repertoire in the three conditions of the choice/no-choice experiment. In the choice condition, students solved 29 percent of the problems using mental calculation, but this varied both between problems (from 18 percent of mental calculation for problem 6 to 56 percent for problem 1) and between students: 40 percent of the students never used mental calculation in the choice condition, 30 percent used it at least once but for less than half of the problems, and 30 percent applied it to half of the problems or more. There were no significant differences between students who did and did not use any mental calculation in the choice condition in terms of gender, $z = 0.24$, $p = .81$, 95% CI [-0.86, 1.10], OR = 1.13, or mathematical ability level, $z = 1.22$, $p = .22$, 95% CI [-0.36, 1.54], OR = 1.80, or interaction between gender and ability, $z = 0.78$, $p = .43$, 95% CI [-0.82, 1.90], OR = 1.72.

Table 4.4: Strategy use in the choice, NC-mental and NC-written calculation condition.

condition	mental/written	dig. alg.	num. alg.	rep. +/−	simp.	rem.
choice	mental (.29)	.01	.14	.46	.20	.18
	written (.71)	.13	.55	.22	.08	.02
NC	mental	.03	.23	.43	.19	.13
	written	.11	.49	.24	.11	.04

Note: dig. alg. = digit-based algorithm; num. alg. = whole-number-based algorithm; rep. +/− = non-algorithmic repeated addition or subtraction; simp. = simplifying strategies; rem. = remaining strategies

In the free strategy choice condition, algorithms (both digit-based and whole-number-based) were used much more often in written than in mental solutions. In contrast, non-algorithmic repeated addition or subtraction and simplifying strategies (and also remaining strategies) were more frequent in mental solutions. The strategy use within mental and within written solutions was similar in the choice and NC-conditions.

4.3.2 Strategy efficiency

We investigated the relative efficiency of mental and written calculation strategies by comparing students' performance in the NC-mental and NC-written calculation conditions (see Table 4.5 for accuracy and speed averages per condition). Students had a higher probability of solving a problem correctly in the NC-written calculation condition (probability of a correct solution (P) of .70) than in the NC-mental calculation condition ($P = .54$), $z = -7.48$, $p < .001$, 95% CI [-1.57, -0.92], OR = 3.48. For below median ability students, the difference in accuracy between NC-written and NC-mental calculation was much larger ($\Delta P = .26$) than for above median ability students ($\Delta P = .06$), $z = 3.72$, $p < .001$, 95% CI [0.34, 1.08], OR = 2.03. The accuracy difference did not depend significantly on student gender, $z = 1.80$, $p = .07$, 95% CI [-0.03, 0.71], OR = 1.40.

As for speed: students solved problems faster in the NC-mental calculation condition (estimated mean problem solving time of 38 s) than in the NC-written calculation condition ($M = 50$ s), $z = -5.52$, $p < .001$, 95% CI [-0.29, -0.14], SMD = -0.39. This speed difference was larger for boys ($\Delta M = 15$ s) than for girls ($\Delta M = 11$ s), $z = -2.47$, $p = .01$, 95% CI [-0.19, -0.02], SMD = -0.20, but did not depend significantly on students' ability level, $z = -1.15$, $p = .25$, 95% CI [-0.14,

Table 4.5: Efficiency of required mental and written calculation in the respective no-choice conditions.

		accuracy		speed	
		(proportion correct)		(problem solving time (s))	
		NC-mental	NC-written	NC-mental	NC-written
gender	girls	.51	.67	48	51
	boys	.56	.65	44	53
ability	below median	.36	.56	49	58
	above median	.68	.74	44	48
total		.53	.66	46	52

0.04], $SMD = -0.09$.

4.3.3 Strategy adaptivity

Student-level correlations

A first indication of adaptivity is a positive relation between the frequency with which a student chooses to use a strategy and the relative performance of that strategy for that student (e.g., more choices for written calculation by students for whom this strategy is generally more accurate and faster than mental calculation). To investigate whether such an adaptive association between strategy choices and performance exists, the total number of choices for written calculation by students was correlated with their relative accuracy with written calculation (number correct with NC-written minus that with NC-mental) and their relative speed (average solution time with NC-mental minus that with NC-written) using Spearman’s rho. Students were found to adaptively choose more written calculation when it was relatively more accurate for them than mental calculation, $\rho = .35$, $df = 156$, $p < .001$, but not significantly so when it was relatively faster, $\rho = .08$, $df = 154$, $p = .32$ (though adaptivity with regard to speed was shown by the subgroup of higher ability students, $\rho_{above} = .24$, $df = 87$, $p = .03$).

Problem level adaptivity scores

However, such correlation analyses - though common in adaptivity investigations (e.g., Kerkman & Siegler, 1997; Siegler & Lemaire, 1997; Torbeyns, Ghesquière, & Verschaffel, 2009; Torbeyns, De Smedt, et al., 2009; Torbeyns et al., 2006) - only reveal general trends at the student level and do not utilize the information that is

available at the problem level in a choice/no-choice experiment, where comparisons can be made between the different strategy conditions in which parallel versions of a single problem are presented. In addition, correlation analyses consider accuracy and speed in isolation, while it is more educationally relevant to consider them simultaneously and define a choice as adaptive when it is for the strategy that produces the correct solution the fastest (as in Luwel, Onghena, et al., 2009; Torbeyns, De Smedt, et al., 2009; Kerkman & Siegler, 1997). Following this definition, the following problem-level adaptivity judgments can be made: when one no-choice strategy was accurate and the other no-choice strategy inaccurate on parallel versions of the same problem for a student (e.g., NC-written correct and NC-mental incorrect on two of the versions of problem 5), a choice for the accurate strategy (in this example, written) on the other version of the problem by that student in the choice condition was defined as adaptive, and a choice for the inaccurate strategy (in this example, mental) as counter-adaptive. When both strategies were accurate, a choice for the faster strategy was defined as adaptive and a choice for the slower strategy as counter-adaptive. The case of two incorrect NC-solutions is undetermined, as then there is no 'best' choice to speak of.

Disregarding the undetermined trials (34 percent of all trials), 62 percent of choices were found to be adaptive using these criteria (of which 67 percent were for written strategies) and 38 percent counter-adaptive. This considerable percentage of counter-adaptive strategy choices was found to hardly vary over gender and ability subgroups (between 61 to 66 percent), though the percentage of undetermined trials was considerably higher in lower (40 percent) compared to higher ability students (29 percent) because of the larger proportion of incorrect answers in the lower ability students.

Relative performance with free strategy choice and required written calculation

In the introduction, it was suggested that requiring students to write down calculations might improve their performance. Therefore, we also investigated the adaptivity of students' strategy choices at the problem level in the following way: we examined whether students performed better in solving a problem when they were required to write down calculations, compared to when they were free to choose whether they wanted to. Table 4.6 shows students' accuracy and speed in the choice and NC-written conditions, separately for mental and written strategy choices in the choice condition. There was no general significant effect of condition on accu-

racy, $z = 1.26$, $p = .21$, 95% CI [-0.15, 0.67], OR = 1.30, but condition did interact with students' strategy choice in the choice condition, $z = 2.15$, $p = .03$, 95% CI [0.07, 1.53], OR = 2.23. There was also an interaction of condition, strategy choice and ability level, $z = -1.95$, $p = .05$, 95% CI [-1.62, 0.00], OR = 2.25: when below median ability students chose mental calculation, their accuracy improved with NC-written calculation (increase in probability of a correct solution of .14), which was not the case for students with an above median ability ($\Delta P = -.02$). When students chose written calculation in the choice condition, accuracy was largely unaffected by condition, both for below median ability students ($\Delta P = .01$) and above median ability students ($\Delta P = .03$). Condition, strategy choice and gender did not interact significantly, $z = -1.33$, $p = .18$, 95% CI [-1.36, 0.26], OR = 1.73.

Requiring written calculation affected speed, $z = -2.42$, $p = .02$, 95% CI [-0.19, -0.02], SMD = -0.22, and this condition effect interacted with strategy choice, $z = 7.51$, $p < .001$, 95% CI [0.43, 0.74], SMD = 1.23: when students chose mental calculation in the choice condition they were slower in the NC-written condition ($\Delta M = 19$ s), which did not hold when students chose written calculation ($\Delta M = -2$ s). This slowing effect of NC-written calculation when students chose mental calculation was stronger for higher ability students ($\Delta M = 21$ s) than for lower ability students ($\Delta M = 17$ s), $z = 2.59$, $p = .01$, 95% CI [0.05, 0.39], SMD = 0.46. Condition, strategy choice and gender did not interact significantly, $z = -0.65$, $p = .51$, 95% CI [-0.22, 0.11], SMD = -0.11.

Teachers' effects on strategy choices

No significant teacher effects on students' choices between mental and written calculation in the choice condition were found. Firstly, there were no significant effects of teacher's responses on the teacher questionnaire. To investigate this, mean scores were calculated for the responses per category (with one question transformed to a five-point scale). For the questions on the whole-number-based versus digit-based algorithm, these mean scores showed that teachers were on average more oriented towards the whole-number-based approach ($M = 2.20$, $SD = 1.33$), but these scores had no significant effect on students' use of mental calculation, $z = -0.42$, $p = .68$, 95% CI [-0.53, 0.34], OR = 1.10. Mean scores for the questions on mental versus written computation showed that teachers on average considered written computation more important ($M = 4.27$, $SD = .49$), but these scores also had no significant effect, $z = 0.26$, $p = .80$, 95% CI [-0.96, 1.25], OR = 1.16. Mean scores for the questions on originality showed that teachers on average found orig-

Table 4.6: Performance in terms of accuracy and speed with free strategy choice and NC-written calculation, split by strategy choice in the choice condition.

		accuracy (proportion correct)			
		mental choice		written choice	
		choice	NC-written	choice	NC-written
gender	girls	.52	.64	.68	.68
	boys	.66	.59	.68	.68
ability	lower	.40	.50	.57	.58
	higher	.73	.69	.73	.76
total		.60	.62	.66	.68
		speed (problem solving time (s))			
		mental choice		written choice	
		choice	NC-written	choice	NC-written
gender	girls	29	48	60	52
	boys	25	46	59	57
ability	lower	33	51	64	60
	higher	23	44	55	49
total		27	47	59	54

inality important ($M = 4.04$, $SD = .76$), but these scores also had no significant effect, $z = -0.21$, $p = .84$, 95% CI [-0.95, 0.76], OR = 1.09. Secondly, there were no significant effects of how the teachers solved the eight problems: neither for the number of times a teacher used mental calculation ($M = 2.13$, $SD = 2.03$), $z = 0.10$, $p = .92$, 95% CI [-0.27, 0.30], OR = 1.01; nor for the number of correctly solved problems ($M = 6.61$, $SD = 1.12$), $z = -0.99$, $p = .33$, 95% CI [-0.79, 0.26], OR = 1.30.

4.4 Discussion

In this study, students’ mental and written solution strategies for multidigit division problems were investigated. Using the choice/no-choice paradigm, the four dimensions of strategy use proposed by Lemaire and Siegler (1995) were charted: repertoire, frequency, efficiency, and adaptivity. The repertoire that students demonstrated contained mental strategies for more than half of the students, half of whom applied it to a majority of the problems. In line with the more informal nature of mental strategies (Blöte, Klein, & Beishuizen, 2000), mental strategies were found to be non-algorithmic and simplifying more often than written strate-

gies. As expected, mental strategies were found to be faster but less accurate than written strategies, and earlier estimates of the inaccuracy of mental strategies (Van Putten, 2005) were probably even still too optimistic because of selection effects (Siegler & Lemaire, 1997): the percentage correct difference between mental and written strategies was smaller in the free strategy choice condition (6 percentage points) than in the unbiased NC-conditions (13 points).

We first investigated adaptivity by evaluating the degree to which students adapted their strategy choices to their relative performance with these strategies. Using student-level correlations, students were found to adaptively choose written strategies more when these were relatively more accurate for them than mental strategies, and above median ability students also when written strategies were relatively faster. However, using problem-level adaptivity scores that labeled a strategy choice as adaptive when it was for the fastest accurate strategy, we found that a considerable portion of the strategy choices was counter-adaptive (around a third), also for higher ability students. Particular counter-adaptivity was indicated for lower ability students who chose mental calculation, as their accuracy improved when they were required to write down calculations - which was also found by Hickendorff et al. (2010), though they did not find the effect to depend on ability level.

Following the suggestion of Verschaffel et al. (2009) of high importance of the sociocultural context, we also devoted attention to adaptivity in the sense of adaptation of solution strategies to that context in the form of the students' teachers attitudes towards various aspects of strategy use and teachers' own strategy application. However, we found no significant effects, suggesting that students' division strategy use may not be very sensitive to that context, at least to the extent that that context is shaped by their current teacher. Other studies of sociocultural context effects which operationalized that context more broadly did find effects, for example by including parents in addition to teachers (Carr & Jessup, 1997), or contrasting vastly different contexts in which Brazilian children functioned as a street vendor or as a student (Nunes, Schliemann, & Carraher, 1993). Sociocultural effects on mental division strategy use might therefore be found by taking broader approaches such as also including teachers from earlier stages of mathematics learning instead of only the teacher from the final year of primary school, or by also including less formal sociocultural influences such as parents and peers. Contrasting distinct contexts could be achieved by comparing mental strategy use in different countries.

Several interesting individual differences were found. Mental strategies offered boys a larger speed advantage relative to written strategies than they did for girls, which could contribute to the finding of Hickendorff et al. (2009) that boys use mental strategies more than girls (though we did not replicate that finding). As for ability level, while the rate of choices for mental strategies did not differ significantly between levels, the accuracy advantage of written compared to mental strategies was larger for lower than for higher ability students, and lower ability students demonstrated less adaptivity (as in several other studies, e.g., Foxman & Beishuizen, 2003; Hickendorff et al., 2010; Torbeyns et al., 2006). These results indicate that mental strategies are especially risky for lower ability students: not only are these strategies especially inaccurate for this group, these weaker students also appear to have problems with determining when they should and should not be applied. What makes this especially worrisome, is that lower ability students nonetheless appear to use mental strategies as often as higher ability students (or even more often, as found by Hickendorff et al., 2009).

The finding that lower ability students benefit from being required to write down calculations while higher ability students do not (who instead are slowed down more) is in line with the expertise reversal effect in cognitive load theory, which states that instructional techniques can have differential (and even reversed) effects on cognitive load (and thereby, performance) depending on the expertise of the learner (Kalyuga, Ayres, Chandler, & Sweller, 2003). In low-expertise students, writing down calculations may free working memory resources for division problems that otherwise pose a cognitive load that is too high, whereas in high-expertise students, writing down calculations may be a redundant activity that places an unnecessary extra load on those resources. Such an expertise reversed effect implies that this technique of requiring writing down calculations should only be used for expertise levels for which it is effective: lower ability students.

4.4.1 Methodological considerations

Two aspects of the methodology of the current investigation warrant further attention. The first is the strategies evaluated in the choice/no-choice experiments. The choice/no-choice paradigm is often employed to compare specific strategies such as direct subtraction and indirect addition (Torbeyns, Ghesquière, & Verschaffel, 2009), but in our case broader categories of strategies are compared. As criticized by Luwel, Onghena, et al. (2009), such broad categories can in turn consist of several strategies, which is indeed the case here (both written and mental strategies are

further classified into five categories). However, we argue that our comparison of mental and written strategies is very meaningful in light of their large performance difference and the apparently important role of this difference in performance level changes (as discussed in the introduction), and note that in their introduction of the choice/no-choice paradigm, Siegler and Lemaire (1997) also compared mental and written strategies. In addition, comparing more specific division strategies in the Dutch situation is complicated, as the division strategies that Dutch students are taught differ and therefore not all students can be expected to be able to execute particular strategies.

The second methodological aspect is the statistical conceptualization of adaptivity. In this study different approaches were taken, that each shed their own light on the degree of adaptivity displayed by (subgroups of) students. A first consideration is the level at which adaptivity is evaluated. Performance on individuals problems may be unreliable, making aggregating over problems necessary for stable results Luwel, Onghena, et al. (2009), but this discards a lot of information and treats problems as if they are interchangeable, which even within a domain as specific as multidigit division seems unreasonable (e.g., see Table 4.2). The ASCM posits that strategy choices are based on a weighted combination of global data averaged over all problems, featural data per particular structural problem feature, and local data per particular problem, and that the weighing depends on the familiarity of the problem (Siegler & Shipley, 1995). Therefore, it might be argued that aggregating over all problems is more suitable when problems are relatively unfamiliar, and less so when problems or problem features are more familiar. The present study appears to lie somewhere in between, as multidigit division should be by a very familiar domain for students, but particular problems are typically not repeatedly encountered, and both problem and individual approaches were taken.

A second consideration in determining adaptivity - also touched upon in the introduction - is whether to consider accuracy and speed in isolation or to combine them. In this study both approaches were taken, and for the combination speed was only considered when both strategies were accurate, defining choices for the fastest accurate strategy as adaptive (as in Luwel, Onghena, et al., 2009; Torbeyns, De Smedt, et al., 2009; Kerkman & Siegler, 1997). Trials where both NC-solutions were inaccurate remained undetermined, which is not the case when speed is considered in isolation, but one could question whether speed differences for inaccurate strategies are as relevant as those for accurate strategies. All in all, we urge investigators of adaptivity to be aware that different choices with regard to analysis level

and accuracy and speed can highlight different aspects of adaptivity.

4.4.2 Implications

The findings of this study have implications for cognitive psychological research on solution strategies and for educational practice. As for cognitive research, we found that written strategies appear to be chosen more for their accuracy, while mental strategies appear to be chosen more for their speed. These considerations did not play in equal measure in everyone: the strength of the accuracy effect depended on mathematical ability level and the strength of the speed effect on gender, and differences in adaptivity indicated that students differ in the extent to which they adapt their strategy choices to strategies' accuracy and speed. Choices between mental and written calculation may therefore in part be determined by individual differences in the relative value assigned to accuracy and speed, and therefore in part reflect students' speed-accuracy tradeoff (MacKay, 1982). Factors that may play a role in the relative favoring of accuracy and speed are traits which are traditionally associated with academic success (Bembenutty, 2009): academic delay of gratification (which is generally higher in girls) parallels sacrificing speed for accuracy, and self-efficacy (higher in boys) could determine the speed that students allow themselves while still feeling confident about their accuracy. Future research on adaptivity could extend existing models such as the ASCM (Siegler & Shipley, 1995) to accommodate individual differences in preferences for accuracy and speed, and provide more insight into the sources of these individual differences by relating them to other factors such as the ones discussed.

As for educational practice, results suggest that for some students it may be too ambitious to strive for what is a central element of mathematics reforms: adaptive expertise in choosing from an array of formal and informal strategies, rather than mastery of a limited set of algorithmic strategies. We found that lower ability students appear to use mental strategies as often as higher ability students, while mental strategies are especially inaccurate for them and adaptivity in choosing when to apply these strategies appears problematic. Lower ability students' performance may therefore be improved by providing them with more direction in their strategy choices. The present study provided support for beneficial effects of doing this directly by simply requiring students to write down calculations, and a broader change in strategy behavior might be accomplished by targeting the sociocultural context (Verschaffel et al., 2009).

As described in a review by Ellis (1997), cultural values in this context concern-

ing various aspects of problem solving exert an important influence on children's strategy choices. She discusses values regarding speed and accuracy, mental strategies, originality, and independent performance, and contrasts these values in different cultures (such as Western cultures as apposed to Navajo, Asian and aborigine cultures). Given the results of the present study, values for speed and accuracy and mental strategies appear especially relevant to performance in multidigit arithmetic. The suboptimal choices for mental strategies that we have observed may be related to typical Western values in these areas: the favoring of fast performance (rather than error-free performance, as for example in the Navajo culture), and of solutions constructed in the head without any external aids. Therefore, performance might be improved by making efforts to adjust these norms so that accuracy is more important than speed, and that solutions constructed in the head are not more desirable than those constructed with the external aids of paper and pencil. The results of the present study suggest that such an adjustment may require a broader approach of sociocultural effects than just the students' current teacher. All in all, we feel that it would be highly relevant for mathematics education to devote more research efforts to investigating the feasibility of the educational goal of adaptive expertise for lower ability students, and evaluating sociocultural influences more broadly to see how strategy choices may be favorably influenced.

Affecting students' choices between mental and written solution strategies for division problems

Abstract

Making adaptive choices between strategies is a central element of current day mathematics, but not all students may be able to do so. Suboptimal choices between mental and written division strategies are indicated for lower mathematical ability students. Strategy choices in this domain were related to student and teacher factors for 323 sixth graders, and for 224 lower ability students an intervention promoting choices for relatively accurate written strategies was evaluated using a pretest-posttest design. Written strategy choices and performance increased considerably for students receiving intervention or control training, but not for students who did not receive any training. Results suggest that students' strategy choices may also be affected by targeting their motivation and the sociocultural context for strategy use.

5.1 Introduction

Tasks are executed using a variety of strategies during all phases of development (Siegler, 2007). For example, infants vary in their use of walking strategies (Snapp-Childs & Corbetta, 2009), first graders in their use of spelling strategies (Rittle-Johnson & Siegler, 1999), and older children in their use of transitive reasoning strategies (Sijtsma & Verweij, 1999). This large variance in strategies goes together with widely differing performance rates of the different strategies, thereby having

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profound effects on performance levels. As such, strategies have been a topic of continued investigation.

Children's and adults' solution strategy use has been investigated for many cognitive tasks, such as mental rotation (A. B. Janssen & Geiser, 2010), class inclusion (Siegler & Svetina, 2006), and analogical reasoning (Stevenson, Touw, & Resing, 2011). A cognitive domain that has featured prominently in strategy research is arithmetic. Many studies have been conducted on elementary addition (e.g., Barrouillet & Lépine, 2005; Geary et al., 2004), subtraction (e.g., Barrouillet et al., 2008), multiplication (e.g., Van der Ven et al., 2012) and division (e.g., Mulligan & Mitchelmore, 1997), which concern operations in the number domain up to 100 that are taught in the lower grades of primary school. Some studies have also addressed strategy use on the more complex multidigit (involving larger numbers and decimal numbers) arithmetical tasks in the higher grades (e.g., Van Putten et al., 2005; Selter, 2001; Torbeyns, Ghesquière, & Verschaffel, 2009).

5.1.1 Determinants of strategy choices

Different aspects of strategy use for both elementary and multidigit arithmetical problems can be discerned (Lemaire & Siegler, 1995): individuals' strategy repertoire (which strategies are used); frequency (how often each strategy is used); efficiency (the accuracy and speed of each strategy); and adaptivity (whether the most suitable strategy for a given problem is used). These four aspects together shape arithmetical performance. With reforms that have taken place in various countries over the past decades (Kilpatrick et al., 2001), the aspect of adaptivity has become particularly important. Building on students' own strategic explorations and developing adaptive expertise in flexibly using an array of strategies now take a central place, instead of perfecting the execution of a single algorithm per problem type (Gravemeijer, 1997; Verschaffel et al., 2009). This makes choosing the most suitable strategy for a given problem (i.e., making an adaptive strategy choice) crucial.

There are several ways in which the adaptivity of a strategy choice can be defined, as described by Verschaffel et al. (2009). One way is to define adaptivity purely based on task variables: the characteristics of a problem determine which strategy is adaptive (e.g., the adaptive strategy choice for a problem like $1089 \div 11$ is compensation: $1100 \div 11 - 1$). However, individuals differ in their mastery of different strategies, and the strategy that is most effective for one person does not have to be that for another person. Therefore, a second way to define adaptivity also takes subject variables into account: the strategy that is the adaptive choice

is the one that is most effective for a given problem for a particular person. A third way looks even further and includes context variables in the definition. These can be variables both in the direct context of the test (e.g., time restrictions and characteristics of preceding items) and in the broader sociocultural context. In their discussion of adaptive expertise in elementary mathematics education, Verschaffel et al. (2009) stress the importance of more educational research attention to these sociocultural context variables.

Ellis (1997) reviewed research on this topic and argues that the sociocultural context is very important in shaping individuals' strategy repertoire and choices. Students have an implicit understanding of which ways of problem solving are valued by their community: whether speed or accuracy is more important; whether mental strategies are valued over using external aids; whether using conventional procedures or original approaches is preferred; and whether asking for help in problem solving is desirable. Ellis (1997) describes examples of existing differences in strategy use between different cultures (e.g., Western, Asian, aborigine and Navajo cultures). What is also interesting, and moreover, highly practically relevant, is to investigate in what way the context may be manipulated to favorably influence strategy choices.

5.1.2 Influencing students' choices between mental and written division strategies

A case in which influencing students' strategy choices could have large beneficial effects for performance, is that of mental and written strategies for multidigit division problems. As previously described, the attention to traditional algorithms decreased during the reforms of mathematics education. In the Netherlands, this was most extreme for the operation of division, for which the traditional algorithm was abandoned in favor of a new standardized approach (Buijs, 2008; J. Janssen et al., 2005). The traditional and newer approach (see Table 5.1 for examples) differ in that the traditional algorithm is digit-based in the sense that it breaks the dividend up into digits (e.g., in Table 5.1, the 54 part of 544 is considered separately in subtracting 34, and the rest of the dividend is only considered in a later step), whereas the newer approach is whole-number-based and considers the dividend as a whole (e.g., in Table 5.1, 340 is subtracted from 544; Van den Heuvel-Panhuizen et al., 2009). Dutch national assessments in 1997 and 2004 showed the expected decrease in sixth graders' use of the digit-based algorithm, but use of the whole-number-based approach did not increase accordingly; instead, students made more

Table 5.1: Examples of the digit-based algorithm, whole-number-based algorithm, and non-algorithmic strategies applied to the division problem $544 \div 34$.

digit-based algorithm	whole-number- based algorithm	non-algorithmic written strategies
$34 \overline{)544} \setminus 16$	$544 : 34 =$	$10 \times 34 = 340$
$\underline{34}$	$\underline{340} - 10 \times$	$13 \times 34 = 442$
204	204	$16 \times 34 = 544$
$\underline{204}$	$\underline{102} - 3 \times$	
0	102	
	$\underline{102} - \underline{3 \times} +$	
	0 $16 \times$	

use of strategies without any written work (Hickendorff et al., 2009).

These mental strategies turned out to be very inaccurate compared to written strategies (digit-based or otherwise), suggesting a lack of adaptivity of strategy choices with regard to accuracy, and a large performance decline for multidigit division was observed on the assessments (Hickendorff et al., 2009). In follow-up studies, Fagginger Auer, Hickendorff, and Van Putten (2016) and Hickendorff et al. (2010) showed that requiring (lower mathematical ability) students who answer without any written work to write down calculations improved their performance. This shows that requiring the use of more efficient strategies can affect performance favorably in the short term, providing a concrete suggestion for educational practice. A valuable extension of this finding would be an investigation of instructional contexts that increase students’ *choices* for efficient strategies in the longer term, thereby instilling more sustainable improvements in performance.

5.1.3 Present study

The present study is intended as a first step of such an investigation of the determinants of sixth grade students’ choices between mental and written division strategies. In the first part of the study, existing differences in these strategy choices are related to students’ motivations and attitudes in mathematics and to the sociocultural context for mathematics provided by the students’ teachers. In the second part of the study, an intervention designed to increase students’ free choices for written rather than mental strategies (and thereby, their performance) is evaluated. Since mental strategies appear especially inaccurate for lower ability students (Fagginger Auer et al., 2016; Hickendorff et al., 2010), our intervention

focuses on this group. Using a pretest-posttest design, an intervention training condition consisting of training sessions designed to promote writing down calculations is compared to a control training condition where strategy use is not targeted, and to a no training condition.

A meta-analysis by Kroesbergen and Van Luit (2003) on mathematics interventions for low ability students showed that effect sizes were larger for interventions that featured direct instruction and self-instruction compared to interventions with mediated instruction, and smaller effect sizes for interventions with computer-assisted instruction and peer tutoring compared to interventions without those elements. More specifically, in another meta-analysis on this topic, Gersten et al. (2009) identified explicit instruction as an important component of effective interventions. This explicit instruction involves a step-by-step problem solving plan for a specific type of problems, that is demonstrated by an instructor and that students are asked to use. In order to maximize the potential efficacy of the intervention training in the present study, this training therefore involves direct instruction by a human, adult instructor using a step-by-step plan.

Hypotheses

The investigation of determinants of existing differences in mental versus written division strategy choices is exploratory in nature, and involves of a number of potentially relevant factors. Several of the aspects of the sociocultural context (as seen by the teacher) described by Ellis (1997) as influential with regard to strategy choices are considered: importance of speed versus accuracy, preference for mental strategies versus use of external aids, and preference for conventional versus original approaches. In addition, students' self-rated functioning in mathematics and motivation, teachers' characteristics, and the mathematics textbook and division algorithm instruction are considered.

As for the effects of the intervention: written strategy choices are expected to increase more from pretest to posttest in the intervention than in the control training group, given that they are only promoted in the former group. Given the higher accuracy of written compared to mental strategies, performance is therefore expected to increase more in the intervention than in the control training group (though the control group should also improve because of the additional practice and attention that students receive). In the no training group, no large changes in strategy choices or performance are expected because of the lack of training and the limited amount of time that passes between the pretest and posttest.

The effect of the intervention training may depend on students' characteristics. As boys appear to use more mental strategies for division than girls (Fagginger Auer et al., 2013; Hickendorff et al., 2009, 2010), there is more room for improvement through training in boys than in girls. Mathematical ability level may also be relevant, as mental strategies are especially inaccurate for lower ability students (Fagginger Auer et al., 2016; Hickendorff et al., 2010), and therefore increases in the use of written strategies may affect performance more when ability is lower. Finally, training may have a larger effect on performance when students' working memory capacity is lower, because then the working memory resources freed up by writing down calculations make more of a difference (in line with cognitive load theory; Paas, Renkl, & Sweller, 2003). This is especially relevant in our sample, given that students with a lower mathematical ability tend to have a lower working memory capacity than higher ability students (Friso-van den Bos, Van der Ven, Kroesbergen, & Van Luit, 2013).

5.2 Method

5.2.1 Participants

A total of 323 sixth graders (53 percent girls) with a mean age of 11 years and 8 months ($SD = 5$ months) from 19 different classes at 15 different schools participated in the study. For all students, a general mathematical ability score from a widely used standardized national student monitoring system (J. Janssen et al., 2010) was available. All students participated in the pretest and posttest, but training was only given to the 147 students with mathematical ability percentile scores between 10 and 50. Students scoring in the lowest performing decile (7 percent in our sample) were excluded, because atypical problems such as dyscalculia could occur in this group. Of the selected students, 74 received intervention training and 73 control training. They were assigned to a training condition using random assignment with gender, ability quartile and school as blocking variables.

For an indication of development independent of training, performance and strategy choices were also investigated for students who did not receive any training. However, no students with the same ability level as the students who received training were available, so data from the 77 students in the adjoining ability groups (the quartile just above the median and the lowest decile) was used, as in a regression discontinuity design (Hahn, Todd, & Van der Klaauw, 2001). The ability scale scores in the untrained group were on average somewhat higher and they were more

varied ($M = 101.9$, $SD = 13.4$) than in the control training ($M = 97.9$, $SD = 5.3$) and intervention training group ($M = 97.3$, $SD = 5.5$).

5.2.2 Materials

Pretest and posttest

The pretest used to assess students' division strategy choices and performance contained the twelve multidigit division problems given in Table 5.2 (for the problems not yet released for publication as they will be in future assessments, parallel versions are given in italics). These problems were taken from the two most recent national assessments of mathematical ability at the end of primary school (J. Janssen et al., 2005; Scheltens et al., 2013), so that our results could be interpreted relative to the national results that called for this line of mathematical strategy research. All problems were situated in realistic problem solving context (e.g., determining how many bundles of 40 tulips can be made from 2500 tulips), except for the problem $31.2 \div 1.2$. The test also contained twelve problems involving other mathematical operations (all from the most recent national assessment), so that it more closely resembled a regular mathematics test to students. The posttest was identical to the pretest to allow for a direct comparison of results, and with the tests being a month apart and students solving similar problems on a daily basis in mathematics lessons during that period, it was very unlikely that students remembered any of the (complex) solutions.

Accuracy (correct or incorrect) and use of written work (yes or no) were scored for every problem. For solutions with written work, a further distinction was made between three strategy categories: the digit-based algorithm; the whole-number-based algorithm; and non-algorithmic written strategies (see Table 5.1 for examples).

Training problems

The problems used in the three training sessions in between the pretest and posttest were three sets of parallel versions of the twelve problems in those tests.

Student and teacher questionnaires

The students filled out a questionnaire on their attitude towards mathematics and mental mathematical strategies consisting of seven questions. The teachers filled out a questionnaire of fifteen questions on their attitude towards and instruction

Table 5.2: The division problems that students had to solve at the pretest and posttest.

problems			
$1536 \div 16 = 96$	$872 \div 4 = 218$	<i>$31.2 \div 1.2 = 26$</i>	<i>$6496 \div 14 = 464$</i>
<i>$544 \div 34 = 16$</i>	$11585 \div 14 = 827.5$	<i>$47.25 \div 7 = 6.75$</i>	$157.50 \div 7.50 = 21$
$2500 \div 40 = 62$	$1470 \div 12 = 122.50$	$736 \div 32 = 23$	$16300 \div 420 = 39$

Note: Parallel versions of problems not yet released for publication are in italics.

of division algorithms, writing down calculations, and various aspects of flexible strategy use. Both questionnaires can be found in the Appendix.

Working memory tests

The verbal working memory capacity of students who received training was assessed using a computerized version (Stevenson, Saarloos, Wijers, & De Bot, in preparation) of the digit span test from the WISC-III (Wechsler, 1991), and their spatial working memory using a computerized version (Stevenson et al., in preparation) of the Corsi block test (Corsi, 1972).

5.2.3 Procedure

The experiment was conducted over a period of five weeks in the fall of 2014. In the first week, the students first completed the pretest in a maximum of 45 minutes in their classroom. They then did the two working memory tasks on the computer and filled out the student questionnaire. The teacher also filled out the teacher questionnaire in this first week. In the following three weeks, the students participated in three individual training sessions of fifteen minutes each (one per week) with the experimenter. The experiment was concluded in the fifth week, in which students did the posttest in again a maximum of 45 minutes in their classrooms.

The training sessions consisted of the students working on the set of training problems for that week. The experimenter evaluated each solution when it was written down and told the student whether it was correct or incorrect. When correct, the students proceeded to the next problem. When incorrect, the student tried again. Accuracy feedback was provided again, and regardless of whether the solution was correct this time, the student proceeded to the next problem. The session was terminated when fifteen minutes had passed.

 $\dots / \dots \mid$	18 / 234 \	234 : 18 =
$\times$ $\begin{array}{r} 1x \dots \\ 2x \dots \\ 3x \dots \\ 4x \dots \\ 5x \dots \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 3x \ 54 \\ 4x \ 72 \\ 5x \ 90 \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 4x \ 72 \\ 8x \ 144 \\ 10x \ 180 \\ 5x \ 90 \end{array}$
$\downarrow$ $\begin{array}{r} ?? / ??? \mid \dots \\ \dots \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 3x \ 54 \\ 4x \ 72 \\ 5x \ 90 \end{array}$	$\begin{array}{r} 234 : 18 = \\ 180 \overline{) 10x} \\ 54 \end{array}$
— $\begin{array}{r} ??? : ?? = \\ ??? \overline{) ???} \\ \dots \end{array}$	$\begin{array}{r} 18 / 234 \setminus 1 \\ 18 \overline{) 18} \\ 54 \end{array}$	$\begin{array}{r} 234 : 18 = \\ 180 \overline{) 10x} \\ 54 \end{array}$
$\times$ $\begin{array}{r} 6x \dots \\ 7x \dots \\ 8x \dots \\ 9x \dots \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 3x \ 54 \\ 4x \ 72 \\ 5x \ 90 \end{array}$	$\begin{array}{r} 234 : 18 = 13 \\ 180 \overline{) 10x} \\ 54 \\ 54 \overline{) 3x} + \\ 0 \ 13x \end{array}$
$\downarrow$ $\begin{array}{r} ?? / ??? \mid \dots \\ \dots \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 3x \ 54 \\ 4x \ 72 \\ 5x \ 90 \end{array}$	
— $\begin{array}{r} ?? / ??? \setminus ? \\ ?? \overline{) ???} \\ \dots \end{array}$	$\begin{array}{r} 18 / 234 \setminus 13 \\ 18 \overline{) 18} \\ 54 \\ 54 \overline{) 0} \end{array}$	
$\times$ $\begin{array}{r} 6x \dots \\ 7x \dots \\ 8x \dots \\ 9x \dots \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 3x \ 54 \\ 4x \ 72 \\ 5x \ 90 \end{array}$	
$\downarrow$ $\begin{array}{r} ?? / ??? \mid \dots \\ \dots \end{array}$	$\begin{array}{r} 1x \ 18 \\ 2x \ 36 \\ 3x \ 54 \\ 4x \ 72 \\ 5x \ 90 \end{array}$	
— $\begin{array}{r} ?? / ??? \setminus ? \\ ?? \overline{) ???} \\ \dots \end{array}$	$\begin{array}{r} 18 / 234 \setminus 13 \\ 18 \overline{) 18} \\ 54 \\ 54 \overline{) 0} \end{array}$	

Figure 5.1: The step-by-step plans (the lower one for students using the digit-based algorithm, and the upper one for students using the whole-number-based algorithm).

Though these elements of the training were the same for the control and training conditions, two important aspects differed. The first is that students in the control condition were free in how they solved the problems (just as in the pretest), whereas the students in the intervention condition had to write down their calculations in a way that would allow another child to see how they had solved the problem (but otherwise, strategy choice was free). In addition, while students in the intervention condition made their first attempt at solving the problem independently (using a written strategy of their own choice), if they failed, they were provided with systematic feedback on writing down calculations in a standardized way at the second attempt. The students in the control condition received no such feedback and made both their first and second attempt independently.

A step-by-step plan was used for providing the feedback on writing down calculations in the intervention condition, while there was no such plan in the control training condition. The step-by-step plan was always on the table for the intervention training students so they could use it whenever they wanted, and when intervention students were stuck in their problem solving, the experimenter used the plan and standardized instructions to help the students with writing down calculations. No feedback was given on the accuracy of what students wrote down (e.g., mistakes in the multiplication table), except for the final solution.

There was a version of the plan for students taught the digit-based algorithm and one for students taught the whole-number-based algorithm (see Figure 5.1). Both versions consist of five highly similar steps (with step 3 and 4 repeated as often as necessary): (1) writing down the problem; (2) writing down a multiplication table (optional step); (3) writing down a number (possibly from that table) to subtract; (4) writing down the subtraction of that number; and (5) finishing when zero is reached, which in the case of the whole-number-based algorithm requires a final addition of the repeated subtractions. Each step is represented by a symbol to make the step easy to identify and remember (the symbols in the ellipses on the left side of the scheme). Below this symbol, a general representation of the step is given, with question marks for problem-specific numbers already present at that step and dots for the numbers to be written down in that step. On the right-hand side of the plan, an example of the execution of each step for the particular problem $234 \div 18$ is given in a thinking cloud. On both sides, the elements to be written down in the current step are in bold font.

5.2.4 Statistical analysis

Correlation analyses

To explore possible relations between the questions on the student and teacher questionnaires and students' written strategy choices on the pretest, correlations rather than formal models were used because of the high number of questions involved. Point-biserial correlations were used for dichotomous questionnaire responses and Spearman's rank correlations for scales.

Explanatory IRT models

More formal tests were conducted using explanatory item response theory (IRT) models. As argued by Stevenson, Hickendorff, Resing, Heiser, and de Boeck (2013), measuring learning and change has inherent problems that can be addressed using explanatory IRT. These are problems such as the dependence of the meaning of scale units for change on pretest score, because of the non-interval measurement level of non-IRT scores (e.g., an increase of one in the number correct does not necessarily mean the same for a person who already had a nearly perfect score as for someone who had a lower score).

IRT models place persons and items on a common latent scale (Embretson & Reise, 2000). The distance between the persons and items on that scale determines the probability of a correct response: if person ability and item difficulty are close together that probability is around fifty percent, whereas it is lower if ability is lower than difficulty, and higher if ability is higher than difficulty. In its most basic form, the (Rasch) model for the probability of a correct response of person p with ability θ_p on item i with difficulty β_i is $P(y_{pi} = 1|\theta_p) = \frac{\exp(\theta_p - \beta_i)}{1 + \exp(\theta_p - \beta_i)}$. The estimated ability parameters for persons are more likely to have an interval measurement level than simple sum scores.

This model becomes explanatory when explanatory factors for items' difficulty or persons' ability are included, which can be item covariates (not used in the present study), person covariates (condition and student gender, ability score and working memory in the present study), and person-by-item covariates (solution strategy choice in the present study). This type of models can be estimated as multilevel logistic regression models using general purpose generalized linear mixed model (GLMM) software, by fitting a binomial model with solution accuracy (correct or incorrect) as the dependent variable, a random intercept for students as the ability parameter, and the covariates of interest as fixed effects (De Boeck &

Wilson, 2004).

In the present study, different explanatory IRT models were fitted using the `lme4` package in R (Bates, Maechler, Bolker, & Walker, 2014; De Boeck et al., 2011). All models were random person-random item Rasch models (RPRI; De Boeck, 2008), with a random intercept for students, and also a random intercept for the item effects (as they were considered a draw from the larger domain of multidigit division). The different covariates were added in stepwise fashion (as in Stevenson et al., 2013), so that the added value of each addition could be evaluated by comparing the models based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and likelihood ratio tests. The AIC and BIC balance model fit and parsimony and lower values of these criteria are better, and a significant likelihood ratio test indicates that of the two models that are compared, the more complex model fits significantly better. Of the final best fitting model according to these various criteria, the regression parameters were interpreted. Since our research question did not only concern accuracy (correct vs. incorrect) but also strategy choice (written vs. not written), and IRT models accommodate dichotomous variables regardless of content, strategy use was modeled in the same way. The person parameter θ_p then reflects individual differences in the tendency to use written strategies.

For an indication of the size of significant effects, the probability P of a correct response or of using a written strategy is given for different levels of the covariate, with all other covariates in the model set at the mean in the sample. For example, for the effect of testing occasion (pretest or posttest), the probability of a correct solution for an average student on an average problem on the pretest and on the posttest is given. For numeric covariates (e.g., ability score) the effects of a difference of one standard deviation around the mean ($M - 0.5SD$ to $M + 0.5SD$) are given.

5.3 Results

5.3.1 Relation between student and teacher factors and written strategy choices

First, an exploration of pre-existing differences in choices for written strategies based on students' attitudes with regard to mathematics and teachers' strategy instruction was made using the pretest data. Students used written strategies in 62

percent of their pretest solutions, which varied between 51 percent for the problem $31.2 \div 1.2$ and 87 percent for the problem $11585 \div 14$.

Student questionnaire

The Appendix shows what all students ($N = 323$) reported on the student questionnaire on their mathematical attitudes. The proportion of students choosing each alternative is given in brackets after the respective alternative. After each question, the correlation between the question response and the overall proportion of pretest division problems solved with written strategies is also given.

On average, the students had a slightly positive attitude towards mathematics ($M = 3.2$ on a 5-point scale) and were slightly positive about their mathematical ability ($M = 3.3$), and the more positive their attitude and the higher their judgment of ability, the higher their frequency of choices for written strategies ($r(322) = .17$ and $r(322) = .21$ respectively). Students reported putting quite some effort into math ($M = 4.3$) and almost all (98 percent) reported valuing accuracy over speed, but these factors were unrelated to written strategy choices. A majority of students (72 percent) found it more important to be able to solve mathematical problems with than without paper, and this was positively related to using written strategies ($r(318) = .19$). Students reported sometimes answering without writing down a calculation ($M = 2.8$), and indeed, reporting more frequent mental calculation was negatively related to using written strategies ($r(322) = -.17$).

Students also reported on reasons they had for not writing down calculations, on the occasions that they used this approach (which were less frequent for some students and more frequent for others). The most popular reason (chosen by 60 percent of students) was because they did not feel it was necessary, followed by doing it because it was faster (37 percent), because of not feeling like it (19 percent), and because of guessing the solution instead of calculating it (19 percent). Some students also reported better accuracy with mental strategies (13 percent) and finding it smarter to be able to solve a problem mentally (11 percent). Virtually no students (1 percent) perceived mental calculation as cooler. Indicating not finding writing down calculations necessary as a reason for not doing it was positively related to written strategy choices ($r(322) = .20$), whereas indicating not feeling like writing anything down and considering mental calculation more accurate as reasons were negatively related to written strategy choices ($r(322) = -.12$ and $r(322) = -.23$).

Teacher questionnaire

The Appendix also shows what the teachers of the students ($N = 19$) reported on the teacher questionnaire on their strategy instruction. As for the student questionnaire, the proportion of teachers choosing each alternative is given, and the mean is given for the 5-point scales. Correlations were also calculated, but none of them were significant, possibly due to low power because of the small N .

A small majority of the teachers was male (58 percent) and the teachers were on average 38 years old. Almost half (47 percent) used the textbook 'Wereld in Getallen' and their students solved 54 percent of the problems using written strategies, while the students of teachers using other textbooks ('Pluspunt', 'Alles telt' and 'Rekenrijk') used written strategies on 66 to 69 percent of the problems.

Most teachers taught their students the whole-number-based algorithm exclusively (58 percent) or in combination with the digit-based algorithm (26 percent), and 16 percent taught their students the digit-based algorithm exclusively. On average, teachers did not prefer one algorithm over the other ($M = 3.0$), but did prefer use of an algorithm to non-algorithmic approaches ($M = 2.2$). During their own training, the whole-number-based algorithm (53 percent) or digit-based algorithm (42 percent) was emphasized, and for one teacher both algorithms. On average, teachers found performing calculations well on paper and mentally equally important for their students ($M = 3.0$). They reported instructing their students in writing down calculations frequently (on average almost daily, $M = 4.2$).

Concerning multidigit division problems specifically, teachers on average found writing down calculations somewhat more important for their students than trying to do it mentally ($M = 2.4$) and valued accuracy somewhat over speed ($M = 2.5$). Making a good estimation of the solution was more important than being able to determine the exact solution ($M = 3.5$), as was knowing more solution procedures than just one ($M = 3.4$). Teachers considered using an algorithm versus choosing a custom solution strategy on average equally important ($M = 3.0$), and valued convenient shortcut strategies somewhat more than using a method that can always be applied ($M = 3.3$).

5.3.2 Content of the training

After the pretest, students with a mathematical ability percentile rank between 10 and 50 ($N = 147$) received intervention or control training. During the three training sessions, the students in the intervention condition completed on average

5.1 division problems per session and the students in the control condition 6.1 problems. The number of problems that students attempted a second time (when the solution was incorrect the first time) was 1.6 for the intervention and 1.8 for the control condition. During all the second attempts of a session combined, intervention students received feedback 3.3 times on average. This feedback most often concerned writing down a multiplication table (0.8 times) and selecting a number from that table (1.1 times), and less often the writing down of the problem (0.5 times), subtracting the selected number (0.5 times) and finishing the procedure (0.5 times).

As instructed, the students in the intervention condition virtually always wrote down a calculation (for 98, 99 and 99 percent of the problems in the first, second and third session respectively). Though not instructed to do so, the students in the control condition also often wrote down a calculation and this appeared to increase over sessions, with 81 percent in the first session and 87 and 93 percent in the second and third session. The use of written calculations that were algorithmic (digit-based or whole-number-based) increased over sessions in both groups and appeared higher overall in the intervention condition (84, 93 and 96 percent in the three sessions in the intervention condition and 63, 71 and 76 percent in the control condition).

5.3.3 Effects of the intervention and control training

The effects of the training were evaluated using a series of explanatory IRT models on the pretest and posttest data with successively more predictors (see Table 5.3).

Written strategy choices

First a baseline model for the probability of a written strategy choice was fitted with only random intercepts for students and problems and no covariates (model M_0). In model M_1 , main effects were added for the student characteristics gender, ability and working memory capacity, which improved fit according to all criteria (see Table 5.3). Fit was further improved by adding a main effect for testing occasion (pretest or posttest; model M_2). However, the change in written strategy choices from pretest to posttest did not significantly differ for the control and intervention training groups (model M_3). Adding interactions between condition, testing occasion and student characteristics also did not improve the model (these models are not included in Table 5.3 for brevity).

Table 5.3: Explanatory IRT models for training effects on written strategy choices and accuracy (all comparisons are to M_{n-1}).

intervention vs. control training ($N = 147$)						
strat.	added fixed effects	LL	# pars	AIC	BIC	LRT
M_0		-1337.6	3	2681.1	2699.4	
M_1	gender, ability and WM	-1315.7	6	2643.3	2679.8	$\chi^2(3) = 43.8, p < .001$
M_2	testing occasion	-1216.5	7	2447.0	2489.5	$\chi^2(1) = 198.3, p < .001$
M_3	condition $\times$ occasion	-1215.6	9	2449.2	2503.9	$\chi^2(2) = 1.7, p = .42$
acc.	added fixed effects	LL	# pars	AIC	BIC	LRT
M_0		-1801.0	3	3607.9	3626.1	
M_1	gender, ability and WM	-1785.3	6	3582.5	3619.0	$\chi^2(3) = 31.4, p < .001$
M_2	testing occasion	-1711.1	7	3436.3	3478.8	$\chi^2(1) = 148.3, p < .001$
M_3	condition $\times$ occasion	-1710.8	9	3439.6	3494.2	$\chi^2(2) = 0.7, p = .70$
training vs. no training ($N = 224$)						
strat.	added fixed effects	LL	# pars	AIC	BIC	LRT
M_0		-2107.4	3	4220.8	4240.3	
M_1	gender and ability	-2069.2	5	4148.3	4180.8	$\chi^2(2) = 76.5, p < .001$
M_2	testing occasion	-2016.9	6	4045.8	4084.8	$\chi^2(1) = 104.6, p < .001$
M_3	condition $\times$ occasion	-1962.8	8	3941.7	3993.7	$\chi^2(2) = 108.1, p < .001$
M_{4a}	gender $\times$ condition $\times$ occasion	-1962.2	11	3946.5	4018.0	$\chi^2(3) = 1.2, p = .76$
M_{4b}	ability $\times$ condition $\times$ occasion	-1961.5	11	3945.0	4016.4	$\chi^2(3) = 2.7, p = .43$
acc.	added fixed effects	LL	# pars	AIC	BIC	LRT
M_0		-2724.1	3	5454.2	5473.7	
M_1	gender and ability	-2668.5	5	5347.0	5379.4	$\chi^2(2) = 111.2, p < .001$
M_2	testing occasion	-2610.9	6	5233.8	5272.8	$\chi^2(1) = 115.2, p < .001$
M_3	condition $\times$ occasion	-2593.2	8	5202.4	5254.4	$\chi^2(2) = 35.4, p < .001$
M_{4a}	gender $\times$ condition $\times$ occasion	-2592.7	11	5207.4	5278.9	$\chi^2(3) = 1.0, p = .81$
M_{4b}	ability $\times$ condition $\times$ occasion	-2591.6	11	5205.2	5276.7	$\chi^2(3) = 3.2, p = .36$

Table 5.4: Strategy use proportions on the pretest and posttest in the intervention, control and no training conditions.

training	pretest			posttest		
	interv.	control	none	interv.	control	none
digit algorithm	.09	.09	.19	.13	.13	.20
number algorithm	.37	.40	.32	.61	.62	.32
non-alg. written	.19	.19	.15	.13	.08	.12
no written work	.35	.30	.34	.13	.17	.37
other	.01	.02	.01	.00	.00	.01

The best fitting model, M_2 , shows that girls used more written strategies ($P = .94$) than boys ($P = .74$), $z = -6.0$, $p < .001$, and that general mathematics ability score was positively associated with using written strategies ($P = .80$ vs. $P = .92$ for one standard deviation difference), $z = 4.3$, $p < .001$. Working memory (sum score of the verbal and spatial working memory scores) had no significant effect, $z = -0.6$, $p = .55$. Students used more written strategies at the posttest ($P = .94$) than at the pretest ($P = .76$), $z = 13.5$, $p < .001$.

Table 5.4 gives a more detailed categorization of strategies than just written or non-written, as intervention and control training may differ in the type of written strategies they elicit. It shows that the frequency of use of the digit-based and whole-number-based algorithms, non-algorithmic written strategies, non-written strategies and other strategies is almost identical (differences of no more than 5 percentage points) in the two training groups - both at the pretest and at the posttest. In both groups, similar increases in the use of both algorithms and decreases in the use of non-written strategies and non-algorithmic strategies occurred.

Accuracy

As for written strategy choices, first a baseline model for the probability of a correct response was fitted (M_0), and again, this model was improved by adding student gender, ability and working memory (M_1) and by adding testing occasion (M_2), but not by adding condition effects (M_3). The best fitting model, M_2 , shows that girls ($P = .43$) performed better than boys ($P = .28$), $z = -3.8$, $p < .001$, and that general mathematics ability score was positively associated with performance ($P = .28$ vs. $P = .43$ for one SD difference), $z = 4.5$, $p < .001$. Working memory had no significant effect, $z = 0.04$, $p = .97$. Students performed better at the posttest ($P = .48$) than at the pretest ($P = .24$), $z = 11.9$, $p < .001$.

The difference in accuracy between written and non-written strategies was investigated by fitting a model for accuracy with main effects for all previous predictors (student characteristics, testing occasion, and condition) and strategy choice (written or not), and all first-order interactions between strategy choice and the other predictors. This showed that written strategies were much more accurate ($P = .40$) than non-written strategies ($P = .19$), $z = 4.1$, $p < .001$, and that this did not depend significantly on testing occasion, $z = 1.1$, $p = .27$, gender, $z = 0.0$, $p = .99$, ability, $z = 1.0$, $p = .32$, working memory, $z = 0.3$, $p = .75$, or condition, $z = -1.0$, $p = .33$.

5.3.4 Differences with no training group

Given the similar changes in strategy choices and accuracy in both training groups, it was investigated whether these changes also occurred in students who did not receive any training. The previous analyses were repeated, this time comparing trained students ($N = 147$) to untrained students from adjoining ability groups ($N = 77$). Working memory was omitted from these models, as this was only assessed for the children who received training.

Written strategy choices

This time, the fit of the models for written strategy choices was best for model M_3 (which also included an effect of condition; see Table 5.3). The effect of the intervention did not differ significantly by gender or ability level (models M_{4a} and M_{4b}). Model M_3 once more showed more written strategy choices for girls ($P = .90$) than boys ($P = .63$), $z = -6.9$, $p < .001$, and a positive association with ability ($P = .72$ vs. $P = .86$ for a difference of one SD), $z = 6.9$, $p < .001$. There was no significant effect of testing occasion, $z = -1.4$, $p = .15$, and no overall difference between the trained and untrained students, $z = 0.5$, $p = .64$. However, the change in use of written strategies from pretest to posttest was different for trained ($P = .75$ to $P = .93$) than for untrained students ($P = .73$ to $P = .69$), $z = 9.8$, $p < .001$.

Comparisons of more specific strategies in Table 5.4 show that at pretest, the untrained students appear to have used the digit-based algorithm somewhat more often and the whole-number-based algorithm somewhat less often than the trained students. Most notably, however, strategy choices on the pretest and posttest are almost identical for the untrained children, whereas the trained children increased

their use of algorithms and decreased their use of non-written strategies and non-algorithmic strategies.

Accuracy

The fit of the models for accuracy was also best for model M_3 with the condition effect (see Table 5.3). This model again showed higher accuracy for girls ($P = .41$) than boys ($P = .28$), $z = -4.3$, $p < .001$, and a positive association with ability ($P = .26$ vs. $P = .44$ for one SD difference), $z = 10.1$, $p < .001$. There was no significant effect of testing occasion, $z = -1.4$, $p = .15$, and no overall difference between the trained and untrained students, $z = -1.8$, $p = .07$. However, the increase in accuracy from pretest to posttest was higher for trained ($P = .25$ to $P = .49$) than for untrained students ($P = .31$ to $P = .35$), $z = 5.9$, $p < .001$.

Written strategies were again found to be much more accurate ($P = .41$) than non-written strategies ($P = .21$), $z = 3.0$, $p = .002$, and this did not depend significantly on testing occasion, $z = 1.6$, $p = .12$, gender, $z = 0.2$, $p = .88$, ability, $z = 0.8$, $p = .44$, or condition, $z = 1.1$, $p = .28$.

5.4 Discussion

The determinants of students' choices between mental and written division strategies were investigated. First, an exploration was carried out of the relation between existing differences in these choices and students' motivations and attitudes in mathematics and the sociocultural context for mathematics provided by the students' teachers. For an important part, students' choices for mental strategies appear to be related to their motivation: mental strategies are used more by students who report liking mathematics less and being less good at it, and who report not writing down calculations because they do not feel like it. Mental strategies are also used more by students reporting higher accuracy with these strategies. Though this higher accuracy could be true for high ability students (Fagginger Auer et al., 2016), it mostly appears to be a misjudgment as the reporting of it is negatively correlated with ability level, $r(322) = -.24$, $p < .001$.

No statistically significant relations between teacher reports and students' strategy choices were found, even though several aspects of the sociocultural context described as influential on mathematical strategies by Ellis (1997) were investigated, but this could very well be due to a lack of power (there were only 19 teachers in our sample). Overall, teachers reported frequent instruction in writing down cal-

culations, preferred use of an algorithm to non-algorithmic approaches, and valued written strategies somewhat over mental strategies and accuracy somewhat over speed. These reports suggest a sociocultural context in which there is room for written strategies, but where it is not the highest priority.

In the second part of the study, an intervention training designed to promote lower mathematical ability students' choices for written rather than mental strategies (and thereby, their performance) was evaluated. As intended, written strategy choices and accuracy were considerably higher after training than before training. However, similar changes occurred in the control training condition. This means that the extra elements of the intervention training specifically targeted at strategy use did not add to the effect of the training. The common elements of the control and intervention training do appear to be responsible for the observed changes in strategy choices and accuracy, as no such changes occurred in the students who received no training (though these students were of a different ability level, limiting the comparison). An important question is therefore which of the training elements not specifically targeted at strategy use nonetheless affected it.

5.4.1 Elements of the intervention and control training

Practicing written strategies

While writing down calculations was not required during control training (it was a specific part of the intervention training), it did occur frequently in this condition. During the first control training session, calculations were written down for 81 percent of the problems - considerably more than the 70 percent during the pretest. This increased up to 93 percent in the third training session. As such, students practiced written calculations almost as much in the control training as in the intervention training condition, reducing the contrast between the two conditions.

The generally higher level of written strategy choices in the control training compared to the pretest may be due to the different settings in which the pretest and training occurred: in a classroom versus one-on-one with an experimenter. An individual setting is likely to increase students' motivation to do well, and since the student questionnaire suggested that an important reason for using mental strategies is a lack of motivation, this increased motivation may cause the students to use less mental strategies. Another possibility is that students use written strategies because they think the experimenter may expect or prefer that (i.e., demand characteristics; Orne, 1962), in line with the students' teachers' light inclination

towards written rather than mental strategies. Supporting the explanation of the higher level of written strategy choices by setting (individual versus classroom), the increase in written strategy choices from pretest to first training session was followed by a decrease from final training session to posttest (93 to 87 percent).

A possible cause of the further increase in the use of written strategies over sessions in the control training group is the direct accuracy feedback after each solution, and the requirement to do a problem again when the first solution was incorrect. Direct accuracy feedback allows for an immediate evaluation of the success of the strategy that was applied, and this evaluation should often be in favor of written rather than mental strategies given the considerably higher accuracy of the former. Combined with the extra effort associated with an incorrect solution (redoing the problem), this is likely to be an important incentive for written strategy choices. The possibility of accuracy feedback promoting mathematical strategy change was also demonstrated by Ellis, Klahr, and Siegler (1993).

Step-by-step plan

The only training element that was truly unique to the intervention condition was the step-by-step plan for writing down calculations. Though the meta-analysis on mathematics interventions for low ability students by Gersten et al. (2009) identified such plans as an important component of effective interventions, the lack of differences between the training conditions shows that the plan did not make a significant contribution in our study. Indeed, students turned out to require little feedback based on the plan, and the feedback that was given mostly concerned an optional element of written division algorithms (the multiplication table). This suggests that by sixth grade, even lower ability students do not require further instruction in the notation of the division algorithm (even though the algorithm was introduced only one or two years earlier).

Given that the only real difference between the control and intervention training turned out to be mostly redundant, there was no chance for student characteristics to interact with type of training in the effect on changes from pretest to posttest. Our hypotheses regarding the effects of gender, ability and working memory were therefore not confirmed. An interaction with having training or not could have been detected if present given the differences found between these two conditions, but was also not found. Working memory was not included in these analyses, as it was only measured in the children who received training, and ability scores were different in the training and no training conditions. Gender, however, could very

well have interacted with condition: as expected from the literature (Fagginger Auer et al., 2013; Hickendorff et al., 2009, 2010), boys used written strategies far less frequently than girls, and therefore had more room to improve with training than girls. However, training may not eliminate boys' general preference for more intuitive, less formal strategies (Carr & Jessup, 1997; Davis & Carr, 2002), which may therefore continue to limit their choices for (formal) written strategies to some extent.

5.4.2 Future directions

The results of the present study provide several suggestions for future research on strategy training programs. Firstly, they underline the necessity of very careful consideration of the content of the control condition(s). With regard to control groups, U. Fischer, Moeller, Cress, and Nuerk (2013) stress the importance of these groups being performance-matched to the intervention group, as learning trajectories are highly dependent on ability level, and equal in motivational appeal and training time, as these two non-specific factors also contribute to performance. The untrained group in the present study does not meet these demands, which may have inflated the effects we found (U. Fischer et al., 2013), but the control training group certainly does. In fact, the control training even matched the intervention training too closely, which shows that attention should also be devoted to which control training elements may be (unintentionally) effective.

Some of the elements of the present study are promising for future training investigations. The results suggest that direct accuracy feedback (possibly with some cost involved in incorrect solutions) may be conducive to beneficial changes in strategy choices. They also show that considerable changes in strategy choices and improvements in performance may be achieved with as few as three training sessions of fifteen minutes (in line with the finding of Kroesbergen & Van Luit, 2003, that longer mathematics interventions are not necessarily more effective). A follow-up test after a longer period of time (e.g., several months) should be used to establish whether the changes are lasting.

The results also provide two suggestions for other possible ways to influence students' choices between mental and written strategies. A first possibility is to target students' motivation: since strategy choices appear to be related to motivation, increasing students' motivation may also increase their choices for written strategies. In a review, Middleton and Spanias (1999) concluded that students' motivation in mathematics depends for an important part on their perception of success in

this area, but also that it can be positively affected by instruction. This may be achieved with teacher practices such as asking students to make daily recordings of what they learned or excelled at, and prompting them to attribute failures to lack of effort and encouraging them to try harder (Siegle & McCoach, 2007). However, the relation found in the present study was purely correlational, so it should be established experimentally whether changes in motivation actually lead to changes in strategy choices.

A second possibility for increasing students' choices for written strategies lies in the sociocultural context for mathematical strategy use provided by the teacher. The results from the teacher questionnaire show that while teachers generally give instruction on writing down calculations frequently, they only have a slight preference for written over mental strategies and for accuracy over speed. Since cultural values regarding the use of external aids (e.g., paper and pencil) in constructing solutions and regarding accuracy versus speed can have large effects on students' strategy choices (Ellis, 1997), targeting these aspects of the sociocultural context could affect written strategy choices beneficially. This might be done by having teachers express more appreciation of the use of external aids in problem solving, and of accuracy compared to speed, since written strategies offer more accuracy and mental strategies more speed (Fagginger Auer et al., 2016).

5.A Student questionnaire

The proportion of students choosing each alternative is given in between brackets, and for five-point scales, the mean is also given. The correlations are between the question response and the frequency of written strategy choices on the pretest.

1. How much do you like math? ($M = 3.24$) ($r(322) = .17, p = .002$)
not at all (.06) / not so much (.13) / it's okay (.40) / quite a bit (.32) / a lot (.08)
2. How much effort do you put into doing math? ($M = 4.29$) ($r(323) = .08, p = .17$)
none (.00) / not so much (.02) / a bit (.06) / quite a lot (.54) / a lot (.39)
3. How good do you think you are at math? ($M = 3.27$) ($r(322) = .21, p < .001$)
not good at all (.04) / not so good (.17) / okay (.31) / quite good (.44) / very good (.04)
4. What is more important to you when you solve a mathematics problem?
 $(r(320) = .06, p = .28)$
solving the problem quickly (.02) / finding the correct solution (.98)

5. What is more important to you when you solve a mathematics problem?
 $(r(318) = .19, p = .001)$
being able to do it mentally (.28) / being able to do it using paper (.72)
6. How often do you solve problems without writing down a calculation? ($M = 2.80$)
 $(r(322) = -.17, p = .002)$
almost never (.11) / not often (.24) / sometimes (.43) / often (.19) / very often (.03)
7. When you do not write down a calculation, why is that? (*tick boxes that apply*)
 - because it is faster (.37) ($r(322) = -.04, p = .52$)
 - because then you get a correct solution more often (.13) ($r(322) = -.23, p < .001$)
 - because doing mental calculation shows you are smart (.11) ($r(322) = -.02, p = .71$)
 - because it is cooler to do mental calculation (.01) ($r(322) = -.18, p = .001$)
 - because you do not feel like writing anything down (.19) ($r(322) = -.12, p = .03$)
 - because you guessed the solution (.19) ($r(322) = -.05, p = .37$)
 - because it is not necessary to write down a calculation (.60) ($r(322) = .20, p < .001$)

5.B Teacher questionnaire

The proportion of teachers choosing each alternative is given in between brackets, and for five-point scales, the mean is also given. The correlations are between the question response and the frequency of the teachers' students' written strategy choices on the pretest.

1. What is your gender? *male (.58) / female (.42)* ($r(19) = .03, p = .91$)
2. What is your birth year? ... ($M = 1976$) ($r(19) = -.23, p = .35$)
3. Which mathematics textbook do you use in sixth grade? *Alles Telt (.21) ($M = .66$) / Wereld in Getallen (.47) ($M = .54$) / Pluspunt (.26) ($M = .69$) / Rekenrijk (.05) ($M = .69$)*
4. Do you teach your students the whole-number-based algorithm, digit-based algorithm or non-algorithmic approaches for solving multidigit problems (such as $544 \div 34$ or $12.6 \div 1.4$)? When multiple approaches apply, tick multiple boxes.
whole-number-based algorithm (.58) / both whole-number-based and digit-based algorithm (.26) / digit-based algorithm (.16) ($r(19) = .07, p = .77$)

5. To what extent do you as a teacher prefer a division algorithm?
strong preference whole-number-based - strong preference digit-based (5-point scale)
 $(M = 3.0) (r(19) = .28, p = .24)$
6. To what extent do you as a teacher prefer an algorithmic over a non-algorithmic approach?
strong preference algorithmic - strong preference non-algorithmic (5-point scale)
 $(M = 2.2) (r(19) = -.15, p = .55)$
7. Which division approach was emphasized most during your own training?
whole-number-based algorithm (.53) / both whole-number-based and digit-based algorithm (.05) / digit-based algorithm (.42) $(r(19) = .25, p = .29)$
8. Which ability do you find more important in general for your students?
performing calculations well on paper - performing calculations well mentally (5-point scale) $(M = 3.0) (r(19) = .02, p = .92)$
9. How often do you instruct your students in writing down intermediate steps or calculations? *almost never - daily (5-point-scale) $(M = 4.2) (r(19) = .07, p = .77)$*
10. What is more important to you when your students solve multidigit division problems? *(six 5-point scales)*
 - *that they write down all calculations - that they try to do it mentally $(M = 2.4) (r(19) = .06, p = .82)$*
 - *that they keep trying until they get the correct solution, even if that takes a lot of time - that they can do it quickly, even if they sometimes make mistake $(M = 2.5) (r(19) = -.08, p = .78)$*
 - *that they can determine the exact answer - that they can make a good estimation of the answer $(M = 3.5) (r(19) = .35, p = .15)$*
 - *that they know one solution procedure - that they know multiple solution procedures $(M = 3.4) (r(19) = .35, p = .15)$*
 - *that they use an algorithm - that they choose their own solution strategy $(M = 3.0) (r(19) = .24, p = .33)$*
 - *that use a method that can always be applied - that they use convenient shortcut strategies (such as $1089 \div 11 = 1100 \div 11 - 1$) $(M = 3.3) (r(19) = .19, p = .44)$*

Single-task versus mixed-task mathematics performance and strategy use: Switch costs and perseveration

Abstract

The generalization of educational research to educational practice often involves the generalization of results from a single-task setting to a mixed-task setting. Performance and strategy use could differ in these two settings because of task switching costs and strategy perseveration, which are both phenomena that have yet to be studied with more complex educational tasks. Therefore, the problem solving of 323 primary school students in a single-task and mixed-task condition was investigated. The tasks that students had to do were typical educational tasks from the domain of mathematics that are especially interesting with regard to strategy use: solving twelve multidigit division problems that were intended to be solved with written, algorithmic strategies, and twelve non-division mathematical problems that do not call for such strategies. The results indicated no condition differences in performance or strategy use. This suggests that generalization of problem solving in single-task setting to a mixed-task setting is not necessarily problematic.

6.1 Introduction

An important challenge for educational research is its generalization to educational practice. The present study addresses a possible issue in generalization that does

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not appear to have been investigated so far: the generalization of single-task research to mixed-task practice. In the daily educational practice of lessons and tests, students generally do not work on one task exclusively, but switch between different tasks as they go from problem to problem: for example, a mathematics test usually does not concern only a single mathematical operation (e.g., multiplication), but consists of different types of problems that require different operations. Also at the higher level of evaluating educational achievement in (inter)national assessments, tasks are presented mixed with each other rather than in isolation (e.g., Mullis & Martin, 2014; Scheltens et al., 2013).

Yet, much of educational research consists of single-task experiments, such as multiplication (Siegler & Lemaire, 1997), addition (Torbeyns et al., 2005), or spelling (Rittle-Johnson & Siegler, 1999). Sometimes, single-task experiments are even used for explanation of results of mixed-task assessments (e.g., Hickendorff et al., 2010). The use of single-task designs for experiments is logical, given the nature of experiments: the evaluation of the effects of controlled manipulation of only one or a few factors at once. However, when using single-task designs, it is important to know to what extent this may limit the generalizability of results to educational practice. Therefore, in the present study two aspects of problem solving are considered that may differ for single-task versus mixed-task designs: performance and solution strategy use.

6.1.1 Possible causes of differences between single-task and mixed-task results

Two phenomena could play a role in creating differences in problem solving.

Switch costs

The first is the well-established phenomenon of task switching costs in terms of accuracy and speed. A long line of research has established in increasingly advanced experiments that switching between tasks incurs costs. Various explanations for this phenomenon have been proposed (Kiesel et al., 2010). One is that costs occur because of active preparation for the upcoming task, while another posits passive decay of the previous task. Another explanation is interference from the other task (that was previously performed or is expected to be performed) in performing the current task. The research on task switching usually concerns very simple tasks, such as determining whether a number is even or odd or whether a stimulus is a

number or a letter, and describes switch costs in terms of milliseconds. In contrast, most tasks in education are much more complex, and therefore the extent to which switch costs will occur in an educational context is not self-evident and has yet to be investigated.

Strategy perseveration

The second phenomenon that could play a role is that of strategy perseveration. This topic has not been studied widely yet, but has received recent research attention (Lemaire & Lecacheur, 2010; Luwel, Schillemans, Onghena, & Verschaffel, 2009; Luwel, Torbeyns, Schillemans, & Verschaffel, 2009; Schillemans, Luwel, Bulté, Onghena, & Verschaffel, 2009; Schillemans, Luwel, Onghena, & Verschaffel, 2011a, 2011b). Strategy perseveration is the continuing use of the same strategy as in previous solutions, even though another strategy may be more suitable or efficient for the problem at hand. Schillemans (2011) has described several explanations for this perseveration. One is the Einstellung effect, which is individuals' tendency to become blinded to other strategies, even though they may be more suitable than the previously applied strategy. A second explanation is priming, where the strategy that was previously used is more highly activated and therefore more likely to be selected. A third explanation is strategy switch costs, which are the costs involved in switching between strategies (which may occur through similar mechanisms as task switching costs; Lemaire & Lecacheur, 2010).

Perseveration has been shown to occur in single-task settings (Lemaire & Lecacheur, 2010; Luwel, Schillemans, et al., 2009; Luwel, Torbeyns, et al., 2009; Schillemans et al., 2009, 2011a, 2011b), but what occurs in a mixed-task setting has yet to be investigated: the mixing would seem to prevent perseveration as the alternation of tasks makes it impossible to keep applying the same strategy, but possibly perseveration in a similar but not identical strategy could occur (e.g., an algorithmic approach on one task might increase the probability of a (different) algorithmic approach on a subsequent other task).

6.1.2 The present study

Given these possible and as of yet unknown effects of task switching costs and strategy perseveration in an educational setting, the present study compares performance and strategy use in a single-task versus a mixed-task condition. The task used is the solving of mathematical problems in the domain of multidigit division

(division with larger numbers or decimal numbers, such as $1536 \div 16$ or $31.2 \div 1.2$). This task is a typical educational task, making it suitable for the goal of investigating task switching and strategy perseveration in an educational context, and is also especially interesting with regard to the latter strategy phenomenon.

This is because multidigit division problems are traditionally associated with solution strategies that involve writing down calculations (especially algorithmic strategies), or even defined as problems that make such an approach necessary of desirable (J. Janssen et al., 2005; Scheltens et al., 2013). However, in mixed-task large-scale assessments only around half of students' solutions involve written (mostly algorithmic) strategies (Scheltens et al., 2013), even though these strategies are much more accurate than non-written strategies (Hickendorff et al., 2009). Possibly, the mixing of multidigit division problems with other problems that do not call for written, algorithmic strategies makes students persevere in using mental, non-algorithmic strategies, or conversely, prevents students from persevering in written algorithmic strategies on the division problems. The comparison of single-task and mixed-task division problem solving in the present study could shed light on the extent to which this is the case.

The division problems are contrasted with other mathematical problems that do not involve division and that were selected to elicit mental, or at least non-algorithmic strategy use. Rather than contrasting division with a single other task, non-division problems from (nearly) all regularly assessed mathematics domains were included, to more closely approximate educational practice. Division and non-division problems from the two most recent national large-scale assessments of mathematics at the end of primary school in the Netherlands were used, because they reflect typical problems in Dutch primary school mathematics and were rigorously pretested.

Research questions

The first research question addressed by this study was the following: to what extent does mathematical performance differ in single-task and mixed-task conditions? Given the well-established existence of switch costs, it was expected that in the case of any differences between conditions, performance (whether in accuracy or speed) would be worse in the mixed-task than in the single-task conditions. However, because the task of multidigit division problem solving is much more complex than the elementary tasks usually employed in task switching, it could be that so many facets are already involved in performing just the mathematics task, that additional

costs in switching between different mathematical tasks are negligible. In that case, performance in both conditions would be comparable.

The second research question that was addressed was: to what extent does the occurrence of strategy perseveration differ in single-task and mixed-task conditions? Two types of perseveration could occur. One is perseveration in applying the mental, non-algorithmic strategies suitable for the non-division problems to the division problems in the mixed-task condition, where division problems always occur directly or shortly after non-division problems (which is not the case in the single-task condition). The other is perseveration in applying written, algorithmic strategies to the division problems when they are presented together in the single-task condition (which is not possible when the division problems are interspersed with non-division problems that cannot be solved with a division algorithm in the mixed-task condition).

6.2 Method

6.2.1 Participants

A total of 323 students at the end of primary school (sixth grade; 11-12-year-olds) from 15 different schools participated in the experiment, of whom 53 percent were girls and 47 percent were boys. Data on students' mathematical ability was available from standardized national tests that are administered at most Dutch primary schools (J. Janssen et al., 2010). Students were assigned to the single-task (50 percent of students) and mixed-task condition (the other 50 percent) according to a randomized block design (with blocking based on gender, ability quartile and school).

6.2.2 Materials

Students made a test consisting of twelve multidigit division problems and twelve problems of other types (see Table 6.1 for the problems). The problems came from the two most recent (2004 and 2011) national large-scale assessments of mathematics performance at the end of primary school (Scheltens et al., 2013; J. Janssen et al., 2005). All problems were open-ended, and all problems except $31 \div 1.2$ and $\frac{3}{8} + \frac{1}{4}$ were presented in a realistic problem solving context (such as determining how many bundles of 40 tulips can be made from 2500 tulips). The non-division problems were from (nearly) all mathematics domains investigated in the assess-

ments except addition, subtraction, multiplication and division, as these problems were intended to evoke non-algorithmic, mental strategies.

The problems were printed in A4-booklets with two problems per page, so that there was ample space for writing down calculations. In the single-task condition, the first twelve problems in the test booklet were the division problems and the next twelve the non-division problems (or vice versa for half of the students that condition), whereas in the mixed-task condition, every time one or two non-division problems were followed by one or two division problems in an unpredictable way (see Table 6.1). The single task did not consist of solely division problems so that the total difficulty and time required for the test was the same in both conditions.

6.2.3 Procedure

Students made the tests in their classroom in the presence of the experimenter and had 45 minutes to do so. Students were instructed that if they wanted to write down calculations, they should do so in the test booklet. When a student had finished, the test completion time in minutes for that student was written down by the experimenter.

After students had made the test, their solutions were scored for accuracy and strategy use. For division problems, four categories of strategy use were discerned: the digit-based algorithm (a more traditional approach, where numbers are broken up into digits that can be handled without an appreciation of their magnitude in the whole number); the whole-number-based algorithm (a newer approach where every step towards obtaining the solution requires students to understand the magnitude of the numbers they are working with; Treffers, 1987a); non-algorithmic written solutions (such as only writing down intermediate steps); and no written work (see Table 6.2 for examples). For the non-division problems, the two algorithm categories were merged into one category, as whole-number-based algorithms are very infrequent for other operations than division (Buijs, 2008), and the other categories were the same.

6.2.4 Statistical analysis

Mixed models

The effects of condition (single-task or mixed-task) and student gender (boy or girl) and mathematical ability score and their interactions on speed and accuracy were investigated using mixed models: linear mixed models for test completion time and

Table 6.1: The twelve division and twelve other problems (order shown for the mixed condition).

type	item
surfaces	determining the surface of a triangle covering half of a 4×4 grid
division	$1536 \div 16 = 96$
tables	looking up the lesson taking place at a given time in a timetable
division	$872 \div 4 = 218$
division	$31.2 \div 1.2 = 26$
geometry	determining the number of windows based on a building scheme
money	determining the number of 20 cent coins in 80 euro
division	$6496 \div 14 = 464$
fractions	$\frac{3}{8} + \frac{1}{4}$
number line	? - 8 - 8.125 - 8.250 - 8.375 - 8.500
division	$544 \div 34 = 16$
division	$11585 \div 14 = 827.5$
length	converting 3.1 meters to centimeters
division	$47.25 \div 7 = 6.75$
division	$157.50 \div 7.50 = 21$
volume	reading off 1.5 liters from 2 liter container with 0.5 liter marks
time	determining the difference between 09:15 and 08:55
division	$2500 \div 40 = 62$
division	$1470 \div 12 = 122.50$
measurement	determining the height of a mentally rearranged tower of cubes
division	$736 \div 32 = 23$
weight	converting 3959 grams to kilograms
number line	2.06 - ? - 2.07
division	$16300 \div 420 = 39$

Note: Parallel versions of problems not yet released for publication are in italics.

Table 6.2: Examples for the different strategy coding categories for the division problem $544 \div 34$.

digit-based algorithm	whole-number- based algorithm	non-algorithmic strategies	no written work
$34/544 \setminus 16$	$544 : 34 =$	$10 \times 34 = 340$	16
<u>34</u>	<u>340</u> - $10 \times$	$15 \times 34 = 510$	
204	204	$16 \times 34 = 544$	
<u>204</u>	<u>102</u> - $3 \times$		
0	102		
	<u>102</u> - <u>3</u> $\times$ +		
	0 $16 \times$		

logistic mixed models for accuracy (correct or incorrect). Both types of models included a random effect for schools, and the accuracy model also random effects for students and items (De Boeck, 2008) since it modeled data at the item level. The analyses were conducted using the package `lme4` in the statistical computing software `R` (Bates & Maechler, 2010).

Latent class analysis

Students’ patterns of strategy use on the twelve division items were investigated using multilevel latent class analysis (MLCA). In LCA, individuals are classified in latent classes that are each characterized by a particular pattern of response probabilities for a set of items (Goodman, 1974; Hagenaars & McCutcheon, 2002). The multilevel aspect makes individuals’ probability of being in latent classes dependent on the group they are in (in this study, the groups that are formed by the classes of the different teachers). Covariates can also be added to predict latent class membership. The multilevel latent class analysis was conducted with version 5.0 of the Latent GOLD program (Vermunt & Magidson, 2013). All twelve division strategy variables were entered as observed response variables and a teacher identifier variable as the grouping variable for a nonparametric multilevel effect. The optimal number of latent students and teacher classes was determined based on the Bayesian Information Criterion (BIC; Schwarz, 1978) and the effects of covariates were evaluated using Wald tests.

Table 6.3: Performance in the single and mixed task condition in terms of accuracy and speed.

condition	accuracy (percentage correct)		speed (minutes)
	non-division problems	division problems	whole test
single-task	69	44	37
mixed-task	70	45	36
total	70	45	36

Table 6.4: Strategy use in the single-task and mixed-task condition.

condition	non-division problems			division problems			
	A	NA	NW	DA	WA	NA	NW
single-task	2	7	91	13	36	20	32
mixed-task	3	7	90	17	34	19	30
total	2	7	91	14	35	19	31

Note: A=algorithm, NA=non-algorithmic, NW=no written work, DA=digit-based algorithm, WA=whole-number-based algorithm

6.3 Results

As can be seen from the performance descriptives in Table 6.3, students provided correct solutions to 70 percent of the non-division and 45 percent of the division problems, and completed the test in 36 minutes on average ($SD = 8$ minutes). Table 6.4 gives the frequencies of students' use of the different strategies. As intended, students almost never applied an algorithmic strategy to non-division problems (2 percent), and most often solved such problems without writing down any calculations (91 percent). For the division problems, students used an algorithmic strategy approximately half of the time: they applied the whole-number-based algorithm to 35 percent of the problems and the digit-based algorithm to 15 percent of the problems. Solutions without any written work were also frequent (31 percent), as were non-algorithmic written strategies (19 percent).

6.3.1 Task switching costs

To investigate whether the switching between division and non-division problems in the mixed-task condition incurred switch costs that did not occur in the single-task condition, accuracy and speed in the two conditions were compared.

Accuracy

Table 6.3 shows that the observed percentage of correct answers to division problems was nearly identical in the two conditions: 44 percent in the single-task and 45 percent in the mixed-task condition. A comparison of models using likelihood ratio tests confirmed a lack of differences between the conditions: the null model for the accuracy of division solutions (with only an intercept) was significantly improved by adding the student characteristics gender and ability (and their interaction) as predictors, $\chi^2(3) = 231.4$, $p < .001$, but adding a condition effect (and condition interactions with gender and ability) did not provide further improvement, $\chi^2(4) = 6.7$, $p = .15$. In the model with student characteristics, accuracy was found to be lower for boys than for girls, $z = -3.41$, $p < .001$, and accuracy was found to be positively related to ability score, $z = 10.25$, $p < .001$. The interaction between gender and ability was non-significant, $z = 1.75$, $p = .08$.

Speed

Table 6.3 also shows that average time in which students completed the whole test was nearly identical in the two conditions: 37 minutes in the single-task and 36 minutes in the mixed-task condition. Again, a comparison of models confirmed a lack of differences between the conditions: the null model for test completion time (with only an intercept) was significantly improved by adding student gender and ability, $\chi^2(3) = 27.3$, $p < .001$, but adding condition effects provided no further improvement, $\chi^2(4) = 4.4$, $p = .36$. In the model with student characteristics, boys were found to be faster than girls, $z = -5.23$, $p < .001$. Ability score did not have a significant effect, $z = -0.31$, $p = .38$, nor did the interaction between gender and ability, $z = 0.49$, $p = .31$.

6.3.2 Strategy perseveration

To investigate the effects of mixing division and non-division problems on strategy use, patterns of strategy use in the two conditions were compared. Table 6.4 shows that the overall percentage of division problems solved with each strategy was nearly identical in the single-task and mixed-task conditions: 13 and 17 percent respectively for the digit-based algorithm; 36 and 34 percent for the whole-number-based algorithm; 20 and 18 percent for non-algorithmic written strategies; and 32 and 30 percent for strategies without any written work.

A latent class analysis identified four different patterns of strategy use on the division problems (the BIC was lowest for a model with four latent student and three latent teacher classes): 44 percent of the students predominantly used the whole-number-based algorithm (mean probability of using that strategy on the different items of .72); 23 percent of students used mainly non-algorithmic written strategies (mean probability of .55) and answering without written work (mean probability of .28); 18 percent mostly answered without any written work (mean probability of .87); and 15 percent predominantly used the digit-based algorithm (mean probability of .71).

Again, adding student characteristics to the null model improved it, $\chi^2(9) = 58.4$, $p < .001$, while the subsequent addition of condition effects did not provide further improvement, $\chi^2(12) = 15.3$, $p = .23$. In the model with student characteristics, gender was significantly related to strategy use (the probability of the whole-number-based algorithm pattern was lower for boys than for girls, while the probability of the answering without any written work pattern was higher), $W^2 = 18.0$, $p < .001$. Ability score also had a significant effect (it was positively related to the probability of the algorithm patterns and negatively to the probability of the non-algorithmic written and no written work patterns), $W^2 = 10.4$, $p = .02$. The interaction between gender and ability was not significant, $W^2 = 6.9$, $p = .07$.

6.4 Discussion

As the generalization of educational research to educational practice often involves the generalization of results from a single-task setting to a mixed-task setting, the present study compared students' problem solving in these two conditions. The tasks that students had to do were typical educational tasks from the domain of mathematics that are especially interesting with regard to strategy use: solving multidigit division problems that are intended to be solved with written, algorithmic strategies, and non-division mathematical problems that do not call for such strategies. Differences in performance and strategy use on these tasks in the single-task and mixed-task conditions could occur because of task switching costs (both in terms of accuracy and speed) and because of strategy perseveration.

However, no differences between conditions were found: accuracy and speed did not differ, and though different patterns of strategy use were identified, students were equally likely to have those patterns in both conditions. There were gender

and ability level differences in accuracy, speed and strategy use, but there were no significant interaction effects of these student characteristics with condition. Therefore, no support was found for task switching costs with these educational tasks. Possibly, the larger complexity of educational tasks compared to typical tasks from the task switching literature (such as deciding whether a number is odd or even) makes switching costs negligible, as the task itself already requires the switching between many different sub-tasks.

There was also no indication of strategy perseveration. There was a group of students who quite consistently answered without any written work on not only the non-division, but also the division problems. This might have indicated perseveration if this strategy choice pattern occurred more often in the mixed-task condition (where the division problems were preceded by non-division problems that elicited this strategy) than in the single-task condition, but this was not the case. There were also two groups of students who quite consistently used the digit-based or whole-number-based algorithms for division, which might have indicated perseveration if this pattern occurred more often in the single-task (where all division problems were presented in a row) than in the mixed-task condition, but this was also not the case.

All in all, the results of the present study therefore suggest that a generalization of performance and strategy use in a single-task setting to a mixed-task setting is not necessarily problematic.

6.4.1 Limitations

However, the detection of possible task switching costs and strategy perseveration may have been hindered by some limitations in the design of the present study.

Task switching costs

A limitation that may have prevented the finding of task switching costs is that a comparison of complete single-task blocks with mixed-task blocks is quite crude. A more refined comparison could be made between problems directly after a switch (switch trials) and problems not directly after a switch (repeat trials; Kiesel et al., 2010). This is not possible with the current data, however, as a fair comparison requires that each problem features as often in a switch as in a repeat trial (otherwise, type of trial and problem difficulty are confounded). This would necessitate extra versions of the problem set.

Another limitation is that switching costs in terms of speed were investigated using the amount of minutes it took students to solve all (division and non-division) problems combined, rather than the much more precise amount of seconds per problem. The latter could be assessed by making students do the test on a computer or individually in the presence of an experimenter who records the time, but both these situations are likely to affect students' performance and strategy use.

Another issue is the type of tasks that were used. The tasks in the present study may have been so complex that switching costs became negligible, but educational practice also involves simpler tasks where this may not be the case. In addition, division problems were mixed with many other tasks from the domain of mathematics, whereas in the task switching literature usually just two tasks are contrasted. Doing the latter could make differences between conditions more pronounced, though it would also reduce the similarity to educational practice.

Strategy perseveration

There are also two factors that may have prevented us from finding strategy perseveration effects. One is that strategy perseveration has only been demonstrated in the context of a single task for which different strategies are most appropriate depending on the characteristics of the problem at hand (Lemaire & Lecacheur, 2010; Luwel, Schillemans, et al., 2009; Schillemans et al., 2009, 2011b). In contrast, in the present study mental, non-algorithmic strategy use was elicited with non-division problems and the effect of this on strategy use on division problems was evaluated. Perseveration within the division problems could still have occurred in the single-task condition, but presumably in the form of repeated use of a written algorithm, and since this strategy is most accurate for this type of problem (Fagginger Auer et al., 2013) that would not constitute persevering in using a suboptimal strategy.

In addition, both Schillemans et al. (2009) and Lemaire and Lecacheur (2010) did not find perseveration or strategy switch costs generally, but only for problems with specific characteristics. Lemaire and Lecacheur (2010) found strategy switch costs particularly for easier problems, while the division problems in the present study were difficult (45 percent correct solutions), so strategy perseveration may be found with easier educational tasks.

6.4.2 Conclusion

It can be concluded that the results of the present study do not indicate particular problems for the generalization of performance and strategy use in single-task experiments to mixed-task educational practice. However, less complex tasks may induce more switch costs and strategy perseveration, and several adjustments to the experimental set-up would allow for a more thorough investigation (though possibly at the cost of similarity of the experiment to educational practice).

General discussion

The previous five chapters of this dissertation described investigations of what factors affect students' mathematical solution strategy use and performance, and of techniques that can be used to conduct such investigations. This research was carried out in the domain of multidigit multiplication and division at the end of Dutch primary school, in which large changes in students' solution strategy use and performance have taken place, and in which the educational goal of adaptive strategy choices appears not to be achieved by a considerable amount of students.

In Chapters 2 and 3 of this dissertation, the relation between the instruction that takes place in classrooms and students' multiplication and division solution strategy choices and performance was investigated, by the means of secondary analyses of large-scale assessment data using latent variable models. Instruction was considered both as the formal curriculum provided by mathematics textbooks and the instructional practices. In Chapters 4 and 5, students' division strategy choices (and through these, performance) were targeted in experiments in schools. Specifically, choices between relatively accurate written and inaccurate mental strategies were manipulated: students had to write down calculations (Chapter 4) or received a training intended to encourage them to do so (Chapter 5). In Chapter 6, a comparison was made of strategy choices and performance in tasks in which multiple operations are mixed together (as in Chapters 2 and 3) versus tasks that only concern one mathematical operation (as in Chapters 4 and 5), and no particular problems for generalization of results from one setting to another were indicated. In all the chapters, the effects of different student characteristics were considered (gender, mathematical ability, SES, working memory and attitudes with regard to mathematics and mathematical strategy use).

7.1 Substantive conclusions

Various findings with regard to students' solution strategy choices and performance were described in Chapters 2 to 6.

7.1.1 Solution strategy choices

In line with previous research on division alone (Hickendorff et al., 2009), around one third of students was found to predominantly answer both multiplication and division problems without writing down any calculations (Chapter 2). Also similarly, one fifth of students predominantly used the digit-based algorithm. However, following the suggestion of Van den Heuvel-Panhuizen et al. (2009), the remaining written strategies were not classified into a single 'realistic' strategy category. Instead, a distinction was made between the whole-number-based algorithm and more informal non-algorithmic approaches. The results described in Chapter 2 and 3 indicate that this is an important distinction: different latent classes for whole-number-based algorithm use and non-algorithmic written approaches were found, and the digit-based and whole-number-based algorithms did not differ significantly in accuracy, while the digit-based algorithm and non-algorithmic approaches for multiplication did (and a similar, though non-significant difference was found for division). These results suggest that it may be more relevant to distinguish between non-algorithmic and algorithmic approaches, than to distinguish between 'traditional' and 'realistic' approaches. This is in line with a review by the Royal Netherlands Academy of Arts and Sciences (2009) that concluded that achievement differences between traditional and realistic curricula are smaller than differences between methods of the same type. Of course, the category of non-algorithmic written approaches is still very heterogeneous, but further splitting it up results in categories with very low numbers of observations in them (Fagginger Auer et al., 2013).

In Chapters 2, 4, 5 and 6, factors affecting choices between the strategies were investigated. With the multilevel latent class analysis in Chapter 2, it was found that while students' probability of using the different written strategies depended strongly on the teacher, this was not the case for the strategies without any written work. Teachers' responses to the questionnaires on their strategy instruction and attitudes in Chapters 4 and 5 were also not significantly related to students' choices between mental and written strategies. On the other hand, a relation was found between students' characteristics and the frequency of choices for mental strategies

in Chapters 2, 5 and 6 (but not 4): this frequency was higher for boys and for students with a lower mathematical ability. For boys, this appears to be mainly at the cost of algorithmic strategies, while for lower mathematical ability the picture is less clear (Chapters 2 and 6). This tendency of boys to use less algorithmic and more mental strategies than girls is also described in the literature (Carr & Jessup, 1997; Davis & Carr, 2002; Fennema, Carpenter, Jacobs, Franke, & Levi, 1998). Lack of motivation (that does not appear to be more common in boys) appears to be a reason for choosing mental strategies (Chapter 5). These results suggest that the characteristics of students may be more relevant to mental strategy choices than common variations in teacher behaviors. However, intervening in these common teaching practices can be effective: Chapter 5 shows that an instructional intervention can reduce mental strategy choices (both for boys and girls).

Findings on the adaptivity of strategy choices were also described. Adaptivity was considered as the degree to which students adapt their choices between strategies to the relative accuracy and speed with which they can execute those strategies for the type of problem at hand (Siegler & Lemaire, 1997). In mathematics instruction that builds on the variety of students' own strategic explorations rather than focusing on a few specific algorithmic strategies (Treffers, 1987b), adaptivity is vital to performance. However, Chapter 4 indicated that weaker students may not always be able to make adaptive choices between strategies, as was also found in some previous research (e.g., Hickendorff et al., 2010; Torbeyns et al., 2006), but not all (e.g., Siegler & Lemaire, 1997; Torbeyns et al., 2005). Accuracy and speed were considered both separately and simultaneously (the adaptive strategy being the one that leads to the correct solution the fastest; Kerkman & Siegler, 1997; Luwel, Onghena, et al., 2009; Torbeyns, De Smedt, et al., 2009), and the relative relevance of accuracy and speed in choices between mental and written strategies was found to depend on students' gender and mathematical ability: mental strategies appeared to be especially inaccurate for lower ability students and offered a larger speed advantage relative to written strategies for boys than for girls. These and other potentially relevant factors to students' speed-accuracy tradeoff (MacKay, 1982) could therefore be included in models for strategy choices such as the Adaptive Strategy Choice Model (ASCM; Siegler & Shipley, 1995). Verschaffel et al. (2009) also stressed the importance of the sociocultural context for the adaptivity of strategy choices, and in this dissertation, the part of the sociocultural context formed by the teacher was considered. As described in the first part of this section, many teacher behaviors and attitudes that were expected to be relevant were

not found to be related to students' choices between mental and written strategies (whereas Ellis, 1997, did describe sociocultural effects on such choices), but there was a considerable teacher effect on choices between different written strategies.

7.1.2 Performance

The effects of instruction on performance were also investigated; both direct effects and effects occurring indirectly through strategy use. The indirect effects can occur because of the large accuracy differences between strategies: as in previous research (Hickendorff, 2013; Hickendorff et al., 2009, 2010; Van Putten, 2005), written strategies were found to be much more accurate than mental strategies. This was not only the case when potentially biasing strategy selection effects (Siegler & Lemaire, 1997) of student and problem characteristics were statistically corrected for (Chapters 3 and 5), but also when they were eliminated through experimental design (with the choice/no-choice design of Siegler & Lemaire, 1997; Chapter 4). Within written strategies, the digit-based and whole-number-based algorithms were found to be comparable in accuracy, while non-algorithmic approaches appeared less accurate than the algorithms (as discussed previously). This suggests that while attention to informal strategies may be very fruitful in earlier stages of the educational process (Treffers, 1987b), performance may benefit from a focus on standardized procedures at the end of the instructional trajectory. This may be especially relevant to students with a lower mathematical ability, who appear to benefit less from more free forms of instruction with attention to multiple solution strategies than from more direct forms of instruction (Royal Netherlands Academy of Arts and Sciences, 2009).

Given the strategy accuracy differences, the associations between instruction and strategy choices discussed in the previous section also indirectly affect performance (though it should be noted that a thorough investigation of the chain of effects would involve a mediation analysis). The effects of teachers' instruction on students' choices between relatively inaccurate mental and accurate written strategies were limited, and thereby also the indirect effects of that on performance. However, teachers' strategy instruction was found to be related to choices between written strategies. Choices for the somewhat less accurate non-algorithmic strategies were associated with instruction in the whole-number-based algorithms for multiplication and division, in line with the link between such algorithms and informal approaches envisioned in the development of these algorithms (Treffers, 1987a). These results concern the effects of normal variations in instructional be-

haviors reported by teachers. In Chapters 4 and 5, interventions in this daily teaching practice were described. In Chapter 4, it was shown that instructing students with a below (but not above) average mathematical ability to write down calculations results in an immediate improvement in their performance, whereas Hickendorff et al. (2010) found such an improvement regardless of ability level. In Chapter 5, it was shown that a training for lower ability students that increases choices for written strategies also improves performance.

In Chapter 2, direct effects of instruction on performance were investigated. Teaching practices turned out to be more relevant to multiplication and division performance than the formal curriculum (as it is laid down in mathematics textbooks) and teacher characteristics, as had also been found for mathematics more generally (Royal Netherlands Academy of Arts and Sciences, 2009; Slavin & Lake, 2008; Wenglinsky, 2002). Particularly, the amount of time that teachers spend on instruction to the whole class was found to be positively related to students' performance, in line with the positive effect of time spent on active academic instruction rather than other activities reported in the process-product literature (Hill et al., 2005). This may be in conflict with the trend of decreasing whole class instruction and increasing differentiation of instruction based on students' mathematical ability level (Scheltens et al., 2013).

7.2 Methodological conclusions

To obtain these substantive conclusions, several methods were used that are not very commonly applied in educational research, but that have great potential for other investigations of this type.

7.2.1 Latent variable models

Firstly, latent variable models were used. Advanced modeling techniques were necessary because the data posed several statistical challenges (depending on the chapter), many of which frequently play a role in educational investigations: the multi-level structure of the data (item responses within students, who are within classes); the nominal measurement level of the strategies; the measurement of change; the large number of items in the teacher questionnaire in the large-scale assessment; and the incomplete design of the large-scale assessment, in which students do not complete all items but only systematically varying subsets of items. These challenges were met with two statistical techniques that model item responses as dependent on

a latent variable: latent class analysis (LCA) and item response theory (IRT). The latent variable reflects individual differences between students, and these differences can be more quantitative or more qualitative (De Boeck, Wilson, & Acton, 2005). In IRT, the latent variable is dimensional and students are modeled as differing from each other only in degree, whereas in LCA, the latent variable is categorical and students in different latent classes are modeled as qualitatively different from one another.

In this dissertation, LCA was used to discern qualitatively different strategy choice profiles (latent classes) based on students' strategy choices on items. Chapters 2 and 6 show that this is a very insightful way to deal with nominal strategy data that is richer than just a dichotomization (e.g., mental versus written strategies), and its merit has also been demonstrated in previous educational research (e.g., Geiser et al., 2010; Hickendorff et al., 2009, 2010; Lee Webb et al., 2008; Yang et al., 2005). However, what previous studies usually lacked, is the modeling of teacher effects that was implemented in this dissertation through use of multilevel LCA (MLCA; Vermunt, 2003). Given the central role of teachers in the educational process, such multilevel effects are theoretically of high importance in educational research, and Chapter 2 also shows that the effects are so large that not modeling them results in a serious misspecification of the latent class model. In addition, it was shown that modeling the multilevel effect as nonparametric (creating latent classes of teachers as well as of students; Vermunt, 2003) allows for interesting substantive interpretations of teacher effects. Finally, Chapters 2 and 6 illustrated the versatility of MLCA: it can be used to deal with the challenges of large-scale assessment data, but can also easily be applied to data from a cognitive experiment.

IRT models were employed in Chapters 3, 4, 5, and 6; not as measurement models that only describe individual differences in performance, but as explanatory models that include factors that explain performance (De Boeck & Wilson, 2004). Different approaches were taken that illustrate the flexibility of the explanatory IRT framework: person covariates (e.g., gender and ability level) as well as person-by-item covariates (strategy use) were used as explanatory factors, item difficulties were modeled as fixed and as random effects (De Boeck, 2008), different response variables (accuracy and mental versus written strategy choices) were modeled, and teacher effects were included. IRT was used to evaluate condition effects in experiments, both in designs where children were only tested once (Chapters 4 and 6) and in a pretest-posttest design (Chapter 5). IRT offers special benefits in

the latter case, as it addresses problems inherent to measuring learning and change (Stevenson et al., 2013). Finally, a new application of explanatory IRT was introduced (Chapter 3): a combination with LASSO penalization (Tibshirani, 1996), that enables the simultaneous consideration of high numbers of potentially relevant covariates while optimally modeling achievement differences (making it especially suitable for large-scale assessments).

7.2.2 Strategy coding

A second methodological approach in this dissertation that could benefit other educational investigations is not statistical, but concerns the way in which the solution strategies that students use are determined. In all chapters, strategy use was inferred from the calculations that students wrote down while solving problems. As discussed by Fagginger Auer et al. (2015), a more common approach is to use students' verbal reports, but this approach has important disadvantages: verbal reports can be inaccurate and the reporting can influence students' strategy choices and performance (Crutcher, 1994; Ericsson & Simon, 1993; Kirk & Ashcraft, 2001). This plays a lesser role when written work is used, as students write down calculations as a natural part of the problem solving process. In addition, much larger sample sizes can be achieved with written strategy identification, as verbal reports can only be obtained in an individual setting with a trained interviewer, whereas written work can be collected using group administration and can be efficiently coded for strategy use afterwards. An important disadvantage of written identification is that parts of the problem solving process that have not been written down cannot be recovered, and that no written work could reflect anything from guessing to mental execution of an algorithm. However, with supplementary interviews it has been found that in cases of no written work students most frequently use non-algorithmic approaches (such as clever shortcut strategies like compensation), while guessing and estimation are very infrequent (Fagginger Auer & Scheltens, 2012; Hickendorff et al., 2010).

7.3 Future directions

The findings in this dissertation on factors affecting strategy choices and performance and on methods that can be used to study this, provide several directions for future research in this area and educational research more generally. For the domain under study, results indicate that what teachers are currently doing has a

relatively limited effect on the strategy choices that matter most to performance (mental versus written strategies). These results are based purely on self-reports of the teachers, so it would be valuable to include actual observations of teaching practices in future investigations. However, results may be quite similar in both cases according to Desimone (2009), who has argued that early studies that suggested low correlations between classroom observations and teacher self-reports were flawed, and that more methodologically rigorous studies (with self-reports on concrete teaching behaviors, as was the case for many of the teacher reports in this dissertation) have demonstrated moderate to high correlations.

Aside from apparently limited teacher effects, the findings in this dissertation indicate that instructional interventions targeted at the desired strategy use can be effective. The most fruitful direction for future research therefore appears to be to develop interventions targeting students' strategy use, with careful attention for exactly which investigation elements are effective (e.g., direct accuracy feedback; Ellis et al., 1993), and possibly with training in making strategy choices that are adaptive at the student-level rather than promoting use of one generally well-performing strategy (for example, Chapter 4 indicated that written strategies are not necessarily more accurate than mental strategies for stronger students). When further research on the effects of the sociocultural context on strategy use is conducted (as recommended by Verschaffel et al., 2009), the present results indicate that this context should be considered more broadly than just in terms of the current teacher: parents and peers could be considered (Carr & Jessup, 1997), and teachers from earlier grades in which strategies were first encountered.

Larger than the effects of teachers on strategy choices, were the effects of student characteristics. Gender differences were found multiple times, with girls being more likely to use algorithmic, written strategies, and boys more likely to use mental strategies. Such gender differences have been found already at younger ages (Carr & Jessup, 1997; Davis & Carr, 2002; Fennema et al., 1998) and an interesting direction for future research would be to investigate how they may be explained by other traits in which boys and girls differ. For example, girls' lower self-confidence in math (J. A. Hyde, Fennema, Ryan, Frost, & Hopp, 1990; Mullis, Martin, & Foy, 2008) and their higher potential for academic delay of gratification (Bembenuddy, 2009) may cause them to choose the less risky written strategies, at the cost of speed. Students' motivation also appears to be related to their strategy choices, so it may be fruitful to investigate the effects of a motivation intervention (e.g., Siegle & McCoach, 2007) on strategy use.

Students' working memory also seems a highly relevant factor for choices for mental strategies: for students with a lower working memory capacity, the working memory resources freed up by writing down calculations should be especially important (in line with cognitive load theory; Paas et al., 2003). No effects of working memory were found in this dissertation, but this factor was only investigated once, with a new computerized version of existing instruments of which the reliability and validity has not been established yet (Stevenson et al., in preparation), and only for lower ability students. Since mathematical ability and working memory are related (Friso-van den Bos et al., 2013), it may be that a restriction of range of working memory prevented the finding of effects. So, working memory seems to be a very important factor for mental strategy use to investigate, but a proper investigation should be done with an appropriate measurement instrument and enough variance in memory capacities.

In addition to providing specific substantive suggestions for research on strategies, this dissertation illustrates an approach more generally applicable in educational research. The starting point of this dissertation was a large-scale assessment finding, and the dissertation itself consists of secondary analyses of assessment data and follow-up experiments. This approach combines the best of two worlds: it uses the wealth of data obtained from a large, representative sample for a large-scale assessment to scout for factors correlated with outcomes, which then enables targeted follow-up experiments in which the causality of the found correlations can be established, potentially resulting in interventions beneficial to educational practice. There is a very large amount of assessment data (e.g., TIMSS, PIRLS, PISA; Mullis, Martin, Foy, & Akora, 2012; Mullis, Martin, Foy, & Drucker, 2012; OECD, 2013), and secondary analyses help to make full use of this data. The discussed multilevel LCA and variations of explanatory IRT can be used to analyze the complex assessment data, as well as the data from follow-up experiments. And finally, to conclude with the central theme of this dissertation, solution strategies can be coded from readily available written work and are very important to performance, so including these in educational investigations is both easy and vital to obtaining a complete picture of students' learning.

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Nederlandse samenvatting

De afgelopen decennia zijn de prestaties van leerlingen aan het einde van de basisschool bij bewerkingen met vermenigvuldigen en delen sterk gedaald (J. Janssen et al., 1999, 2005; Scheltens et al., 2013). Het gaat hierbij om opgaven met grotere getallen en kommagetallen, zoals 23×56 en $31.2 \div 1.2$. Deze prestatiedaling ging samen met een verandering in de strategieën die leerlingen gebruiken om dergelijke opgaven op te lossen: het gebruik van relatief accurate algoritmes (zoals de staartdeling) nam af, terwijl het relatief inaccurate beantwoorden van opgaven zonder daarbij een berekening op te schrijven toenam (Fagginger Auer et al., 2013; Hickendorff et al., 2009; Van Putten, 2005). De verschuiving in strategiegebruik lijkt daarmee (deels) de waargenomen prestatiedaling te verklaren. In dit proefschrift wordt getracht meer inzicht te krijgen in deze ontwikkelingen (en hoe ze mogelijk ten goede te keren) door de factoren die invloed hebben op het rekenstrategiegebruik en de prestaties van leerlingen te onderzoeken. Ook wordt er dieper ingegaan op de statistische technieken die bij dergelijk onderzoek kunnen worden gebruikt.

Strategiegebruik is een belangrijk onderzoeksgebied binnen de cognitieve psychologie en speelt een rol bij zeer diverse taken en ontwikkelingsfasen (Siegler, 2007): bijvoorbeeld de manieren waarop peuters een speeltje proberen te pakken dat buiten hun bereik ligt, waarop basisschoolkinderen woorden spellen, en waarop oudere kinderen transitieve redeneerproblemen oplossen. Een populair onderwerp van onderzoek zijn rekenstrategieën. Vaak worden strategieën onderzocht voor relatief simpele optel-, aftrek-, vermenigvuldig- en deelopgaven met getallen onder de 100 die worden onderwezen in de lagere groepen van de basisschool (zie bijvoorbeeld Barrouillet et al., 2008; Blöte et al., 2001; Mulligan & Mitchelmore, 1997), maar er bestaat minder onderzoek naar strategiegebruik voor complexere opgaven. Dit strategiegebruik is juist interessant omdat er bij dit soort opgaven vaak veel verschillende aanpakken mogelijk zijn. De adaptiviteit (Lemaire & Siegler, 1995)

van de keuzes die leerlingen maken tussen die verschillende aanpakken is heel belangrijk: kiest de leerling de strategie die voor hem of haar het meest geschikt is voor de opgave? De accuratesse (kans op een goed antwoord) en snelheid van de verschillende mogelijke strategieën voor een leerling zijn hierbij belangrijk (Siegler & Shipley, 1995), maar ook de socioculturele context waarin de strategie wordt gebruikt (Verschaffel et al., 2009).

Het belang van strategiekeuzes in het rekenonderwijs is in de loop der jaren toegenomen. Zoals beschreven door de Koninklijke Nederlandse Academie van Wetenschappen (KNAW; 2009), schokte de lancering van de satelliet Spoetnik door de Sovjet-Unie in 1957 het Westen en volgden daarop hervormingen van het onderwijs die moesten zorgen voor snellere technologische vooruitgang. De uitwerking van deze hervormingen verschildte per land, maar een belangrijk aspect was vermindering van nadruk op algoritmes gezien de opkomst van computers en rekenmachines. In Nederland ontstond het 'realistisch rekenen', met vijf karakteristieke grondprincipes (Treffers, 1987b): het zelf kennis construeren door leerlingen; het gebruik van modellen en schema's; reflectie van leerlingen op hun eigen producties; leren van elkaar door interactie; en het stimuleren van het ontdekken van verbanden binnen de leerstof. Zo nam dus de nadruk op een vaste algoritmische aanpak af en werden de vele informele strategieën van leerlingen belangrijker. In 2002 waren er alleen nog realistische rekenboeken voor het basisonderwijs op de markt (KNAW, 2009; inmiddels is er een meer traditioneel georiënteerde methode bijgekomen).

Naast de verscheidenheid aan informele strategieën die in het realistisch rekenen wordt benadrukt, werd er ook een nieuwe, niet-cijferende aanpak met vaste stappen en een schematische notatie geïntroduceerd, als tussenvorm tussen hoofdrekenen en cijferen: het kolomsgewijs rekenen (Treffers, 1987a). Bij deze kolomsgewijze algoritmes blijft de getalwaarde van de cijfers intact (bijvoorbeeld dat bij 23×56 de 2 voor 20 staat), wat bij cijferen niet het geval is. Met de opkomst van het realistisch rekenen nam dan ook het gebruik van cijferalgoritmes af. Het gebruik van kolomsgewijze algoritmes en strategieën met een minder formele notatie nam echter niet in dezelfde mate toe: in plaats daarvan was er een grote toename van het aantal opgaven dat werd beantwoord zonder dat daarbij een berekening werd genoteerd (Fagginger Auer et al., 2013; Hickendorff et al., 2009). Vervolgonderzoek liet zien dat leerlingen in dit geval veelal hoofdrekenen (Hickendorff et al., 2010). Antwoorden zonder schriftelijke uitwerking bleken veel minder vaak goed dan antwoorden met uitwerking, en verschuivingen in het strategiegebruik tussen nationale peilingen van het rekenniveau in 1997 en 2004 gingen dan ook samen met

een sterke prestatiedaling (Hickendorff et al., 2009). Tussen 2004 en 2011 bleef het strategiegebruik grotendeels stabiel en bleven de prestaties op het lage niveau van 2004 (Fagginger Auer et al., 2013; Scheltens et al., 2013).

Opzet van dit proefschrift

Naar aanleiding van deze ontwikkelingen richt dit proefschrift zich op onderzoek naar de factoren die het strategiegebruik en de prestaties van groep-8-leerlingen bij het oplossen van vermenigvuldig- en deelopgaven beïnvloeden. Zowel de invloed van de instructie die leerlingen krijgen (dagelijks in de klas en bij speciale interventies) als van kenmerken van leerlingen en leerkrachten wordt onderzocht. Dit onderzoek wordt op twee manieren uitgevoerd: door middel van aanvullende analyses van bestaande data van een grote nationale rekenpeiling van Cito (Scheltens et al., 2013) en door middel van experimenten op basisscholen.

De eerste aanpak - aanvullende analyses van peilingsdata - wordt gebruikt in hoofdstuk 2 en 3, waar respectievelijk het strategiegebruik en de prestaties van groep-8-leerlingen worden gerelateerd aan kenmerken van de leerlingen en aan rapportages van de leerkrachten van deze leerlingen over de inhoud van hun rekenlessen. De rekenpeilingsdata die wordt gebruikt in deze hoofdstukken zorgt voor verschillende statistische complicaties: het grote aantal items in de leerkrachtvragenlijst; de multilevelstructuur van de data (opgaven, leerlingen, leerkrachten); het nonimale meetniveau van de strategieën; en het zogenaamde 'onvolledige design' van de peiling, waarbij elke leerling slechts een klein deel van de grote totale itemset maakt. Met latente-variabele-modellen wordt hiervoor een oplossing gezocht. In hoofdstuk 2 wordt een eerste toepassing van multilevel latente-klassen-analyse (MLCA; Vermunt, 2003) op peilingsdata beschreven en in hoofdstuk 3 wordt een nieuwe combinatie van LASSO-penaliserende (Tibshirani, 1996) en explanatory item-respons-theorie (IRT; De Boeck & Wilson, 2004) geïntroduceerd.

De tweede aanpak - experimenteel onderzoek op basisscholen - wordt gebruikt in hoofdstuk 4 en 5. Terwijl met de eerste aanpak alleen de samenhang tussen instructie en uitkomsten in kaart kan worden gebracht (correlationele verbanden), kan met de tweede aanpak daadwerkelijk worden onderzocht wat de gevolgen zijn van instructiepraktijken (causale verbanden). De nadruk ligt bij de experimenten qua strategieën op het wel versus niet noteren van berekeningen, vanwege het eerder beschreven grote verschil in prestaties tussen schriftelijke en hoofdrekenstrategieën, en op de effecten van de leerkracht en van leerlingkenmerken. In hoofdstuk 4

wordt met een choice/no-choice-experiment (Siegler & Lemaire, 1997) onderzocht of leerlingen beter presteren wanneer ze worden geïnstrueerd berekeningen op te schrijven en in welke mate ze verstandige (adaptieve) keuzes maken tussen wel en niet berekeningen opschrijven wat betreft accuratesse en snelheid. In hoofdstuk 5 wordt het effect van een training in het opschrijven van berekeningen op spontane strategiekeuzes en prestaties onderzocht. Dit wordt gedaan door verschillen hierin voor en na de training te meten (pretest-posstest-design) bij drie groepen leerlingen: een groep die de training krijgt, een groep die een controletraining krijgt en een groep die geen training krijgt.

Tenslotte wordt in hoofdstuk 6 met een experiment onderzoek gedaan naar de vergelijkbaarheid van resultaten verkregen met de aanpak in hoofdstuk 2 en 3 en de aanpak in hoofdstuk 4 en 5. Er wordt hierbij gekeken naar de mate waarin strategiegebruik en prestaties vergelijkbaar zijn wanneer verschillende soorten rekenopgaven door elkaar gemengd worden afgenomen (zoals doorgaans bij peilingen en in de onderwijspraktijk) versus wanneer alleen maar opgaven van één type worden afgenomen (zoals vaak bij experimenten). Er zou sprake kunnen zijn van verschillen door de cognitieve kosten van het wisselen tussen taken (Kiesel et al., 2010) en door perseveratie in het gebruik van strategieën (Lemaire & Lecacheur, 2010; Luwel, Schillemans, et al., 2009).

Bevindingen

Deze onderzoeken hebben geresulteerd in verschillende bevindingen over het strategiegebruik en de prestaties van leerlingen en de methoden die kunnen worden gebruikt om dit te onderzoeken.

Strategiegebruik en prestaties

Ongeveer een derde deel van de leerlingen bleek voornamelijk opgaven te beantwoorden zonder daarbij berekeningen te noteren, terwijl een vijfde deel vooral cijferalgoritmes gebruikte (hoofdstuk 2). Om tegemoet te komen aan de opmerkingen van Van den Heuvel-Panhuizen, Robitzsch, Treffers en Köller (2009) werd in de overige 'realistische' oplossingen verder onderscheid gemaakt tussen kolomsgewijze algoritmes en meer informele, non-algoritmische schriftelijke strategieën. Net als in eerder onderzoek (Hickendorff, 2013; Hickendorff et al., 2009, 2010; Van Putten, 2005) bleken leerlingen een veel grotere kans te hebben op een goed antwoord wanneer zij wel dan wanneer zij niet een berekening noteerden (hoofdstuk 3, 4 en 5).

Binnen de schriftelijke strategieën bleken de cijferende en kolomsgewijze algoritmes vergelijkbaar in hun accuratesse, terwijl non-algoritmische strategieën wat minder accuraat leken (hoofdstuk 3).

De dagelijkse onderwijspraktijken van leerkrachten bleken vooral samen te hangen met de keuzes die leerlingen maken tussen schriftelijke strategieën, en minder met de keuzes tussen schriftelijke en hoofdrekenstrategieën (hoofdstuk 2, 4 en 5). Daarmee lijkt het indirecte effect van die praktijken op prestaties via strategiegebruik beperkt. Wel bleken speciale interventies gericht op strategieën de prestaties en strategiekeuzes van zwakkere rekenaars positief te kunnen beïnvloeden, zowel op de korte termijn (als leerlingen werden geïnstrueerd hun berekeningen op te schrijven; hoofdstuk 4) als op de wat langere termijn (als leerlingen over een langere periode werden getraind met het doel hun spontane strategiekeuzes en prestaties te veranderen; hoofdstuk 5). Er werd ook een direct, positief effect van de hoeveelheid klassikale instructie op prestaties gevonden (hoofdstuk 3).

Kenmerken van leerlingen bleken sterk samen te hangen met het kiezen voor hoofdrekenen: dit werd vaker gedaan door jongens (vooral in plaats van het gebruiken van algoritmes) en door zwakkere rekenaars (hoofdstuk 2, 5 en 6). Hoofdrekenen bood een groter snelheidsvoordeel ten opzichte van schriftelijke strategieën voor jongens dan voor meisjes en was extra inaccuraat voor zwakkere rekenaars (hoofdstuk 4). Deze zwakkere rekenaars bleken op basis van hun prestaties met schriftelijke en hoofdrekenstrategieën ook niet altijd verstandige keuzes tussen deze twee aanpakken te maken, terwijl sterkere rekenaars niet per se (direct) baat hebben bij gedwongen worden hun berekeningen op te schrijven (hoofdstuk 4). Motivatie lijkt een rol te spelen bij keuzes voor hoofdrekenen (hoofdstuk 5).

Het wel of niet mengen van deelopgaven met andere opgaven hing niet samen met het strategiegebruik en de prestaties van leerlingen (hoofdstuk 6).

Methoden

Deze conclusies over het strategiegebruik en de prestaties van leerlingen werden getrokken met behulp van analyses van de data met latente-variabele-modellen. In deze modellen worden de responsen van leerlingen op opgaven (goed/fout of de gebruikte strategie) gemodelleerd als zijnde afhankelijk van een niet-geobserveerde (dus latente) variabele. Bij item-respons-modellen is deze latente variabele een continue schaal waarop je hoger of lager kan scoren, die bijvoorbeeld kan staan voor rekenvaardigheid. Bij latente-klassen-modellen is de latente variabele categorisch en bestaat hij uit verschillende groepen met elk een karakteristiek responspatroon

op een reeks items, bijvoorbeeld groepen leerlingen die elk een specifiek patroon van strategiekeuzes hebben. Deze modellen kunnen op een beschrijvende manier worden gebruikt, als er bijvoorbeeld alleen interesse is in wat de rekenvaardigheidsscore van individuele leerlingen is, maar ook op een verklarende manier, waarbij de scores op de latente variabele worden verklaard aan de hand van andere variabelen. Dit laatste stond centraal in dit proefschrift: er werd steeds gekeken naar hoe instructiepraktijken en leerlingkenmerken samenhangen met rekenvaardigheid en met de kans om in een bepaalde latente strategieklassse te komen.

Latente-variabele-modellen werden in dit proefschrift op veel verschillende manieren toegepast, waarvan sommige manieren nieuw waren. Zo worden in latente-klassenmodellen meestal maar twee niveaus (bijvoorbeeld opgaven en leerlingen) gemodelleerd, maar in hoofdstuk 2 werd een eerste toepassing van multilevel-latente-klassen-analyse (met een extra niveau voor de leerkrachten) op peilingsdata beschreven. In hoofdstuk 3 werd een nieuwe combinatie van item-respons-theorie met verklarende variabelen voor de rekenscores (explanatory IRT) met LASSO-penalisatie geïntroduceerd. Deze penalisatie is een manier om uit een grote groep voorspellende variabelen de variabelen te selecteren die het sterkst samenhangen met de uitkomstvariabele (rekenscores in dit geval). Deze nieuwe toepassingen werden gedaan op peilingsdata, waarvoor vaker latente-variable-modellen worden gebruikt vanwege de uitdagingen die dit type data biedt. In hoofdstuk 4, 5 en 6 werden de modellen ook ingezet voor de data van de experimenten en ze boden daar ook belangrijke voordelen, bijvoorbeeld bij het modelleren van de groei in prestaties bij het trainingsonderzoek (hoofdstuk 5).

Naast deze statistische methoden stond ook een andere methodologische benadering in dit proefschrift centraal: het in kaart brengen van het strategiegebruik van leerlingen aan de hand van de berekeningen die ze hebben genoteerd. Zoals besproken door Fagginger Auer, Hickendorff en Van Putten (2015), wordt strategiegebruik normaal vaak bepaald door de gebruikers van de strategieën daar verbaal over te laten rapporteren. Dit rapporteren kan echter het strategiegebruik zelf beïnvloeden, en het verzamelen van de rapportages is erg arbeidsintensief en vereist de aanwezigheid van een getrainde interviewer. Het noteren van berekeningen is daarentegen een natuurlijk onderdeel van het oplossen van opgaven en de berekeningen kunnen op grote schaal worden verzameld, waarna achteraf kan worden bepaald welke strategieën zijn gebruikt. Een belangrijk nadeel van het gebruiken van berekeningen is wel dat in het geval van het ontbreken van genoteerde berekeningen onbekend blijft wat een leerling precies heeft gedaan.

Dit proefschrift als geheel genomen illustreert een meer algemeen toepasbare methode voor onderwijsonderzoek. Het bouwt voort op bevindingen bij onderwijspeilingen en bestaat uit aanvullende analyses van bestaande peilingsdata en daarop gebaseerd experimenteel vervolgonderzoek. Deze aanpak combineert het beste van twee werelden: de grote hoeveelheid data van een grote, representatieve steekproef van een rekenpeiling wordt gebruikt om factoren te vinden die gerelateerd zijn aan onderwijsopbrengsten, en de causaliteit van die relaties kan vervolgens worden vastgesteld met gericht experimenteel vervolgonderzoek, dat mogelijk resulteert in interventies waar de onderwijspraktijk baat bij heeft. Er is nationaal en internationaal een grote hoeveelheid bestaande peilingsdata die nog beter kan worden benut door er aanvullende analyses op uit te voeren. De besproken multilevel-latente-klassen-analyse en variaties van item-respons-theorie-modellen kunnen worden gebruikt om de complexe peilingsdata te analyseren, evenals de data van vervollexperimenten. En ten slotte, om af te sluiten met het centrale thema van dit proefschrift: de oplossingsstrategieën van leerlingen kunnen veelal worden afgeleid uit beschikbaar schriftelijk werk en zijn een cruciaal onderdeel van hoe leerlingen rekenen, dus deze opnemen in onderwijsonderzoek is zowel relatief eenvoudig als essentieel voor het verkrijgen van een compleet beeld van het leren van leerlingen.

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Curriculum vitae

Marije Fagginger Auer werd op 8 mei 1988 te Utrecht geboren. In 2006 behaalde zij haar vwo-diploma op R.S.G. Broklede te Breukelen. Hierna deed zij haar bachelor Psychologie aan de Universiteit Leiden, die zij combineerde met keuzevakken bij de studie Wiskunde en een bestuursjaar bij het Leids Studentenkoor en -Orkest Collegium Musicum. In 2009 rondde zij haar bachelor cum laude af en begon zij met een onderzoeksmaster Developmental Psychology aan dezelfde universiteit, die zij in 2011 eveneens cum laude afrondde. Direct hierop volgend werd zij aangesteld als promovenda bij de afdeling Methodologie en Statistiek van het Instituut Psychologie aan de Universiteit Leiden, op een project in samenwerking met Cito Instituut voor Toetsontwikkeling te Arnhem. In deze rol leverde zij een bijdrage aan de rapportage van de nationale Periodieke Peiling van het Onderwijsniveau (PPON) voor rekenen-wiskunde in 2011 en was zij lid van de Interuniversitaire Onderzoeksschool voor Psychometrie en Sociometrie (IOPS), waar zij in het bestuur de promovendi vertegenwoordigde. Daarnaast construeert ze sinds 2009 bij Cito toetsopgaven voor rekenen-wiskunde, en beoordeelt ze sinds 2015 psychodiagnostische instrumenten voor de Commissie Testaangelegenheden Nederland (COTAN).