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Exploring the relation between visualizer–verbalizer cognitive styles and performance with visual or verbal learning material

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ABSTRACT

A student might find a certain representational format (e.g., diagram, text) more attractive than other formats for learning. Computer technology offers opportunities to adjust the formats used in learning environments to the preferences of individual learners. The question addressed in the current study was: does the match between a student's preference regarding the format of learning materials have any relation with performance when learning with a specific format? For example, do learners with a preference for visual materials indeed perform better with visual learning materials? In a study with a pre-test post-test design, 48 participants were randomly assigned to one of two conditions. Both conditions completed a mathematical learning task about combinatorics and probability theory. In one condition learning materials were mainly diagram-based in the other condition they were mainly text-based. Afterward, the relations between cognitive style (visualizers–verbalizers), cognitive abilities (e.g., spatial and verbal ability), and learning performance were examined. The findings showed that cognitive style and learning outcomes were unrelated, for example, learners with a preference for visual materials do not necessarily perform better with visual learning materials. Learning results seem to be influenced by cognitive ability (in particular spatial visualization) and the extent to which a format affords cognitive processing, rather than a match between used and preferred format. It is argued that students should not choose on the basis of their preference, because it might lead them to selecting a format that is less effective for learning.

1. Introduction

Most students have outspoken ideas about how they like information to be presented in instruction: some like visual information (e.g., diagrams, pictures, graphs), whereas others prefer verbal information that can be read or listened to. The idea of matching the individual's preference (or style) and the representational format of the learning materials has been appealing in the eyes of many, particularly practitioners. A match between format and preference promises to facilitate learning processes and to enhance learning performance (Klein, 2003). However, there is not much empirical evidence to support this verbalizer–visualizer hypothesis (Cronbach & Snow, 1977; Kirby, Moore, & Schofield, 1988; Massa & Mayer, 2006; Mayer & Massa, 2003; Messick, 1994). The increasing omnipresence of computer technology in instruction, gives a new impetus to the interest in individual differences, in particular the verbalizer–visualizer hypothesis. Computer technology provides increasing levels of flexibility and opportunities to adjust the representations used in learning environments to the needs of individual learners. For example, multimedia making it possible to flexibly combine different representational formats and modalities (Mayer, 2003; van Someren, Reimann, Boshuizen, & de Jong, 1998), computer simulations enabling students to manipulate representations (de Jong, 2005, 2006), and hypermedia providing students with the possibility to choose the format and modality in which the information is presented (Gerjets, Scheiter, Opfermann, Hesse, & Eysink, 2009; Scheiter & Gerjets, 2007). The new possibilities also involve new questions and challenges. For example, is it wise to let students choose themselves in which format and modality the learning material will be presented? A student might find a certain representational format more attractive than others, but the question is: will that representation also be the best choice from an instructional point of view? In other words, do learners with a preference for visual materials indeed perform better with visual learning materials and verbal learners perform better with verbal material? Put more broadly, to what extent can preferences predict learning performance?

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1.1. Theoretical background

With regard to categories such as visualizers and verbalizers a distinction should be made between what people like or prefer (style) on the one hand and what they are actually good at in terms of performance (ability) on the other hand.

1.1.1. Cognitive abilities and styles

In the literature a distinction is made between cognitive *abilities* and *styles* (e.g., cognitive styles, learning styles). The way in which these terms are used, is not always consistent (Mayer & Massa, 2003; Plass, Chun, Mayer, & Leutner, 1998).

Cognitive abilities refer to general and specific intellectual capabilities (e.g., spatial ability, memory). Measurement of abilities emphasizes how well individuals can perform at their best and most accurate. Abilities are often considered value directional, that is, the more one has of a certain ability the better.

Cognitive style refers to people's information-processing habits. Cognitive styles reflect stable attitudes, dominant or preferred modes of perceiving, remembering, thinking, and problem solving (Green & Schroeder, 1990; Messick, 1976). Cognitive styles tend to be bipolar (e.g., visualizer–verbalizer) and value differentiated, that is, each pole of a style dimension has different adaptive implications, it depends on the circumstances whether it is better to use a certain style or another (Green & Schroeder, 1990; Messick, 1994).

An example of cognitive style is the distinction between so-called visualizers and verbalizers. Massa and Mayer (2006) found some support for the verbalizer–visualizer hypothesis. In a learning environment about electronics it was found that students who preferred visual modes of presentation tended to select pictorial help screens whereas students who preferred verbal models of presentation tended to select verbal help screens.

1.1.2. Two types of visualizers

In studies in mathematics education empirical findings often suggest that visualizers tend not to perform as well as verbalizers (Friedman, 1995; Krutetskii, 1976; Lean & Clements, 1981; Presmeg, 1986; Woolner, 2006). However, other studies point out that within the category "visualizers", actually two types of visualizers should be distinguished: individuals who excel in schematic, spatial imagery and individuals who excel in pictorial, object imagery (Hegarty & Kozhevnikov, 1999; Kozhevnikov, Hegarty, & Mayer, 2002; Kozhevnikov, Kosslyn, & Shephard, 2005). Results of a series of studies by Kozhevnikov et al. (2005) suggested that spatial and object visualizers encode and process mental images in different ways. Spatial visualizers showed a tendency to encode and process images part by part, using spatial relations to analyze the components. Object visualizers showed a tendency to encode images globally as single perceptual units, which were processed holistically. Support for the distinction between spatial and object visualizers comes from studies in which significant relationships have been observed between spatial ability and mathematical achievement (Battista, 1990; Hegarty & Kozhevnikov, 1999; Smith, 1964; Tolar, Lederberg, & Fletcher, 2009), whereas the use of pictorial representations was found to be negatively correlated with achievement.

1.1.3. Relation cognitive styles, abilities, representations, and learning performance

Many studies that focus on the visualizer–verbalizer hypothesis try to establish if and to what extent cognitive styles relate to cognitive abilities, and (general) achievement measures (e.g., SAT scores). Few studies however, relate the visualizer-verbalizers hypothesis to external representations used to present subject matter, although in some studies the format of parts of the learning materials are manipulated, like help screens in electronic learning environments (e.g., Massa & Mayer, 2006; Plass et al., 1998). The other way around, studies that focus on the effects of representational formats in learning materials often do not take into account the role of individual differences. The aim of the current study was to connect the two approaches: relating the effects of different representational formats on learning performance to individual differences.

1.2. Research questions

The overall research question of this study was: Is there a relation between cognitive style, cognitive ability, representational format of the learning materials, and learning performance? In this study two conditions were compared that differed from each other with respect to the representational format of the learning materials. In one condition the learning materials were mainly visual (diagrams), in the other condition the instructional materials were verbal. In order to make a fair comparison, the representational formats used in both conditions were selected on the basis of the following four criteria:

(1) The instruction in both conditions should be identical, except for the representational format used to present the subject matter. The domain of the instruction was a subdomain of mathematics: combinatorics and probability theory.
(2) The representations used in both conditions should be informationally equivalent, which is the case if all information that can be inferred from one representation can also be inferred from the other (Larkin & Simon, 1987; Palmer, 1978; Simon, 1978). Touchstone of informational equivalence is that one representation can be built on basis of the other and vice versa.
(3) Third, the representations used in both conditions should require equal amounts of time to be processed, and the selected formats should not differ from each other with regard to the amounts of cognitive load they impose on students.
(4) Fourth, both versions should use either single or multiple representations. Combining two or more representational formats into what is called a multiple representation (e.g., van Someren et al., 1998) is assumed to affect learning and understanding (Ainsworth, 1999, 2006; Seufert, 2003). First, different formats can complement each other by focusing the students' attention to different aspects of a domain. Second, one representation might help to interpret and understand the other. Third, learners' integration of information from different representations is thought to support the construction of deeper understanding (Ainsworth, 1999, 2006; van der Meij & de Jong, 2006). In order to prevent artifacts in the data caused by using a single representation in one condition and multiple representations in the other condition, both conditions should use either single or multiple representations.

The study followed a pre-test post-test design and the conditions were compared in terms of their effects on learning results. Furthermore, cognitive styles and abilities of the participants were measured and related to their learning performance.

The research question was split into several sub-questions. (1) Is there a relation between cognitive style and cognitive abilities? Based on findings in other studies, the correlations were expected to be small or even absent (Alesandrini, 1981; Antonietti & Giorgetti, 1998; Green & Schroeder, 1990; Kirby et al., 1988). (2) To what extent can cognitive style predict learning performance? Since cognitive style reflects a preference rather than actual performance, we did not expect to find a strong correlation here. Nonetheless, this question can give important clues in answering practically relevant questions like: is it wise to give students the opportunity to choose a format in which the learning materials will be display, given that students probably will base their choice on their representational preferences? (3) To what extent can cognitive abilities predict learning performance in general and when learning with a specific representational format? Both spatial and verbal ability was assumed to be related to learning performance in general. Spatial ability because it is often found to be related to mathematical achievement; verbal ability because of the assumed influence of domain characteristics (in particular the strictly sequential nature of problem solutions and the reasoning required to solve these problems). With regard to the relation between cognitive abilities and learning performance when learning with a specific representational format it was hypothesized that verbal ability was positively related to learning performance in learning with verbal material. Spatial ability was assumed to be positively related to learning performance when learning with diagrams. Iconic visual ability was assumed not to be related to learning performance in either condition and there might even be a negative correlation between this ability and learning outcomes.

2. Method

2.1. Participants and design

The participants were 48 students of Psychology or Educational Sciences. The mean age was 20.34 years ($SD = 2.29$). The percentage of women was 83.30 ($n = 40$) and the percentage of men was 16.70 ($n = 8$). The participants received credits for their participation.

The experiment employed a between-subjects pre-test post-test design, with the representational format (verbal or visual) of the learning materials as independent variable. Participants were randomly assigned to either the Visual Instruction condition or to the Verbal Instruction condition. In the first there were 22 women and 2 men. Their mean age was 20.25 years ($SD = 2.69$). In the latter condition there were 18 women and 6 men with a mean age of 20.43 ($SD = 1.83$).

2.2. Domain

The domain of instruction was combinatorics and probability theory. Combinatorics can be used to determine the number of combinations that can be made with a certain set or subset of elements. Probability theory can be used to calculate the chance that a certain combination will be observed empirically. The following PIN-code problem is typical for this domain:

> *Your bank distributes a random four-digit code as a personal identification number (PIN) for its credit card. What is the probability that a thief finding the card and trying to get money with it will guess the correct code in one go, and will be able to plunder your account?*

In order to determine the number of possible combinations, one also needs to know 1) whether elements may occur repeatedly in a combination (replacement) and 2) whether the order of elements in a combination is of interest (order). On the basis of these two criteria, four problem categories can be distinguished (for an overview, see Fig. 1). The PIN-code example matches category 3 (replacement; order important).

2.3. Materials

2.3.1. Learning environment

The learning environment used in the current study was Probe. This environment was created with SIMQUEST authoring software (van Joolingen & de Jong, 2003). Probe contained simulations (see Fig. 2 for an example) and a series of questions (both open-ended and multiple-choice items) and assignments. In the case of the multiple-choice items, the students received feedback from the system about the correctness of their answer. If the answer was wrong, the system offered hints about what was wrong with the answer.

Two versions of the Probe learning environment were used. Both versions were identical except for the representational format used in the simulations. In the Verbal Instruction-version a combination of text + arithmetic was used (see Fig. 2) and in the Visual Instruction-version a combination of tree diagram + arithmetic (see Fig. 3).

Following the four criteria for selecting representational formats in this study (see Section 1.2), these representations were informationally equivalent, that is, they were constructed in a process in which one was built on basis of the other, and back again. Furthermore, both

		ORDER IMPORTANT?	
		Yes	**No**
REPLACEMENT?	**No**	Category 1: No replacement; Order important	Category 2: No replacement; Order not important
	Yes	Category 3: Replacement; Order important	Category 4: Replacement; Order not important

Fig. 1. Problem categories within the domain of combinatorics.

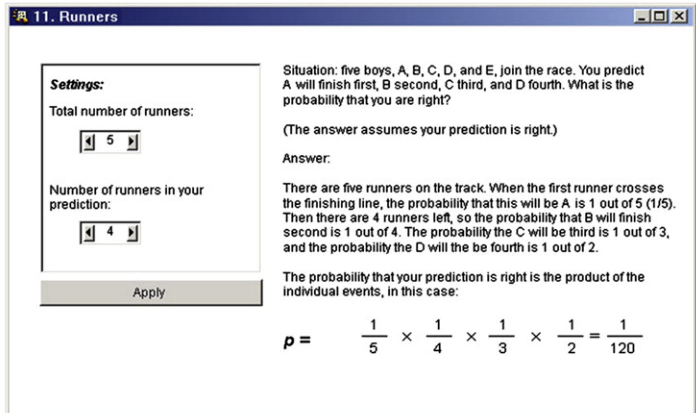

Fig. 2. Screen dump probe simulation (Text + Arithmetic version).

versions were found to impose equal levels of cognitive load on learners and the recorded learning times were equal (Kolloffel, Eysink, de Jong, & Wilhelm, 2009). In accordance with the fourth criterion, both learning environments used multiple representations.

2.3.2. Measuring cognitive (visualizer–verbalizer) style

Perhaps the most well-known instrument for assessing the individual preference for visual or verbal learning is the Visualizer–Verbalizer Questionnaire (VVQ) devised by Richardson (1977). The 15 true-false items is a subset taken from Paivio's (1971) 86-item Ways of Thinking questionnaire. The items of the VVQ are coded in such a way that higher scores indicate a visual style and lower scores a verbal style. Over the years, the VVQ has been subject of debate, in particular its assumption that people have a tendency to use *either* visual *or* verbal representations and strategies. Several studies examined the VVQ's psychometric properties and no evidence was found for one, bipolar dimension separating visualizers and verbalizers. The VVQ was found to measure several constructs. Most of these studies conclude that the scale measured (at least) two distinct components: visual style and verbal style (Antonietti & Giorgetti, 1996, 1998; Boswell & Pickett, 1991; Green & Schroeder, 1990; Kirby et al., 1988). Kirby et al. (1988) used principal components analysis to analyze the responses of 119 students to the VVQ. They found support for three factors: verbal preference, dream vividness, and mental imagery. In order to obtain sufficient items per scale, they extended the VVQ by adding items until there were 10 items for each subscale (verbal, visual, dream). This extended VVQ was used in the current study.

2.3.3. Cognitive ability measures

Different tests were used to measure verbal and spatial abilities. Some of the ability tests used in this study were subtests drawn from the Groninger Intelligentie Test 2 (GIT2), a Dutch intelligence test developed by the University of Groningen, The Netherlands (Luteijn & Barelds, 2004). This test has been proven reliable, and can be used as an alternative to the Wechsler Adult Intelligence Scale (WAIS). Three ability tests were used: one for measuring verbal ability, and because of the distinction between two types of visualizers (spatial ability and iconic visual ability), two different visual ability tests were used.

In a previous section (see Section 1.1.2), a distinction was made between spatial and object visualizers. A closure speed test, a subtest drawn from the GIT2 intelligence test, was used to measure *object visualization*. Participants were shown 20 incomplete drawings of increasing difficulty and have to indicate what is depicted.

Second, *spatial visualization* was measured by a revised version of the Object Perspective Taking Test (Hegarty & Waller, 2004; Kozhevnikov & Hegarty, 2001). Spatial visualization correlates highly with mental rotation. In the revised Object Perspective Test, a configuration of seven objects was drawn on the top half of an 8.5 $\times$ 11 in. sheet of paper. On each item, the participant was asked imagine being at the position of one object in the display (the station point) facing another object (defining their imagined heading or perspective within the array) and was asked to indicate the direction to a third (target) object. The bottom half of the page showed a picture of a circle, in

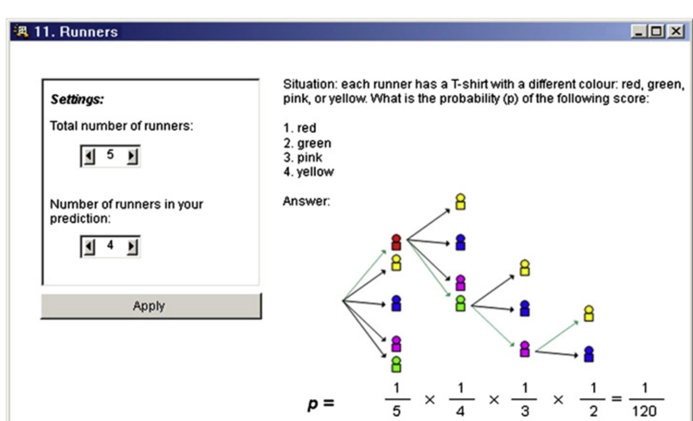

Fig. 3. Screen dump probe simulation (Diagram + Arithmetic version).

which the imagined station point (e.g., the stop sign) was drawn in the center of the circle, and the imagined heading (e.g., direction to the house) was drawn as an arrow pointing vertically up. The task was to draw another arrow from the center of the circle indicating the direction to the target object (e.g., the traffic light). Participants were prevented from physically rotating the test booklet (which would provide them with a view of the array from another perspective). All items involved an imagined perspective change of at least 90°. The direction of the target object relative to the heading was varied systematically by dividing the circle into four quadrants, 0°–90°, 90°–180°, and so on. There were 12 items in the test, and the answers of three of the items fell in each of the four quadrants. The score for each item was the absolute deviation in degrees between the participant's response and the correct direction to the target (absolute directional error). A participant's total score was the average deviation across all attempted items. Participants had five minutes for the test.

Verbal ability was measured by means of the "Reasoning" subtest of the GIT2. This test measures the ability of reasoning (induction and deduction) with verbal materials. The test consists of 20 items of increasing difficulty, in which participants have to discover a logical connection between two pairs of words and apply the connection to a third word pair.

2.3.4. Knowledge measures

Two knowledge tests were used in this experiment: a pre-test and a post-test. The pre-test contained 12 items and the post-test 26 items. The reliability and sensitivity of the test items have been established in a number of studies performed across Germany and The Netherlands (see e.g., Berthold & Renkl, 2009; Eysink et al., 2009; Gerjets et al., 2009; Kolloffel et al., 2009; Wouters, Paas, & Van Merriënboer, 2007, April). The pre-test was aimed at measuring (possible differences in) the prior knowledge of the students. Well-structured and organized mathematical knowledge is thought to include conceptual, intuitive, procedural, and situational understanding (e.g., Fuchs et al., 2004; Garfield & Ahlgren, 1988; Hiebert & Lefevre, 1986; Rittle-Johnson & Koedinger, 2005; Rittle-Johnson, Siegler, & Alibali, 2001; Sweller, 1989). The post-test consisted of different types of items, each aimed at measuring one of these types of knowledge. *Conceptual knowledge* is "implicit or explicit understanding of the principles that govern a domain and of the interrelations between units of knowledge in a domain" (Rittle-Johnson et al., 2001, p. 364). Conceptual knowledge develops by establishing relationships between pieces of information or between existing knowledge and new information. As learners' conceptual knowledge becomes sufficiently advanced, well-integrated, and automated, their ability to assess meaningful situations and predict the outcomes of complex events can become so quickly that learners are even not capable anymore of verbalizing the reasoning on which their assessments are based. This kind of conceptual knowledge is called *intuitive knowledge* and is assumed to be particularly fostered by simulation-based inquiry learning (for an extensive discussion, see Swaak & de Jong, 1996). *Procedural knowledge* is "the ability to execute action sequences to solve problems" (Rittle-Johnson et al., 2001, p.346). *Situational knowledge* (de Jong & Ferguson-Hessler, 1996) enables students to analyze, identify, and classify a problem, to recognize the concepts that underlie the problem, and to decide which operations need to be performed to solve the problem. The post-test contained 26 items and was specifically designed to measure the different knowledge types: conceptual knowledge (4 items), intuitive (8 items), procedural (10 items), and situational knowledge (4 items).

2.4. Procedure

The sessions were held in a room that contained a personal computer. First, participants completed a series of tests, starting with the extended Visualizer–Verbalizer Questionnaire, followed by GIT2-Perceptual Speed Test, the Object Perspective Taking Test (time limit of 5 min), and the GIT2-Reasoning test. After each test, the experimenter introduced the next test and checked if the participants had understood the instructions. In the case of the Object Perspective Taking Test the experimenter watched the time limit. After completing the tests, the participants were introduced to the learning task. They were told that they could work at their own pace. The participants started the learning task by completing the pre-test. It was announced that the post-test would contain more items of greater difficulty than the pre-test, but that the pre-test items nonetheless would give an indication of what kind of items to expect on the post-test. After completing the pre-test the participants received a printed introductory text introducing the domain. Along with the introductory text the participants received information about how to enter the learning environment. After finishing the last section of the learning environment, the participants received the post-test.

3. Results

3.1. Performance measures

The performance measures, that is, scores on cognitive abilities, pre-test, and post-test are displayed in Table 1.

Two-tailed *T*-tests were applied to the data displayed in Table 1. With regard to the scores on the extended VVQ it was found that the scores on the visual scale in the Verbal Instruction condition were higher ($t(46) = -2.35$, $p < 0.05$). Because participants had been assigned randomly to conditions, this difference is due to chance. No differences between conditions were found with regard to cognitive abilities or pre-test scores. It was found however that participants in the Verbal Instruction condition obtained significantly higher post-test scores ($t(46) = -2.24$, $p < 0.05$; Cohen's $d = 0.65$). With regard to conceptual, intuitive, and situational knowledge, no differences between conditions were observed. With respect to procedural knowledge it was found that participants in the Verbal Instruction condition outperformed participants in the Visual Instruction condition ($t(46) = -2.49$, $p < 0.05$; Cohen's $d = 0.72$).

3.2. Correlational analyses

3.2.1. Relation between cognitive styles and cognitive abilities

The correlations between cognitive styles (VVQ-Verbal, VVQ-Visual, and VVQ-Dream) and cognitive abilities (spatial visualization, object visualization, and verbal ability) were calculated. No correlations were found between cognitive styles and cognitive abilities. A small correlation was observed between two cognitive abilities: spatial visualization and object visualization ($r = 0.29$, $p < 0.05$).

Table 1
Descriptive statistics for performance measures.

	Representational format			
	Diagram + Arithmetic ($n = 24$)		Text + Arithmetic ($n = 24$)	
	M	*SD*	*M*	*SD*
Cognitive style				
Verbal	6.63	1.58	6.71	1.81
Visual	6.00	1.53	7.04	1.55
Dream	7.96	1.97	8.63	1.72
Cognitive ability				
Spatial visualization	37.64	19.94	38.49	25.66
Object visualization	12.83	1.90	13.54	1.77
Verbal ability	13.42	1.61	13.92	1.93
Pre-test	5.67	1.55	6.75	2.33
Post-test				
Conceptual knowledge	3.33	0.82	3.67	0.57
Intuitive knowledge	7.25	1.54	7.54	0.72
Procedural knowledge	4.21	2.02	5.67	2.04
Situational knowledge	3.54	1.18	3.67	0.92
Total	18.33	3.86	20.54	2.90

3.2.2. *Relation between cognitive styles and learning outcomes*

In general, no correlations were observed between cognitive styles and learning outcomes. When each condition is considered separately, only one correlation is observed in the Visual Instruction condition. Here, a moderate correlation is found between a verbal cognitive style and conceptual knowledge ($r = 0.44$, $p < 0.05$). In the Verbal Instruction condition, no correlations were found between cognitive style and learning outcomes.

3.2.3. *Relation between cognitive abilities and learning outcomes*

The correlations between cognitive abilities and learning results are displayed in Table 2. Here, no distinction is made yet between conditions. The correlations show moderate relations between cognitive abilities and post-test scores. Spatial visualization shows moderate correlations with situational knowledge and the post-test overall score. Verbal ability is, besides the post-test overall performance and situational knowledge, also moderately related to the procedural knowledge scores. In order to explore the relation between this set of predictor variables (spatial visualization and verbal ability) and situational knowledge scores and post-test total scores, two stepwise multiple regression analyses were conducted.

The first analysis indicated that spatial visualization and verbal ability together accounted for 27.3% (24.0% adjusted) of the variance in situational knowledge scores, $R^2 = 0.273$, $F(2,45) = 8.44$, $p < 0.001$. Spatial visualization uniquely accounted for 10.6% ($sr^2 = 0.11$, $\beta = 0.34$, $t(44) = 2.57$, $p < 0.05$). Verbal ability uniquely accounted for 8.9% ($sr^2 = 0.09$, $\beta = 0.31$, $t(44) = 2.35$, $p < 0.05$). The second analysis showed that verbal ability accounted for 19.4% (17.6% adjusted) of the variance of post-test total scores, $R^2 = .194$, $F(1,46) = 11.05$, $p < 0.01$. Spatial visualization did not contribute significantly.

When the correlations between cognitive abilities and learning outcomes are considered for each condition separately, then the following is found.

In the Visual Instruction condition no correlations are observed. In the Verbal Instruction condition the correlations displayed in Table 3 were found.

In the Verbal Instruction condition, spatial visualization was moderately and positively correlated with conceptual, procedural, and situational knowledge, and post-test total scores. Object visualization turned out to be moderately and positively correlated with conceptual knowledge and post-test total scores. Verbal ability was found to be positively related to procedural and situational knowledge and post-test total scores.

These observations in the Verbal Instruction condition were further explored by means of stepwise multiple regression analyses. Spatial visualization was found to be the only significant predictor of the variance in test results of the participants in this condition (see Table 4).

Spatial visualization accounted for 25.7% of the variance in conceptual knowledge, 21.5% of the variance in procedural knowledge, 30.0% of the variance in situational knowledge, and 29.2% of the variance in post-test total.

4. Discussion

The purpose of this study was to examine the relation between cognitive style, cognitive ability, representational format of the learning materials, and learning performance. The research question was split into several sub-questions. The first focused on the relation between

Table 2
Correlations between cognitive abilities and learning outcomes.

	Knowledge type				
	Concept.	Intuitive	Proced.	Situat.	Total
Spatial visualization				0.43[b]	0.32[a]
Object visualization					
Verbal ability			0.38[b]	0.41[b]	0.44[b]

[a] Correlation is significant at the 0.05 level (2-tailed).
[b] Correlation is significant at the 0.01 level (2-tailed).

Table 3
Correlations between cognitive abilities and learning results in Text + Arithmetic group.

	Knowledge type				
	Concept.	Intuitive	Proced.	Situat.	Total
Spatial visualization	0.51[a]		0.46[a]	0.55[b]	0.54[b]
Object visualization	0.45[a]				0.41[a]
Verbal ability			0.42[a]	0.43[a]	0.49[a]

[a] Correlation is significant at the 0.05 level (2-tailed).
[b] Correlation is significant at the 0.01 level (2-tailed).

cognitive style and cognitive abilities; the second focused the relation between cognitive style and performance in a learning task; and the third aimed at examining the relation between cognitive abilities and learning performance in general and when learning with a specific representational format. The first two sub-questions will be addressed in Section 4.1 about cognitive styles, the third sub-question will be answered and discussed in more detail in Section 4.2 on cognitive abilities.

4.1. Cognitive styles

This article started with the observation that the idea of matching the individual's preference (cognitive style) and the representational format of the learning materials promises to facilitate learning processes and to enhance learning performance.

The first sub-question was: Is there a relation between cognitive style and cognitive abilities? Cognitive style reflects what people like or prefer, cognitive abilities reflect what they are actually good at in terms of performance. The data showed that there were no correlations between cognitive style and cognitive abilities. This implies that the participants' inclination or preference to use a certain format is not related to their cognitive abilities. This finding is in line with other studies in which correlations between cognitive style and cognitive abilities were also found to be quite small or absent (Alesandrini, 1981; Antonietti & Giorgetti, 1998; Green & Schroeder, 1990; Kirby et al., 1988).

The second sub-question was: To what extent can cognitive style predict learning performance? Since cognitive style reflects a preference rather than actual performance, we did not expect to find a strong correlation here. It was found that cognitive style showed no correlation with learning performance, except for a moderate, positive relation in the Visual Instruction condition between a preference for verbal material and conceptual knowledge scores.

A practical question underlying this study was: is it wise to let students choose themselves in which format and modality the learning material will be presented? The answer to this question must be in the negative: preference does not play a role in learning performance. The findings suggest that it can even be counterproductive to give students the opportunity to choose. In previous studies we observed that almost all students preferred learning with tree diagrams rather than learning with text. They found the tree diagrams "appealing", whereas the textual format was considered "boring". It is likely that students will choose the format they find the most attractive. However, the results showed that significantly higher learning outcomes (procedural knowledge and post-test total scores) were obtained with the "boring" verbal format. Therefore, choosing a format on the basis of one's own preference can lead the student to selecting a format that is less effective for learning.

4.2. Cognitive abilities

The third sub-question addressed in the current study was: to what extent can cognitive abilities predict learning performance in general and when learning with a specific representational format? In general, both spatial and verbal ability were assumed to be related to learning performance in general. Spatial ability because it is often found to be related to mathematical achievement; verbal ability because of the assumed influence of domain characteristics (in particular the strictly sequential nature of problem solutions and the reasoning required to solve these problems). It was found that verbal ability was a moderately strong predictor of learning performance. This observation was in line with the expectations and provided some support for the hypothesized match between verbal ability and the reasoning required to solve problems in the current domain. Unlike the expectations though, was the finding that spatial ability did not contribute to the prediction of learning outcomes in general.

With respect to the relation between cognitive abilities and learning performance when learning with a specific representational format it was hypothesized that verbal ability was positively related to learning performance in learning with verbal material. Spatial ability was assumed to be positively related to learning performance when learning with diagrams. The data did not confirm these expectations and showed a different pattern that will be discussed in the following sections.

4.2.1. Visual instruction: cognitive abilities and learning performance

The expected positive relation between spatial ability and learning performance in the Visual Instruction condition was not found. In fact, there was no relation at all between cognitive abilities and learning performance in this condition. The question is: why was spatial visualization *not* related to learning performance? Spatial ability seems important when learning with a spatial representation such as tree

Table 4
Variance explained by spatial visualization in the verbal instruction condition.

	R^2	R^2 adjusted	F	p
Conceptual knowledge	0.26	0.22	7.61	$p < 0.05$
Procedural knowledge	0.22	0.18	6.03	$p < 0.05$
Situational knowledge	0.30	0.27	9.43	$p < 0.01$
Post-test total scores	0.29	0.26	9.09	$p < 0.01$

diagrams. Information about probability distributions can be perceived at a single glance in tree diagrams. Information about the probabilities of specific events can be inferred from tree diagrams by analyzing the separate pathways through tree diagrams. The latter activity apparently taps the spatial visualization ability. Spatial visualizers tend to encode and process images part by part, using spatial relations to analyze the components (Kozhevnikov et al., 2005).

Furthermore, the learning outcomes in the Visual Instruction condition were in general significantly lower than in the Verbal Instruction condition and although spatial visualization (and associated working memory capacity) usually has a positive correlation with mathematics achievement, it does not in the Visual Instruction condition. In other words, having a high working memory capacity normally is an advantage for mathematics learning, but in the Visual Instruction condition it does not seem to help learners to obtain better learning results. This lack of correlation suggests that the cognitive processing when learning with tree diagrams is not optimal. One explanation could be that learning with tree diagrams is more difficult. However, this explanation seems to be refuted by findings in another study in which the cognitive load imposed by the representations used in both conditions was found to be equal (Kolloffel et al., 2009).

On the other hand, tree diagrams may appear easier to read and interpret than they actually are, possibly causing what is called an "illusion of knowing", that is, believing that comprehension has been attained when, in fact, comprehension has failed (Glenberg, Wilkinson, & Epstein, 1982). Students might think after a single glance at a tree diagram that they have all the information they need and move on, only to find at the post-test that their knowledge is incomplete. A third explanation can be that tree diagrams are more suited for people who already have domain knowledge (e.g., math teachers) rather than learners without domain knowledge. Tabachneck-Schijf, Leonardo, and Simon (1997) argue that experts in particular benefit from diagrams because for them diagrams serve as an aid to access information stored in long term memory. An implication could be that tree diagrams are less suited for people (e.g., students) with little or no prior knowledge, who use tree diagrams as a source of information to build up their knowledge.

4.2.2. Verbal instruction: cognitive abilities and learning performance

In the Verbal Instruction condition, a positive relation between verbal ability and learning performance was expected. Indeed, verbal ability was found to be positively correlated with procedural and situational knowledge scores and the post-test total scores. However, a multiple regression analysis showed that not verbal ability, but spatial visualization was the one and only significant predictor of learning performance. This applied to conceptual, procedural, and situational knowledge scores and to the post-test total scores.

The observation that spatial visualization plays a major role in learning with non-spatial representational formats (text and arithmetic) suggests it was not the spatial component per se that explains this observation. Some support for this idea can be found in the literature. Spatial processing is found to be related to executive functions (i.e., the ability to control attention) associated with working memory (e.g., Miyake, Friedman, Rettinger, Hegarty, & Shah, 2001; Tolar et al., 2009). Individuals with higher working memory capacity may be more proficient at processing spatial information than those with lower working memory capacity, and, as a consequence, perform better on mathematical (or arithmetical) problems that require much working memory capacity. This is supported by other studies in which evidence is reported for a positive correlation between spatial ability and mathematics achievement (e.g., Battista, 1990; Hegarty & Kozhevnikov, 1999; Smith, 1964; Tolar et al., 2009).

4.3. Implications and limitations

The main theoretical implication of this study is that the effectiveness (or ineffectiveness) of a format is not mediated by how well it matches the preference of the learner. It is rather a matter of how well a format generally affords cognitive processing, thinking, reasoning, and knowledge construction. One format might be more effective in facilitating these processes than another format. In the current study for example, the learning results in the Verbal Instruction condition were significantly better than in the Visual Instruction condition. Individual differences do play a role, a well-considered choice for a representational format can optimize the learning opportunities for most students. How much they can benefit is to some extent mediated by their cognitive abilities.

A practical implication is that when designing learning materials it is recommendable to first (experimentally) compare the effectiveness of different formats. Such comparisons provide a basis for an informed, evidence-based decision about which format (or combination of formats) to use in the instructional materials. This approach promises to be more effective than giving learners the options to select their favorite format. Moreover, the findings suggest that it can even be counterproductive to give students the opportunity to choose a format in which the learning materials will be presented.

A limitation of the current study is the extent to which the findings can be generalized. This is not only due to the relatively low number of participants, but particularly because it is unknown if and to what extent the beneficial effects of learning with verbal instruction can be generalized to other domains and other target populations. The effectiveness of a format depends on the domain (Cheng, Lowe, & Scaife, 2001; Scaife & Rogers, 1996; Zhang, 1997) and the expertise level of the target population (Leung, Low, & Sweller, 1997; Tabachneck-Schijf et al., 1997; Tarr & Lannin, 2005). Therefore, the effectiveness of a format always needs to be examined carefully, taking into account the domain and the characteristics of the target population.

5. Conclusion

Computer technology provides increasing levels of flexibility and opportunities to adjust the representations used in learning environments to the needs of individual learners. Matching the individual's preference and the representational format of the learning materials promises to facilitate learning processes and to enhance learning performance. The findings of the current study however suggest that this idea is too simplistic. It was found that cognitive style and learning outcomes were unrelated, for example, learners with a preference for visual materials do not necessarily perform better with visual learning materials. Learning results seem to be influenced by cognitive ability (in particular spatial visualization) and the extent to which a format affords cognitive processing, rather than a match between used and preferred format. Therefore, it is recommended that designers of learning materials search for the format (or combination of formats) that in general is most effective for learning rather than trying to provide students with the option to choose their favorite format. The data suggest that giving students the option to choose their favorite format can even be counterproductive because it might lead them to selecting a format that is less effective for learning.

Some of the observations in the current study raise new questions. For example, it would be interesting to investigate why spatial visualization did not play a role in the Visual Instruction condition. Normally, cognitive abilities such as spatial visualization facilitate learning and are related to enhanced learning performance. It is strange that no relation at all was observed. Could it be that a format is less effective because it prevents students from calling specific cognitive abilities into play when processing the learning materials? And if so, how can instruction be designed in such a way that it enables learners to make optimal use of their abilities?

Some other suggestions for further research have to do with the effectiveness of representational formats within and across domains. With regard to the effectiveness *within* domains it would be interesting to examine the interaction between level of expertise of the users (students) on the one hand and the representational format of the instruction on the other hand. This can be useful for answering questions such as: which is the most effective format for beginners and, as time and expertise progress, when would it be appropriate to switch to another (more advanced) representational format? With respect to the effectiveness of formats *across* domains it would be interesting to compare the effects of formats on learning in different domains and to see if formats can be linked to specific aspects of learning tasks across domains. On the practical side, this could accumulate to an integrated overview of guidelines for designers of learning materials. On the theoretical side, it could provide a deeper understanding of the conditions for a specific format to be effective or ineffective.

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