Metacognitive support promotes an effective use of instructional resources in intelligent tutoring

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A B S T R A C T
We tested whether the provision of metacognitive knowledge on how to cope with the complexity of a learning environment improved learning. In an experimental setting, high-school students (N = 60) worked through a computer-based geometry lesson either with or without metacognitive support in the form of a cue card. This cue card encouraged students to use instructional resources in the learning environment (i.e., textual and graphic representations and different help facilities) more strategically. During learning, the learners’ gaze and log-file data were recorded. The metacognitive support made learning more efficient (i.e., less learning time without impairing outcomes). In addition, low-prior knowledge students developed deeper conceptual understanding. The effects on learning outcomes were mediated by reducing the non-strategic use of help facilities. Our findings suggest that a lack of metacognitive conditional knowledge (i.e., in which situation to use which help facility) can account for learning difficulty in computer-based learning environments.

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1. Introduction

There is a growing tendency to confront learners with rich learning tasks to prepare them for a highly dynamic and increasingly complex world (Field, 2006). This trend is reflected in complex computer-based learning environments (CBLEs) (Azevedo, 2005; Van Merriënboer & Suijksmans, 2009). These environments offer learners multiple sources of information (Ainsworth, 2006) and a variety of help facilities (tools) serving different instructional purposes (Hannafin, Hall, Land, & Hill, 1994). On one hand, the availability of different instructional resources has the potential to stimulate beneficial learning activities (Sawyer, 2006). For example, the successful coordination and integration of information distributed over different resources offers learners opportunities to acquire a deeper level of understanding and to improve their skills in dealing with complexity (Spiro & Jehng, 1990). Therefore, CBLEs should not free learners from all instructional decisions (e.g., by adding further intelligence to an environment). On the other hand, we must acknowledge that these complex and demanding learning environments “meet” relatively limited cognitive equipment on the learners’ side. This contrast contributes to the difficulty learners have in effectively regulating their learning in CBLEs, which becomes especially apparent in complex domains such as science and mathematics (e.g., Aleven & Koedinger, 2000; Azevedo, 2005; Moos & Azevedo, 2008).

1.1. What makes a computer-based learning environment complex?

A CBLE typically includes different information resources (e.g., texts, illustrations, and help facilities) intended to support understanding and learning. These resources can be functionally differentiated into resources representing the subject matter (e.g., principles of geometry) and resources supporting the acquisition of the subject matter (i.e., help facilities or tools such as a glossary). Both types of resources are often constructed of multiple external representations: A geometry word problem might be accompanied by a diagram showing known and unknown angles as described in a word problem; a definition of a geometry principle in a glossary might be illustrated by a diagram.

To make effective use of these external information resources, learners need to adequately allocate and regulate their cognitive and attentional resources during learning. However, with each additional external resource, tactical decisions as to where and when to use one or the other resource become harder to make...
(Lajoie, 1993). Multiple information sources can, therefore, easily overwhelm learners’ self-regulatory capacities (Ainsworth, Bidby, & Wood, 2002). As a consequence, information resources are often used in less than optimal ways, being underused (Clarebout & Elen, 2007), or overused (e.g., Schofield, 1995), and occasionally even “misused” (see Baker, Corbett, & Koedinger, 2004).

Research on multiple external representations (e.g., Ainsworth, 2006; van Someren, Reimann, Boshuizen, & de Jong & van Joolingen, 1998) and on tool use (e.g., Aleven, Stahl, Schworm, Fischer, & Wallace, 2003; Clarebout & Elen, 2008) has contributed to our understanding of (a) typical difficulties that learners experience in complex environments, (b) typically more and less successful ‘copying’ strategies in complex learning environments, and (c) promising approaches to support learners to better cope with such complexity.

1.2. Multiple external representations

Information in CBLEs is typically presented as different types of external representations (e.g., text, diagrams). Research on learning from such multiple external representations is mainly interested in how learners make sense of different symbol systems (e.g., text, numbers, and realistic pictures) and how they can be combined to foster understanding and learning. Multiple external representations can fulfill (at least) three different cognitive functions. First, they can complement each other and thus provide a more complete picture of a difficult concept. For example, a verbal description of a mathematical function (e.g., \(\frac{y}{x^2} = 2\)) is accompanied by a line drawing depicting that function. Second, multiple representations can help to constrain the interpretation of each other. For example, a scatter plot is accompanied by a table with data from which the scatter plot was drawn. Finally, and probably most importantly, they can be integrated (by the learner) to construct a more abstract internal representation of the externally presented material (Ainsworth, 2006). For example, from a scatter plot and a table presented together, learners infer a general rule about functional relationships among the data depicted.

However, learners often have difficulty learning from multiple external representations (e.g., Ainsworth et al., 2002). They frequently use different external representations in isolation, or they use only a subsample of available representations, even when a learning task strongly suggests attending to the different representations. Constructing referential connections between the concepts depicted by different external representations seems to be particularly difficult for learners (Ainsworth, 2006). Some of these difficulties can be attributed to the learners’ limited knowledge of the roles or functions of external representations. For example, Schwonke, Berthold, and Renkl (2009) found that even advanced learners who studied worked examples with multi-representational solutions (i.e., word problems accompanied by tree diagrams and equations) in the domain of ‘probability’ were largely unaware of the cognitive functions of these external representations (e.g., complementing or constraining interpretation of one another). In a subsequent intervention study, simply informing about the cognitive functions (especially of tree diagrams in the worked-out examples) led to deeper conceptual understanding of probability problems and better procedural skills in solving probability problems. The effect of providing the information on learning outcomes was mediated (i.e., was attributable to) a reduction in non-strategic inspection time of the diagrams and equations (as determined by eye-tracking analyses).

In summary, students have difficulty (a) in relating the contents of different external representations to one another and (b) in understanding how different external representations can contribute to understanding and learning.

1.3. Tools to support cognitive and metacognitive processes in CBLEs

CBLE tools are artefacts designed to support cognitive and metacognitive processes related to the actual learning task (e.g., a pocket calculator embedded in a CBLE for algebra or geometry). Tool use can, thus, be defined as student–system interactions (with help facilities in CBLEs) that aim to overcome or prevent problems during learning (Aleven & Koedinger, 2000). Research into tool use has described typical ways in which learners use available help facilities and how such use affects learning outcomes. Learners often ignore available tools, even when the tools have proven to be useful (Clarebout & Elen, 2007). In addition, they often use tools inadequately or at least not as intended by the instructional designers (e.g., Aleven et al., 2003; Clarebout & Elen, 2006). In a log-file analysis on how school children in a geometry course used an intelligent tutoring system (a Cognitive Tutor Geometry), Aleven and Koedinger (2002) found that students did not use errors as a signal to ask for a hint. They thus tended to wait too long before asking for help (e.g., a solution-specific hint message). When students requested help, they tended to proceed to the most solution-specific hints, “clicking” more general hints away. This “bottom-out hint strategy” indicated that at least some learners tended to use available help facilities in a non-learning-oriented way (Aleven & Koedinger, 2002). Such “gaming the system” behaviour related negatively to learning outcomes (Baker et al., 2004). However, when learners take the time to study bottom-out hints, then learning outcomes can be improved (Shih, Koedinger, & Scheines, 2008).

In summary, learners use help facilities either not enough, not at the right occasion, too much, or for the “wrong” purpose. Learners have difficulty in mapping help facilities to impasses during learning, especially in deciding when to refer to which type of support.

1.4. How to explain suboptimal use of information resources in CBLE?

In most CBLEs, learners decide much on their own whether, when, and how to make use of available information resources. Within the context of this self-regulated nature of using external resources (Karabenick, 2011), theories of self-regulated learning (SRL; e.g., Boekaerts, 1999; Schiefele & Pekrun, 1996; Winne, 1996; Winne & Perry, 2000) can serve as a framework for the role of external resource use. Self-regulated learning is described as the behaviourally, metacognitively, and motivationally active participation in one’s own learning (Zimmerman, 1986). Self-regulated learners employ cognitive strategies (e.g., elaboration) to achieve learning goals. Choice of strategies, their application, and the quality of the outcomes of strategy application are embedded into and controlled by metacognitive activities such as planning, monitoring, and self-evaluation (Zimmerman, 1990). Metacognitive knowledge as the knowledge about factors affecting cognitive activities (Flavell, 1979) refers to three broad categories: the person, task, and strategies. In Flavell’s classic definition, the ‘task’ category includes information about a proposed task that is available to a person, including knowledge about tangible resources necessary for task completion. As such, knowledge about information resources belongs to this category.

Contemporary models of SRL such as the four-stage model of SRL (e.g., Winne & Perry, 2000) differentiate between two broad knowledge categories: (a) knowledge about cognitive conditions (e.g., knowledge of study tactics and strategies; domain knowledge) and (b) knowledge about task conditions (e.g., knowledge about instructional cues, time, and social context). Here, knowledge about external resources belongs to the ‘task conditions’ category.
In this context, knowledge about external resources can be conceptualised as a kind of metacognitive knowledge.

Models of self-regulated learning, however, have never strongly emphasised this sub-category of ‘knowledge about external resources’; therefore, there is little empirical research on how this type of knowledge influences strategy use and learning outcomes. Acknowledging the contextual nature of (self-regulated) learning (Aleven, Roll, McLaren, & Koedinger, 2010; Karabenick, 2011; Winne, 2010), it is important to consider what learners know about the context at hand. Learning never occurs in a vacuum, but rather in close interaction with some sort of artifacts in some sort of external environment. Thus the physical environment where learning takes place is an important contextual factor to consider. More specifically, we assume that knowledge about the role or cognitive functions of external representations and help facilities within a specific CBLE and, particularly, about conditions for their use, can (a) affect whether, how, and how effective learners make use of these information resources, and thereby (b) can affect learning outcomes.

With respect to the help facilities, we put special emphasis on knowledge about conditions for their use (i.e., metacognitive conditional knowledge). In theories of metacognition (e.g., Efklides, 2008; Veerman, Van Hout-Wolters, & Afflerbach, 2006), conditional knowledge is referred to as knowledge about “when” and “why” to use a given cognitive strategy. Such conditional knowledge is often regarded as an integral part of strategy knowledge (Paris & Jacobs, 1984). To select and apply a strategy in a timely manner and adequately, it is essential that the learners are able to relate strategies to specific, relevant situations. Conditional knowledge in this sense is not the same as conditionalised knowledge in production system models such as the ACT-R theory (e.g., Anderson & Lebiere, 1998). Whereas (metacognitive) conditional knowledge is knowledge about relationships between (types of) situations and the to-be-applied knowledge or strategies, conditionalised knowledge is procedural knowledge with built-in tight connections to specific situations by internalised production rules (Renkl, Mändl, & Gruber, 1996). For simplicity we will use the term “conditional knowledge” in the following when referring to metacognitive conditional knowledge.

Conditional knowledge does not necessarily develop together with strategy knowledge (Schraw, 1998). For example, learners are usually able to correctly apply mathematical procedures as long as they are told which procedure to apply; they know how to apply the procedure. However, the same learners may fail when they have to decide on their own which of different procedures to use (e.g., in a test). In other words, they often do not know when to use a procedure. With regard to the use of information sources, conditional knowledge refers, for example, to knowledge about situations in which an online glossary should be consulted. Although most students nowadays might know how to use an online glossary (i.e., browsing, finding, selecting, and extracting information from the artefact), many might lack knowledge about when to choose the glossary among other available help facilities. The provision of conditional knowledge related to the use of help facilities should help learners better associate outcomes of their monitoring of processing difficulty with control processes (i.e., the selection of appropriate tools).

We assume that conditional knowledge about information sources does not necessarily develop just by being exposed to a CBLE – especially not when a CBLE is complex and demanding. This assumption is supported by findings that even learners with a lot of CBLE experience demonstrate inadequate use of information sources. For example, Aleven and Koedinger (2000) found suboptimal use in Cognitive Tutors even in learners who had already spent more than 500 min in that learning environment. It therefore seems necessary to support students explicitly in developing conditional knowledge about information resources so that they can make better use of resources.

1.5. The role of prior knowledge

Prior knowledge provides the context for interpreting new information and, as such, provides the background for any metacognitive considerations on the learner’s part (e.g., deciding on the need for help). Generally speaking, metacognitive knowledge and regulation have been found, together with expertise, to improve within a particular domain. However, although domain-specific knowledge can facilitate the acquisition and use of metacognition, high levels of domain knowledge do not guarantee high levels of metacognition (Schraw, 1998).

Prior knowledge affects whether and how effective learners process external representations (e.g., Wood & Wood, 1999). For example, in contrast to novices, experts in the domain of chemistry were able to conceptually group related external representations into larger meaningful chunks (Kozma & Russell, 1997). Prior knowledge also affects learners’ need for help and how strategically they ask for it (e.g., Renkl, 2002). In a study on tool use in the domain of middle-school mathematics (Wood & Wood, 1999), low-prior knowledge learners used tools of an intelligent tutoring system more frequently than high-prior knowledge learners. Low-prior knowledge learners seeking help after an error was positively related to learning outcomes, but not for high-prior knowledge learners. On the other hand, errors during learning correlated negatively with learning outcomes only in low-prior knowledge learners. The authors concluded that the encouragement of low-prior knowledge learners, especially those who refused to ask for help spontaneously, to seek help more strategically (i.e., not necessarily more frequently) could be a promising approach to reduce confusion and enhance learning performance. Similarly, Baker et al. (2004) found that especially low-prior knowledge learners used tools in a non-learning-oriented way, which was negatively related to learning outcomes.

How do learners with different levels of prior knowledge benefit from metacognitive support? On one hand, understanding and using a metacognitive strategy (in real time) is a cognitively demanding activity. Therefore, low-prior knowledge learners in particular may be easily overwhelmed when they are advised to follow, for example, prescribed rules on when to use certain help facilities. On the other hand, especially low-prior knowledge students have also been observed using available information resources suboptimally (e.g., Baker, 1994). In addition, low-prior knowledge can impede metacognitive functioning (e.g., judging whether another hint would help to overcome an impasse; Schraw, 1998). Moreover, low-prior knowledge learners are usually more dependent on structure and scaffolding than are high-prior knowledge students (e.g., Kalyuga, 2007; Renkl, Stark, Gruber, & Mändl, 1998). Therefore, low-prior knowledge learners might need metacognitive support more than high-prior knowledge learners. The instructional challenge is to implement metacognitive support in a cognitively manageable way.

In summary, prior knowledge affects how much learners depend on information resources and how effectively learners make use of them. In addition, prior knowledge can also affect how much learners might profit from metacognitive support. In the present study we, therefore, included prior knowledge as potential moderating variable.

1.6. The present study

The main purpose of the present study was to show that the provision of metacognitive knowledge (related to external
information resources) can affect how learners use these resources, which should in turn influence learning outcomes. Our approach was to equip learners with knowledge about how and when to best use available information resources.

A crucial question pertained to the implementation of such support. Clarebout and Elen (2007), for example, provided metacognitive support in advance (i.e., before the learning phase in a CBLE). This intervention was successful at influencing the use of external resources. However, the increased tool use did not improve learning outcomes. Hence, it might be more effective to embed metacognitive support in the learning phase because it is widely accepted that metacognitive skills should be taught closely intertwined with domain-specific knowledge (e.g., Baker, 1994).

On the other hand, situating metacognitive support in the context of domain learning is also known to impose additional cognitive demands (e.g., Gama, 2004; Wood & Wood, 1999). Anderson, Corbett, Koedinger, and Pelletier (1995), therefore, argue for minimalist explanations in computer-based tutoring. Even when explanations are provided sparingly, the timing of support seems also crucial. Roll et al. (2006), for example, developed a computer-based approach to foster help seeking in Cognitive Tutors. In their evaluation study, the ‘help tutor’ was able to detect deficient help-seeking behaviour (e.g., help avoidance, help misuse, and over-use) which related negatively to learning outcomes. In addition, hints provided by the help tutor reduced suboptimal help-seeking behaviour. However, the help tutor did not improve learning outcomes. The metacognitive hints were given when the program detected suboptimal help-seeking behaviour. Roll and colleagues assumed that the timing of the hints might have interfered with students' problem-solving attempts, and thus, with the attention students devoted to the hints.

In this context, it is sensible to use an embedded, but parsimonious intervention that does not induce too many additional processing demands (see also Renkl, 2002; Schonweke, Berthold, et al., 2009; Schonweke, Renkl, et al., 2009) and let the learners decide whether and how intensively to use the support (so as not to interfere with their learning processes). We therefore implemented metacognitive support in form of a cue card with short hints on how to use the external resources. Students could use this cue card during a Cognitive Tutor lesson on geometry. The aim of the cue card hints was to alter how learners interact with the learning environment and, thereby, to improve learning outcomes. Three of six available hints, for example, were designed to facilitate tactical processing demands (see also Gama, 2004; Wood & Wood, 1999).

Specific hypotheses were formulated: Either low-prior knowledge learners profit more from the cue card than high-prior knowledge learners because they are more dependent on metacognitive support, or high-prior knowledge learners profit more from the cue card than low-prior knowledge learners because they have sufficient cognitive resources left to consider the support during learning. Hypothesis 2: We anticipated that metacognitive support would affect how learners would interact with the external resources available in the learning environment. On the one hand, one might expect increased learning time due to greater use of the resources because learners were instructed to use the resources in situations in which they might have refrained from using them spontaneously. On the other hand, one could expect an overall reduction in learning time due to the more strategic (and, thus, selective) use of available resources. It was especially the cue card hints on when to use available help facilities (i.e., tools) that aimed to direct learners’ attention to situations when to use the tools to their greatest benefit. We anticipated more strategic use of the resources to be observable in the requests for Cognitive Tutor hints. These hints were available at three levels of specificity. We regarded patterns of Cognitive Tutor hint requests favouring general hints over specific hints as an indicator of a strategic (and conditional) use of the hints. Differences in learning time together with differences in such tool usage patterns between experimental conditions were analysed to decide whether metacognitive support would encourage learners to use help facilities more often (but not necessarily more strategically) or would rather encourage a more strategic and selective use of available help facilities.

Hypothesis 3: Finally, we assumed that the hypothetical positive effects of metacognitive support on learning outcomes would be mediated by differences in the use of help facilities (Hypothesis 3a) and external representations, that is, the geometry word problems and diagrams (Hypothesis 3b). We performed mediation analyses to test this hypothesis (MacKinnon, 2008).

2. Method

2.1. Sample and design

Sixty German high-school students (“Realschule”: grade eight; age: $M = \bar{14.06}$; $SD = \bar{4.3}$; gender: 38 female; 22 male) participated in the study. The students received € 20.00 for their participation. Each participant was randomly assigned to one of two conditions. Half of the participants ($n = 30$) worked on a geometry lesson in a CBLE with metacognitive support (in form of a cue card) – the other half worked without support. We collected as dependent variables information about the learning process (i.e., learning time, duration and frequency of using mathematical problems and available help facilities) and the learning outcomes (procedural and conceptual knowledge in the domain of geometry). Effects of providing metacognitive knowledge (experimental variation) and potential interactions with domain-specific prior knowledge on the learning process and learning outcomes were analysed within a mediation framework (MacKinnon, 2008).

2.2. Learning domain and learning environment

Geometry is part of the German junior high-school curriculum. The topic used in the present study (“angles in intersecting lines”) is not taught before grade nine. Thus our participants could rely on their general geometry knowledge, but not too much on topic-specific prior knowledge.
The learning environment was a Geometry Cognitive Tutor (e.g., Koedinger & Corbett, 2006), an intelligent tutoring system based on ACT-R theory (e.g., Anderson & Lebiere, 1998). The overall effectiveness of Cognitive Tutors has been proven in several studies (e.g., Anderson et al., 1995; Koedinger, 2002). Nevertheless, Cognitive Tutors are good examples of complex learning environments whose effective use is far from trivial (Schwonke, Berthold, et al., 2009; Schwonke, Renkl, et al., 2009). The learners work on a number of increasingly difficult and complex word problems from a circumscribed part of a domain (e.g., a geometry unit on angles as in the present experiment).

Cognitive Tutor versions as used in the classroom rely on two key algorithms to diagnose learners’ knowledge states and need of help — model tracing and knowledge tracing. Knowledge tracing provides a constantly updated estimate of the current knowledge state of each learner. This estimate is mainly used to decide whether to provide additional remedial problems. As we wanted to keep the number of problems constant, knowledge tracing was not put into effect in the Cognitive Tutor version. Model tracing is used to provide appropriate just-in-time feedback (e.g. in form of the hints). Model tracing was in effect in this study. The Cognitive Tutor further supports the learning process through different help tools (e.g. by non-verbal and sometimes verbal error feedback).

All participants worked with the same tutor version in this study (Fig. 1). This version supported learners with on-demand solution-specific hints, a glossary with definitions of mathematical principles and illustrating geometry diagrams, and a table that provided learners with an overview of achieved and to-be-achieved sub-goals within the geometry word problems. The Cognitive Tutor hints aim at preventing learners from engaging in unproductive problem-solving attempts (Anderson, Conrad, & Corbett, 1989; McKendree, 1990). The glossary aims at getting students to pay closer attention to the geometry principles with the overarching goal of fostering deeper understanding (Aleven & Koedinger, 2000). The overview tool makes a problem's sub-goal structure visible.

In addition, this Cognitive Tutor version had been enriched with worked steps (Fig. 1, grey box in the left; for the effectiveness of worked steps in Cognitive Tutors, see Salden, Koedinger, Renkl, Aleven, & McLaren, 2010). In worked steps (in contrast to to-be-solved steps) learners sequentially accessed several solution steps and the final solution (e.g., an angle). In worked steps the learners’
task was to carefully study the single solution steps and to state the correct geometry principle.

In Fig. 1 we see a relatively complex text problem including five sub-problems. Each sub-problem requires the application of different mathematical rules. The problem statement is provided as a text in the worksheet (Fig. 1, upper left). The learners interact with the Cognitive Tutor directly in the geometry diagram (Fig. 1, lower left). The Cognitive Tutor frees learners from (some low-level) activities such as mental calculations. Learners can enter an equation into a numeric answer entry field (e.g., 30.9 + 26.9) and leave the calculations to the Cognitive Tutor. Similarly, learners can enter a reason (i.e., the name of a mathematical principle) either by typing it into an entry field or by double clicking on the principle from the glossary. The Cognitive Tutor then copied the selected principle into the active entry field. Problem-solving performance and the acquisition of the to-be-learned skills were permanently monitored by the system and compared to a cognitive model of performance (model tracing). The online performance data were used to generate solution-specific hints.

2.3. Metacognitive support (experimental variation)

Metacognitive support was implemented as a set of six hints arranged in two sections on a cue card (on cardboard: 8.4 × 5.9 inch). The first section (labelled ‘How do I solve the problem?’) referred to the external representations of the subject matter (i.e., problem statements and corresponding geometry diagrams). The second section (labelled ‘What can I do when I get stuck?’) referred to the help facilities:

1. How do I solve the problem?
   a. What are the known values in the problem text? Can you locate them in the geometry diagram?
   b. Which are the unknown values in the problem text? Can you locate them in the geometry diagram?
   c. How are the known values and unknown values related mathematically?

2. What do I do when I get stuck?
   a. When you need to find out which value to calculate next, consult the overview tool!
   b. When you need to find out about the relevant mathematical principle consult the glossary tool!
   c. When you need to find out how to proceed in a particular problem, consult the hints tool!

The order of the sections reflected our intention for students to first focus their attention on the learning task, and then only on the help facilities. The cue card provided a simple model of how an intelligent novice would approach this type of learning task.

The six hints were intended to help students to make informed decisions with respect to the use of informational resources. The first three hints (1a–c) were designed to stimulate a structured approach towards the mathematical problems. First, learners were to locate and extract relevant information from each external representation (e.g., from a problem statement; from the geometry diagrams; hints 1a and 1b). Second, learners were to relate the extracted pieces of information (hint 1c). Overall, we expected that these first three hints would support the integration of the information from problem statements and the graphic representations (Butcher & Aleven, 2008).

Three additional hints provided conditional knowledge (i.e., information in which situations to use which tool) for each of the three available tools (i.e., overview, glossary, and hints). We believed these hints would support more effective monitoring and more appropriate self-regulation in case of impasses and errors (hints 2a–c).

The cue card was available to the learners in the experimental condition (cue card group; \( n = 30 \)) during the learning phase; the learners in the control group (no-cue-card group; \( n = 30 \)) worked without such support. The cue card was introduced while the students were working on two introductory geometry problems (from a different curriculum). Students in the control group worked through these two geometry problems without the cue card.

2.4. Instruments

2.4.1. Pretest

To assess prior procedural and conceptual knowledge, we asked learners to solve four multi-step word problems with corresponding geometry diagrams in the Cognitive Tutor. The pretest word problems were similar to the problems presented later on in the learning phase. The Cognitive Tutor hints were turned off during the pretest. The glossary was accessible, but it only provided the names of the four geometry principles under consideration (i.e., complementary angle, angle addition, linear pair, and vertical angle); no descriptions of the principles were available. The first three problems required applying two different geometry principles (e.g., complementary angle and angle addition, or linear pair and vertical angle). The last problem required applying all four mathematical principles. During the pretest participants were asked to calculate six numerical values and to “justify” each numerical entry by typing in the corresponding mathematical principle into an entry field (or by copying the principle from the glossary). They were also asked to assign values given in the problem texts to corresponding entry fields in the geometry diagrams and label them as “given”. One point could be earned for a correct numerical solution, one point for the correct principle (or “given”) label. Another point could be earned for a correctly-assigned given value, and one point for the “given” label. Points for correctly-calculated numerical given values and correctly-assigned given values were added up in a procedural knowledge score, while points for correctly-labelled principles and “given” labels were added up in a conceptual knowledge score. These raw scores of procedural and conceptual prior knowledge were substantially correlated (\( r = .61, p < .001 \)). Therefore, we aggregated these scores to an overall pretest score (\( M = 11.82, SD = 4.07, \text{range: } 0–19 \text{ points} \)). Finally, the overall pretest score was divided by the maximum of 30 possible points (i.e., 10 correct numerical solutions + 5 correctly-assigned given values + 10 correct principles + 5 correct “given” labels). The pretest score, therefore, represents the proportion of correct responses (Cronbach’s \( \alpha = .671 \); see Table 1).

2.4.2. Post-test

Learning outcomes in terms of procedural and conceptual transfer were assessed in a paper and pencil test. Procedural

| Table 1 |

| Means and standard deviations (in parentheses) of measures of learning pre-requisites, time, and learning outcomes, by experimental condition. |
|-----------------|------------------|------------------|
|                  | Without cue card | With cue card    |
|                  | \( (n = 30) \)   | \( (n = 30) \)   |
|                  | \( M \) (SD)     | \( M \) (SD)     |
| Math grade\( ^a \) | 3.29 (1.08)      | 2.89 (1.83)      |
| Experience with computers\( ^b \) | 3.23 (1.68)      | 3.10 (1.85)      |
| Pretest \( ^c \) | 37.77 (14.34)    | 41.11 (12.73)    |
| Conceptual transfer \( ^c \) | 48.70 (24.11)    | 58.16 (17.14)    |
| Procedural transfer \( ^c \) | 56.21 (27.71)    | 63.29 (25.74)    |
| Learning time (min) | 70.14 (27.67)    | 56.37 (24.00)    |
| Post-test time (min) | 32.67 (10.20)    | 35.23 (9.45)     |

\( ^a \) Range of German math grades: 1 — “grade A” to 6 — “grade F”.

\( ^b \) Five-point rating scale: 1 — “very low” to 5 — “very high”.

\( ^c \) Percentage correct.
knowledge (i.e., students’ ability to solve numerical problems) was assessed with six tasks (maximum of 18 points) comprising two near transfer tasks (4 + 4 = 8 points) and four far transfer tasks (3 + 3 + 2 + 2 = 10 points). The raw scores were summed up in a procedural-transfer score (Cronbach’s α = .792) and transformed to proportions of correct responses.

In near transfer tasks we presented learners a problem text and a related geometry diagram, for example, a diagram consisting of two intersecting lines, and asked them to solve the problems much like during the learning phase (in the post-test, however, no help was available). In a typical task, for example, one angle was given and the participants had to calculate two of the remaining three angles. Each of these tasks required applying two geometry principles, in the current example, “angle addition” and “linear pair.” One point was assigned for the correct solution, another point for the correct solution path or, alternatively, when the correct geometry principle was stated.

In far transfer tasks, we asked learners to solve story problems (instead of word problems). In two (relatively simple) story problems, we used the path of the sun during the day as cover story. In two more difficult problems, the cover story was about navigating a sailing ship. Each far transfer task required the correct application of one geometry principle. One point was assigned for the correct solution, another point for the solution path (two points in the more difficult problems). In far transfer tasks, we explicitly requested them to state the geometry principles (one point).

Conceptual knowledge (i.e., students’ deeper understanding of the mathematical principles) was assessed with six tasks (maximum of 53 points) comprising three near conceptual-transfer tasks (4 + 12 + 9 = 25 points) and three far conceptual-transfer tasks (9 + 11 + 8 = 28 points). Raw scores were summed up in a conceptual-transfer score (Cronbach’s α = .858) and transformed to proportions of correct responses. Conceptual-transfer tasks required learners to complete unlabelled geometry diagrams, to contrast known with new principles, to decide on the applicability of principles, and to generate geometry diagrams and ideas for real-world applications of the principles. In contrast to procedural items, the conceptual tasks required no calculations.

In the first conceptual near transfer task, we asked learners to draw the four different types of angles (e.g., a complementary angle, vertical angle) into four unlabelled geometry diagrams (one angle per diagram). One point was assigned for the correct angle. In the second conceptual near task, learners were asked to draw geometry diagrams based on a specific word problem (similar to the word problems during the learning phase). Points were assigned for correct lines, angles and labels. In a third conceptual near transfer task, learners had to decide whether the problems (i.e., word problems plus geometry diagrams) were solvable, partly solvable or not solvable, and if so, to state the relevant principles. In one of such decision tasks, for example, the participants were to discover that they could solve two of three unknown angles according to the principles taught during the Cognitive Tutor session. Calculation of the third angle required a principle not taught during the session (i.e., “sum of angles in a triangle”). Thus, a correct solution required the participants mark which angles were solvable and which were not, and that they state the relevant geometry principles for the solvable angles (here, ‘linear pair’ and ‘complementary angle’). Points were awarded for the correct decision and correctly stated principles.

In a first far conceptual-transfer task, we asked learners to draw geometry diagrams according to story problems from different domains (e.g., “If an analogue watch shows two o’clock, the hour hand and minute hand enclose an angle of 60°. How many degrees does the hour hand move when the watch shows three o’clock?”). Points were assigned for correct lines, angles and labels.

We presented new geometry principles to the learners (e.g., angle subtraction) in a second far conceptual-transfer task, which was to identify the most similar known geometry principles and to explain the decision. In a third far transfer task, learners had to generate real-world examples in which each of the four geometry principles to-be-learned could be applied. One point was assigned for each real-world situation stated. Another point was assigned for an explanation that related the situation to a geometry principle.

2.4.3. Learners’ interactions with the CBLE

To assess learners’ interactions with the learning environment, we recorded log-file and gaze data during the learning phase. Log-file data were available for interactive screen elements (i.e., elements that could be manipulated by mouse or keyboard) such as the glossary or hints. To assess learners’ ‘interactions’ with screen elements that could be inspected but not manipulated (e.g., the overview table, problem statements, and geometry diagrams), we recorded gaze data using a Tobii 1750 Eye Tracker (with a sampling rate of 60 Hz).

For interactive tools, frequency was determined as the number of times a learner accessed the tool (by mouse click). Frequency of accesses was counted irrespective of the duration of each access. To obtain a roughly equivalent frequency measure for non-interactive screen elements, we counted the frequency of gaze durations on the elements (a gaze duration starts with fixation on a specific screen element, for example, the geometry diagram, and ends with the first fixation outside that screen element).

Duration was determined as the total amount of time the learners spent using a screen element during learning. For interactive screen elements, duration was assessed by cumulating the time of all episodes from the opening to closure of the element (by mouse click). For non-interactive elements, we calculated the cumulative fixation duration, that is, the sum of all single fixations on the screen elements during the learning phase.

Measurements of the time learners spent using the single tools (i.e., glossary, hints, and overview) were correlated to each other (between r = .555 and r = .781). Similarly, the inspection time of problem statements was correlated highly with the inspection time of corresponding geometry diagrams (r = .798). To prepare for the mediation analysis we therefore aggregated the duration of glossary, hints, and overview tool use to an overall measure of duration of tool use (by calculating the mean of the three z-standardised duration measures). Accordingly, we aggregated the duration of problem-statements inspection and geometry diagrams to an overall measure of duration of studying mathematical problems (again by calculating the mean of the two z-standardised measures). For ease of presentation, the analysis of learner–system interactions was based on these aggregated duration measures (an analysis of comparable aggregated frequency measures yielded the same pattern of results).

2.5. Procedure

The experiment was conducted in individual sessions lasting about 90 min. The participants worked in front of a 19” flat screen of the Tobii 1750 eye tracker. After completing a questionnaire on demographic data (paper & pencil), all students received a brief introduction on how to use the Cognitive Tutor via an on-screen slide show that explained screen elements and basic functions. All students worked on two introductory examples (from a different curriculum) to gain some experience with the CBLE. They then all completed a geometry pretest in the Cognitive Tutor. After the pretest, all students read an instructional text with definitions and illustrations of the four to-be-learned geometry principles. We then randomly assigned the participants to one of two conditions. One half of the students worked through a geometry
lesson with the cue card available, the other half without. After the learning phase, all students completed the post-test.

2.6. Data analysis

We assumed that potential effects of metacognitive support on learning outcomes would be due to differences in how learners used available information resources. To test this mediation assumption, we performed a set of related simultaneous multiple regression equations (products-of-coefﬁcients strategy; see MacKinnon, 2008). For a mediated effect, an independent variable (here, cue card availability) must signiﬁcantly affect a potential mediator (here, the duration of tool use). This effect is called path a within the mediation model. Second, the mediator must signiﬁcantly affect an outcome variable (i.e., path b; here, learning outcomes) when effects of the independent variable on the outcome variable are controlled.

In the product-of-coefﬁcients approach, there is no need for a signiﬁcant total effect from the independent variable on the outcome variable (i.e., path c) in the ﬁrst place (see MacKinnon, 2008). However, as we assumed we would detect such an effect of metacognitive support on learning outcomes, we also tested path c.

The signiﬁcance of the mediation effects was tested with asymmetric conﬁdence intervals (MacKinnon, Fritz, Williams, & Lockwood, 2007) for the products of unstandardised beta-coefﬁcients representing the association between metacognitive support and tool use (path a) and the association of tool use and learning outcomes controlling for direct effects (path b). Mediation would be indicated by signiﬁcant products of coefﬁcients (i.e., conﬁdence intervals of the product of coefﬁcients not including zero).

3. Results

For all statistical analyses an alpha level of α = .05 was used. Prior knowledge was included as a potential moderating variable in all analyses. In our sample, prior knowledge was characterised as low to medium (rendering the learning task of medium difﬁculty) in the ﬁrst place (see MacKinnon, 2008). However, as we assumed we would detect such an effect of metacognitive support on learning outcomes, we also tested path c.

Table 2

<table>
<thead>
<tr>
<th>Conceptual transfer</th>
<th>Procedural transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔR²</td>
<td>B</td>
</tr>
<tr>
<td>Constant</td>
<td>.552</td>
</tr>
<tr>
<td>Step 1</td>
<td></td>
</tr>
<tr>
<td>Prior knowledge</td>
<td>.217**</td>
</tr>
<tr>
<td>Cue card</td>
<td>.032</td>
</tr>
<tr>
<td>Step 2</td>
<td></td>
</tr>
<tr>
<td>Cue card × prior knowledge</td>
<td>.061*</td>
</tr>
<tr>
<td>Total R²</td>
<td>.278**</td>
</tr>
</tbody>
</table>

*p < .05. **p < .01.

interaction plot (Fig. 2) shows that low-prior knowledge students performed poorly on the conceptual-transfer test without metacognitive support. With metacognitive support, however, they performed almost as well as high-prior knowledge students. The difference between learning outcomes at lower levels of prior knowledge was reliable, indicated by a signiﬁcant β-coefﬁcient of the experimental variation at minus one standard deviation of prior knowledge, t(51) = 2.335, p = .02, b = −.394. High-prior knowledge students performed well with and without metacognitive support (as indicated by a non-signiﬁcant β-coefﬁcient of the experimental variation at plus one standard deviation of prior knowledge), t(51) = −.509, ns, b = −.088. These results demonstrate that with metacognitive support, low-prior knowledge learners acquired a deeper conceptual understanding of the geometry principles rather than being overwhelmed by the support’s additional cognitive demands.

A comparable regression analysis of procedural transfer on prior knowledge and metacognitive support yielded neither a direct effect of metacognitive support, t(51) = .590, ns, b = .078, nor an interaction effect of metacognitive support and prior knowledge, t(51) = −.46, ns, b = −.061. Rather, procedural-transfer performance was primarily due to prior knowledge, t(51) = 2.816, p < .01, b = .373. However, an explorative comparison of procedural-transfer performance between experimental conditions of those third of the total sample (n = 20) with the lowest pretest scores revealed a positive effect of metacognitive support. The pretest

![Fig. 2. Plot of a significant interaction effect of metacognitive support and prior knowledge on conceptual-transfer performance.](image-url)
scores of these low-prior knowledge learners were highly similar between the metacognitive-support group (M = .287; SD = .076) and the no-support group (M = .287; SD = .097), t(18) < 1. In terms of procedural transfer, low-prior knowledge learners in the metacognitive-support group (M = .63; SD = .21) outperformed the comparable subsample in the no-support group (M = .40; SD = .24), F(1,118) = 5.23, p = .035, η² = .24 (strong effect; ANCOVA controlling for prior knowledge). The results of the explorative analysis suggest that at least in a subsample of students with very little prior knowledge, metacognitive support helped them to acquire better procedural skills.

In summary, metacognitive support (in form of a cue card) was not effective in all learners. Rather, we noted that the support fostered conceptual understanding (and procedural skills) in low-prior knowledge learners. High-prior knowledge students did not profit from metacognitive support (but they were also not affected in negative ways).

3.2. Effects of metacognitive support on learning time (Hypothesis 2a)

First, we tested how metacognitive support affected how long the participants needed to work through the Cognitive Tutor geometry lesson (i.e., learning time). Overall, they spent about 63 min (SD = 26.602) working through the geometry lesson (see Table 1). Learning time differed significantly according to the experimental condition, F(1,56) = 5.075, p = .028; η² = .09 (ANCOVA, controlling for prior knowledge), which did not significantly interact with prior knowledge, F(1,56) = 2.68, p = .107; η² = .05. Thus, the learning time difference between supported and unsupported learners was relatively homogeneous across different levels of prior knowledge. The metacognitive-support group spent about 20% less time working through the Cognitive Tutor lesson than the no-support group (Table 1). Learning time correlated negatively with prior knowledge (r = -.451, p < .001). Partial correlations controlling for prior knowledge revealed that learning time also correlated negatively with learning outcomes in terms of both procedural (rₚ = -.422, p < .01) and conceptual transfer (rᵦ = -.406, p < .01).

Metacognitive support reduced learning time substantially. It is important to note that all participants worked on the same number of problems during the learning phase. Moreover, we instructed them to work through the lesson to the end, which all participants did. Hence, the metacognitive-support group spent less time per problem than the no-support group – rather than working fewer problems. Taking into account that the metacognitive-support group acquired overall at least as much knowledge as the no-support group, the reduction in learning time indicated greater learning efficiency through metacognitive support. To investigate what was behind this effect on learning efficiency, we performed more specific analyses on the time learners spent working on the geometry problems and the time they spent consulting the help facilities (i.e., tools).

3.2.1. Effects on absolute amounts of learning time devoted to learning task and tool use

The assumption of enhanced learning efficiency for low-prior knowledge learners was confirmed by a hierarchical regressions of tool-use duration (as outcome variable) on prior knowledge and cue card, including product terms of prior knowledge and cue card (as predictors). There was no (significant) overall effect of metacognitive support on the duration of tool use, rather, the effect varied with learners’ prior knowledge (Table 3). The interaction plot (Fig. 3) indicated that metacognitive support reduced the duration of tool use in low-prior knowledge students, t(51) = -2.716, p < .01, b’ = .310. The statistical significance of this difference was confirmed by a significant beta-coefficient (b’ = .43, t(51) = -2.994, p < .01) of the experimental variation at minus one standard deviation of prior knowledge. A non-significant beta-coefficient (b’ = .13, t(51) = .812, p = .812) at plus one standard deviation indicated that metacognitive support did not lengthen the duration of tool use in high-prior knowledge students. Similar analyses confirmed this pattern for each of the tools (i.e., glossary, hints, and overview).

Regression analyses of the time learners spent inspecting the mathematical problems (i.e., problem statements and geometry diagrams) as outcome variable also displayed a very similar pattern of results. There was no general reduction, but in the metacognitive-support group, low-prior knowledge students spent less time inspecting the problems (Table 3). Separate analyses of the time spent inspecting problem statements or the geometry diagrams, respectively, confirmed this interaction pattern for each type of external representation.

Thus far we can maintain that with metacognitive support, the time low-prior knowledge students spent inspecting available help facilities and the learning task itself (i.e., problem statements and geometry diagrams) was reduced to approximately the length of time high-prior knowledge learners spent spontaneously. This finding is further indication that metacognitive support increased learning efficiency. Although the pattern of the reduction was very

<table>
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<th>Table 3</th>
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<tr>
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<td></td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Step 1</td>
</tr>
<tr>
<td>Prior knowledge</td>
</tr>
<tr>
<td>Cue card</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

*p < .05, **p < .01, ***p < .001.

Fig. 3. Plot of a significant interaction effect of metacognitive support and prior knowledge on inspection time of tools.
similar for time spent working on the mathematical problems and tool use, the amount of reduction was much more pronounced in terms of the duration of tool than the reduction in time spent working on the mathematical problems (Table 4). Thus, the reduction in learning time through metacognitive support (as reported before) can be primarily interpreted as a reduction in the time learners spent consulting the help facilities.

3.2.2. Effects on the relative amounts of learning time devoted to learning task and tool use

The percentages of inspection times (Table 4) reveal that the relative amounts of time the metacognitive-support group spent using tools fell substantially, whereas we noted a small increase in the percentage of time working on the mathematical problems (i.e., the learning task). These differences suggest that a central effect of the cue card (i.e., metacognitive support) was not necessarily (or not only) the reduction in (non-strategic) tool use, but rather an increase in the relative length of time the learners devoted to the learning task. To test this alternative explanation, we compared the percentage of time learners spent on the learning task among experimental conditions. To base our analysis on a more direct comparison of the relative amounts of time spent on tool use vs. time spent on the learning task, this percentage was computed as the sum of the time spent inspecting problem statements and diagrams, divided by the sum of the time spent on each available type of external representation (i.e., problem statements and diagrams) or tool (i.e., glossary, hints, and overview table). In preparation for this analysis, we identified two outliers (outliers = values greater than three times the interquartile-range; both cases were located in the no-support group). To diminish an undue influence by these obvious outliers, we replaced the percentage of time spent on the learning task of these two cases with the next lower values (within the no-support group) plus one or two measurement units, respectively (Field, 2005). Using this procedure, one value changed from 69% to 41%, the other value from 92% to 42%. Even after this correction, the percentages of time spent on the learning task were not normally distributed in the no-support group, $D(26) = .72, p < .001$ (Shapiro–Wilks’s test). Moreover, variances were homogeneous across condition, $F(1, 51) = 19.92, p < .001$ (Levene’s test). Due to the violations of normality assumption (and homogeneity of variances assumption), we performed the Mann–Whitney test to compare the percentages between experimental conditions, which showed that the metacognitive-support group’s median rank ($Mdn = 30.67$) was significantly higher than the no-support group’s ($Mdn = 23.19$), $U = 450, p < .05$ (one-tailed). We can this conclude that metacognitive support did indeed increase the percentage of time that learners spent on the learning task. How these differences related to learning outcomes is described in Section 3.3.

3.2.3. Effects on Cognitive Tutor hints use

To discover whether metacognitive support helped learners to be more selective in their use of the tools, we performed a detailed analysis of Cognitive Tutor hint requests during the learning phase, during which participants on average requested about 19 hints ($M = 18.55$, $SD = 18.35$; range: 0–70). As already suggested by the wide variation, we detected three distinct hint-usage profiles in our sample ($N = 60$): The majority of participants ($n = 37; 61.7\%$ of the sample) requested all three levels of Cognitive Tutor hints. Another 17 participants (28.3% of the sample; metacognitive-support group: $n = 8$; no-support group: $n = 9$) requested only the most general level of hints, but no hints of more specific levels. A small number of participants ($n = 6; 10\%$ of the sample; metacognitive-support group: $n = 3$; no-support group: $n = 3$) requested no Cognitive Tutor hints (Table 5). That group of 6 participants was not included in the hints analysis. We observed no association between the distribution of participants with different hint-usage profiles and experimental condition, $\chi^2(2) = .09, ns$, which indicates that metacognitive support did not affect the general decision to use hints (of different levels of specificity) or not to use hints at all.

However, for the largest subsample of participants — those learners requesting all levels of Cognitive Tutor hints ($n = 37$) — comparisons of the percentage of hint use between experimental conditions are represented in Table 5. This analysis included those participants who requested all levels of hints ($n = 37$; representing 61.7% of the sample).

### Table 4

<table>
<thead>
<tr>
<th>Tools</th>
<th>Without cue card</th>
<th>With cue card</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min.</td>
<td>M (SD)</td>
<td>% of Study time</td>
</tr>
<tr>
<td>Tools total</td>
<td>37.80 (21.05)</td>
<td>53.9</td>
</tr>
<tr>
<td>Math. problems</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Problem statement</td>
<td>5.18 (2.99)</td>
<td>7.4</td>
</tr>
<tr>
<td>Geometry diagrams</td>
<td>14.67 (7.31)</td>
<td>20.9</td>
</tr>
<tr>
<td>Representations total</td>
<td>19.85 (9.83)</td>
<td>28.3</td>
</tr>
<tr>
<td>Representations total (z-score)</td>
<td>.19 (1.05)</td>
<td>- .05 (.85)</td>
</tr>
</tbody>
</table>

### Table 5

<table>
<thead>
<tr>
<th>Hint level</th>
<th>Number of hints requested</th>
<th>Percentage of hints requested</th>
</tr>
</thead>
<tbody>
<tr>
<td>With cue card</td>
<td>Without cue card</td>
<td></td>
</tr>
<tr>
<td>($n = 19$)</td>
<td>($n = 19$)</td>
<td>($n = 19$)</td>
</tr>
<tr>
<td>General (level 1)</td>
<td>15.32 (2.33)</td>
<td>18.21 (2.33)</td>
</tr>
<tr>
<td>Medium specific (level 2)</td>
<td>4.37 (1.19)</td>
<td>8.95 (1.22)</td>
</tr>
<tr>
<td>Specific (level 3)</td>
<td>2.33 (.74)</td>
<td>4.98 (.76)</td>
</tr>
</tbody>
</table>

Note. This analysis included those participants who requested all levels of hints ($n = 37$; representing 61.7% of the sample).
conditions confirmed that metacognitive support did significantly change the patterns of Cognitive Tutor hint use, \( F(2, 33) = 4.05, p = .027 \) (Pillai’s trace). Univariate comparisons revealed that learners in the metacognitive-support group requested higher percentages of general hints, \( F(1, 34) = 8.32, p = .007, \eta^2 = .20 \), and, accordingly, lower percentages of medium-specific hints, \( F(1, 34) = 6.03, p = .019, \eta^2 = .15 \), or highly-specific hints, \( F(1, 34) = 6.14, p = .018, \eta^2 = .15 \) (Table 5). This result indicates that metacognitive support affected the patterns of hint use. Metacognitive support positively affected how selectively learners used available help facilities. Comparisons of the absolute numbers of hint requests according to the experimental condition revealed that the metacognitive-support group requested fewer medium-specific hints, \( F(1, 34) = 7.04, p < .012, \eta^2 = .17 \), as well as fewer highly-specific hints, \( F(1, 34) = 6.06, p < .019, \eta^2 = .15 \) (Table 5). The absolute number of general-hint requests did not, however, differ significantly, \( F < 1 \). These results demonstrate that the effect of metacognitive support on the hint-usage patterns (as reported before) can mainly be attributed to a substantial reduction in medium- and highly-specific hint requests.

In that subsample of participants who requested only the most general level of hints (\( n = 17 \)) there were no differences in the absolute number of (level-one) hint requests (metacognitive-support group: \( M = 7.38, SD = 3.08 \); no-support group: \( M = 6.33, SD = 2.33 \), \( F < 1, ns \). Thus, metacognitive support did not affect the hint usage of that subsample of learners. Taking into account that the total number of hint requests related generally negatively to prior knowledge and that these ‘level-one-hint only requesters’ were among those learners who requested the fewest number of hints, we conclude that metacognitive support primarily affected the hint-usage patterns of low-prior knowledge learners.

In summary, metacognitive support reduced learning time, indicating increased learning efficiency. We attributed this reduction in learning time mainly to a reduction in the time that especially low-prior knowledge learners spent consulting the help facilities. As a result of this reduction, the relative amount of time those learners spent on the learning task increased. For the majority of participants (those who used all available levels of hints), metacognitive support also altered the pattern of hint requests. With metacognitive support, the learners requested a higher percentage of general (first-level) hints, and, accordingly, lower percentages of more specific levels of hints.

### 3.3. Are effects of metacognitive support on learning outcomes associated with differences in the use of external resources (Hypothesis 3)

When we regressed learning outcomes simultaneously on inspection times of tools and mathematics problems (controlling for effects of metacognitive support and prior knowledge), we found inspection time of tools to be a substantial predictor of learning outcomes, both in terms of conceptual and procedural transfer (Table 6). In this complete model, the time learners spent on the mathematics problems (i.e., problem statements and geometry diagrams) was not a significant predictor of learning outcomes.

At the same time, the effect of metacognitive support (mediated by prior knowledge) on conceptual knowledge was substantially reduced from a significant beta-coefficient of \( b^* = -.248, p < .05 \) (Table 2) to a non-significant coefficient of \( b^* = -.107, ns \) (Table 6). This diminishment of an effect from being significant to non-significant (here the interaction effect of the cue card with prior knowledge) indicated full mediation (see MacKinnon, 2008).

In other words, the positive effect of metacognitive support on learning outcomes in low-prior knowledge students is largely due to the reduction in inspection times of tools (i.e., tool use). Importantly, the inspection time of tools correlated quite negatively with learning outcomes. Table 7 provides an overview of the significance tests of the mediation effects.

The percentage of the time spent on the learning task (Section 3.1) correlated positively with learning outcomes in terms of conceptual transfer \( (r = .26, p = .06) \) and procedural transfer \( (r = .30, p < .05) \), and the correlation with prior knowledge was weakly positive \( (r = .17, ns) \); bivariate correlations). However, the percentage of the time spent on the learning task (i.e., the mathematics problems) was not a significant mediator of effects of metacognitive support on learning outcomes. When we monitored the relationships between learning outcomes and amounts of time spent on the learning task and tools (as reported in the last paragraph), the percentage of time spent on the learning task revealed a weak negative relationship to both conceptual \( r = -.32, t(46) = -1.35, ns \), and procedural transfer \( b = -.20, t(46) = -.84, ns \). In the complete mediation model, only small amounts of variation in conceptual-transfer performance could be attributed to percentage of time spent on the learning task, \( \Delta R^2 = .02, F(1, 146) = 2.33, p = .107 \) (Table 6).

**Table 6** Effects of inspection times of tools and math problems on learning outcomes controlling for effects of cue card (metacognitive support) and prior knowledge (Hierarchical multiple regression; path b; \( N = 53 \)).

| Tool use | Conceptual transfer | | Procedural transfer | |
|---|---|---|---|---|---|---|---|---|
| | \( \Delta R^2 \) | \( B \) | \( SE_b \) | \( \beta \) | \( \Delta R^2 \) | \( B \) | \( SE_b \) | \( \beta \) |
| Constant | .547 | .024 | | | | | | |
| Step 1 | | | | | | | | |
| Prior knowledge | .177** | .039 | .026 | .190 | .158* | .017 | .031 | .066 |
| Cue card | | .014 | .024 | .067 | | -.013 | .029 | -.050 |
| Step 2 | | | | | | | | |
| Cue card \( \times \) prior knowledge | .061* | | | -.022 | .025 | -.107 | .004 | | | | -1.55 |
| Step 3 | | | | | | | | |
| Tools | | | | | | | -.321*** | | | |
| Mathematical problems | | | | | | .017 | .044 | -.524** | | | |
| Total \( R^2 \) | .420*** | | | | | | | .428*** |

*p < .10, **p < .05, ***p < .01, ****p < .001.
Note. *p < .05, **p < .01, ***p < .001.

The aims of the present study were twofold. One theoretical goal was to contribute to the understanding of the interplay between the cognitive and metacognitive processes involved in computer-based learning. A practical goal was to investigate how learners could be supported to better cope with complex computer-based learning environments through metacognitive support focusing on the information resources with which learners typically interact. Our student-centred approach was to equip learners with some ideas on how to more systematically inspect related external representations of the subject matter (here, word problems from the domain of geometry and corresponding diagrams), and how to use available help facilities (i.e., tools) more strategically. The metacognitive support was implemented as a set of hints on a cue card that learners could use during a computer-based lesson on geometry in an intelligent tutoring environment (i.e., Cognitive Tutor Geometry).

### 4. Discussion

Within the context of our findings, our research questions can be answered as follows: First of all, metacognitive support reduced the total learning time (main effect), and for low-prior knowledge students especially, the time they spent inspecting available help facilities and external representations of the subject matter (ATI-effect). Taking into account that the number of mathematics problems the participants worked on was held constant across conditions, the reduction in overall learning time meant that with metacognitive support, learners needed (on average) less time to solve the problems. This result reveals that metacognitive support does increase learning efficiency (Hypothesis 2).

The parsimonious intervention of providing a cue card during learning did not, however, improve learning success for all learners (Hypothesis 1a). Rather than overextending the cognitive capacities...
of low-prior knowledge participants, it was that subsample of learners who acquired a deeper conceptual understanding of the geometry principles with metacognitive support than without (Hypothesis 1b). We attribute the effectiveness of the cue card for low-prior knowledge learners mainly to the parsimonious implementation with just moderate additional cognitive demands. These results further confirm that it is especially low-prior knowledge learners who lack the necessary metacognitive knowledge to effectively learn from complex (computer-based) learning environments.

An analysis of how learners used the Cognitive Tutor hints – that differed in their level of specificity (from very general hints rephrasing the problem to highly-specific hints pointing directly to the solutions) – showed that metacognitive support changed hint-usage patterns from a rather arbitrary use of all available levels of specificity to more selective use. Even when we controlled for effects of prior knowledge, the percentage with which general hints were requested correlated positively with learning outcomes, whereas the percentage with which medium-specific and highly-specific hints were requested correlated negatively with learning outcomes. These results, therefore, demonstrate that metacognitive support fosters a learning-oriented use of available help facilities. As confirmed by statistical mediation analysis, the positive effects of metacognitive support on learning outcomes in low-prior knowledge students is mainly attributed to the reduction in the time these learners had to spend consulting available help facilities (Hypothesis 3). Neither the reduction in the time they spent inspecting available external representations (i.e., problem statements and geometry diagrams), nor the percentage of time they devoted to the learning task, nor the reduction in the percentage of highly-specific Cognitive Tutor hints could account for additional variation in the learners’ post-test scores beyond the reduction in tool-use time.

4.2. Reduction in non-strategic use of help facilities

Why should a reduction in the time spent inspecting available help facilities be beneficial for learning? One possible explanation is that a reduction in the time consulting the help facilities saved time that the learners later invested in concentrating more on the learning task at hand. However, our analysis of the percentage of time spent on the learning task revealed that this percentage correlated negatively with learning outcomes when other mediation variables were controlled. The change in sign (from a positive bivariate correlation with learning outcomes to a weakly negative relationship found in the regression analysis) suggests that a high percentage of time spent on the learning task is more likely an indicator of learning difficulties than a sign of deliberate focus or concentration on the learning task.

Hence, a more likely explanation for our results is the reduction in non-strategic use of the help facilities. Strategic tool use would imply that available tools are used (a) when needed and (b) as a means to control and regulate one’s learning. In an ideal world, learners would compare outcomes of their monitoring (i.e. specific deficits) with the support on offer in different tools for help with deciding which type of help to use, and when to use it. Wrong decisions in either sense (i.e., when to request help and the type of help to request) would imply that learners would have difficulty making sense of the information provided by the tools. Trying to figure out how the provided information maps to the problem at hand would consume learning time. Therefore, difficulty in mapping support to the learning task (resulting from making the wrong choice of available help facilities) might be why participants without metacognitive support spent more time on tool use without profiting from it. Although metacognitive support substantially reduced the time spent using the help facilities, the amount of time that participants with metacognitive support used them was still substantial (with support: about 27 min; without metacognitive support: about 38 min). Thus we did not observe that learners with metacognitive support avoided using help facilities completely. Rather, with metacognitive support they were probably able to make informed decisions as to whether to request for more help (e.g., another Cognitive Tutor hint). As the low-prior knowledge students were the ones who spontaneously used help facilities most intensively, they revealed the effect of metacognitive support on decisions to request help most conspicuously in them.

We further assume that the ‘double’ lack of experience in our sample (German high-school students) (a) with the computer-based learning environment (i.e., Cognitive Tutor), and with intelligent tutoring systems in general, and (b) with the learning domain accounts for this non-strategic use of help facilities in the control situation. These students were going through an early phase of skill acquisition (Van Lehn, 1996), both with respect to the learning domain (i.e., being confronted with a content problem) and the CBLE (i.e., also being confronted with an interaction problem).

In the Help Tutor study by Roll et al. (2006), metacognitive support in the form of hints had a positive effect on seeking help but not on domain learning. In the present study we found — as suggested in a mediation analysis — that the effects on domain learning (for low-prior knowledge learners) is attributable to effects of the intervention on seeking help. The contents of the metacognitive hints provided in both studies were similar, and both studies provided hints during the learning phase. A potentially crucial difference between the intervention of Roll and colleagues and ours may be the degree of self-regulation (or self-determination) with respect to the metacognitive support. In Roll’s study the hints were given when the program detected suboptimal help-seeking behaviour, and they themselves assumed that the timing of the hints could have interfered with students’ problem-solving attempts. In the present study, the participants received the cue card in advance, and were instructed to refer to the hints in case of impasses. This way our learners could decide on their own whether, when, and how often to use the support. We conclude that some degrees of freedom can alleviate learners from some of the additional demands that such support measures pose on their cognitive systems.

4.3. The role of prior knowledge

What can be learned with respect to the role of prior knowledge in tool use and use of external representations? The aptitude–treatment interaction effect between experimental condition and prior knowledge confirmed that low-prior knowledge learners would profit more from metacognitive support than high-prior knowledge learners. One could have argued the other way around, namely that only learners with enough prior knowledge should have profited from metacognitive support because of the additional cognitive demands the intervention posed on the participants. Learners with poor learning requisites (in this case: a lack of prior knowledge) should have been more easily overwhelmed by these additional demands. We believe that the very parsimonious implementation of metacognitive support (Anderson et al., 1995) as a cue card — with a few short hints — is why the intervention worked well for low-prior knowledge students. The cue card did not pose too many additional demands on the learners. The cue card was obviously of little help to the high-prior knowledge learners, which may be due to the fact that high-prior knowledge learners were better able to assess when to request help and which type of help would benefit them most. This latter explanation is compatible with assumptions that metacognitive
knowledge progresses in tandem with domain knowledge (Schraw, 1998).

One might question whether our sample’s characteristics limit the general applicability of our results. However, we already assume that the results concerning the effects of conditional knowledge on the use of help facilities do apply to more experienced and more knowledgeable learners. This notion is supported, for example, by results of Aleven and Koedinger (2000), who reported that even learners with extensive experience in a Cognitive Tutor environment and with a strong domain knowledge background still used available help facilities rather ineffectively. The nature of help-seeking deficiencies, however, seems to change with both CBLE experience and domain-specific knowledge. In the present study we also observed the tendency of high-prior knowledge learners to use the help facilities relatively rarely.

4.4. Implications for educational practice

The metacognitive aid in the form of a cue card (on cardboard) was easy to implement, as it requires no modifications of a given CBLE. Hence, the cue card intervention — at least the general idea — is widely applicable, for example, in self-regulated open (computer-based) learning scenarios. We can assume that especially in open learning environments with ample learner control, instances of non-strategic help seeking are even more apparent (Claret & Elen, 2009) than in Cognitive Tutors that are more constrained in those respects. Moreover, in open learning environments, we can also assume that non-strategic help seeking has more negative implications for learning. In addition, support measures such as a cue card with metacognitive hints might help to reduce the detrimental consequences of heterogeneity in learning pre-requisites. In this study, the cue card helped low-prior knowledge students to learn as effectively and efficiently from a complex and visually-rich learning environment as their high-prior knowledge mates. For most high-prior knowledge students, the metacognitive support was ineffective. However, the support did not interfere with their strategies, because they could decide whether and how intensively to use the cue card. Moreover, both high- and low-prior knowledge learners profited from a reduction in learning time.

4.5. Limitations

Given our relatively small sample size, we cannot completely rule out the possibility that the interaction effect between experimental condition and prior knowledge on conceptual understanding has occurred by chance. Comparisons of person variables potentially related to the constructs under consideration (i.e., prior knowledge, math grade, and experience with computers) were distributed evenly across experimental conditions. We acknowledge that other unmeasured variables could have affected both process and outcome measures. Yet we are confident that our results are substantial.

One potentially and theoretically relevant limitation is the combination of two elements in a single treatment package (i.e., the cue card). This treatment package included three hints related to the construction of referential connections between external representations and, moreover, another three hints related to conditions for effective use of different help facilities. The mediation analyses findings help to figure out which part of the treatment package might have been more effective. Metacognitive support reduced tool-use time, but not the time spent on the problem representation. Moreover, conceptual transfer correlated significantly negatively to the time spent inspecting the tools but revealed little to no association with the time inspecting the mathematical problems. These findings suggest that the hints related to the conditions for tool use were more effective. An explanation for the varying effectiveness of these hints as compared to the hints on how to map problem text to geometry diagrams lies in the specificity of these hints. The three hints related to tool use were constructed as condition—action pairs (‘if-then’ rules), whereas those hints related to geometry problems and diagrams were formulated as questions. Most probably, the condition—action pairs helped learners to associate outcomes of monitoring processes (e.g., procedural vs. conceptual comprehension deficits) with control processes more easily (i.e., the selection of tools) than did the questions. Moreover, hints on tool use provided both conceptual knowledge (on effective tool use) and support for the problem-solving process (e.g., ‘which value to calculate next’, ‘how to proceed’).

4.6. Future studies

In the present study we brought together findings from research on tool use and research on learning from multiple external representations to contribute to our understanding of the self-regulated learning activities involved in learning a complex subject in a computer-learning environment. In further studies, it might be worthwhile comparing the effects of instructing learners in which situations to use different information resources and when not to use them. In addition, the actual use of metacognitive-support instruments (such as a cue card) should explicitly be taken into account (e.g., as a moderating variable). Future studies should also address the role of conditional knowledge in other contexts and with a variety of qualitatively different tools. It seems also worth investigating how knowledge (or a lack of knowledge) about affordances and constraints in the learning environment affect habitually-used learning strategies, and how such knowledge interacts with those strategies. Furthermore, deeper analyses of the processes of tool use are necessary. For example, it would be interesting to investigate how adequately learners select certain tools as a consequence of the availability of conditional knowledge.

References
