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Enhancing scientific discovery learning through metacognitive support

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ABSTRACT

Using a virtual physics lab, we analyzed the impact of metacognitive support on simulation-based scientific discovery learning (SDL). The dependent variables for learning outcome were the immediate conceptual knowledge gain and the retained conceptual knowledge three weeks later. Additional dependent variables were the actual use of a domain-specific cognitive strategy, motivation, emotions, and cognitive load. To contrast the effects of metacognitive support with possible effects of goal specificity, the experimental study followed a 2×2 design with a sample of $N = 129$ ninth grade students and with metacognitive support (yes vs. no) and learning goals (specific vs. nonspecific) as factors. The results showed positive effects of metacognitive support on learning outcome, on actual cognitive strategy use, and on learning emotions. No interaction effect of metacognitive support and goal specificity on learning outcome was observed.

1. Introduction

This study examines the impact of metacognitive support on knowledge gain, strategy use, motivation, and emotions as important criteria for scientific discovery learning. As a main essence of various definitions, Alfieri, Brooks, Aldrich, and Tenenbaum (2011) suggest that *discovery learning* (Bruner, 1961) occurs when learners have to discover the knowledge of a target concept in a self-regulated way with only the provided materials. *Scientific discovery learning* (SDL; de Jong & van Joolingen, 1998; Klahr & Dunbar, 1988) focuses specifically on learning science (e.g., in physics) and is close to inquiry learning (Lazonder, Wilhelm, & Hagemans, 2008). SDL involves stating and testing hypotheses in a self-regulated cycle of planning, conducting, and evaluating scientific experiments (Friedler, Nachmias, & Linn, 1990; Künsting, Wirth, & Paas, 2011; Rivers & Vockell, 1987). Many studies on SDL used virtual, simulation-based environments (de Jong & van Joolingen, 1998; Künsting et al., 2011; van der Meij & de Jong, 2006), which can be an effective method (Zacharia & Olympiou, 2011).

However, SDL requires self-regulation, which is problematic for many learners (de Jong & van Joolingen, 1998; Lazonder et al., 2008). During the experimentation in a process of SDL students have to regulate their use of cognitive strategies, their motivational and emotional states, and their effort. The process of learning is to be planned, monitored, and evaluated on a metacognitive level (de Jong et al., 2005; Veenman, Elshout, & Busato, 1994; Wirth & Leutner, 2008). Thus, students' success during SDL depends on their metacognitive skills used to cope with these demands (de Jong et al., 2005). Adequate instruction can avoid excessive cognitive demands with detrimental effects on learning (Kirschner, Sweller, & Clark, 2006; Mayer, 2004). Because many students do not have enough metacognitive skills, they need metacognitive instruction, which also applies to SDL (de Jong & van Joolingen, 1998; Zion, Michalsky, & Mevarech, 2005).

Successful SDL requires the metacognitive regulation of general cognitive strategies (e.g., selecting and memorizing) and domain-specific cognitive strategies (de Jong et al., 2005). One domain-specific cognitive strategy that particularly promotes SDL is to design unconfounded experiments by varying only one variable at a time while holding constant all others (e.g., Chen & Klahr, 1999; de Jong et al., 2005; Künsting et al., 2011). This *control of variables strategy (CVS)* is crucial for scientific reasoning because it is a prerequisite for valid causal inferences. However, many learners do not use CVS, which can even apply to university students (Vollmeyer, Burns, & Holyoak, 1996). Metacognitive support including instructions to think about a systematic plan and to control the appropriateness of learning activities during SDL should stimulate a systematic learning behavior on the cognitive level, such as the use of CVS. So far research offers very little empirical evidence for effects of metacognitive support on the actual use of CVS during simulation-based SDL.

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Beyond, detrimental effects that occur when students feel unable to cope with learning demands also pertain to low motivation and negative emotions, which in turn can affect the learning outcome (Boekaerts, 1997, 2002). However, if at all, so far there are very few studies on SDL that have examined whether metacognitive support as an aid to cope with learning demands can promote learning outcome *and* both motivation and emotions. In previous studies on SDL, students were supported, for instance, by metacognitive instructions (Veenman et al., 1994), by the help to structure the scientific process (Linn & Songer, 1991) and to design systematic experiments (Rivers & Vockell, 1987), by model progression and assignments (Swaak, van Joolingen, & de Jong, 1998), and by given learning goals that are similar to assignments (Künsting et al., 2011).

However, providing learners with specific learning goals in addition to metacognitive support has been shown to promote transfer task performance but not declarative knowledge gain and recall (Bannert, 2003). One explanation for this finding could be that processing both specific learning goals *and* metacognitive support have engaged a great proportion of the students' cognitive resources. Thus, the cognitive capacities available for a declarative knowledge gain at the same time might have been restricted. With regard to simulation-based SDL this explanation is supported by the study of Künsting et al. (2011) that revealed specific learning goals to impose a higher cognitive load than nonspecific learning goals. It is thus possible that combining metacognitive support with nonspecific learning goals instead of specific learning goals could be a better method to foster knowledge gain during SDL. To our knowledge, no study has addressed this question so far.

The present study focuses on the effectiveness of a metacognitive support that covers a cyclic process of simulation-based SDL from an orienting phase to an evaluating phase. After testing the general impact of such a metacognitive support on knowledge gain during SDL, this study tries to answer further important research questions the existing research left unaddressed: *First*, there is very little evidence for the impact of metacognitive support on the actual use of CVS. *Second*, although motivational and emotional states are crucial agents for the quality of all learning processes, no studies to our knowledge have examined the impact of metacognitive support on students' motivational and emotional states during simulation-based SDL. *Third*, it remains open whether the impact of metacognitive support on learning outcome depends on the specificity of additionally set learning goals.

1.1. Metacognitive support to foster simulation-based SDL

Previous research has revealed the effectiveness of metacognitive support (e.g., instructions to plan and to monitor a learning process) in computer-based learning, for example, in hypermedia learning (Bannert, 2003; Bannert, Hildebrand, & Mengelkamp, 2009) and simulation-based SDL (Lin & Lehman, 1999; Veenman et al., 1994). Simulation-based SDL offers interactivity, which refers to a learner's choice to change values of input variables and then observe the corresponding change of output variables as a result (cf. Bodemer, Plötzner, Feuerlein, & Spada, 2004). This result is generated by the computer in terms of static or dynamic visualizations that, in turn, can prompt learners to another change of input variables. However, many learners do not use the full potential of interactivity in a structured and goal-oriented way, which can be due to low metacognitive skills or limited intelligence (Veenman et al., 1994).

According to Friedler et al. (1990), successful SDL requires defining a scientific problem; stating a hypothesis; designing experiments; observing, collecting, analyzing, and interpreting the data generated by experiments; applying the results; and predicting on the basis of the results. These *transformative processes* directly generate new knowledge (de Jong & Njoo, 1992) and should include cognitive strategies. With regard to domain-specific cognitive strategies, designing effective experiments requires the use of CVS. Additionally, general cognitive strategies (e.g., organizing, elaborating, and memorizing) should help to observe, collect, analyze, and interpret the experiments' results in a way that promotes understanding and knowledge gain. These processes are to be managed on a metacognitive level, which requires planning, goal setting, and monitoring (*regulative processes* according to de Jong & Njoo, 1992). Thus, metacognitive strategy use includes the planning, the monitoring and the regulation of cognitive strategies (Boekaerts, 1999).

To enhance SDL correspondingly, learners can be assisted by planning support (White, 1984) and monitoring support (Schauble, Raghavan, & Glaser, 1993). For example, Zion et al. (2005) demonstrated that metacognitive instructions significantly contribute to students' achievement in designing experiments and drawing conclusions. In their study on discovery learning with computer simulations, Veenman et al. (1994) found that students' performance can be enhanced by "metacognitive mediation". Learners in this condition received assignments similar to goals and were prompted to paraphrase questions, to generate hypotheses, to plan the actions, and to make notes (Veenman et al., 1994, p. 97).

The inefficient use of metacognitive strategies is a problem not only in the context of SDL. For example, studies on hypermedia learning also demonstrated that learners often need support because they are not able to self-regulate their learning (Lawless & Brown, 1997). To address this need, Bannert (2003) developed a model of metacognitive support based on approaches of successful learning (Pressley, Borkowski, & Schneider, 1989). In Bannert's model, learning in hypermedia starts with orientation, specification of goals, and planning. These activities direct the search, appraisal, and processing of information by the use of general cognitive strategies (e.g., organizing, elaborating, and memorizing). This process is permanently to be monitored, evaluated in between, and controlled at its end.

We argue that these metacognitive activities are also relevant for the experimentation during SDL. A metacognitive support of simulation-based SDL should provide learners with explanations of a structured and holistic overview of metacognitive learning activities that cover the process of SDL. It should begin with orienting, which is a metacognitive strategy used to gain an overview of materials, variables, and what can be done in a learning environment. Similar to a scientific problem that is to be defined at first, a given learning goal should be understood before experimentation starts, and it should be tested whether it can be helpful to divide it into subgoals. Planning includes thinking about adequate experimentation steps and other learning activities in order to execute systematic experiments during the pursuit of a goal. Monitoring and controlling involve appraising the comprehension of experimental results and the adequacy of cognitive strategies used during SDL. Evaluating assesses whether the goals set at the start of a process of SDL are achieved.

On the basis of Bannert's (2003) model of metacognitive support we expected that an adapted support with the characteristics of SDL (e.g., to plan the generating of information by experimentation) promotes students' conceptual knowledge gain during simulation-based SDL in physics. *Students provided with metacognitive support are expected to gain more conceptual knowledge than students without metacognitive support (Hypothesis 1).*

SDL involves stating and testing hypotheses about relations between variables. The testing of hypotheses is characterized by planning, conducting, and evaluating scientific experiments (de Jong & van Joolingen, 1998; Klahr & Dunbar, 1988; Kuhn, Black, Keselman, & Kaplan, 2000; cf. Lazonder & Kamp, 2012). To verify hypotheses, systematic experiments can be conducted. The new

information generated by experimentation confirms the hypothesis, confutes it, and/or leads to new hypotheses, which creates a cyclic process of SDL. For systematic experiments that allow for valid inferences, CVS is an important prerequisite and has a positive impact on learning outcome (e.g., Chen & Klahr, 1999; Künsting, Thillmann, Wirth, Fischer, & Leutner, 2008; cf. Künsting et al., 2011). CVS is used if only a single contrast is made between experimental conditions in order to examine relations between variables. For example, a student's hypothesis could be: "If the density of a fluid is less than the density of a solid placed in that fluid, then the solid sinks". To use CVS, the student could observe in a *first experiment* whether a solid with a certain density sinks, floats, or rises in a fluid with a certain density. In a *second experiment*, another solid with a different density is to be chosen, while keeping all other elements constant. The results of the experiments would have to be observed and interpreted correctly.

However, many learners often fail to plan, to monitor, and to adapt their own experimentation during SDL (de Jong & van Joolingen, 1998; cf. Alfieri et al., 2011). They regulate their experimentation unsystematically on a metacognitive level, which increases the probability for unsystematic experimentation on a cognitive level. That is, students with low metacognitive abilities, who hardly think about a plan of how to achieve learning goals at best and rarely monitor the appropriateness of learning activities during experimentation, should correspondingly design less systematic experiments (e.g., reflected by a less frequent use of CVS). We argue that metacognitive instructions to think about a plan of what could best be done to achieve a learning goal and to control the appropriateness of actions during SDL can stimulate a correspondingly systematic learning behavior. That is, to think about a plan to learn systematically can stimulate the use of cognitive strategies as a systematic learning behavior to fulfill this plan. During SDL, CVS is an essential cognitive strategy. *Students who receive metacognitive support are expected to use CVS more frequently than students who receive no metacognitive support (Hypothesis 2).*

1.2. Goal-setting, metacognitive support, and knowledge gain

Goals can be seen as regulatory agents for initiating self-regulated learning and creating standards to be reached during learning (Sitzmann & Ely, 2011). When a learning goal is known, a learning process can be guided, monitored, and evaluated (e.g., Pintrich, 2000). Given that SDL is a highly self-regulated form of learning, goal setting is often problematic, in particular for students with low prior knowledge (Charney, Reder, & Kusbit, 1990). Therefore, it should be supported. For example, Swaak et al. (1998) used assignments as goals to focus students' attention on the relationship between variables.

However, learning goals can influence a learning process differently as a function of goal specificity. Externally set learning goals can be specific or nonspecific, that is, they differ in the degree to which they precisely define for learners what is to be learned. Sweller and Levine (1982) were among the first to show the goal specificity effect: Students provided with nonspecific goals performed better than those who received specific goals (cf. Burns & Vollmeyer, 2002; Künsting et al., 2011).

Pursuing a *specific learning goal* (e.g., "Find out how the variables *a* and *b* are interrelated and try to understand and remember this.") entails keeping several elements in working memory: a current mental state, a mental goal state, the relation between these two states, the relation between different learning approaches, and possible subgoals (Künsting et al., 2011; Winne & Hadwin, 1998). Pursuing a *nonspecific learning goal* (e.g., "For as many variables as possible, find out how they are interrelated and try to understand and remember this.") does not necessarily imply processing these elements in working memory because the goal does not provide specific states of knowledge to be achieved. Rather, monitoring and evaluating a learning process initiated by a nonspecific learning goal only involves estimating whether additional knowledge has been gained in a current mental state.

This explanation follows Sweller's (1994) argument in the field of problem solving that specific goals cause a higher element interactivity and hence impose a higher cognitive load than do nonspecific goals. This has been empirically confirmed in the field of simulation-based SDL with regard to learning goals (Künsting et al. 2011): Specific learning goals imposed a higher cognitive load than nonspecific learning goals, although specific and nonspecific learning goals caused significant differences neither in the use of CVS nor in knowledge gain. It can be assumed for both specific and nonspecific learning goals that attaining them requires learning and thus prompt the use of CVS as a domain-specific learning strategy to a comparable extent. However, in terms of a cognitive cost-benefit ratio, the knowledge gain in relation to cognitive load was more favorable in the case of nonspecific learning goals (Künsting et al. 2011). Thus, when students have to process also other instructions *in addition*, nonspecific learning goals could leave more cognitive capacities in working memory that can be invested in processing the additional instructions. Hence, nonspecific learning goals could be more adequate when students have to process metacognitive instructions *and* given learning goals.

In line with our assumption, in Bannert's (2003) study on hypermedia learning the group with only specific learning goals gained and recalled as much declarative knowledge compared to the group with specific learning goals *and* metacognitive support. However, neither studies on hypermedia learning nor studies on simulation-based SDL to date have investigated whether the impact of metacognitive support on knowledge gain depends on the specificity of additionally given learning goals. It is conceivable that combining nonspecific learning goals with metacognitive support enables the investment of more cognitive capacities in knowledge gain. We suppose an interaction. *Students with metacognitive support and nonspecific learning goals are expected to gain more knowledge than students with metacognitive support and specific learning goals (Hypothesis 3).* According to the findings of Künsting et al. (2011) a main effect of goal specificity on cognitive load is also presumed. *Students provided with specific learning goals are expected to experience a higher cognitive load than those provided with nonspecific learning goals (Hypothesis 4).*

1.3. Metacognitive support, learning motivation, and learning emotions

Learning is accompanied by motivational and emotional states (Boekaerts, 2011). States of *low motivation* could result when a student is not interested in the task, perceives no challenges, or deems the task too difficult. States of *negative emotions*, such as irritation, anxiety, anger, or frustration, could occur when a student experiences failure or feels unable to cope with the task's demands. In contrast, *high motivation* and states of *positive emotions,* such as delight, excitement, relaxation, or relief, can benefit learning (Boekaerts, 1997, 2002).

Correspondingly, research indicated relations with learning performance for both motivation (Vollmeyer & Rheinberg, 2006) and emotions (Pekrun, Goetz, Titz, & Perry, 2002). Emotional states during learning direct students' attention toward or away from aspects relevant for learning in a specific situation (Boekaerts, 1997; Ellis & Ashbrook, 1988) and can result in action or state orientation (Kuhl, 1994). Positive emotional states are related to a more effective cognitive task approach that is conceptually driven, while negative emotional states could lead to constricted task attention and a stimulus-driven task approach (Clore & Huntsinger, 2007;

Fredrickson & Branigan, 2005). This reflects the complex link between affect and cognition (D'Mello & Graesser, 2012).

If students without enough self-regulative competences rely entirely on themselves in a demanding learning process, the risk of perceived and experienced failure is increased (cf. Boekaerts, 2011). Failure arouses negative emotions that can have detrimental effects on motivation and learning outcome (Pekrun et al., 2002). Thus, SDL should be supported through instruction that helps students to reduce excessive demands, the risk of failure, and the related negative emotions. One of the highest demands in SDL is the effective use of metacognitive strategies (e.g., de Jong & van Joolingen, 1998; Wirth & Leutner, 2008). Providing students with metacognitive support to help them to cope with this demand should affect their motivational and emotional states. *Compared to students without metacognitive support, students with metacognitive support are hypothesized to exhibit states of higher motivation (Hypothesis 5a) and emotional states that are more positive (Hypothesis 5b).*

1.4. Cognitive ability and SDL

On the one hand, interactive computer-based learning environments enabling SDL have been proven to be an effective method to foster students' knowledge gain in physics (Triona & Klahr, 2003; Zacharia & Olympiou, 2011). On the other hand, SDL requires self-regulated experimentation and reasoning to find relations between independent and dependent variables, which is a process that can impose a high cognitive load (Tuovinen & Sweller, 1999). One of the mental demands contributing to this cognitive load is *scientific reasoning*, that is, finding and understanding the relations between independent and dependent variables by experimentation (e.g., the relation between the volume of a solid and its buoyant force in water). This central component of SDL has also been called *inductive learning* (e.g., Greeno, Collins, & Resnick, 1996) because the learner has to infer a more general relation between variables or a concept from concretely observed information. Inductive cognitive ability is regarded as one of the major components of *intelligence* (cf. Klauer, Willmes, & Phye, 2002; Undheim & Gustafsson, 1987) and is often assessed using tests in which participants have to identify analogies (Klauer et al., 2002). Hence, this part of intelligence can affect SDL in particular and was included as a control variable in the present study.

2. The present study

2.1. Method

2.1.1. Design and participants

To test our hypotheses, the present experiment followed a 2×2-factorial between subjects design with three sessions: (1) pretests, (2) main assessment including posttests, and (3) follow-up test. The two factors were metacognitive support (yes vs. no) and specificity of learning goals (specific vs. nonspecific). Within their classes, students were randomly assigned to one of the four groups: with metacognitive support and with specific learning goals ($N = 32$), with metacognitive support and with nonspecific learning goals ($N = 33$), without metacognitive support and with specific learning goals ($N = 32$), or without metacognitive support and with nonspecific learning goals ($N = 32$).

Altogether, $N = 129$ *ninth grade students* from five classes at three German high track secondary schools (German Gymnasiums) participated in the study, with one or two classes per school (67 girls, 62 boys; age: $M = 14.33$, $SD = .69$). We included only classes that had not yet received any lessons on buoyancy in fluids.

2.1.2. Computer-based learning environment

We used a computer-based learning environment (CBLE), which is representing a virtual physics lab on "buoyancy in fluids" (Fig. 1).

Following the *modality principle*, we ensured that students did not have to process all information visually because this can result in an excessive cognitive load, which impedes the learning process (Mayer, 2009). To that end, we restricted textual guidance to short bullet points accompanied by more elaborate acoustic explanations. Buoyancy in fluids, the subject of our CBLE, has a high curricular validity as an integral part of physics education in secondary schools. Based on the anchored-instruction approach (Bransford, Sherwood, Hasselbring, Kinzer, & Williams, 1990), the CBLE featured a fictional scientist to attract students' attention and guide them through the lab. This character also presented the learning goals (called "assignments" for the students).

In line with the influential model of *scientific discovery as dual search* (SDDS) of Klahr and Dunbar (1988), which is based on the dual space-model (Simon & Lea, 1974), our CBLE (Fig. 1) is divided into an *experiment space* as a science lab to generate information (left screen) and a *hypothesis space* as a tool for charting assumptions and conclusions (right screen). The SDDS model theoretically describes scientific knowledge as being searched and represented within these two interrelated spaces.

In the experiment space of our CBLE new information can be generated by planning, designing, and conducting experiments to test whether and to what extent variables affect other variables. Students can place solids of different masses and volumes into two tanks with fluids of different densities. Once a solid is in a tank, how it moves (sinking, floating, or ascending) and the occurring physical forces represented by arrows and numbers (e.g., buoyant force and weight force) can be observed online. This makes it possible to observe the forces affecting the solids' behavior. There are 14 relations between variables to discover in the experiment space (e.g., When a solid is in a fluid, and if the solid's buoyant force is greater than its weight force, then it ascends in the fluid.). The hypothesis space of our CBLE is a graphical tool enabling the students to make notes in a specific kind of concept map. Imagine that a student has found by experimentation that a solid ascends in a fluid when the solid's buoyant force is greater than its weight force. This relation can then be noted in the hypothesis space with the help of the drawing tool (Fig. 1). Thus, consistent with the cycle of SDL in the framework of the SDDS model (Klahr & Dunbar, 1988), the present CBLE enables an interaction between the experiment space and the hypothesis space.

2.1.3. Metacognitive support and learning goals

Metacognitive support. In accordance with Bannert's (2003) concept of metacognitive support for hypermedia learning, which is based on approaches of successful learning (e.g., Pressley et al., 1989), we developed seven components of metacognitive support. We adapted these components to the specific aspects of SDL according to Friedler et al. (1990) and Linn and Songer (1991; e.g., including planning and executing experiments). Our components were: *Orienting*, *Clarifying*, *Planning*, *Executing*, *Monitoring*, *Controlling*, and *Checking Finally*. This concept of metacognitive support consists of a main part conducted prior to the actual process of SDL and a short supplemental part during SDL later on.

The main part of metacognitive support. In a first step, the two groups with metacognitive support were provided with an introductory modeling of metacognitive learning strategies that lasted 20 min. We developed this introductory part as a standardized instructional pattern adapted to SDL. With the help of PowerPoint, this part was presented to the students by a trainer who acted as a role model, explained the usefulness of the metacognitive strategies, and showed how to apply them. For example, at the beginning it was explained to the students why it is important to first get an

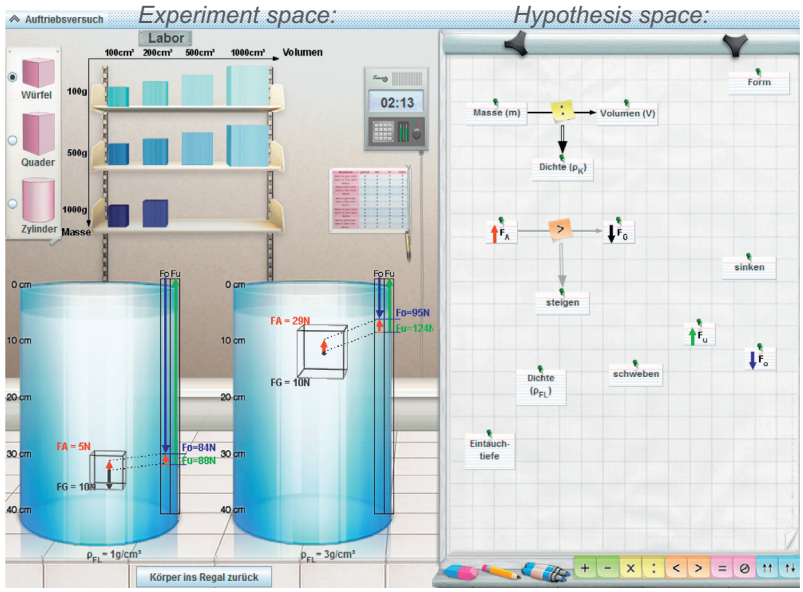

Fig. 1. Excerpt from the computer-based learning environment (CBLE).

overview of a learning environment and to clarify a learning goal, how to plan the course of action, and how to monitor and control one's own comprehension and memory during the learning process and at its conclusion. The students additionally received a short summarizing overview paper of the seven components of metacognitive support (Fig. 2) that have been introduced in more detail by the trainer. Students were told that they should use this short paper as an overview and reminder also during the learning phase that will follow later on.

Some of the metacognitive strategies in the introductory part, such as orienting, were illustrated with the help of a picture of a second virtual lab. It is a chemistry lab on the pH value (Gößling, 2010) and was presented on a slide within the PowerPoint presentation. The content of this chemistry lab differed entirely from that of the physics lab, although the structure was similar. To keep this precondition (except for metacognitive support) constant before the process of SDL started in the physics lab later on, the same picture of the chemistry lab was also explained in the same standardized way to the groups without metacognitive support. They were introduced the same constituent parts (e.g., chemical solutions), structures, and features of the chemistry lab in the same way and at the same time, but without being given any demonstrations of metacognitive activities. Explaining only the chemistry lab in the groups without metacognitive support took five instead of 20 min. This difference of 15 min was exclusively due to the metacognitive support as the treatment in terms of a yes–no condition.

Because the groups without metacognitive support were assigned to different rooms, the experiment for all groups has continued independently without a delay. The procedure and all materials (e.g., instructions, tests, tutorials, time commitment, and the whole CBLE) were the same for all groups.[3] That is, the time students were involved in the whole experiment after the yes–no precondition of metacognitive support was equal for all groups.

The supplemental part of metacognitive support. During the subsequent phase of SDL (cf. Section 2.1.5) students were prompted verbally and briefly three times (after 5, 10, and 15 min) to follow the components of metacognitive support demonstrated by the trainer before. To assist this, the students should use the overview paper as a short reminder. To limit the demands, the overview paper had to be short because during the learning phase (the phase of SDL) the students also had to process learning goals.

Learning goals. Building on previous work, we further developed the learning goals for the present study. In this study the learning goals (announced as "assignments" for the students) consisted of three components: (1) *focusing*, (2) *generating*, and (3) *integrating*. First, learners' attention is focused on core concepts (or parts of a concept) to be learned in the next step. Second, students are called on to generate knowledge about concepts. Third, students are to try to understand what they found and to keep it in mind, that is, to integrate it. This third part is a general feature in all learning goals of this study because successful and sustainable SDL should always imply understanding and memorizing the explored information, independent of the concept the goal requires to explore. An example for a specific learning goal is: "You already know that a solid has a certain volume. Let's concentrate now on the buoyant force of a solid: [*focusing*] Find out the impact of the volume of a solid on its buoyant force in a fluid. [*generating*]. Try to understand it and keep it in mind! [*integrating*]." An example for a nonspecific learning goal is: "A solid in a fluid is impacted by different physical forces: [*focusing*] Find out as best as possible whereof it depends how great the forces are. [*generating*]. Try to understand it and keep it in mind! [*integrating*]."

Two groups received 14 specific learning goals; the other two groups were provided with three nonspecific learning goals. Each specific learning goal addressed one of the 14 relations (one relation = one goal), whereas each nonspecific learning goal combined a cluster of some of the 14 relations (several relations = one goal). While the number of goals differed as a function of goal specificity, the number of relations to be learned that were addressed by each set of goals did not. To attain the full set of nonspecific learning goals it was necessary to encounter the same 14 relations addressed by the full set of specific learning goals.

2.1.4. Measures

Conceptual knowledge. A computer-based multiple-choice test within the CBLE was constructed to measure conceptual knowledge. This test was administered to assess prior knowledge (pretest), knowledge gain directly after learning (posttest), and retained knowledge that participants could recall three weeks later (follow-up test). The test covers the conceptual relations of the to-

[3] Except for the described supplemental part of metacognitive support.

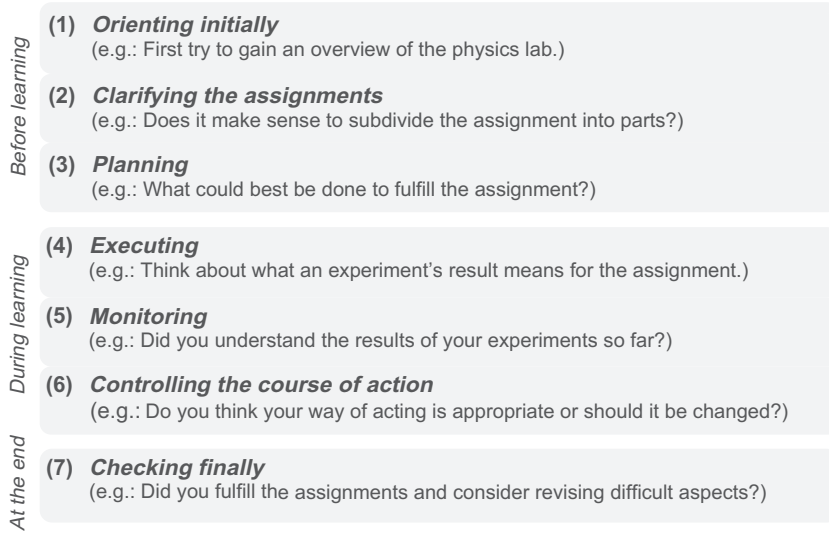

Fig. 2. Overview of the components of metacognitive support used in the present study.

pic "buoyancy in fluids" in the CBLE. Each of 12 items comprises a total of five response alternatives (e.g., "Solid A has a mass of 100 g and a volume of 200 cm^3. Solid B has a mass of 500 g and a volume of 200 cm^3. Both solids are in the same fluid. Which of the following declarations is correct? (1) The weight force of solid A exceeds the weight force of solid B; (2) The weight force of solid A is less than the weight force of solid B; (3) The buoyant force of solid A exceeds the buoyant force of solid B; (4) The buoyant force of solid A is less than the buoyant force of solid B; (5) Don't know."). Reliability and descriptive statistics were satisfactory for all three time points of assessment (pretest: Cronbach's $\alpha = .77$, $M = .33$,[4] $SD = .24$; posttest: Cronbach's $\alpha = .80$, $M = .48$, $SD = .26$; follow-up test: Cronbach's $\alpha = .80$, $M = .47$, $SD = .26$).

Strategy use. The use of CVS was measured following a process-based approach during SDL in the CBLE. That is, in the CBLE, all mouse clicks were recorded online and saved automatically into log files during data acquisition (Wirth, 2008). Afterwards, we tracked whether the sequence of students' clicks within the experiment space was strategic in terms of having used CVS or not. Using macro-analyses with an algorithm to calculate the strategy use (see Gößling, 2010; cf. Künsting et al., 2011), participants were considered to have used CVS if they had kept all but one independent variable constant from the first to the second experiment in two subsequent experiments (e.g., in a first experiment a learner drags a solid with a volume of 200 cm^3 and a mass of 100 g into a tank of fluid with a density of 1 g/cm^3. In a second experiment the student varies the mass only). Subsequently, the ratio of the number of experiments conducted using CVS to the number of experiments conducted in total was computed as our measure for the actual use of CVS.

This strategy assessment ensures capturing only strategic behavior that is actually shown (Wirth & Leutner, 2008). To estimate the reliability of this algorithm, we divided the total number of conducted experiments during the learning phase into three parcels. For every parcel we then calculated the proportion of experiments in which CVS was used. The reliability is acceptable when it is taken into account that only three items (parcels) could be included (Cronbach's $\alpha = .61$). On average the students completed $M = 18.71$ experiments ($SD = 14.97$), from which $M = 10.40$ were CVS experiments ($SD = 8.77$).

[4] To simplify all measures in this paper into a unitary depiction, we standardized all of them to a range from zero to one.

Basic cognitive ability. To control for the basic cognitive ability, we applied the nonverbal subscale "figural analogies" (25 items; Cronbach's $\alpha = .84$, $M = .77$, $SD = .19$) of a standard intelligence test (Heller & Perleth, 2000). This subscale "figural analogies" is appropriate to measure cognitive ability relevant for SDL (see Section 1.4). Additionally, this scale correlates highly with the g-factor of general intelligence (Heller & Perleth, 2000).

Cognitive load. To assess self-perceived overall cognitive load, we developed a scale partly adapted from the concepts of Braarud (2001), Hart and Staveland (1988), and Tsang and Velazquez (1996). The scale's 11 items consider cognitive demands on working memory resulting from special requirements of the goals and of our CBLE (Cronbach's $\alpha = .88$, $M = .59$, $SD = .16$; for example, simultaneous demands, time pressure, or processing of visual-spatial and textual information; sample item: "To what extent was it a mental effort for you to comprehend the text of the assignments? [1 = hardly; ...7 = very much])".[5]

Motivational states. To account for motivation directly before and after participants learned from our CBLE, we administered two scales of the questionnaire on current motivation with nine items altogether (QCM; Rheinberg, Vollmeyer, & Burns, 2001; pretest: Cronbach's $\alpha = .84$, $M = .59$, $SD = .16$; e.g., "After reading the instructions, I'm very interested in the task [1 = not at all; ...7 = very much]"; posttest: Cronbach's $\alpha = .77$, $M = .51$, $SD = .16$; e.g., "After finishing the task I'm very interested in it [1 = not at all; ...7 = very much])".

Emotional states. To account for current emotions directly before and after the learning phase, we developed 14 items according to an emotion subscale of the online motivation questionnaire (Boekaerts, 2002). Pretest items were preceded by the prompt "How do you feel right now, just before starting the task?" (Example items: 1 = not at ease; ...7 = at ease; or 1 = not frustrated; ...7 = frustrated; Cronbach's $\alpha = .89$, $M = .67$, $SD = .15$). Posttest items were preceded by the prompt "How do you feel right now,

[5] The cognitive load scale has been self-developed and partly adapted from existing scales in English. Additionally, the emotional states scale has been developed according to a scale in English. For the adapted items we tested their cultural transferability by expert ratings; their correct and suitable translation into German has been assured using *back-translation* (van de Vijver & Hambleton, 1996). For all scales we conducted expert ratings and pilot studies, to ensure that they meet all statistical standard criteria (e.g., reliability). As we will reason in the discussion, we intended to measure overall cognitive load, but not to separate the three types of cognitive load.

just after finishing the task?" (Cronbach's $\alpha = .92$, $M = .64$, $SD = .18$). Negative items were inverted to enable a mean score reflecting the extent to which the students' learning emotions were positive.

2.1.5. Procedure

The experiment was divided into three sessions (cf. Section 2.1.1) in the school classrooms. In the *first session* we assessed students' conceptual prior knowledge and basic cognitive ability using paper-based tests (30 min). In the *second session* a week later the metacognitive support (20 min) as the treatment and additional tests were administered. At first, within their classes the students were randomly divided into different classrooms to separate the condition of the metacognitive support (Section 2.1.3) acoustically and visually from the condition without it. Students were then randomly assigned to specific or nonspecific learning goals that were presented later on during the learning phase (see below). Except for these different goals and the complementary metacognitive prompting during SDL only for the two groups who also received the main part of metacognitive support before, the procedure was then the same for all groups.

In preparation for the session with the CBLE, students put on their earphones and started with a computer-based training on using the graphical tools in the hypothesis space, followed by an introduction to the experiment space and the rest of the CBLE (15 min). The participants were then tested on the two short scales on motivational and emotional states (4 min) as a pretest immediately before the learning phase (the phase of SDL) began. The learning goals were automatically and individually presented one after another as text windows on the computer screen during the learning phase (for the students the goals were named "assignments"). Immediately after this learning phase (20 min), participants were tested on the cognitive load scale (2 min) to measure the cognitive effort they perceived they had to invest in the learning phase they were just leaving at that moment. In direct succession participants worked on the scales on motivational and emotional states as a posttest (4 min) and on the conceptual knowledge posttest (15 min). In the *third session* three weeks later, the students completed the knowledge test as a follow-up measure to ascertain the sustainability of acquired conceptual knowledge (15 min). With all teachers it was agreed not to mention any contents of the test at all in the meantime within the study.

3. Results

3.1. Preceding analyses

For each experimental group, means and standard deviations of the variables used in the present study are depicted in Table 1. To provide an overview of the relations between the variables, we present Pearson correlations for the entire sample in Table 2. Using a MANOVA, we found no significant differences between the four groups in their prerequisites before the experiment with regard to conceptual prior knowledge, $F(3, 111) = .77$, $p = .512$, basic cognitive ability, $F(3, 111) = .41$, $p = .744$, motivational states, $F(3, 111) = 1.11$, $p = .350$, and emotional states, $F(3, 111) = .78$, $p = .511$. The sample as a whole showed a significant gain of conceptual knowledge from the pretest to the posttest, $t(114) = 5.50$, $p < .001$, Cohen's $d = 0.51$. Because some students could not attend the third session three weeks later, the sample was reduced to $N = 96$ remaining participants for the follow-up test. The rest of the students were absent in the sense of missing at random, which was distributed equally over all groups (group sizes remain comparable: 24, 22, 24, and 26). The follow-up test knowledge of the remaining students was still significantly higher than their pretest knowledge, $t(95) = 5.60$, $p < .001$, Cohen's $d = 0.55$.

Table 1
Means and standard deviations of the variables in the present study.

	With metacognitive support		Without metacognitive support	
	Specific goals *M* (*SD*)	Nonspecific goals *M* (*SD*)	Specific goals *M* (*SD*)	Nonspecific goals *M* (*SD*)
Knowledge (pre)	.27 (.23)	.38 (.21)	.36 (.28)	.30 (.21)
Knowledge (post)	.50 (.25)	.58 (.26)	.43 (.27)	.40 (.23)
Knowledge (follow-up)	.46 (.29)	.54 (.26)	.44 (.25)	.43 (.23)
Strategy use (CVS)	.63 (.19)	.62 (.22)	.47 (.26)	.54 (.23)
Basic cognitive ability	.74 (.19)	.76 (.20)	.75 (.21)	.80 (.17)
Cognitive load	.37 (.11)	.37 (.08)	.40 (.11)	.36 (.11)
Motivational states (pre)	.55 (.17)	.60 (.16)	.62 (.15)	.61 (.16)
Motivational states (post)	.46 (.13)	.54 (.16)	.49 (.17)	.51 (.16)
Emotional states (pre)	.65 (.13)	.70 (.15)	.65 (.14)	.68 (.16)
Emotional states (post)	.69 (.16)	.71 (.17)	.55 (.18)	.62 (.19)

The extent of the gained knowledge hardly changed from the posttest to the follow-up test ($p = .627$) and, thus, could be retained at least for three weeks.

Significant gender effects were visible. Boys showed a higher prior knowledge, $F(1, 112) = 16.37$, $p < .001$, $\eta^2 = .13$, a higher posttest knowledge, $F(1, 112) = 10.36$, $p = .002$, $\eta^2 = .09$, a higher cognitive ability,[6] $F(1, 112) = 5.12$, $p = .026$, $\eta^2 = .04$, emotional states that were more positive before, $F(1, 112) = 9.01$, $p = .003$, $\eta^2 = .07$, and after learning, $F(1, 112) = 6.36$, $p = .013$, $\eta^2 = .05$, and a lower cognitive load, $F(1, 112) = 10.35$, $p = .002$, $\eta^2 = .09$.

3.2. Tests of hypotheses

To test our hypotheses 1 to 5b, we first conducted a MANCOVA. To reduce error variance, we controlled for conceptual prior knowledge, basic cognitive ability, motivational states (pretest), and emotional states (pretest) as covariates. The dependent variables were: acquired conceptual knowledge (posttest), strategy use (CVS), cognitive load, motivational states (posttest), and emotional states (posttest). The multivariate effect of metacognitive support on all dependent variables simultaneously was shown to be significant and explained 27% of the variance, $\Lambda = .73$, $F(5, 102) = 7.68$, $p < .0001$, $\eta^2 = .27$. The multivariate effect of the specificity of learning goals was not significant ($p = .66$). Because of the reduced sample at the third assessment (see Section 3.1), for the test of our hypotheses a separate ANCOVA with the same covariates was applied for the follow-up test knowledge as a dependent variable. Fig. 3 contains the adjusted means for the group comparisons relevant for the hypotheses.

3.2.1. Effects of metacognitive support on conceptual knowledge and strategy use

Hypothesis 1. As expected, the metacognitive support fostered the knowledge gain during simulation-based SDL. Significant main effects of metacognitive support were shown on the acquired knowledge directly after learning, $F(1, 106) = 17.16$, $p < .0001$, $\eta^2 = .14$, and on the follow-up test scores three weeks later,

[6] This gender effect on basic cognitive ability is rather small and might not reflect general differences in intelligence. Although the used subscale correlates highly with general intelligence, it is relevant specifically for scientific reasoning. Thus, it could be a small domain-specific gender effect in the present sample.

Table 2
Pearson correlations between the variables of the study.

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Knowledge (pre)									
2. Knowledge (post)	.51**								
3. Knowledge (follow-up)	.54**	.69**							
4. Strategy use (CVS)	.19*	.40**	.43**						
5. Basic cognitive ability	.33**	.43**	.41**	.30**					
6. Cognitive load	−.44**	−.22*	−.24*	−.11	−.03				
7. Motivational states (pre)	.19*	.31**	.27*	−.04	.12	.05			
8. Motivational states (post)	.18*	.36**	.29**	.13	.06	.00	.67**		
9. Emotional states (pre)	.37**	.27**	.32**	−.08	−.03	−.41**	.37**	.41**	
10. Emotional states (post)	.29**	.28**	.18	.09	−.05	−.50**	.22*	.40**	.53**

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

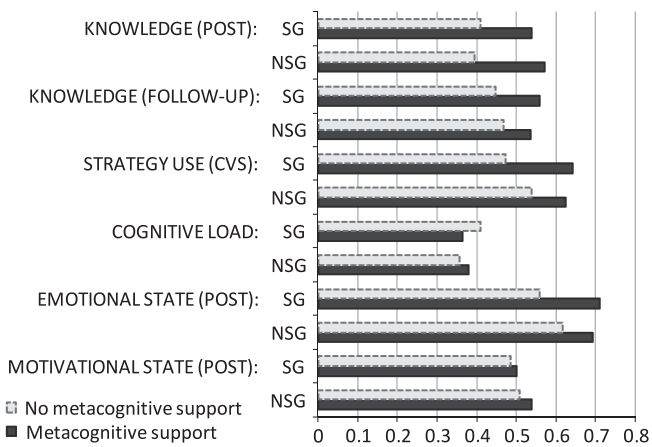

Fig. 3. Means of the dependent variables as a function of metacognitive support and goal specificity, adjusted for prior knowledge, basic cognitive ability, initial motivation, and initial emotions. *Notes*: SG = specific learning goals, NSG = nonspecific learning goals; depicted in one graphic, the range is standardized to a range from zero to one.

$F(1, 77) = 4.13$, $p = .046$, $\eta^2 = .05$ (Fig. 3). With regard to the covariates, significant parts of variance in the posttest knowledge could be explained by prior knowledge, $F(1, 106) = 14.92$, $p < .001$, $\eta^2 = .12$, by pretest motivation, $F(1, 106) = 8.82$, $p = .004$, $\eta^2 = .08$, and by basic cognitive ability, $F(1, 106) = 16.42$, $p < .0001$, $\eta^2 = .13$. That is, the higher the prior knowledge, the motivation, and the basic cognitive ability for figural analogies were as prerequisites, the more knowledge could be gained through SDL. Concerning the follow-up test scores, significant effects of covariates were only found for prior knowledge, $F(1, 77) = 9.18$, $p = .003$, $\eta^2 = .11$, and basic cognitive ability, $F(1, 77) = 14.20$, $p < .001$, $\eta^2 = .16$.

Hypothesis 2. We also found evidence for the second hypothesis that metacognitive support leads to more strategic experimenting during SDL. Compared to participants without metacognitive support, those with metacognitive support used CVS significantly more frequently in proportion to all experiments they conducted in total, $F(1, 106) = 9.34$, $p = .003$, $\eta^2 = .08$ (Fig. 3). Additionally, basic cognitive ability as a covariate contributed to a higher frequency of strategy use, $F(1, 106) = 7.24$, $p = .008$, $\eta^2 = .06$.

3.2.2. Effects of metacognitive support and goals on knowledge gain and cognitive load

Hypothesis 3. No evidence appeared to support the third hypothesis. The interaction effect of metacognitive support and goal specificity on both immediate knowledge gain and follow-up test knowledge was not shown to be significant ($p = .542/.621$). Thus, it made no difference whether metacognitive support was combined with specific or with nonspecific learning goals (Fig. 3).

Hypothesis 4. No significant main effect of goal specificity on cognitive load could be replicated by the data ($p = .291$). However, there was a marginally significant interaction effect of metacognitive support and goal specificity on cognitive load, $F(1, 106) = 3.86$, $p = .052$, $\eta^2 = .04$. The univariate model with the same covariates was shown to be significant, $F(1, 107) = 4.07$, $p = .046$, $\eta^2 = .04$. This result indicates a trend that specific learning goals compared to nonspecific learning goals caused a higher cognitive load only in the two conditions without additional metacognitive support (Fig. 3). Correspondingly, the contrast effect within a MANCOVA and an ANCOVA (with the four experimental groups as one factor but the same dependent variable/s and covariates as before) revealed that students provided only with specific learning goals experienced a significantly higher cognitive load than did those who received only nonspecific learning goals ($p = .030/.030$, Cohen's $d = 0.47/0.46$). A clear negative impact on cognitive load was revealed for the covariates prior knowledge, $F(1, 106) = 19.00$, $p < .0001$, $\eta^2 = .15$, and initial emotions, $F(1, 106) = 12.66$, $p = .001$, $\eta^2 = .11$. That is, the lower the prior knowledge and the less positive the emotions directly before learning were, the higher the cognitive load in the learning phase was perceived. The initial motivation had a somewhat lower, positive effect on cognitive load, $F(1, 106) = 7.59$, $p = .007$, $\eta^2 = .07$.

3.2.3. Effects of metacognitive support on motivation and emotions

Hypotheses 5a and 5b. The fifth hypothesis asserted that metacognitive support would be a beneficial condition for participants' motivational and emotional states. While no significant main effect occurred for posttest motivation, $p = .378$, metacognitive support was clearly shown to have a positive effect on posttest emotions, $F(1, 107) = 14.67$, $p < .001$, $\eta^2 = .12$ (Fig. 3). Only three significant effects of covariates were observed (expectably positive effects): The emotions directly after learning were affected by the emotions directly before learning, $F(1, 107) = 26.28$, $p < .0001$, $\eta^2 = .20$, but not by motivation before learning ($p = .400$). The motivation after learning was highly affected by its counterpart measured before learning, $F(1, 107) = 64.95$, $p < .0001$, $\eta^2 = .38$, and less highly by emotions before learning, $F(1, 107) = 5.19$, $p = .025$, $\eta^2 = .05$. Prior knowledge and cognitive ability did not affect the motivational and emotional states after learning ($p \geqslant .328$).

3.3. Additional analyses

Compared to students without metacognitive support, students with metacognitive support used CVS more frequently in relation

to all experiments they executed. To ensure that differences in the use of CVS account for differences in learning outcome in the present study, we additionally conducted *structural equation modeling (SEM)* with AMOS (Arbuckle, 2008). We tested CVS as a predictor of knowledge gain. Knowledge gain was computed as knowledge of which prior knowledge has been partialed out using standardized regression residuals.

Model complexity was to be kept parsimonious because this study is experimental and has a maximum sample size of $N = 129$ cases. Analyses for subsamples and multi-group comparisons were not possible because the subsamples are too small. We applied item parceling to optimize the relation between sample size and parameters in order to serve stability and accuracy for model fit estimation (Bandalos & Finney, 2001). For the use of CVS, the parcels described in Section 2.1.4 were included. To handle missing data we used the *full information maximum likelihood* algorithm (*FIML*, Graham, 2009). We tested our model fit using the Chi^2-statistics, the incremental fit (*IFI*), the comparative fit index (*CFI*), the Tucker–Lewis index (*TLI*), and the root-mean-squared error of approximation (*RMSEA*). For *IFI*, *CFI*, and *TLI*, values > .90 indicate an acceptable fit, and values > .95 a good fit of the model to the data. For *RMSEA*, values from .05 to .08 are acceptable, and values $\leqslant$ .05 are good (Hu & Bentler, 1999). Fig. 4 shows *latent standardized regression coefficients.*

Because there was no further treatment after the posttest, the variable "Knowledge gain from pretest to follow-up test" (Fig. 4) reflects knowledge students were able to gain from the pretest to the posttest *and* to retain until the follow-up test three weeks later. As a result, *model 1* (Fig. 4) showed CVS to predict both the pure conceptual knowledge gain from the pretest to the posttest and the gained knowledge that also could be retained until the follow-up test. Controlled for cognitive ability as a second independent variable, *model 2* showed that CVS is still a significant predictor. Both models 1 and 2 fit the data well (Fig. 4).

4. Discussion

The aim of the present study was to examine the impact of metacognitive support in combination with goal setting mainly on conceptual knowledge gain, cognitive strategy use, learning motivation, and learning emotions during simulation-based scientific discovery learning (SDL, de Jong & van Joolingen, 1998). Our computer-based learning environment (CBLE) is a virtual physics lab that allows for SDL according to the theory of scientific discovery as dual search (SDDS, Klahr & Dunbar, 1988). Using log files we applied a process-based measure of the actual use of the control of variables strategy (CVS), which appears very little in previous research. Our metacognitive support was a short modeling introduction before learning, combined with prompting during learning.

Hypotheses 1 and 2. The present experiment enriches previous research on enhancing SDL through instructional support. Controlled for prior knowledge, basic cognitive ability, initial motivation, and initial emotions, we demonstrated that metacognitive support significantly promotes strategy use and conceptual knowledge gain. Compared to the students without metacognitive support, those with metacognitive support used CVS more frequently in relation to all experiments they conducted, they acquired more knowledge, and they still performed significantly better on the delayed knowledge test after three weeks. Though, the effect after three weeks was weaker than the immediate effect on the posttest scores. In sum, *hypotheses 1 and 2* could be confirmed. To our knowledge, no previous studies on simulation-based SDL showed a short metacognitive support of 20 min to be effective for secondary school students' actual use of CVS and for their conceptual knowledge gain. In line with previous research (e.g., Chen & Klahr, 1999; Künsting et al., 2008), our additional analyses in Section 3.3 showed that the use of CVS predicts

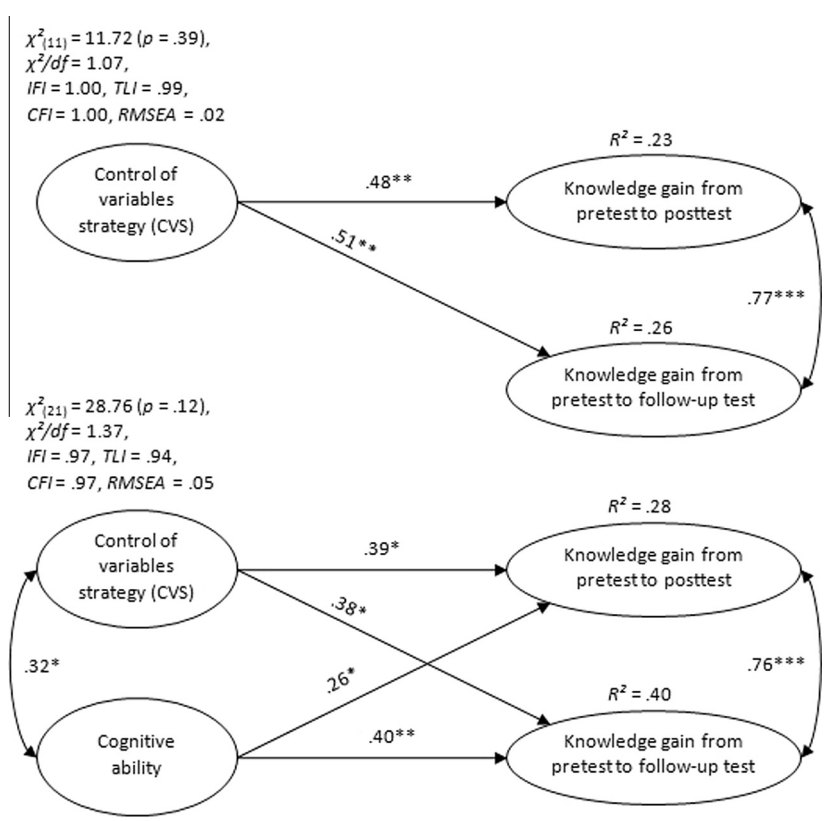

Fig. 4. The use of CVS as a predictor of conceptual knowledge gain ($^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$).

knowledge gain and the extent to which this gained knowledge could be retained for three weeks (controlled for cognitive ability).

Hypotheses 3 and 4. Based on the framework of cognitive load theory (e.g., Sweller, 1994) we assumed metacognitive support to facilitate a greater knowledge gain when combined with nonspecific learning goals instead of specific learning goals. However, students with metacognitive support and nonspecific learning goals gained only a slightly greater amount of knowledge than those with metacognitive support and specific learning goals (Fig. 3). Neither the interaction effect of metacognitive support and goal specificity on knowledge gain (*hypothesis 3*) nor the main effect of goal specificity on cognitive load (*hypothesis 4*) was significant. However, for participants who received specific or nonspecific goals without metacognitive support, the contrast effect identified specific goals as imposing a significantly higher cognitive load than nonspecific goals. This is in line with predictions and findings from previous research (Künsting et al., 2011; Sweller, 1994).

These results of the present study suggest to some degree the opposite of our original assumption expressed in hypothesis 3 (Section 1.2) because we have not found that combining specific learning goals with metacognitive support fosters knowledge gain less or increases cognitive load. Rather, metacognitive support appeared to prevent students from experiencing a higher cognitive load when confronted with specific learning goals. The metacognitive support possibly equipped the students with the prerequisite to demonstrate a strategic learning behavior that helps to better cope with the demands that arise when attempting to achieve specific learning goals during SDL. Thus, enough cognitive capacities for knowledge gain apparently were available by the help of metacognitive support. This interpretation is underlined by our result of a positive influence of metacognitive support on actual strategy use, knowledge gain, and emotional states.

Hypotheses 5a and 5b. Compared to participants without metacognitive support, those with metacognitive support reported a higher motivation only on a descriptive level when completing the learning phase (Fig. 3). This group difference was not significant, that is, *hypothesis 5a* could not be confirmed. By contrast, students who received metacognitive support clearly experienced emotional states that were more positive. This empirical evidence endorses the assumption (*hypothesis 5b*) that the effects of metacognitive support are not restricted to cognitive outcomes but also contribute to preferable states of positive learning emotions, which for their part were related to the acquired conceptual knowledge (Table 2). As far as we know, the present study is the first that shows metacognitive support to have a positive impact on learning emotions during simulation-based SDL.

At first view, this result could be in line with the assumption of positive learning emotions as a resource (Fredrickson & Losada, 2005). The findings of Boekaerts (2007) support the resource hypothesis insofar as students' negative emotions during mathematics homework were found to be accompanied by the belief to have insufficient resources to accomplish the task, which was related to a decrease in cognitive effort. By contrast, students' belief of having sufficient resources was related to an increase in cognitive effort.

At second view, there is another perspective on emotions and cognitive effort.

Imagine learners with high motivation but with low prior knowledge and low metacognitive competences. To decrease the risk of discouragement and failure, metacognitive support can be provided. In this case, the learners perceive help and receive help. Their effort would be accompanied by an assuredness to accomplish the task. Thus, the emotional *willingness* to maintain the effort would be high. It could be invested in knowledge gain (cf. Boekaerts, 2011), which increases the chance of success. Consequently, positive emotions and effective patterns of task coping might result. Imagine other learners with equal prerequisites but without metacognitive support. In this case, the learners perceive no help and receive no help, which increases the risk of discouragement and failure. Their invested effort would be accompanied by a lower assuredness to accomplish the task. If further attempts to complete the task are nonetheless made, they could feel impelled to search for coping strategies single-handedly. These learners would perceive a *necessity* to maintain a high cognitive effort. If they then perceive that the task exceeds their competence during goal pursuit, negative emotions and, consequently, ineffective patterns of task coping arise (Boekaerts, 2011; Clore & Huntsinger, 2007; Fredrickson & Branigan, 2005).

In the present study the cognitive load scale is conceptualized to assess students' self-perceived extent of *necessity* to invest cognitive effort in the learning phase. Accordingly, the cognitive load was clearly negatively related to the extent to which the emotions were positive immediately after learning (see Table 2).

Desiderata and perspectives. Some requirements for future research should be noted. To maintain students' motivation to attend the experiment and to prevent them from losing concentration, we used materials that are not overtaxing. Therefore, no additional measures on students' actual use of *metacognitive* strategies were administered. Excluding some tests relevant for this study and including complementary qualitative measures would help to detect metacognitive activities (e.g., Beishuizen & Stoutjesdijk, 1999). However, that would have gone beyond the scope of the present study, which was designed to examine the effects of metacognitive support as instruction rather than to follow a diagnostic approach.

Furthermore, it should be mentioned that we used "buoyancy in fluids" as a topic in physics with high curricular validity, but we did not test the metacognitive support for other contents (e.g., topics in chemistry). Further research is required to evaluate the effectiveness of a parsimonious metacognitive support used in this study with adapted versions for other school subjects. It should also be considered that the sample of the present study consisted solely of ninth-grade students. Indeed, students with low prior knowledge and competences to self-regulate a process of SDL need instructional support (de Jong & van Joolingen, 1998). However, for a student in a lower grade whose domain-specific prior knowledge and strategy knowledge are even too low to be able to benefit from an instructional format (e.g., a metacognitive support), its effect may fail to appear or could be even detrimental (Clark, 1990; cf. Prins, Veenman, & Elshout, 2006). By contrast, older students with higher prior knowledge and further-developed metacognitive competences would need less help. Possible aptitude treatment interactions (ATI; Snow & Corno, 1986) could appear.

Concerning the used method to assess cognitive load it is worthy of mentioning that subjective rating scales turned out to be economic and reliable (e.g., Ayres, 2006). It has been often argued that students can introspect aspects of their own cognitive effort (e.g., Paas, Tuovinen, Tabbers, & van Gerven, 2003) and that their cognitive load can be assessed using a numeric scale (e.g., Gopher & Braune, 1984). However, the potential of subjective rating scales to differentiate between cognitive *load* and cognitive *overload*, and between the three types intrinsic load, extraneous load, and germane load (Sweller, 1994; cf. Künsting et al., 2011), is limited (de Jong, 2010). One example of a reason might be that it is not easy to develop items that enable students to distinguish between the three cognitive load types according to the idea they were concep-

tualized by the research. Thus, to date the proportion of the three cognitive load types is not devoid of interpretation (cf. Künsting et al., 2011).

In sum, the present study extends existing work by demonstrating the positive impact of a parsimonious metacognitive support on scientific discovery learning. This effectiveness was found to be independent of goal specificity. Furthermore, the metacognitive support was shown not only to be effective for the knowledge gain but also for the actual use of the control of variables strategy during learning and the emotional states at the end of the learning process. Hence, from a practical viewpoint this pattern of metacognitive support could become a complementary method to foster scientific discovery learning in the classroom and could be easy to implement in schools.

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