The goal specificity effect on strategy use and instructional efficiency during computer-based scientific discovery learning

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A B S T R A C T

Using a computer-based scientific discovery learning environment on buoyancy in fluids we investigated the effects of goal specificity (nonspecific goals vs. specific goals) for two goal types (problem solving goals vs. learning goals) on strategy use and instructional efficiency. Our empirical findings close an important research gap, because in earlier studies the goal specificity effect either was restricted to one goal type or goal type was confounded with goal specificity. In addition, there is hardly a study with empirical evidence for the goal specificity effect on strategy use, which counts even more for a cognitive cost-benefit ratio as a dependent variable. Instead, in earlier studies the goal specificity effect has been attributed to differences in strategy use and cognitive cost-benefit ratio in a rather theoretical way. In the present study for strategy use an interaction was found between goal specificity and goal type, indicating that the goal specificity effect occurs only in case of problem solving goals, but not in case of learning goals. Compared to students provided with specific problem solving goals, students who worked on nonspecific problem solving goals, used a control of variables-strategy more frequently. Additionally, we found a main effect of goal specificity on instructional efficiency for both of the goal types, pointing at a more favorable relationship between performance gain and cognitive load caused by nonspecific goals.

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1. Introduction

Previous problem solving research on goal setting has often found empirical evidence for the goal specificity effect on performance (Sweller, 1988, 1994; cf. Trumpower, Goldsmith, & Guynn, 2004): Nonspecific goals (e.g., “ill defined goals”) lead to higher performance (learning outcome) than specific goals (e.g., “well defined goals”; cf. Kluwe, 1993). This effect could be shown with maze problems (Paas, Camp, & Rikers, 2001), mathematical problems (Owen & Sweller, 1985; Sweller, 1988), and complex and dynamic problems in computer-based learning environments (e.g., Burns & Vollmeyer, 2002; Vollmeyer & Burns, 2002).

Following Sweller and Levine (1982), goal specificity is the extent to which a set goal is clearly defined for a person (e.g., in the context of trigonometric tasks: “Find the value for the angle X” as a specific goal vs. “Find the value of as many angles as possible” as a nonspecific goal; Sweller, 1994). Referring to the goal specificity effect on strategy use, Vollmeyer, Burns, and Holyoak (1996; cf. Burns & Vollmeyer, 2002) revealed that nonspecific goals promote the use of a learning strategy during computer-based discovery learning stronger than specific goals. However, strategy use during discovery learning (see Section 1.4) with goal setting was not shown yet as a computer-based online standard of assessment that ensures to only capture strategic behavior students actually show (see Wirth & Leutner, 2008).

According to Sweller (1994) the goal specificity effect during problem solving is due to the fact that specific problem solving goals elicit strongly the use of a pure problem solving strategy, straining the working memory in a way that is not effective for schema acquisition. Thus, it causes a high cognitive load that is not assisting in learning. Nonspecific problem solving goals, on contrast, allow much more for investing cognitive load that serves learning processes, because they do not elicit the use of a pure problem solving strategy. They rather focus learners’ attention on aspects of a task that are relevant for learning. Correspondingly, goal specificity can be seen as a factor influencing which type of cognitive load is invested.

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Cognitive load is divided into three types (Sweller, 1994; Paas, Renkl, & Sweller, 2004; cf. Holzinger, Kickmeier-Rust, Wassertheurer, & Hessinger, 2009): 1. **Intrinsic load** refers to task-inherent complexity (element interactivity), due to the number of interrelated basic task elements. 2. **Extraneous or ineffective load** is load imposed by the instructional design of the task (e.g., poor structural, graphical, and textual arrangement, or inappropriate strategies) and is associated with learner activities, which does not contribute to learning. 3. **Germane or effective load** is load imposed by the instructional design and is associated with learner activities that foster schema acquisition and, thus, serves learning. In this article we decided to use the terms **ineffective load** (in case of extraneous load) and **effective load** (in case of germane load), because we want to focus clearly on the effectiveness of invested cognitive capacities with respect to learning outcome.

In the present paper we empirically measured cognitive load and related it to performance gain to get a cognitive cost-benefit ratio in terms of instructional efficiency (Sections 1.5 and 2.3). As dependent variables we mainly focus on strategy use and instructional efficiency, influenced by the specificity of goals within a computer-based learning environment designed for scientific discovery learning. Scientific discovery learning (SDL, Klahr & Dunbar, 1988; Kuhn, Black, Keselman, & Kaplan, 2000) is a strongly self-regulated form of constructivistic learning. It includes a cycle of planning, conducting and evaluating scientific experiments, for example in the field of physics, chemistry or biology (e.g., Friedler, Nachmias, & Linn, 1990; Rivers & Vockell, 1987). That is, for instance in physics, a learner could state a hypothesis about the relation between two variables, like volume and buoyant force of an all-solid (e.g., “The greater the volume of an all-solid, the greater its buoyant force in water”). Based on this hypothesis, the learner could carry out the respective experiments to test it. However, to verify the hypothesis adequately, the experiment has to be conducted systematically, at best via strategy use (see Section 1.4). Also the results of the experiment (e.g., the different sizes of buoyant force of different all-solids) have to be observed and interpreted correctly. In turn, new information generated by experimenting can lead to new hypotheses. Klahr and Dunbar (1988) conceptualized this kind of identifying new information in their influential theory of scientific-discovery-as-dual-search (SDDS). Based on the dual space-model (Simon & Lea, 1974), in the SDDS-theory Klahr and Dunbar (1988) describe scientific knowledge theoretically as being searched and as being represented within two interrelated spaces: In an “experimental space” and in a “hypothesis space” (cf. Section 2.2).

Interactive computer-based learning environments, on the one hand, have been proved to be an effective method to foster students’ knowledge gain of physics concepts by SDL (Triona & Klahr, 2003; Zacharia & Olynyk, 2010). On the other hand, SDL in general and SDL within a computer-based and interactive simulation requires self-directed experimentation and reasoning to find out the relations between independent and dependent variables, which can impose a high cognitive load (e.g., Tuovinen & Sweller, 1999; cf. Holzinger, Kickmeier-Rust, & Albert, 2008; Holzinger et al., 2009). One of the mental demands contributing to this cognitive load is scientific reasoning, that is, to find out and to understand the relation between independent and dependent variables by experimenting (e.g., the relation between the volume of an all-solid and its buoyant force in water). This central component of SDL was also 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 concrete observed information. Inductive cognitive activities, in turn, can be regarded as one of the major components of intelligence (cf. Klauser, 2001; Undheim & Gustafsson, 1987). Thus, particularly this component of intelligence can be regarded as influencing SDL (cf. Section 2.3). However, SDL as a highly self-regulated form of learning can also be influenced crucially by motivation (cf. Boekaerts, 1999). If a learner is not sufficiently motivated to start or proceed his own self-regulated learning process in a current learning situation, he would likely invest a relatively low cognitive load in the task. As a result, the learning outcome might be accordingly low. Thus, during SDL it is also important to consider the current motivation of the learners (cf. Rheinberg, Vollmeyer, & Burns, 2001).

Taking the possibility of ineffective and effective load into account, the consequence is to design instructions that cause mainly effective load during computer-based SDL. With respect to goal specificity, presenting nonspecific goals has been found to be a more efficient instructional method than presenting specific goals, also in computer-based SDL (e.g., Burns & Vollmeyer, 2002; Vollmeyer & Burns, 2002). However, up to now the goal specificity effect was not analyzed for all variables that can be regarded as to be relevant for learning processes. Most of the studies investigated facets of performance as dependent variables (e.g., Miller, Lehman, & Koedinger, 1999; Paas et al., 2001; Sweller, 1988, 1994) and only a few studies also focused on strategy use (e.g., Vollmeyer et al., 1996), or they did not separate clearly between different types of goals (e.g., Geddes & Stevenson, 1997). For instructional efficiency as a dependent variable that combines performance and cognitive load strategies (Paas & Van Merriënboer, 1993), the goal specificity effect has not been shown yet. In addition, there is no investigation on strategy use and instructional efficiency during computer-based SDL.

In the following passages we will first clarify why it is important to distinguish not only between specific and nonspecific goals but also between two types of goals: Problem solving goals and learning goals (Section 1.1). Based on this introductory distinction we then define the two goal types more concretely, and we describe the differential, but partly analogous mechanisms underlying the effects of goal specificity on learning processes for both, problem solving goals (Section 1.2) and learning goals (Section 1.3). Afterwards we concentrate on the impact of goal specificity on the cognitive load (Section 1.4). In Section 1.5 we will have a closer look at instructional efficiency as a relational measure of performance and cognitive load. As a consequence of the existing empirical findings and theoretical requirements we derive our research questions and hypotheses in Section 1.6 and report and discuss our own empirical study on the impact of goal specificity on SDL in a computer-based learning environment (Sections 2, 3, and 4).

1. **Goal type and its confoundation with goal specificity**

Besides differences in specificity, externally set goals can be classified as to be different in type. For example, Schunk and Swartz (1993; cf. Zimmerman & Kitsantas, 1996) found process goals leading to a higher writing performance than product goals. These two kinds of goals establish a difference in goal type, but not in goal specificity. Since process goals are designed to focus learners’ attention on process-related knowledge gain, they comprise both, a process-based and a learning oriented task approach. Thus, they are rather similar to a learning goal. In contrast, product goals resemble problem solving goals, because they are designed to focus learners’ attention only on the product-related creation of a desired goal state without a call for learning. In the present study, we refer the difference between learning goals and problem solving goals as to goal type, because this term points at a qualitative character that is not due to specificity. However, the existing studies on the goal specificity effect during traditional paper-based learning and computer-based SDL are mainly limited to problem solving. Besides the work of Künsting, Wirth, and Thillmann (2007) and Wirth, Künsting, and Leutner (2009), to our knowledge there are no studies on the goal specificity effect that separate between learning goals and problem solving goals: Existing studies on goal setting did either not analyze
learning goals at all, or they allowed for a confounding of goal specificity (specific goals vs. nonspecific goals) and goal type (problem solving goals vs. learning goals, see Sections 1.2 and 1.3). For instance, specific problem solving goals were compared to nonspecific learning goals, but the explained variance in strategy use or in learning outcome, respectively, was ascribed only to goal specificity (Burns & Vollmeyer, 2002; Geddes & Stevenson, 1997). That way it cannot be determined which part of the explained variance in the respective dependent variables is due to goal specificity and which part is due to goal type. Consequently, to know which features of externally set goals are relevant for SDL, it is important to investigate these effects separately in an unconfounded way.

1.2. Specificity of problem solving goals

Setting specific problem solving goals for learners very likely induces the application of the means-ends analysis (Newell & Simon, 1972), a problem solving strategy solely efficient for solving a problem, but not for learning about the problem (Sweller, 1988, 1994). Solving a given specific problem solving goal (e.g., in a mathematical context: “Calculate the value for the variable X”) using means-ends analysis would require to keep in mind the initial state, the goal state, the relations between a current problem state and a goal state, inferring differences between these states and finding problem operators adequate to reduce these differences. These elements and possible subgoals must be processed simultaneously in the working memory, causing a high element interactivity of cognitive operations in terms of increased ineffective load (extraneous load) instead of effective load (germane load; Sweller, 1988, 1994). This process of problem solving can be defined as a transformation of a given state (“initial state”) into a desired state (“goal state”; Greeno, 1978) in the situational (external) environment of a problem solver (cf. Klahr, 1988). This means that a given specific problem solving goal is successfully achieved as soon as the desired goal state is reached (e.g., having calculated the value for the variable X just by applying the right formula), regardless whether knowledge about the problem was gained or not.

Furthermore, specific problem solving goals can create a dual task condition, which is more demanding than a single task condition. In this dual task condition a person needs to invest mental effort in solving a given specific problem to create the explicitly desired state, and at the same time in gaining knowledge about the problem. Indeed, solving a specific problem by means-ends analysis (primary task) and to learn about the structure of the problem (secondary task) simultaneously is possible, but it might result in a cognitive overload, since it means to tackle two cognitive tasks instead of one (Sweller, 1988, 1994).

In contrast to specific problem solving goals, nonspecific problem solving goals (e.g., “Calculate as many values as you can”) do not provide a specific goal state. Therefore, instead of prompting means-ends analysis, which imposes ineffective load, nonspecific problem solving goals should direct the learners’ attention rather to those aspects of the problem relevant for learning and, thus, imposes effective load (Sweller, 1988, 1994). An additional explanation for the goal specificity effect could be that nonspecific goals, due to their open character, offer more degrees of freedom to decide how to reach the goal, as opposed to specific goals. This, in turn, could offer a greater chance to replace a given problem solving goal by an own learning goal.

In conclusion, goal specificity influences whether cognitive load is invested in pure problem solving or in learning and, thus, can influence test performance (Ayres & Van Gog, 2009).

1.3. Specificity of learning goals

In contrast to problem solving goals, learning goals can be defined as specific or nonspecific internal mental states (Klahr, 1988) of the learners’ knowledge. Consequently, in order to attain a learning goal, it is necessary to restructure one’s existing knowledge of/and to acquire new knowledge (cf. Brown & Latham, 2002). That means, a given specific learning goal (e.g., “Learn how the value for the variable X is to be calculated and keep it in mind”) is successfully achieved as soon as a learner has gained the knowledge of how to calculate the variable X. On later occasions s/he should be able to solve a task by applying this knowledge. Analogous to the situational environment of specific problem solving goals, pursuing a specific learning goal means to keep in mind a current mental state, a mental goal state, the relation between these two states, the relation between different learning approaches, and possible subgoals (Winne & Hadwin, 1998; Wirth et al., 2009). That is, specific learning goals can be assumed not only to increase effective load, but also to impose ineffective load, due to cognitive processes analogous to means-ends analysis. For nonspecific learning goals the consideration of all these mental elements is not necessary, since for attaining the goal learners have “only” to learn something, but they are not to meet specific and predefined aspects. Thus, monitoring of a learning process initiated by a nonspecific learning goal includes only the evaluation whether there is any transformation of the current mental state in a mental state consisting of more knowledge than before.

Therefore, analogous to the cognitive load of specific problem solving goals, also specific learning goals should strain the working memory more than their nonspecific counterparts. However, regarding performance, nonspecific and specific learning goals should not differ strongly, since both call explicitly for learning.

1.4. Goal specificity and strategy use

While specific problem solving goals strongly prompt the use of means-ends analysis, nonspecific problem solving goals not only tend to detain from it, due to the nonexistent specified end, but they also tend to elicit the use of learning strategies. For instance, solving a nonspecific problem with the “history cued strategy” (Sweller, Mawer, & Howe, 1982) includes attaining subsequent goal states by deriving them from previous goal states, as well as by generating and testing hypotheses about which move will lead to a certain state. Another learning strategy is called the “control of variables-strategy” (CVS), which is one of the most relevant strategies in the context of SDL in traditional and computer-based learning environments, and research has often shown its positive impact on performance (Chen & Klahr, 1999; Klahr, Chen, & Toth, 2001; Klahr & Dunbar, 1988; Künsting, Thillmann, Wirth, Fischer, & Leutner, 2008). The CVS is a method for designing unconfounded experiments in which only a single contrast is permitted between experimental conditions, to investigate the

Note that this kind of element interactivity refers to an alterable strategy use in a task and, therefore, affects extraneous instead of intrinsic load (Sweller, 1994, p. 310).
relationship between dependent and independent variables. For example, a student in a physics lesson has observed the buoyant force of a body with a certain volume and a certain mass in a first experiment. To apply the CVS s/he can, in a second experiment, choose another body with different volume, but the same mass. Pertaining to the effect of goal specificity on strategy use, nonspecific goals were found to promote the use of the CVS significantly better than specific goals (e.g., Vollmeyer et al., 1996). However, this result does not inform us about possible effects of goal type (see Section 1.1).

For the present study we expect to replicate the goal specificity effect on the use of the learning strategy CVS for problem solving goals, but not for learning goals, because both, specific and nonspecific learning goals are designed to call explicitly for learning. Thus, both of them should yield the use of CVS as a learning strategy to a comparable extent.

1.5. Instructional efficiency of learning conditions

Whereas performance in terms of learning outcome is measured nearly always in educational research as a dependent variable, performance in relation to cognitive load is investigated much less periodically. However, Paas and Van Merriënboer (1993; see also Van Gog & Paas, 2008) introduced a useful measure of instructional efficiency by relating performance and cognitive load to each other within one quotient: The lower the cognitive load in the test after a learning phase and the higher the test performance, the higher the instructional efficiency. This cognitive measure of the test phase is to reflect the efficiency of the instructional design of the preceding learning phase. It has been used in a variety of studies, for example those comparing the effects of worked out examples to conventional problem solving (e.g., Halabi, Tuovinen, & Farley, 2005; Van Gog, Paas, & Van Merriënboer, 2006). But most of the other studies used an adapted measure of instructional efficiency, deviating from the original by assessing cognitive load in the learning phase, instead of the test phase (Van Gog & Paas, 2008). Correspondingly the namings fluctuated from “instructional efficiency” to “training efficiency” (e.g., Salden, Paas, Broers, & Van Merriënboer, 2004), “mental efficiency” (e.g., Camp, Paas, Rikers, & Van Merriënboer, 2001), or “performance efficiency” (e.g., Kester, Kirschner, & Van Merriënboer, 2006).

With regard to instructional efficiency measured in the test phase, a moderate or relatively low cognitive load going along with a relatively high performance (i.e., high efficiency) is argued to be reflective of a more favorable relationship between ineffective and effective load in the learning phase (Van Gog & Paas, 2008). As argued by Van Gog and Paas (2008) cognitive load in combination with performance in the test phase provides us with a better, more subtle indicator of the quality of learning outcomes, that is, in terms of the efficiency of cognitive schemata acquired, elaborated, or automated as a result of instruction, and hence, with a better indicator of the quality of different instructional conditions.

If the cognitive load is measured in a direct reference to the learning phase, it can be seen as reflecting cognitive capacities invested in the instructional conditions of the learning phase itself. On the one hand, this is of interest, if the learning environment and its treatment conditions have special features that are supposed to require certain aspects of working memory capacity (e.g., specific arrangements of visual-spatial features and cognitive operations). On the other hand, Van Gog and Paas (2008) regarded this adaptive instructional efficiency measure as providing useful information when the aim is to decrease ineffective load. That is, for example, when comparing specific problem solving goals (increasing ineffective load by causing the use of means-ends analysis) with nonspecific problem solving goals (decreasing ineffective load by not causing the use of means-ends analysis).

To optimize the conclusion to what extent a respective type of cognitive load has probably been involved in the learning process, performance as a single variable should not be ignored, and a process-based assessment of variables that foster learning processes, like the use of a learning strategy, should be considered in addition.

Finally, with respect to instructional efficiency as a dependent variable the résumé is that it has been applied in a line of studies (e.g., Halabi et al., 2005; Paas & Van Merriënboer, 1993; Salden et al., 2004; Van Gog et al., 2006), but it has not been examined yet as a dependent variable of goal specificity. With respect to our presented considerations in this paper we assume nonspecific goals to cause a higher instructional efficiency than specific goals, in case of problem solving goals. The same difference, but smaller in size, is expected in case of learning goals (see Section 1.6 for more concrete deriving of hypotheses).

1.6. Research questions and deriving of hypotheses

1.6.1. Starting point

Without confounding goal specificity and goal type, the study of Wirth et al. (2009) has shown the goal specificity effect on performance and cognitive load, with respect to problem solving goals. That is, they found nonspecific problem solving goals, compared to specific problem solving goals, to cause a higher performance and a lower cognitive load. Concerning learning goals, however, they found the goal specificity effect only for cognitive load. These results indicated that goal specificity affects element interactivity in case of both, problem solving goals and learning goals. - At this point the present paper ties on. It was feasible to assume that goal specificity might also have an impact on the use of the learning strategy CVS (Wirth et al., 2009). But it wasn’t provided with empirical evidence. Additionally, the goal specificity effect on instructional efficiency has not been shown yet. As a consequence of the explained mechanisms underlying the impact of goal specificity on learning, we derived the following research questions.

1.6.2. Problem solving goals

First, we want to answer the question whether the goal specificity effect for problem solving goals can be shown on strategy use (CVS) and on instructional efficiency during computer-based SDL. Compared to specific problem solving goals, which strongly direct the learners’ attention to the use of means-ends analysis, nonspecific problem solving goals should direct learners’ attention rather to aspects that are relevant for learning (Sweller, 1994) and, thus, are assumed to yield a significantly more frequent use of the learning strategy CVS. Furthermore, in accordance with the goal specificity effect, nonspecific problem solving goals cause a lower ineffective load and a higher

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1 Note that this kind of element interactivity refers to an alterable strategy use in a task and, therefore, affects extraneous instead of intrinsic load (Sweller, 1994, p. 310).
performance than specific problem solving goals (Sweller, 1988, 1994; Wirth et al., 2009). Hence, for the present study nonspecific problem solving goals are expected to yield a significantly higher instructional efficiency than specific problem solving goals.

1.6.3. Learning goals

Second, it is an unanswered question whether goal specificity has also an effect on strategy use and instructional efficiency with respect to learning goals during computer-based SDL. It is assumed that specific and nonspecific learning goals have no differential impact on strategy use, because both of them are designed to call explicitly for learning. Thus, for the attainment of both of these kinds of learning goals it is necessary to learn. As a consequence, we expect a significant interaction of goal specificity and goal type on strategy use, indicating that nonspecific goals compared to specific goals foster the use of CVS significantly more only in case of problem solving goals, but not in case of learning goals. Concerning instructional efficiency, the two kinds of learning goals are supposed to yield a smaller difference in instructional efficiency than the two kinds of problem solving goals. This is expected, because both kinds of learning goals, specific and nonspecific ones, should affect a learning oriented task approach, but specific learning goals should elicit a higher element interactivity affecting ineffective load (Section 1.3). In addition, we assume specific learning goals to yield a more intensive guiding to specific relations of to be learned concepts, compared to nonspecific learning goals. Thus, specific learning goals are predominantly to increase effective load, but they cannot also be regarded as to decrease ineffective load. In contrast, nonspecific learning goals do not guide directly to certain states of to be acquired knowledge. Rather they should foster learning by decreasing ineffective load, which deblocks capacities for free learning. In sum, similar to problem solving goals, but smaller in size of difference, nonspecific learning goals should yield a higher instructional efficiency than specific learning goals.

2. Method

2.1. Design and participants

We conducted an experimental study with a $2 \times 2$-between-subjects design (see Table 1) with goal specificity (nonspecific goals vs. specific goals) and goal type (problem solving goals vs. learning goals) as factors. Within their classes $N = 233$ students of a higher track secondary school type in Germany, the so called “Gymnasium” (11 different classes out of 5 different schools) were randomly assigned to four different computer-based experimental conditions, with $54 \leq N \leq 57$ per group (113 girls, 120 boys; age $M = 14.459$, $SD = .771$).

2.2. Material – computer-based learning environment

Using Java 2 with Eclipse SDK 3.1 we developed an interactive computer-based learning environment (CBLE, see Figs. 1 and 2) compatible to the operating system Microsoft Windows (downwards compatible to Windows 98) as a linear system (Funke, 1991). This CBLE (size altogether: 145 MB) is simulating a physics lab on “buoyancy in fluids” that provides the opportunity for SDL (e.g., Klahr & Dunbar, 1988; Kuhn et al., 2000). The content area has a high curricular validity, because it is an integral and typical part of teaching physics in secondary schools. Additionally, to generate students’ interest and to direct their perception, the CBLE was embedded in a context according to the anchored instruction-approach (Bransford, Sherwood, Hasselbring, Kinzer, & Williams, 1990). Therefore, a fictitious character in form of a scientist, who wants to investigate characteristics of all-solids concerning buoyancy in fluids in his lab, was guiding the students via text-windows throughout the whole CBLE by providing short explanations (see Fig. 1 for an example, with translated text). Also the externally set goals (announced as “assignments” for the students) were presented as coming from the scientist.

Referring to Klahr and Dunbar (1988) the CBLE (Fig. 2) consists of an experimental space as a science lab (left screen) and a hypothesis space as a tool for sketching hypotheses and conclusions (right screen; cf. Van Gog, Kester, Nievelstein, Giesbers, & Paas, 2009; see also Section 1). In the experimental space with 360 possible different states, students can run experiments by placing cubes with different mass and volumes into one of the two tanks with fluids of different densities. Once a cube is in a tank, the computer shows its behavior (sinking, floating, or ascending) and the occurring forces are represented by arrows and numbers (e.g., buoyant force and weight force), which allows to observe the forces affecting the cubes’ behavior. Overall there are 14 relevant relations between 11 variables that all students could explore in the experiment space (e.g., “The smaller a cube’s volume, the smaller its buoyant force”). In the hypothesis space students have the opportunity to make notes in terms of a specific kind of a concept-map. Although the students in our sample were sufficiently trained to use both, the experimental and the hypothesis space, they used the experimental space almost exclusively. Thus, the few data of the hypothesis space are not considered in the present study.

2.3. Independent and dependent variables

2.3.1. Goals

Each of the four groups described in Section 2.1 was provided with a set of goals as the treatment (see Table 1), whereas the number of goals within each set varied: Two groups were provided each with three nonspecific problem solving or learning goals, respectively. The

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<td>Goal specificity</td>
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<td>Goal type</td>
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remaining two groups received 14 specific problem solving or learning goals, respectively. Thus, the four groups differed in kind and number of goals, but they did not differ in the number of the 14 explorable relations addressed by each set of goals. Each of the specific learning goals and each of the specific problem solving goals addressed respectively one of the 14 relations. It was ensured that the three nonspecific problem solving goals and the three nonspecific learning goals, respectively, address the same 14 relations (in a nonspecific, clustered way). That is, each of the three nonspecific problem solving goals comprises several relations as a nonspecific bundle, leading to 14 relations.
covered by three goals altogether. The same counts for the three nonspecific learning goals. Thus, to attain a full set of three nonspecific goals, encountering all 14 relations was necessary.

2.3.2. Strategy use

During the phase of SDL in the CBLE we recorded every mouse click automatically into a logfile (Jamieson-Noel & Winne, 2003; Wirth, 2008). Based on these behavioural logfile data in XML-format we tracked the use of CVS, a learning strategy to get knowledge about the relations on our CBLE. Because we recorded and saved every mouse click into logfiles during data acquisition it was possible to check afterwards, if the sequence of students’ clicks within the experimental space was systematic in the sense of CVS or not. The use of CVS was identified, if learners had run two subsequent experiments with keeping all but one independent variable constant from the first to the second experiment (e.g., in a first experiment a learner can drag a cube with a volume of 500 cm³ and a mass of 500 g into a fluid with a density of 3 g/cm³, and in a second experiment s/he varies only the volume, keeping everything else constant). To get this information out of the XML-logfiles in a form that can be statistically analyzed, we developed an EXCEL-VBA macro code. The CVS was computed as the ratio of the number of experiments with CVS and the number of all experiments conducted in sum. As expected, it correlates significantly positive with performance gain ($r = .234, p < .01$; Table 3). This computer-based online standard of strategy assessment ensures to only capture strategic behavior students actually show in the process of learning (Wirth & Leutner, 2008).

2.3.3. Performance

A computer-based conceptual knowledge test consisting of 17 multiple-choice items was administered to assess prior knowledge (pretest) and knowledge after learning in the CBLE. Based on the relevant relations of the CBLE’s content “buoyancy in fluids” (e.g., “What happens to a body in water, if the buoyant force of the body is bigger than its weight force? The body will ...sink to bottom/...float in water/...rise to water surface”). After the reliability-analysis of internal consistency in both of the tests the same 13 items out of the 17 were kept (performance pretest: Cronbach’s $\alpha = .602$; $M^p = .632$; $SD = .17$; performance posttest: Cronbach’s $\alpha = .763$; $M = .623$; $SD = .17$), leading to 13 valid items representing 13 of the 14 explorable relations (see Sections 2.2 and 2.3). The four eliminated items showed low corrected item-total correlations and were designed predominantly to serve as ice breakers. Even though most students gained knowledge from pre- to posttest the mean differences are not statistically significant ($t(230) = .586, p = .558$; pre-post $= .428, p < .001$), because some students showed losses from pre- to posttest (we will refer to this in Sections 3 and 4). To control posttest-performance for prior knowledge we conducted a simple linear regression with pretest-performance as independent and posttest-performance as dependent variable, receiving a standardized residual performance gain with prior knowledge being partialed out. We used this standardized residual performance gain to calculate the mean for instructional efficiency (see below the cognitive load-passage).

2.3.4. Cognitive load

Using subjective rating scales to measure cognitive load turned out to be an economic and reliable method (see Ayres, 2006). Additionally, it can be assumed that students are capable of introspecting own cognitive processes (e.g., Paas, Tuovinen, Tabbers, & Van Gerven, 2003) and of assessing their invested cognitive load on a numeric scale (e.g., Gopher & Braune, 1984). To account for cognitive load concerning the different goals in the present study ten pilot-tested items with the format of a seven-point rating scale were administered immediately after students had finished working on the goals within the CBLE and before they got the performance posttest. Two of these ten items were completely self-designed, the rest was developed adaptively according to Braarud (2001), Hart and Staveland (1988), and Tsang and Velazquez (1996). The construction of the items aimed at incorporating specific mental demands on working memory that result from the specific requirements of the goals (e.g., simultaneous requirements, especially in case of specific problem solving goals; cf. Sweller, 1988, 1994) and of our CBLE (e.g., processing of textual and visual-spatial information, or time pressure). An example item: “To what extent did the assignments make simultaneous demands on you? (1 = hardly; ... 7 = very strong)”. The scale’s internal consistency (Cronbach’s $\alpha = .870$) and corrected item-total correlations ($r_{316} \leq r_{315} \leq .656$) indicate a high reliability, albeit this reflects likewise that the scale does not separate different aspects of cognitive load influenced by different specific demands of our CBLE. However, we did not aim at constructing several sub-dimensions out of ten items. We rather wanted to ensure that the specific aspects of requirement of the goals and of the CBLE are represented in the cognitive load scale. Hence, we used the mean score of the ten items as an indicator for overall cognitive load ($M = .514$, $SD = .205$).

The negative correlations between cognitive load and intelligence ($r = -.182^{**}, p < .01$), and strategy use (CVS; $r = -.168^{*}, p < .05$), respectively, are not very strong but statistically significant, showing a slight evidence of validity (Table 3). This indicates by trend that the higher the intelligence and the more frequent the use of the helpful learning strategy CVS, respectively, the less cognitive load is needed to accomplish the learning phase. The correlation between cognitive load and performance gain is close to zero (see Table 3), indicating that the invested amount of cognitive load in general is not just yet bad or good for performance gain. Instead, it depends on whether the invested cognitive load is rather ineffective or effective for learning. Thus, to look on performance gain at the same time and to use the measure of instructional efficiency is useful.

2.3.5. Instructional efficiency

The original formula to calculate instructional efficiency (Paas & Van Merriënboer, 1993, 1994) comprises as numerator the difference between the z-standardized scores of cognitive load in the posttest, and the z-standardized scores of performance in the posttest. As denominator it contains square root 2 to calculate the distance of a point to a line in a coordinate system (for a more precise description see Paas & Van Merriënboer, 1993, 1994). This calculation is used for a relative positioning of the efficiency scores of instructional conditions in a coordinate system, which is to visualize performance, cognitive load, and instructional efficiency of compared conditions.

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\footnote{Note that these descriptives means are standardized as a range from zero to one, which counts also for the descriptive means of cognitive load, intelligence, and current motivation.}
within one graphic. If only the efficiency scores in general are of interest, square root 2 can be omitted, because the percentual relation of the numerical scores between cases stays constant (the correlation between efficiency with square root 2 and efficiency without square root 2 is \( r = 1.00 \)). In the present study we applied instructional efficiency as an adaptive measure, that is, we focused on cognitive load invested in working on the goals presented during the learning phase and on the performance gain. We subtracted the z-standardized cognitive load of the learning phase from the z-standardized performance gain. If the z-score for performance gain is higher than the z-score for cognitive load, then instructional efficiency (IE) is positive, vice versa, it is negative: \( IE = [z\text{-score Performance gain}] − [z\text{-score Cognitive load}] \).

### 2.3.6. Intelligence and current motivation

Scientific reasoning is an essential cognitive activity during SDL (Klahr & Dunbar, 1988). Focusing on forming new concepts or establishing rules on the basis of experimental evidence, the term inductive reasoning is also used (see also inductive learning, Section 1). This cognitive activity is related strongly to intelligence and is measured by the respective tests, for example in form of “analogy” (see Klauer, Willmes, & Phye, 2002). Thus, the success during SDL could be regarded as being influenced by this component of intelligence. For example, solving tasks concerning presented figural analogies means to identify the kind of change from a first figure (e.g., a triangle, or any geometrical figure) to a second figure (e.g., differences in spatial position, color, or form). Then, this change has to be generalized, so that the rule (the kind of change) can be applied analogously to the change from a third figure to one of five other additional figures (the person has to choose the right figure out of five). A very simple instance for an introduction for learners could be: “The small clear triangle (first figure) is related to the big black triangle (second figure) like the small clear hemicycle (third figure) is related to which of the five other figures?” (e.g., see Heller, Gaedcke, & Weinländer, 1985). We controlled for individual differences in these basic cognitive abilities by applying the scale “figural analogies” (25 items) of a standardized intelligence test (Heller et al., 1985; Cronbach’s \( \alpha = .713, M = .752, SD = .153 \)). Another reason, why we used this economic scale instead of a whole intelligence test is its high correlation with general intelligence (Heller & Perleth, 2000).

However, besides cognitive factors also motivation (cf. Section 1) can influence learning, particularly if the form of learning (like SDL) is highly self-regulated (Boekaerts, 1999). Thus, to account for motivation we administered two scales of the questionnaire on current motivation (QCM; Rheinberg et al., 2001; 9 items; Cronbach’s \( \alpha = .877, M = .538, SD = .227 \); e.g., “After reading the instructions I’m very interested in the task (1 = not at all; . . . 7 = very strong)”.

### 2.4. Procedure

Prior to the data acquisition in the participating schools, we first installed and checked the (pilot-tested) CABLE for proper operation on the desktop-computers and laptops in the computer rooms of the schools. Afterwards the actual data acquisition during regular lessons began with informing students about all materials they would be provided with, including the performance posttest (3 min). Subsequently students worked on some demographical items and some tests without relevance for the present paper (10 min). This part was followed by the standardized intelligence scale (8 min) and the performance pretest (10 min), whereupon students started with a computer-based training for the graphical tools in the hypothesis space. Sufficient data of descriptive statistics and of our experimental design. This new investigation of the goal specificity effect also on strategy use and instructional efficiency is a completion of the analyses of Wirth et al. (2009) and answers important outstanding research questions.

For the present analyses we conducted a MANOVA in advance, with the four goal groups as factor to test homogeneity in pretest-performance, intelligence, and current motivation. There were no significant differences between the four groups (\( .177 \leq F(3, 226) \leq 1.26, .288 \leq p \leq .912 \)). To test our hypotheses we applied an ANCOVA with intelligence and current motivation as covariates and contrast analyses within the ANCOVA for single group comparisons. Table 2 depicts the estimated means and standard deviations from the ANCOVA (controlled for intelligence and current motivation) for the used variables. A slightly negative performance gain (\( M = −.079, SD = .183 \)) appeared only for the group with specific problem solving goals, which corresponds to a residual performance gain (z-scores) of \( M = −.355 (SD = .823) \). In contrast, the remaining three groups showed an increase of performance (residual performance gain: nonspecific problem solving goals: \( M = .091, SD = .922 \); specific learning goals: \( M = .145, SD = 1.072 \); nonspecific learning goals: \( M = .117, SD = 1.115 \)). Descriptively, Table 3 reveals that the correlation of instructional efficiency with intelligence (\( r = .279, p < .01 \)) and strategy use (\( r = .272, p < .01 \)) is, as expected, significantly positive. In Fig. 3 we demonstrate the descriptive comparisons between the four conditions for all dependent variables. To check the statistical sensitivity of our experimental design (Lipsey, 1990) we conducted a post hoc statistical power analysis with G*Mpower (Faul, Erdfelder, Lang, & Buchner, 2007). For special linear main- and interaction effects our 2 × 2-design with an N of 224 subjects and an alpha of .05 is able to detect significant effects from a size of \( \eta^2 = .05 \) with a statistical power of \( 1 − \beta = .93 \).

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5 The difference from \( N = 233 \) to \( N = 224 \) is because not all of the 233 participants had worked on all items or scales concerning the respectively included variables in the analysis.
3.1. Strategy use

3.1.1. Hypothesis 1

We expected to show the goal specificity effect on strategy use only for problem solving goals, but not for learning goals. Congruently with our first hypothesis we found a significant main effect of goal specificity on strategy use (F(1, 140) = 10.854, p < .001, \( \eta^2 = .072 \)), which is due to the specificity of problem solving goals: As we expected, also the interaction of goal specificity and goal type on strategy use is statistically significant (F(1, 140) = 6.151, p = .007 (one-tailed), \( \eta^2 = .042 \); see Fig. 3). This indicates that nonspecific goals yield a substantially more frequent strategy use than specific goals solely in case of problem solving goals (p = .005, d = 1.122), but by no means in case of learning goals (p = .562). The main effect of goal type on strategy use is not significant (F(1, 142) = .496, p = .483). For strategy use the case number was smaller (N = 146) than for the other dependent variables, because of a technical caused loss of the respective logs by random. But this loss of data occurred in nearly all classes (10 out of 11) by random and was distributed approximately equal across the classes and the experimental conditions. Accordingly, there is no difference across these 10 classes concerning strategy use (F(1, 140) = .819, p = .599), and also the Levene-Test of equality of error variances shows no significant differences across the four experimental groups (F(3, 142) = 1.664, p = .178; 34 ≤ N ≤ 41). These statistical findings can be interpreted as allowing for a comparison between the four groups also referring to strategy use.

3.2. Instructional efficiency

3.2.1. Hypothesis 2

We expected to show the goal specificity effect on instructional efficiency for both, problem solving goals and learning goals, but being smaller for learning goals. The main effect confirmed the first part of the hypothesis, pointing at a significantly higher instructional efficiency for nonspecific goals, compared to specific goals (F(1, 218) = 19.210, p < .001, \( \eta^2 = .081 \)), which counts for both, learning goals and problem solving goals, indicated.

Table 2

Descriptives of the dependent variables and covariates.

<table>
<thead>
<tr>
<th></th>
<th>Problem solving goals</th>
<th>Learning goals</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Specific</td>
<td>Nonspecific</td>
</tr>
<tr>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>Intelligence (covariate)</td>
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<td>.118</td>
</tr>
<tr>
<td>Motivation (covariate)</td>
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<td>.209</td>
</tr>
<tr>
<td>Performance gain (z)</td>
<td>-.355</td>
<td>.823</td>
</tr>
<tr>
<td>Strategy use (CVS)</td>
<td>.197</td>
<td>.087</td>
</tr>
<tr>
<td>Cognitive load</td>
<td>.546</td>
<td>.206</td>
</tr>
<tr>
<td>Instructional efficiency (z)</td>
<td>-.468</td>
<td>1.403</td>
</tr>
</tbody>
</table>

Table 3

Correlations (Pearson) between the variables of the present study.

<table>
<thead>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Intelligence (covariate)</td>
<td>.017</td>
<td>.242**</td>
<td>.177*</td>
<td>.269**</td>
<td>-.182**</td>
<td>.279**</td>
</tr>
<tr>
<td>2. Motivation (covariate)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.002</td>
<td>.150*</td>
</tr>
<tr>
<td>3. Performance gain (z)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.097</td>
<td>.739**</td>
</tr>
<tr>
<td>4. Strategy use (CVS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.168*</td>
<td>.272**</td>
</tr>
<tr>
<td>5. Cognitive load</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Instructional efficiency (z)</td>
<td></td>
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</tbody>
</table>

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

Fig. 3. Illustration of comparisons between the four conditions for the dependent variables (the means of strategy use and cognitive load are standardized as a range from zero to one).
by the nonsignificant interaction ($F(1, 218) = .642, p = .424$; see Fig. 3). The second part of the present hypothesis is supported only by trend. Although the effect is stronger for problem solving goals ($p < .001, d = .601$) than for learning goals ($p = .019, d = .485$), the difference in size is not to be regarded as substantial. The main effect of goal type is not significant ($F(1, 218) = .506, p = .477$), indicating that problem solving goals and learning goals lead to a comparable magnitude of instructional efficiency as a relation of performance gain and cognitive load.

4. Discussion

The present results on computer-based SDL are an important extension of the results of previous studies into the goal specificity effect (e.g., Burns & Vollmeyer, 2002; Paas et al., 2001; Sweller, 1988, 1994; Wirth et al., 2009).

First, concerning strategy use, we were able to confirm a significant interaction effect of goal specificity and goal type on the use of the learning strategy CVS: The goal specificity effect occurs only in case of problem solving goals, but not in case of learning goals. Compared to students provided with specific problem solving goals those who worked on nonspecific problem solving goals, used the CVS significantly more frequently with a high effect size ($d = 1.122$). This is a crucial addition to the results of Wirth et al. (2009), because the use of CVS as a significant predictor of knowledge gain (Chen & Klahr, 1999; Künting et al., 2008) can explain very likely a meaningful part of the difference between specific and nonspecific problem solving goals referring to performance gain. Our present results concerning instructional efficiency fit in. Instructional efficiency in this study was operationalized as relation of cognitive load (measured directly after the learning phase) and performance gain (IE = \[ z\text{-score Performance gain} - z\text{-score Cognitive load} \])); see Sections 1.5 and 2.3). The results show that nonspecific problem solving goals caused a significantly higher instructional efficiency than specific problem solving goals. On the one hand, this is because nonspecific problem solving goals yielded less cognitive load and higher performance, leading to a higher instructional efficiency in comparison with specific problem solving goals. But on the other hand, strategy use again can help clarifying parts of the underlying mechanisms. That is, compared to specific problem solving goals, nonspecific problem solving goals caused a lower ineffective load, which is might because they do not elicit the use of the mentally very demanding means-ends analysis, a pure problem solving strategy (Sweller, 1988, 1994). Instead, they apparently prompt rather the use of CVS, a learning strategy affecting knowledge gain positively and, thus, imposing effective load. In conclusion, our results suggest that CVS as a pure learning strategy obviously strains the working memory less and mainly in terms of effective load.

To our knowledge, there is no other study yet that could empirically show the goal specificity effect of clearly separated problem solving goals on strategy use and instructional efficiency during SDL. The sheer examination of the goal specificity effect on a process-based measured strategy use and on an empirically measured cognitive load as a part of instructional efficiency is hard to find, if existing at all.

Second, as expected, also for learning goals we found the goal specificity effect on instructional efficiency, but not on strategy use. Indeed, students provided with specific learning goals and those who worked on nonspecific learning goals exhibited an almost equal performance. But next to this, nonspecific learning goals imposed a significantly lower cognitive load, leading to a higher score of instructional efficiency in the present study. The lower cognitive load caused by nonspecific learning goals can be regarded as mainly due to a decrease of ineffective load (not of effective load), because the performance gain of specific and nonspecific learning goals was not significantly different. But specific learning goals causes a significantly higher cognitive load, leading to a significantly lower instructional efficiency than nonspecific learning goals. Thus, because specific learning goals yielded at least the same performance gain, but a significantly higher cognitive load than nonspecific learning goals, they seem to increase both, ineffective load in terms of element interactivity of cognitive operations (see Sections 1.2 and 1.3) and effective load in terms of learning. However, it is an outstanding question for further research, whether this holds true also for other domains and contexts of learning. Referring to the use of CVS as a learning strategy the results were in line with our hypotheses that both kinds of learning goals lead to a comparable frequency of strategy use, because both of them were prepared to call explicitly for learning.

This differential look on the goal specificity effect for problem solving goals and for learning goals is a further contribution to research on goal setting. From a perspective of a somewhat economic relation of performance gain and cognitive load we found for both, problem solving goals and learning goals that nonspecific goals cause a more favorable cognitive cost-benefit ratio than specific goals. That is, for both, problem solving goals and learning goals, we showed that nonspecific goals, compared to specific goals, caused a higher instructional efficiency, assumed as to be mainly due to lower element interactivity (Sections 1.2 and 1.3). Thus, nonspecific goals decreased ineffective load, which possibly freed up working memory capacities for learning. Compared to specific goals, nonspecific goals have obviously more potential to foster sustained learning, because they came off well on strategy use and instructional efficiency. Thus, they apparently offer enough space for self-regulated SDL. Unfortunately, due to a limited test time, we could not measure motivation twice, directly before learning phase, as we have, and whilst or after the learning phase. Therefore, we do not know how motivating the goals would have been rated by the students. That is an important question that needs further research.

For sure, the results on instructional efficiency do not reveal perfectly the exact fraction of performance gain due to either an increase of effective load or to a decrease of ineffective load (cf. Van Gog & Paas, 2008). However, our study provides insightful and new information about how effective the invested cognitive load was for learning, depending on the set goals as instructional conditions. That is, compared to specific problem solving goals and specific learning goals, their respective nonspecific counterparts were shown to yield a significantly more effective learning process, resulting in a significantly higher instructional efficiency and, in case of problem solving goals, in a significantly higher strategy use.

4.1. Ineffective specific problem solving goals

Specific problem solving goals are a special case in this study, because the very low instructional efficiency of this instructional format is due to both, poor performance gain and high ineffective load. Although it was our hypothesis that specific problem solving goals should be a poorer learning condition, compared to the others; finding even a negative performance gain was beyond our expectations. On the one hand, this decrease of performance from pretest to postest might be due to the moderate or relatively high prior knowledge of (all) students of the sample, which indicates some already existing schemata about buoyancy in fluids. Thus, not so many concepts remained to be learned, but rather already existing ones had to be changed or amplified by integrating new information. But in case of specific problem solving goals...
this way of learning, as well as acquiring completely new schemata, has to share working memory capacities with cognitive activities to solve problems, leading to a dual task condition (Sweller, 1988): Working on specific problem solving goals means predominantly to invest cognitive activities in problem solving by applying means-ends analysis (primary task), which does not leave much capacity of working memory for cognitive activities relevant for acquiring or restructuring schemata (secondary task). But there might be an additional explanation: In an experiment Sweller (1988, p. 281) revealed specific problem solving goals to yield more errors in the knowledge reproduction phase than nonspecific problem solving goals. Analogous, the resulting high cognitive load under specific problem solving goals, which contributes to the low instructional efficiency in the present study, might not only have impeded a successful learning process. It might also have created an error-prone condition in terms of incomplete integration and erroneous modification of schemata, leading to a decrease in posttest-performance. Consistent with this explanation, students with specific problem solving goals also showed the lowest use of CVs. It is very likely that they used more frequently the means-ends analysis instead, a problem solving strategy not assisting in schema acquisition.

In sum, our findings support the assumption that specific problem solving goals impose a very high ineffective cognitive load, which might lead to more or less erroneous schema acquisition, or schema modification, respectively. In contrast, the results for specific learning goals suggest that this condition allows for learning in terms of increasing effective load, but without decreasing ineffective load. Nonspecific problem solving goals and nonspecific learning goals seem to allow for learning by making way for effective load via decreasing ineffective load. Although these explanations are not devoid of interpretation, the present results strongly suggest presenting nonspecific goals during computer-based SDL as to be adequate for promoting the use of the learning strategy CVs, and they yield a clearly higher instructional efficiency than specific goals. It is up to further studies to show whether this is also true for other subjects and content areas in SDL. The results of our study provide useful implications not only from an educational, but also from an engineering perspective (e.g., developers or designers of computer applications). Using a complex CBLE with a computer-based guiding can be an economic tool to create self-regulated learning processes. However, creating a human–computer interaction does not mean to create an effective learning condition per se (see also Holzinger et al., 2008). The effectiveness of a CBLE rather depends on the kind of instructions the CBLE is providing. The present study has found nonspecific problem solving goals and nonspecific learning goals to cause a relatively strategic, gainful and cognitively economic learning process. In contrast, specific problem solving goals turned out to be a highly ineffective instructional condition. These goal specificity effects should be considered not only as implications for educational research or teaching, concerning physics as a subject. They may also provide information for developers and designers of a CBLE that is to serve learning without imposing too much cognitive load.

References
Holzinger, A., Kickmeier-Rust, M., Wassertheurer, S., & Hessinger, M. (2009). Learning performance with interactive simulations in medical education: lessons learned from c problem solving goals turned out to be a highly ineffective instructional condition. These goal specificity effects should be considered not only as implications for educational research or teaching, concerning physics as a subject. They may also provide information for developers and designers of a CBLE that is to serve learning without imposing too much cognitive load.