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Motivation and performance within a collaborative computer-based modeling task: Relations between students' achievement goal orientation, self-efficacy, cognitive processing, and achievement ☆

Patrick H.M. Sins [a,*], Wouter R. van Joolingen [b], Elwin R. Savelsbergh [c], Bernadette van Hout-Wolters [d]

[a] *Research Centre for Learning in Interaction, Utrecht University, P.O. Box 80140, The Netherlands*
[b] *Faculty of Behavioral Sciences, University of Twente, The Netherlands*
[c] *Centre for Science and Mathematics Education, University of Utrecht, The Netherlands*
[d] *Graduate School of Teaching and Learning, University of Amsterdam, The Netherlands*

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Abstract

Purpose of the present study was to test a conceptual model of relations among achievement goal orientation, self-efficacy, cognitive processing, and achievement of students working within a particular collaborative task context. The task involved a collaborative computer-based modeling task. In order to test the model, group measures of mastery-approach goal orientation, performance-avoidance goal orientation, self-efficacy, and achievement were employed. Students' cognitive processing was assessed using an online log-file measure. As predicted, mastery-approach goal orientation had a significant positive effect on achievement, which was mediated through students' use of deep processes. No significant relationships could be found between performance-avoidance goal orientation and surface processing and between surface processing and achievement. Results are discussed with respect to general theoretical implications and lead to suggestions for the design of appropriate scaffolds.

☆ This study reported in this article was conducted during the time the first author was working at the Graduate School of Teaching and Learning of the University of Amsterdam.

* Corresponding author. Fax: +31 302532352.
E-mail address: P.H.M.Sins@fss.uu.nl (P.H.M. Sins).

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1. Introduction

Current models of self-regulated learning integrate motivational and cognitive elements of learning, showing how achievement goals and learning expectancies influence students' use of cognitive processes (Covington, 2000; Nicholls, Patashnick, Cheung, Thorkildsen, & Lauer, 1989; Pintrich, 2003; Schunk, 2005; Schunk & Zimmerman, 2001). The basic assumption of these models is that the achievement motives and the intentions that guide students' academic behavior determine to a great extent the types of cognitive processes they employ in various learning situations. The learning outcome (i.e., achievement) is dependent on how deep students process information (Craik & Lockhart, 1972; Entwistle, 1979, 1988).

The majority of studies that have examined the consequences of students' achievement goal orientation and self-efficacy on their processing of the learning material, concern the *self-reported* use of cognitive processes of *individual* students over a *complete course or curriculum* (e.g., Greene & Miller, 1996; Nolen, 1988; Pintrich, 2000). However, a great deal of learning takes place within collaborative task contexts, in which students construct knowledge through mutual communication and shared use of representations (Pintrich, Conley, & Kempler, 2003). The goal of the present study is to investigate the relationships among students' achievement goal orientation, self-efficacy, cognitive processing, and achievement within a particular collaborative task setting. The variables will be measured at the level of collaborating students (i.e., dyads) rather than at the individual level. In addition, instead of using self-report questionnaires which are traditionally employed within the field of achievement motivation, students' cognitive processing will be assessed by means of an online measure, based on inter-student communication.

1.1. Achievement goal orientation and self-efficacy as predictors of cognitive processing

Many authors in the domain of motivation research have argued that the type and the level of motivation influences students' employment of particular cognitive processes in learning situations (e.g., Atkinson, 1964; Covington, 2000; Nicholls et al., 1989; Pintrich & Schrauben, 1992; Wolters, 1996). Two motivational factors that are presumed to be important predictors of students' cognitive processing are: (a) achievement goal orientation and (b) self-efficacy.

Broadly defined, achievement goal orientation reflects the reasons and the purposes of students to engage in achievement tasks. Two distinct types of achievement goal orientation are traditionally distinguished (e.g., Dweck & Leggett, 1988; Elliot, 1999; Elliott & Dweck, 1988; Nicholls et al., 1989): *mastery goal orientation* and *performance goal orientation*. Mastery goal orientation involves the belief that effort leads to improvement in performance and that competence is malleable. Students who are mastery goal oriented focus on the development of new skills and knowledge, try to elaborate on the task they are given and attempt to reach their own learning goals. Performance goal orientation, in contrast, involves the belief that competence can be demonstrated by performing better compared to peers. Students who are performance goal oriented tend to focus on attaining normative learning goals.

Recent research on achievement goal orientation has questioned the utility and validity of this two-goal model and proposes instead that besides the mastery-performance distinction, another dimension to consider is whether achievement goal orientations lead students to *approach* or *avoid* a task (Elliot, 1997, 1999; Elliot & Church, 1997; Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002). The performance goal orientation construct is bifurcated into a *performance-approach goal orientation* and a *performance-avoidance goal orientation*. Students who are performance-approach oriented aim to achieve higher levels compared to their peers and focus on demonstrating high ability, whereas students who are performance-avoidance oriented are concerned with avoiding failure and with avoiding the demonstration of low ability. Following this logic, mastery goal orientation can also be separated into approach and avoidance goal orientations. Whereas a mastery-approach goal orientation involves striving to develop one's skills and abilities, to advance one's learning, to understand the material, or to complete a task, a mastery-avoidance goal orientation entails focusing on avoiding misunderstandings or not learning the material.

An important issue to consider at this point is that it is ineffective for students to be striving to master a task, if they are less convinced that they have the necessary ability and competence to do so. Thus, the influential role of *self-efficacy* on task performance must be taken into account. Self-efficacy has been defined as students' belief regarding their performance capabilities in a particular domain (Bandura, 1982, 1986).

Achievement goal theorists hypothesize that students who are highly mastery-approach goal oriented attempt to gain rich insight in the given learning material and will therefore engage in deep cognitive processing to increase their comprehension (e.g., Dweck, 1985; Graham & Golan, 1991; Nicholls et al., 1989; Pintrich & DeGroot, 1990). Deep cognitive processing, as described in the work of Marton and Säljö (1976, 1997), Ramsden (1992), and Entwistle (1988, 2001), involves active learning processes, such as relating ideas, looking for patterns and principles and attempting to integrate new information with prior knowledge and experience. Surface cognitive processing, in contrast, entails processes without much reflecting and involves treating the learning material as more or less unrelated bits of information. Surface processing does not implicate elaboration of the learning material and leads to more restricted learning processes. Because mastery-approach goal oriented students tend to attribute learning success to invested effort and attempt to understand the learning material, they may be more likely to employ and value processes that stress understanding, even if these processes require more effort then less elaborate processes. In addition, self-efficacy theory and other theories on self-perception state that self-efficacy beliefs are positively related to the use of deep processes (Schunk, 1991).

Numerous studies have demonstrated that mastery-approach goal orientation and self-efficacy are positive predictors of reported use of deep processes (e.g., Ames & Archer, 1988; Dupeyrat & Mariné, 2005; Garcia, McCann, Turner, & Roska, 1998; McWhaw & Abrami, 2001; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996; Wolters, 1996). In addition, some studies found that both self-efficacy and mastery-approach goal orientation are indirectly related to achievement via a direct relationship with the employment of deep processing strategies (e.g., Elliot, McGregor, & Gable, 1999; Greene & Miller, 1996; Pintrich & DeGroot, 1990). Moreover, Greene and Miller (1996), Greene, Miller, Crowson, Duke, and Akey (2004), Meece, Blumenfeld, and Hoyle (1988), Vrugt, Oort, and Zeeberg (2002) found an additional positive relationship between self-efficacy and mastery-approach goal orientation. Performance-avoidance oriented students, in contrast, focus on the avoidance of demonstration of incompetence relative to peers. As a result, these students resort to the employment of surface cognitive processes, which is linked to decreases in achievement (e.g., Al-Emadi, 2001; Midgley, Kaplan, & Middleton, 2001; Schraw, Horn, Thorndike-Christ, & Bruning, 1995).

For performance-approach and mastery-avoidance goals, more variable and complex patterns in terms of deep and surface processing can be expected, when compared to mastery-approach goals and performance-avoidance goals (Elliot, 1997, 1999). Mastery-approach goal orientation and performance-avoidance goal orientation typically represent pure approach and pure avoidance motivation, respectively. In contrast, mastery-avoidance goal orientation and performance-approach goal orientation may involve both approach and avoidance motivational concerns (i.e., respectively, need for achievement and fear of failure; see Elliot & Church, 1997). When, for instance, performance-approach goals are the result of a need for achievement (i.e., congruent), the pursuit of these goals may prompt the use of deep processes. When performance-approach goals are incongruent with their underlying motivational foundation, the pursuit of these goals represents approach in order to avoid something aversive. This may lead to surface processing of the learning material. Like performance-approach goals, predictions for mastery-avoidance goals are somewhat difficult to generate, since the two components of mastery-avoidance goal orientation are likely to evoke a rather divergent set of processes. That is, the mastery component of this type of goal orientation may facilitate deep processing, whereas the avoidance component may impel surface processing. It is, thus, difficult to predict the exact nature of the processes that will be evoked by these two types of achievement goal orientation, as this is dependent on their motivational foundation.

Although empirical data regarding mastery-avoidance goals are not yet available (see Pintrich et al., 2003), the association between performance-approach goals and students' cognitive processing of the learning material has indeed been shown to be contradictory. Some studies found that performance-approach goals are associated with surface processing (Al-Emadi, 2001; Dupeyrat & Mariné, 2005; Elliot & McGregor, 2001; Greene & Miller, 1996; Middleton & Midgley, 1997), whereas other studies found a positive association between performance-approach goals and deep processing (Meece et al., 1988; Pintrich, 2000; Wolters, 1996; Wolters & Yu, 1996). Furthermore, some studies found that performance-approach goals are positively related to high performance outcomes (Barron & Harackiewicz, 2001; Elliot & Church, 1997; Harackiewicz, Barron, Elliot, Carter, & Lehto, 1997). As the goal of our study is to investigate whether the consistent relationships found in literature reproduce at the level of actually observed processes, performance-approach goal orientation and mastery-avoidance goal orientation were excluded. The present study was framed within the context of a computer-based scientific modeling task.

1.2. Computer-based modeling

Computer-based models are executable external representations of the behavior of complex scientific phenomena, such as ecosystems, water management, and weather (Bliss, 1994; Penner, 2001; Stratford, 1997). The act of modeling is the activity in which models are constructed, evaluated and revised with the help of a computer-based modeling tool, such as STELLA (Steed et al., 1994) and Powersim (Byrknes & Myrtveit, 1997). The construction of models is particularly well suited to provide the basis for meaningful learning experiences. First, models offer students with the opportunity to think scientifically about the behavior of these phenomena, which enables them to understand and experience the issues associated with the construction of models in science (e.g., Bliss, 1994; Hestenes, 1997; Schwarz & White, 2005). Second, models focus on the continuous relations among variables that are part of a phenomenon and provide a platform for understanding how these variables interact. Computer-based modeling tools, thus, enable students to express and manipulate their mental representation of a phenomenon, which supports the reorganization and refinement of their conceptual understanding (e.g., Jonassen, Strobel, & Gottdenker, 2005; White & Frederiksen, 1998; Wild, 1996). Finally, since modeling tools help students to externalize their ideas, they are accessible to criticism and discussion, which is an important prerequisite for collaborative learning (Hogan & Thomas, 2001).

1.3. The current study

The purpose of the present study is to test a conceptual model of relations among motivation, cognitive processing and achievement of students working within a computer-based modeling task (see Fig. 1). More specifically, we investigated whether students' achievement goal orientation and self-efficacy influence their cognitive processing during modeling, and whether the relation between motivation and achievement is mediated by students' processing.

In contrast to most studies in the field of motivation, we did not assess students' processing based on self-report measures, but rather we based our assessments on the process observations of students' reasoning during task execution. This is first because, the validity of self-report on these issues has become under doubt and furthermore because in the present context, where it comes to interpreting the detailed processes of students in a collaborative setting, more fine-grained measures are needed and the interaction between the collaborating partners must be taken into account.

As the modeling task required students to work in dyads, students' cognitive processing (i.e., deep and surface processing) can be naturally measured using this online measure that includes inter-student communication through a chat. In addition, achievement can be operationalized as the quality of model dyads constructed. This also requires measure-

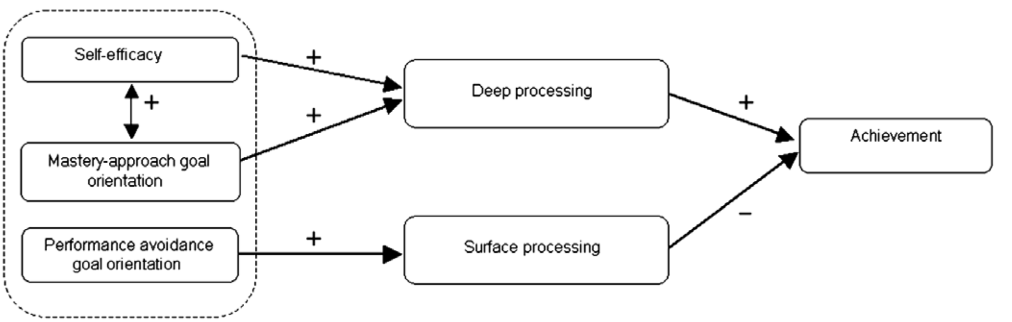

Fig. 1. Conceptual model indicating the hypothesized relations between students' motivation (i.e., mastery-approach goal orientation, performance-avoidance goal orientation, and self-efficacy), cognitive processing (i.e., deep and surface processing), and achievement. Signs indicate the direction of the hypothesized relationship.

ment of all other variables on the dyad-level, in order to test the conceptual model in Fig. 1. This means that we have to relate individual student characteristics, such as self-efficacy, to the same characteristics of a dyad.

2. Method

2.1. Participants

Sixty students (i.e., thirty dyads) from eleventh-grade pre-university education, with a major in science participated in our study. Their science teachers reported that they had no prior experience and hence no prior knowledge of dynamic modeling. The fact that they had chosen a major in science meant that they had followed four years of courses in several science topics, specifically in physics and chemistry, including an introduction to thermodynamics. This means they had encountered the concepts of heat, heat flow, and temperature previously in their school career. These concepts are relevant to the task they performed in the study. They had not previously worked with models of global warming. Students' age ranged between 16–18 years. Participants were awarded € 20 for their participation.

As dyad composition was not a variable in our model, we preferred a heterogeneous group composition, since in previous studies students with different school grades had been generally more successful working together than homogeneous groups (e.g., Gijlers & Jong, 2005; Webb, 1991; Webb, Welner, & Zuniga, 2001). The reason is that higher achieving students can learn from giving explanations, whereas the lower achieving student can learn from these explanations given (Hooper & Hannafin, 1991; Webb & Farivar, 1994). However, the difference in level between students should not be too large. As a measure for group composition, we used the students' average school grade in science. The mean average grade of all students was 7.10 on a scale from 1 to 10, with a standard deviation of 1.03. In order to assure moderately heterogeneous dyads, the group of participants was divided into two equal groups. One group consisted of the top 25% as well as the bottom 25% in average grade for science. The other group consisted of the remaining 50%. Dyads were composed by letting students choose a partner from the other group. This assured a moderate difference between partners in science ability, as well as pairs who had chosen each other to work with. This procedure meant that half of the dyads were low–middle dyads in terms of average grade, whereas the other half was middle–high. Given the low variance in average school grade, as well as the fact that all students were new to the task, we did not expect any differences from this division.

2.2. Material

Students performed the modeling task within the computer-based learning environment Co-Lab (Joolingen, Jong, Lazonder, Savelsbergh, & Manlove, 2005). In Co-Lab students can collaborate online by means of a synchronous chat on inquiry assignments for the science courses.

Participants were asked to extend a simple pre-build model that could give an explanation and prediction of the temperature on earth. The task was simplified to some extent, since the earth in this task was represented by an irradiated black sphere (see Appendix A for the assignment). Because participants had no prior experience with modeling, a completely open modeling task was assumed to be too complex for them to be successful within the time constraints of the modeling task. Therefore, participants were given a model skeleton as a starting point. Such a model revision task enables the novice modeler to concentrate on trying to comprehend and improve a model without having to start from scratch. Students constructed their models in the model editor tool of Co-Lab (see Fig. 2).

The model editor in Co-Lab uses five model building blocks characteristic for system dynamics modeling: stocks, rates, auxiliaries, constants, and connectors. Stocks represent a quantity that can increase or decrease from some starting value. A rate connected to a stock decides how quickly the quantity in the stock will change. Quantities can be represented either as constants (i.e., fixed values), or as auxiliaries (i.e., calculated from other quantities).

Finally, connectors indicate dependencies between individual model elements. To insert a modeling element, students can drag and drop the icons on the screen they think are relevant for the phenomenon being modeled, creating a qualitative diagram of the phenomenon. After creating this diagram, students have to quantify these elements by entering values and formulas. Once the model is quantified it can be executed. When students run their model, the model editor automatically generates the differential equations

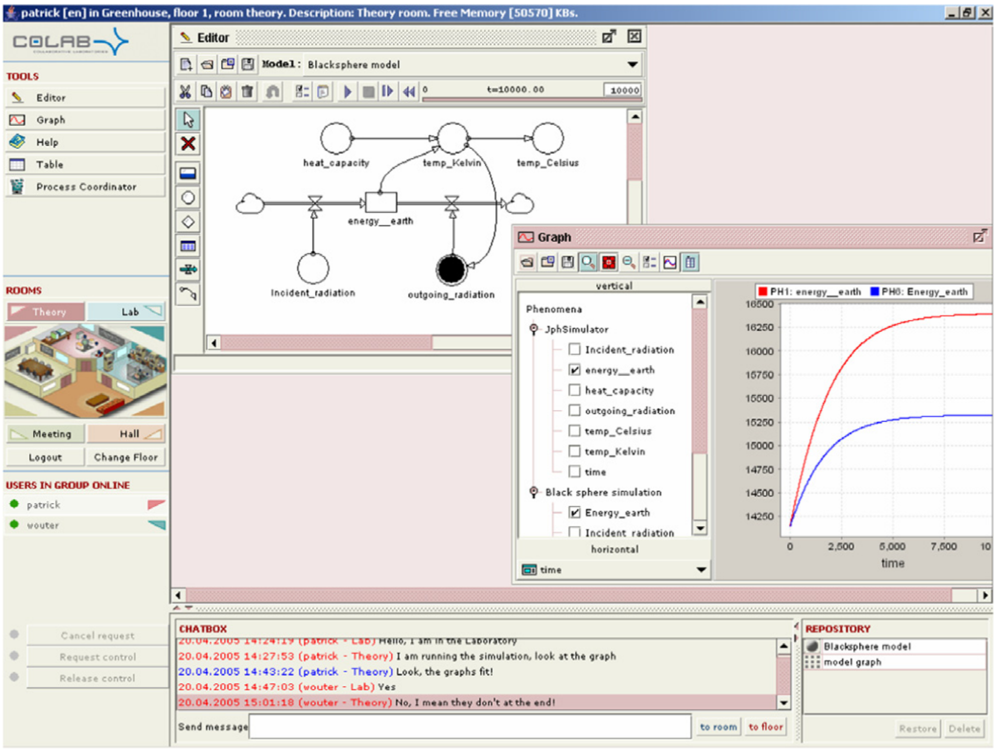

Fig. 2. Screenshot of the model editor in Co-Lab. In this particular example, an accurate model diagram is provided of the black sphere simulation. This model shows that the energy of the earth is influenced by the incident radiation from the sun (i.e., energy inflow) and the outgoing radiation (i.e., energy outflow). The outflow is influenced by the temperature of the earth. Finally the temperature is influenced by the energy of the earth and the heat capacity of the earth.

required to perform calculations. The results of model runs over time can be displayed as graphs or tables. In order to test their models, students can compare the output of their model with data they can obtain from running a simulation of a black sphere (see Fig. 3 for a screenshot of the simulation). Consequently, students may revise their model on the basis of the testing outcomes.

2.3. Instruments

2.3.1. Achievement goal orientation

Achievement goal orientation (i.e., mastery-approach goal orientation and performance-avoidance goal orientation) was measured on the individual level as well as on the dyad-level, employing questionnaires. For measuring mastery-approach goal orientation and performance-avoidance goal orientation of the individual student, items from corresponding subscales of the Goal-Orientation Questionnaire of Seegers and Boeckaerts (1993) were adapted. The questionnaire of Seegers and Boeckaerts (1993) was originally based on the one that Nicholls et al. (1989) describe and which has also been adapted and used in the studies conducted by Duda and Nicholls (1992), Nolen (1988), and Vrugt et al. (2002). For the present study, items from the Goal-Orientation Questionnaire were contextualized by rephrasing them into statements directed at assessing students' goal

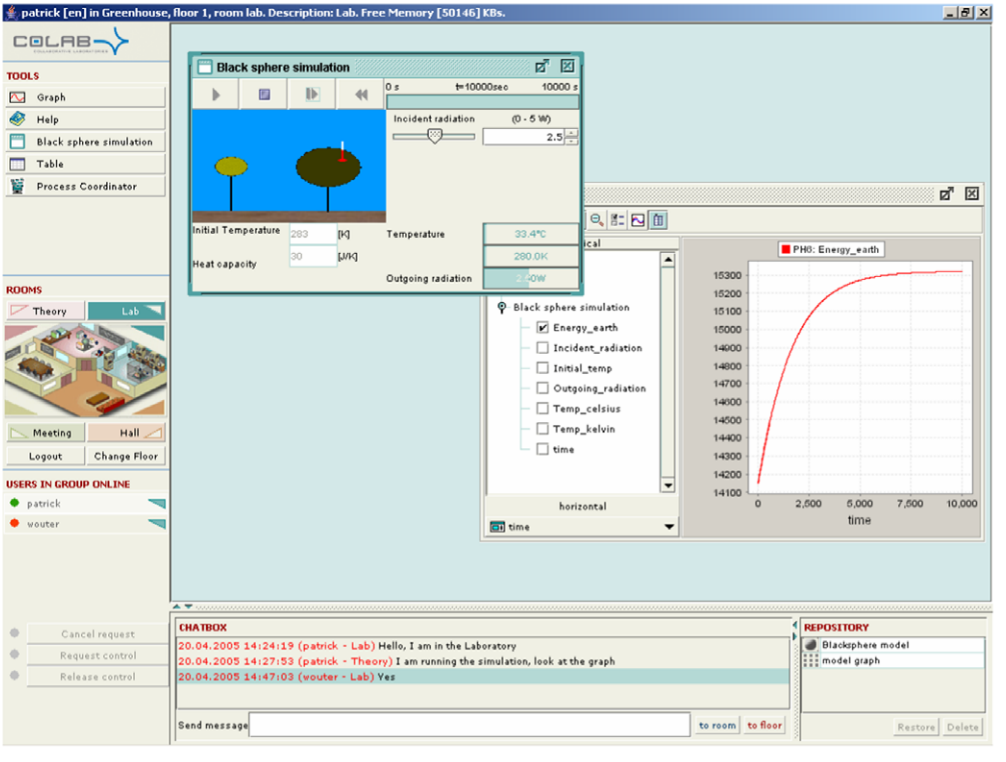

Fig. 3. Screenshot of the simulation of the temperature of an irradiated black sphere. Results of running the simulation are provided in a graph or a table.

orientation regarding physics. The first scale consists of five items formulated to express mastery-approach goal orientation (e.g., "I like to work hard on a physics task"), and the second scale involves six items for performance-avoidance orientation (e.g., "I want to avoid doing poorly in physics class"). Students indicated on a 4-point scale the extent to which they usually react in the described manner. Response alternatives ranged from "never" to "always". Principal-components analysis with varimax rotation supported the presence of two factors, with items loading on its designated factor. The two primary factors accounted for 71% of the total variance. Coefficient alphas were calculated for the two subscales that are focus of this study. Alpha was .80 for mastery-approach goal orientation and alpha was .79 for performance-avoidance goal orientation.

To measure mastery-approach goal orientation and performance-avoidance goal orientation on the dyad-level we employed the same questionnaire, with items being rephrased to fit the group, replacing "I" with "We". Dyads answered this questionnaire together and were prompted to discuss the question before answering it. They needed to agree on the answer. Principal-components analysis with varimax rotation showed that the two factor solution accounted for 69% of the total variance. Coefficient alphas for mastery-approach goal orientation and performance-avoidance goal orientation are respectively .69 and .72.

2.3.2. *Self-efficacy*

As with achievement goal orientation, self-efficacy was also measured within the context of the modeling task on both the individual level and the dyad-level. Self-efficacy was captured with the translated General Self-Efficacy questionnaire of Schwarzer (1992). Students were asked to indicate how adequate they estimated their ability with respect to the modeling task (e.g., "I can solve most problems if I invest the necessary effort"). The scale consisted of ten statements and students were asked to indicate on a 4-point scale the extent to which they agreed with the statement. Response alternatives ranged from "Not at all true" to "Exactly true". Group self-efficacy was measured in a similar fashion as with the group measures of achievement goal orientation. Internal consistencies were found to be .70 and .68 for the individual self-efficacy questionnaire and the group self-efficacy questionnaire, respectively.

2.3.3. *Cognitive processing*

Students' cognitive processing was measured by analyzing the inter-student chat, taken from the log files of the students' sessions, employing the protocol analysis scheme of Sins, Savelsbergh, and Joolingen (2005). The chat logs were scored employing two categories that were taken from the scheme of Sins et al. (2005):[1] (a) students' reasoning processes during modeling and (b) type of reference made by students during reasoning (see Appendix B for the coding scheme). Reasoning processes like analyzing or explaining may be considered to be cognitive processes and mostly involve several turns by both partners in a dyad (Brickell, Ferry, & Harper, 2002). Therefore, the unit of analysis is the process-episode level, an episode being a period of coherent continuous talk on a single issue, rather than single utterances (cf. Chi, 1997).

[1] In addition to these two categories, the protocol analysis scheme of Sins et al. (2005) also includes the category: "topic focus of students' reasoning". We did not include this code in the present analyses, since reasoning processes coupled with the type of reference students make during process-episodes provide sufficient information concerning students' level of processing.

Reasoning episodes in which students are elaborating on the modeling task and connect to knowledge they have available, either gained from the task at hand or as prior knowledge, were designated as deep processing. Episodes in which students employ unelaborated reasoning processes without referring to available knowledge were labeled as surface processing. Only episodes that could be clearly marked as either "deep" or "surface" processing were counted in this analysis, excluding all others. The following specific codes were operationalized as indications of deep processing:

– Evaluating and reference to knowledge
– Explaining and reference to knowledge
– Quantifying and reference to knowledge
– Inductive reasoning and reference to model components
– Inductive reasoning and reference to knowledge
– Analyzing and reference to knowledge

The following codes indicated surface processing:

– Evaluating and no reference to knowledge
– Quantifying and no reference to knowledge
– Analyzing and no reference to knowledge

Chat utterances were segmented into episodes and were scored with the help of our coding scheme. Because protocols differ in length, and because protocol episodes are of different length as well, frequencies of each code were converted to proportions of total time for each dyad, and analyses are based on these proportions. The total proportion of time dyads spent on deep processing was calculated by summing up the proportions of time for the six codes indicating deep reasoning processes. The same procedure was performed for surface processing.

The use of deep versus surface processes was also individually measured using a *self-report questionnaire* in order to investigate the correspondence between results from such questionnaires and the online log-file measure. Items from this questionnaire were based on the available literature (e.g., Greene & Miller, 1996; Entwistle, 1988; Marton & Säljö, 1997; Nolen, 1988; Pintrich & Garcia, 1991) and based on codes from the protocol analysis scheme of Sins et al. (2005). Thirteen items were constructed which were specifically tailored for measuring students' cognitive processing during modeling. The deep processing subscale consisted of seven statements (e.g., "I used my own knowledge during modeling") and the surface processing subscale consisted of six statements (e.g., "I tried to improve our model by changing values most of the time"). Students were asked to indicate the extent to which they agreed with the statements on a 5-point scale. Response alternatives ranged from "Totally agree" to "Totally disagree". Principal-components analysis with varimax rotation supported the presence of two factors, with items loading on its designated factor. The two primary factors accounted for 42% of the total variance. Coefficient alpha was .46 for surface processing and alpha was .59 for deep processing.

2.3.4. Achievement

Achievement on the modeling task was measured on the dyad-level and was operationalized as a model quality score. The models students constructed were judged with the help of a model scoring template. The students' final model was awarded with points for each variable which name and specification was correct. In addition, students were awarded with a point for correct links between variables and with a point for correct specifications for these relations. Finally, for each incorrect relation between quantities a point was subtracted from the total score.

2.4. Procedure

The study consisted of two sessions each of about two and a half hours on two separate days. In the first session, students were given a plenary introduction to the Co-Lab environment and were provided with an individual modeling tutorial. Subsequently, students were asked to complete the individual self-efficacy questionnaire and the individual achievement goal-orientation questionnaire. Afterwards, dyads were composed and a training task was given, in which they were asked to collaboratively extend a pre-build model involving the inflow and outflow of water from a water tank. Students worked with a simulation of a water tank and could investigate background information about this task using the Co-Lab help tool. On the basis of data obtained from this simulation and on the basis of information gathered, students could extend and revise their model. At last, dyads were asked to complete the group measures of self-efficacy and achievement goal orientation.

In the second session, dyads were presented with a modeling task in which they were asked to extend a given model. Students' goal was to extend the model so that it could give an explanation and prediction of the temperature on earth (see Appendix A for the modeling task). Co-Lab provided support for students in order to complete this modeling task: students could consult background information and could work with a simulation of a black sphere. Students worked for 2 h on the modeling task. When working within Co-Lab, members of a dyad each worked on one computer. The Co-Lab environment was shared between students and students communicated through a chat channel. Finally, the individual self-report questionnaire of students' processing was administered and completed.

3. Results

In order to check whether there were any differences between low–middle and middle–high dyads in terms of performance, *t*-tests were performed on all measures with group composition as independent variable. No significant differences were found, indicating that we can treat the sample as one group.

3.1. Validity of group measures for mastery-approach goal orientation, performance-avoidance goal orientation, and self-efficacy

While students worked in dyads on the modeling task, mastery-approach goal orientation, performance-avoidance goal orientation, and self-efficacy were measured on the dyad-level. Table 1 shows the means, standard deviations, and ranges for these variables.

Since, to our knowledge, no studies on group measures of these constructs have been conducted, we attempted to obtain some insight into the validity of these measures. We averaged for each dyad the total individual scores on the self-efficacy questionnaire, mas-

Table 1
Means, standard deviations, and minimum and maximum scores for the motivation variables

	Mean	SD	Observed range
Group mastery-approach goal orientation	3.02	.43	1.00–4.00
Group performance-avoidance goal orientation	1.41	.36	1.00–4.00
Group self-efficacy	3.07	.29	1.00–4.00

tery-approach goal orientation subscale, and performance-avoidance goal orientation subscale and correlated these figures with the corresponding scores of the dyads on the group measures. The zero-order correlations for mastery-approach goal orientation ($r = .56$, $p < .01$), performance-avoidance orientation ($r = .77$, $p < .01$), and self-efficacy ($r = .68$, $p < .01$) are significant and positive. Also, the averaged individual measure for self-efficacy per dyad and the group measure for mastery-approach goal orientation are significantly related ($r = .38$, $p < .05$).

3.2. Correspondence between the online log-file measure and the self-report measure of cognitive processing

The total individual scores on the subscales deep versus surface processing of the self-report questionnaire were averaged per dyad and correlated with the group scores for deep versus surface processing obtained from protocol analysis. As expected, results reveal little or no correspondence between the retrospective self-reporting on the one hand and the online log-file measure of students' cognitive processing on the other ($r = .18$, $p = .32$ for deep processing and $r = .06$, $p = .74$ for surface processing).

Table 2 shows the proportions of time dyads spent on deep versus surface processing, which were obtained from the protocol analysis. This table shows that a small proportion of time was spent on either surface processing ($M = 12.93\%$) or on deep processing ($M = 15.84\%$). Dyads spend the remaining time on talking about modeling actions ($M = 43\%$), on reading the learning material in Co-Lab ($M = 8.58\%$), on off-task communication ($M = 7.69\%$), and on other processes that did not fall under our conceptualization of deep and surface processing ($M = 11.96\%$).

Table 2
Percentage of time spent on deep and surface processing

Reasoning processes	Percentage of total time
Deep processes	
Evaluating and reference to knowledge	.59
Explaining and reference to knowledge	.39
Quantifying and reference to knowledge	4.45
Inductive reasoning and reference to knowledge	5.14
Inductive reasoning and reference to components	3.12
Analyzing and reference to knowledge	2.15
Surface processes	
Evaluating and no reference to knowledge	3.99
Quantifying and no reference to knowledge	5.60
Analyzing and no reference to knowledge	3.34

3.3. Testing the conceptual model

We used the group measures of all variables and the online log-file measure of students' cognitive processing for testing the conceptual model. Relations between the variables of our conceptual model (see Fig. 1) were first examined with Pearson product-moment correlations between variables (see Table 3). The relation between self-efficacy and mastery-approach goal orientation is significant. In addition, both self-efficacy and mastery-approach goal orientation are significantly correlated with deep processing. The correlation between performance-avoidance goal orientation and surface processing is not significant. Deep processing is significantly positive related to achievement on the modeling task. Also, the correlations between mastery-approach goal orientation and achievement and between self-efficacy and achievement are significant.

Second, a series of multiple hierarchical regression analyses were performed (cf. Dupeyrat & Mariné, 2005; Greene & Miller, 1996). Variables were entered into the regression equation based on their temporal sequencing in the conceptual model. Each variable was regressed on the variables that had causal paths leading to it. In the first set of regression analyses, deep processing and surface processing were the dependent variables. The predictors for each of these equations were self-efficacy, mastery-approach goal orientation, and performance-avoidance orientation. The second set of analyses investigated the effects of the motivational variables and students level of cognitive processing on achievement. The dependent variable, in these analyses, was achievement with the three motivational variables entered into the regression equation on the first step, and the two measures for students' processing entered on the second step. The results of these analyses are presented in Table 4.

The first set of regression analyses supports the hypothesized positive associations between mastery-approach goal orientation and self-efficacy on the one hand and deep processing on the other. None of the motivational variables significantly predicts surface processing. The second set of regression analyses, with achievement as dependent variable, show that self-efficacy, mastery-approach goal orientation, and deep processing are significant predictors of achievement. However, the positive influence of mastery-approach goal orientation on achievement is not significant after controlling for the mediating influence of deep processing. The resulting path model is presented in Fig. 4. For surface processing, no such path from performance-avoidance goal orientation can be found.

Table 3
Correlations among motivation variables, deep and surface processing, and achievement

	1	2	3	4	5
1. Group mastery-approach goal	—				
2. Group performance-avoidance goal	.03	—			
3. Group self-efficacy	.59**	−.03	—		
4. Deep processing	.50**	−.10	.48**	—	
5. Surface processing	−.09	.18	−.16	−.02	—
6. Achievement	.38*	−.19	.35*	.46**	−.29

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

Table 4
Multiple regression outcomes

Dependent variable	Predictor	r^2	Δr^2	β on step	Final β
Deep processing	Mastery-approach goal orientation	.248**	.248**	.498**	.328*
	Self-efficacy	.354**	.106*	.288*	.288*
Surface processing	/				
Achievement	Mastery-approach goal orientation	.144*	.144*	.380*	.130
	Deep processing	.417**	.273**	.334*	.334*

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

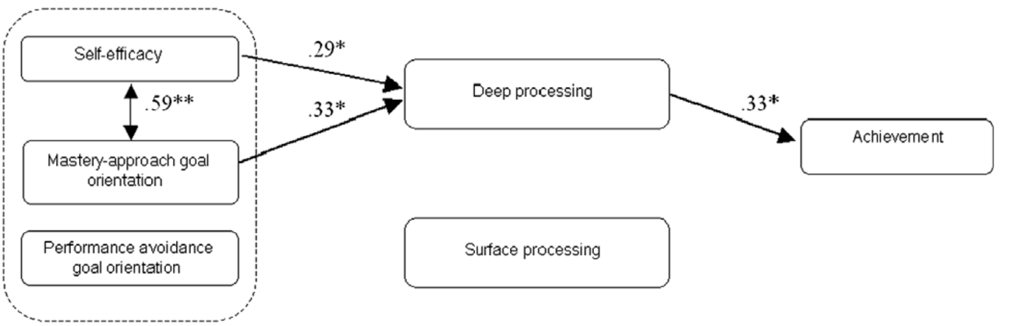

Fig. 4. Results of the path analysis. *p < .05, **p < .01.

4. Discussion

In the present study, we tested a conceptual model linking achievement goal orientation, self-efficacy, cognitive processing, and achievement of dyads working on a computer-based modeling task. In support of our conceptual model, we found that mastery-approach goal orientation and self-efficacy were both positively related to achievement and that these relationships were mediated by dyads' employment of deep cognitive processes, meaning that in these processes reference was made to knowledge, prior or acquired during the modeling task. However, in contrast to our predictions, the path model in Fig. 4 shows that performance-avoidance goal orientation was not significantly related to dyads' employment of surface processes. In addition, no significant relation was found between surface processing and achievement.

Our conceptual model was based on findings from the available achievement motivation literature (e.g., Covington, 2000; Dupeyrat & Mariné, 2005; Elliot et al., 1999; Greene & Miller, 1996; Middleton & Midgley, 1997). Traditionally, studies conducted within this field of research focus on the self-reported learning of individual students over a whole course. We tested our conceptual model for students who worked in dyads within a specific task context. Therefore, group measures of the variables in our model were employed. In addition, we used an online log-file measure to capture collaborating students' cognitive processing.

An indication of the validity of the group measures for mastery-approach goal orientation, performance-avoidance goal orientation, and self-efficacy was reflected in the finding that these measures were significantly positively related to the corresponding scores on the individual questionnaires, aggregated per dyad. This correlation shows that the measures on the individual and group levels are similar.

As expected, the group scores on the self-report questionnaire were not significantly related to the scores obtained from the online log-file measure. If we accept that the log-file measure is closer to actual observation than the post-hoc self-report, this result implies that retrospective self-report measures do not indicate students' factual processing during a given task. However, this finding should be taken with care, since the self-report questionnaire was low on reliability. We found that deep processing positively contributed to achievement, whereas surface processing showed a negative, but non-significant correlation with achievement. This finding may indicate that the online log-file measure is a valid indication of processing quality.

The results of our study are consistent with previous research within the field of achievement motivation, showing that self-efficacy and mastery-approach goal orientation are significantly positively related to students' use of deep cognitive processes (see Fig. 4). In addition, the hypothesis that self-efficacy is related to mastery-approach goal orientation was supported. In the path model of Fig. 4, achievement (i.e., model quality score) is positively affected by self-efficacy and mastery-approach goal orientation, but the effects of these variables are indirect, operating through the observed use of deep processes (i.e., mediation). Unfortunately, we lack detailed data on the origin of the knowledge students' employed during these episodes, as we did not administer a detailed domain knowledge test. With more detailed information about prior domain knowledge it should be possible to determine whether and to what extent prior knowledge about the domain has an independent contribution to the occurrence of deep reasoning processes.

The paths between the variables performance-avoidance orientation and surface processing and between surface processing and achievement were not significant. However, the correlation analysis (see Table 3) showed that for both relationships a trend was visible in the hypothesized direction. With a larger sample size these coefficients could turn out to be significant. On the other hand, recent studies also found that the paths between performance-avoidance goal orientation and surface processing and between surface processing and achievement were not significant (e.g., Dupeyrat & Mariné, 2005).

Dupeyrat and Mariné (2005) and Elliot et al. (1999) found a significant negative relation between performance-avoidance orientation and students' use of deep processes, which implies that students high on performance-avoidance report that they employ less deep processes. However, this finding is not unequivocally replicated as our study, and the studies of Al-Emadi (2001), Wolters (1996) and Middleton and Midgley (1997) have shown.

The present study shows that it is important to consider not only cognition as an important determinant of collaborative computer-based learning, but also to take into account the important impact of motivational factors, such as students' achievement goal orientation and self-efficacy. In addition, our study shows that the conceptual model is also applicable to particular collaborative tasks using an online log-file measure of students' cognitive processing.

An educational implication of this study may be that strategies that promote a mastery-approach goal orientation and advance students' self-efficacy lead to deep reasoning during modeling and ultimately to a higher achievement (cf. Greene & Miller, 1996; Greene et al., 2004). For instance, a mastery-approach orientation can be encouraged when knowledge development is emphasized instead of evaluation of learning. In addition, mastery-approach goal orientation may be stimulated when an assignment provided to students is made interesting and challenging for them. Finally, although one of the strongest ways for students to build self-efficacy is to experience success in accomplishing tasks themselves, external support and encouragement can also be provided. Relating this to collaborative computer-based modeling tasks, mastery-approach goal orientation, and self-efficacy may be promoted by presenting students with modeling tasks that interests them, by avoiding normative comparisons with other students, and by having students exchange their model and ideas with other dyads. Moreover, collaborative learning activities, such as the assignment employed in our study, have also been found to promote students' achievement goal motivation. Further research is needed in order to test these ideas.

Appendix A

A.1. Task Co-Lab blacksphere

There has been a lot of publicity about the earth's changing climate. Scientists all around the world are trying to understand what is going on, in order to predict what will happen next, or maybe more importantly, to give advice on what to do about it. The earth's climate is a very complex system, however, and even with all those scientists working on it, uncertainties remain. In such a situation scientists usually begin by making all kinds of simplifications. They first try to understand this simplified system, for instance by making a computer model. Then they use the computer model of the simplified system to make predictions about the real earth. Then they compare their predictions to reality, and consider what refinements are most needed.

In this module, you'll take a similar approach. We have made a very simplified small scale version of the earth and the sun: in our laboratory, we have ignored the differences between oceans, forests and deserts. All that remains of the earth is a black sphere and at some distance you'll find a strong light, which takes the function of the sun. Not too similar to the world we live in, you'll say, and you are right. Nevertheless, you can investigate how the earth's temperature responds to changes of solar activity, and what the effects will be if the earth's surface changes color, for instance because it becomes covered with ice. Once you have got a computer model to make proper predictions about this simplified situation, you'll have discovered the basic model structure that underlies even the most advanced climate models today.

To summarize, your goal in this module will be to build a model that can predict the temperature of a black sphere (the barren earth) after being exposed to a source of light (the sun) for some while. To assist you, we provide you with an initial but still incomplete model. This model shows that the energy content of the earth is influenced by an energy inflow (incident radiation from the sun) and an energy outflow (outgoing radiation). Your goal is to extend this model in such a way in that it will provide a provide a good match with the data you obtained from the simulation of the black sphere. In order to fulfill this goal, you'll need to find out first which factors play a role, and how they depend on each other.

Appendix B

B.1. Coding scheme for cognitive processes

Categories	Description
Type of reasoning process	
Evaluate	Students positively/negatively evaluate an element(s) in relation to their model. Students make a (elaborate) value judgment on a modeling element.
Explain	Students explain to each other how elements within their model work or why they were included. An explanation must be preceded by a clear-cut question of one of the students.
Quantify	Students talk about quantifying or specifying a quantity or relation within their model.
Inductive reasoning	Students elaborate upon/about elements within or with respect to their model (involves mainly qualitative reasoning).
Analyze	Students talk about/interpret modeling elements without further elaboration. Or identify factors that may be relevant/included in their model without further elaboration (i.e., factors are uttered by the students without further discussion).
Other processes	
Read	Students read or paraphrase.
Off task	Students talk about subjects unrelated to the modeling task.

Categories	Description
Type of reference	
None	No reference to model components or knowledge.
Knowledge	
Physics knowledge	Use of terminology, concepts (i.e., units, quantities), formula's common in physics.
Mathematics knowledge	Use of terminology, concepts, formula's common in mathematics.
Experiential knowledge	Knowledge from everyday experience.
Model components	
Correspondence model graph and data	Students refer to (the extent of) correspondence between model output and experimental data.

Appendix B (*continued*)

Categories	Description
Data from simulation	Experimental data from the simulation (i.e., table/graph).
Html-documents	Information about the blacksphere problem provided in the html-documents.

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