How Motivation Affects Learning

Regina Vollmeyer (VOLLMEYE@RZ.UNI-POTSDAM.DE)
Wolfram Rollett (ROLLETT@RZ.UNI-POTSDAM.DE)
Falko Rheinberg (RHEINBERG@RZ.UNI-POTSDAM.DE)
Institut für Psychologie, Universität Potsdam
Postfach 601553, 14415 Postdam, Germany

Abstract

In our cognitive-motivational process model (Vollmeyer & Rheinberg, in press) we assumed that motivational factors have an impact on how people learn about a task and how well they can perform it. Many motivation theories (if not all) have such assumptions in common. Our approach emphasizes four task specific motivational factors: *mastery confidence, incompetence fear, interest*, and *challenge*. We investigated how these motivational factors influence the learning outcome through mediators. Our framework proposes that the *motivational state* and the *strategy systematicity* could mediate motivational effects on learning. Path analysis supported this assumption in two studies.

Introduction

Simon (1967) emphasized the importance of motivational and emotional influence on cognition. Refering back to Neisser (1963), Simon argued that the critical difference between a computer program and a person consists of two mechanisms: (1) an interruption mechanism, which he sees as emotion, and (2) a goal-terminating mechanism, which is motivation. However, people have multiple goals rather than only one goal. Thus, motivation determines which goal will be activated and has attention allocated to it. If a person pays attention to the goal of learning, motivation would lead to better learning.

However, the construct of motivation has been largely ignored by Cognitive Science. Similarly, in motivation theories cognitive processes have been largely ignored. Motivational factors were mainly conceptualized as drives, habits, or traits which influence the situational behavior (examples of such traits are achievement motive, goal-orientation, or personal interest). The traditional as well as more recent concepts of motivation (e.g., goal theory, see Locke, 1991) do not specify the process by which motivational factors influence cognition and learning. However, the importance of such investigations has been recently pointed out by Schiefele and Rheinberg (in press). The following two studies examine the link between motivation and learning.

Motivational Factors and Learning

When a learner approaches a learning task the literature suggests that several motivational factors can arise and be measured. (1) Learners can vary in their certainty that they will succeed in understanding the task. This factor we will call *mastery confidence* (similar concepts have been proposed, e.g., subjective probability of success [Atkinson, 1957]; self-efficacy [Bandura, 1977]). (2) Learners can be different in anxiety about failing in the task. This factor we will call *incompetence fear* (a similar concept is Atkinson's fear of failure, however, for him this concept is measured as a trait). (3) Learners can perceive this task as a *challenge* (e.g., Czikszentmihalyi, 1975). (4) The task may or may not evoke the learner's *interest* (see Schiefele, 1991). All these motivational factors are said to affect learning, however, it is not clear how.

In our cognitive-motivational process model (Vollmeyer & Rheinberg, in press) we assume that these four motivational factors influence the *motivational state* during the learning process. *Motivational state* is conceptualized as a process variable that monitors states such as fun the participant has during the learning task, his/ her confidence in finding the correct solution, and so on (see Table 1). A second process variable is the systematicity of participants' strategies. Because systematicity requires effortful actions like calculation and induction this variable should be affected by motivation. In the following studies we investigated how the initial level of the four motivational factors described affected learning via the mediating variables *motivational state* and *strategy systematicity*.

For this investigation we needed a learning task which was difficult enough to be challenging and which allowed the possibility of failing to learn the task. Also it should last long enough to allow us to study learning as a process.

Biology-Lab: A Complex System

As in Vollmeyer, Burns, and Holyoak (1996) we used a computer-driven system called biology-lab that was constructed with the shell DYNAMIS (Funke, 1991). In our cover story, participants were told that they were in a biology lab in which there is a tank with three water quality factors (oxygenation, chlorine, temperature). These factors were affected by three input variables (salt, lime, carbon). The structure of the system, illustrated in Figure 1 (which was never shown to our participants), was such that one output is relatively simple to manipulate because it is influenced by only one input (lime -> oxygenation). The other two outputs are more complex, because each is influenced by two factors. One output (chlorine) is affected by two inputs, and the other (temperature) is affected by a decay factor (marked as a circle connected to the output) in addition to a single input variable. The decay factor was implemented by subtracting a percentage of the output's previous value on each trial. Decay is a dynamic aspect of the system, because it yields state changes even if there is no input (i.e., all inputs are set to zero). The system is thus complex in that it involves multiple input variables that must be manipulated to control multiple output variables, and dynamic in that the state of the system changes as a joint function of external inputs and internal decay.

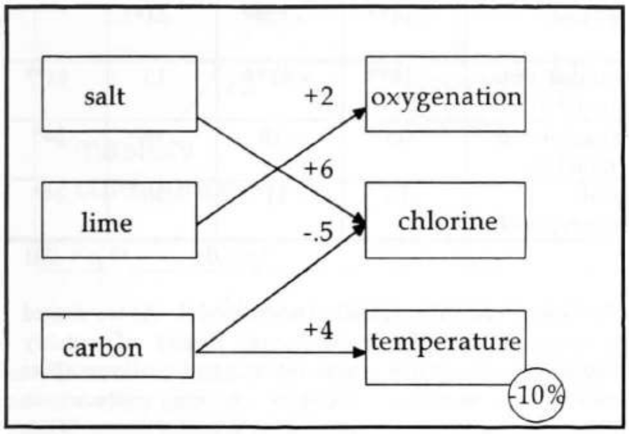

Figure 1: Biology-lab system.

To explore the system, participants in Vollmeyer et al. (1996) were given a learning phase (three rounds of six trials on which participants entered numbers for inputs) and an application round (six trials). In the application round participants had to apply their knowledge about the system's structure in order to reach a certain target amount for each output variable. Vollmeyer et al. showed that a good strategy for learning about the system was to vary only one input variable at a time. This strategy was explained to all participants in the following studies in order to reduce the variance of their performance.

Study 1

Method

Participants. Seventy students from the University of Potsdam and local high schools (17-19 years old) participated in the study and received DM 15 (≅ $US 10).

Procedure. The biology-lab system required participants on each trial to set the levels of the three input variables and to observe the resulting values of the output variables (numbers for each of three factors for water quality). The underlying structure of the system was as depicted in Figure 1. Each series of six trials was defined as a *round*. All participants received three initial learning rounds followed by a fourth round in which they were asked to produce a specfic goal state (namely, 50 oxygenation, 700 chlorine, and 900 temperature).

Before starting to manipulate the system on the computer all participants received general instructions about the task. which emphasized that the best strategy for exploring the system was to vary one input variable at a time. After having read the instructions the participants answered a questionnaire which measured their initial motivation on the four factors *mastery confidence*, *incompetence fear*, *interest*, and *challenge* (see Table 1).

During the learning phase (rounds 1-3), participants completed a *structure diagram* at the completion of each round, in which participants indicated how they believed the input variables affected the output variables. They were provided with a diagram showing the inputs and outputs as in Figure 1, but with all links omitted. The participants' task was to draw links between variables that they believed to be dependent, and also to assign weights indicating how strong they felt each influence was. After filling in the structure diagram, participants answered three items that measured their *motivational state* (see Table 1).

In the application phase (round 4), all participants were presented with a goal state. The entire experiment took one and a half hours to complete.

Table 1: Example items for the motivational factors and all items for the *motivational state*.

	factor score
Mastery confidence	
I think everyone could do this task.	.73
I can't wait to start.	.67
I think I am up to the difficulty of the task.	.65
Challenge	
This task is a real challenge for me.	.76
If I can do this task, I will feel proud of myself.	.75
I'm excited about how well I will perform in this task.	.70
Incompetence fear	
I'm a little bit worried.	.72
I feel paralyzed by the demands of the task.	.72
I'm afraid I will make a fool out of myself.	.71
Interest	
After having read the instruction, the task seems to be very interesting.	.75
I like riddles and puzzles.	.75
I would work on this task even in my free time.	.75
Motivational State (all items)	Cronbach
The task is fun.	$\alpha = .80$
I'm sure I will find the correct solution.	
It's clear to me how to continue.	

Results

Mediating variables. Two mediating variables were measured to explain the process between motivational factors and the learning outcomes. (1) *Strategy systematicity*. Each of the six trials during one learning round was coded for systematicity. We had three categories: high systematicity: only one or no input variable was varied (This is the strategy we explained to the participants at the beginning.), medium systematicity: a systematicity was recognizable (e.g., two variables are varied; for one variable there is a positive number, for two a negative), low systematicity: all input variables are varied. The interrater reliability was $\kappa = .94$ (Cohen, 1960). These six codings for one round were averaged. As many participants chose the highly systematic strategy as instructed this variable had a skewed distribution. Thus we corrected it by applying a logarithmic transformation. Participants had a score for each of the three rounds. (2) *Motivational state*. At the end of every learning round participants answered three questions on a seven-point scale (see Table 1), which were averaged together.

Dependent variables. Two dependent variables measured learning. (1) *Structure score* (acquired knowledge). The structure diagram completed by all participants after each of the first three rounds was used to derive a score reflecting degree of knowledge of the underlying structure of the system. This structure score was computed as the sum of the number of correct specifications of links, directions, and weights, adjusted with a correction for guessing. (2) *Goal achievement*. Goal achievement in reaching the goal state during round 4 (application round) was computed as the sum of the absolute differences between the target and the obtained number for each of the four output variables. As this measure produced a skewed distribution, the variance was corrected by applying a logarithmic transformation. Goal achievement was computed for each of the six trials that comprised round 4, in order to determine how participants were able to approach the target goal. As there was no difference in performance between trials, the mean error for the six trials was used. Note that in Vollmeyer et al. (1996), this measure was referred to as *solution error*, instead of by the term *goal achievement*. However, this meant that high scores were indicators of poor performance. So that all performance measures would be in the same direction, we subtracted all these scores from an arbitrary constant, a linear transformation that has no effect on the correlations that we will report, except to reverse their sign.

Preliminary analyses. The motivational factors were constructed via factor analysis guided by theoretical assumptions. First we factor analyzed preselected items that expressed interest or incompetence fear, and found which items were most important for these factors. We then factor analyzed items expressing *mastery confidence* and *challenge* (for factor scores, see Table 1) and confirmed the expectation of two independent factors, which we named *mastery confidence* and *challenge*. Our theoretical definitions of the concepts implied that the motivational factors should intercorrelate (with the exception of *mastery confidence* and *challenge*), which was the case (see Table 2). To reduce the error variance for each motivational factor, we measured the factors with the factor scores instead of the raw scores.

Table 2: Correlations of the motivational factors and the dependent variables ($N = 70$).

	mastery confidence	incompet. fear	challenge	interest
incompetence fear	-.62**			
challenge	.10	.03		
interest	.54**	-.52**	.44**	
motivat. state (round 3)	.38**	-.41**	.13	.43**
structure score (round 3)	.05	-.18	.14	.24*
goal achievement	.15	.31**	.20	.24*

* $p < .05$ ** $p < .001$

The cognitive-motivational process model. As we wanted to examine how the motivational factors of *mastery confidence, incompetence fear, interest,* and *challenge* affect learning via mediating variables, it was necessary to reconstruct the process with a path analysis (using EQS). The result is presented in Figure 2. The empirical data fitted our theoretical expectations quite well, $CFI = .96$, $X^2(48) = 67.47$, $p < .05$[1]. As expected, there was a cognitive path: Participants using the given good strategy gained a better knowledge over the three learning rounds (links from strategies to structure scores) and with this better knowledge they could reach the goal state more accurately in the application round (structure score -> goal achievement). This result replicated an earlier finding (Vollmeyer et al., 1996). More interesting is how motivation affects this cognitive process. From Table 2 it is evident that *challenge* was not a good predictor for learning on this task as it did not correlate with the dependent variables. Therefore, *challenge* could not be included in the model. Also *interest*, which was correlated with the learning variables (structure score, goal achievement), did not fit into the model. However, *incompetence fear* and *mastery confidence*, combined as the latent variable *motivation*, affected how the participants felt during learning (*motivational state*). Participants who (initially) had less fear and more confidence enjoyed working with the system more, and this positive motivational state had the effect that participants continued to use the systematic strategy in round 2. Participants in a more positive *motivational state* learned

[1] Linear structural equation modeling is a methodology for specifying, estimating, and testing hypothesized interrelationships among a set of meaningful variables. There are two criteria whether the hypothesized model fits the empirical data: (1) the goodness of fit (e. g., Comparative Fit Index), which has the maximum value 1.0, (2) and X^2, which should be not significant. The methodology also calculates regression coefficients (in Figure 2 and 3 there are the weights close to the links).

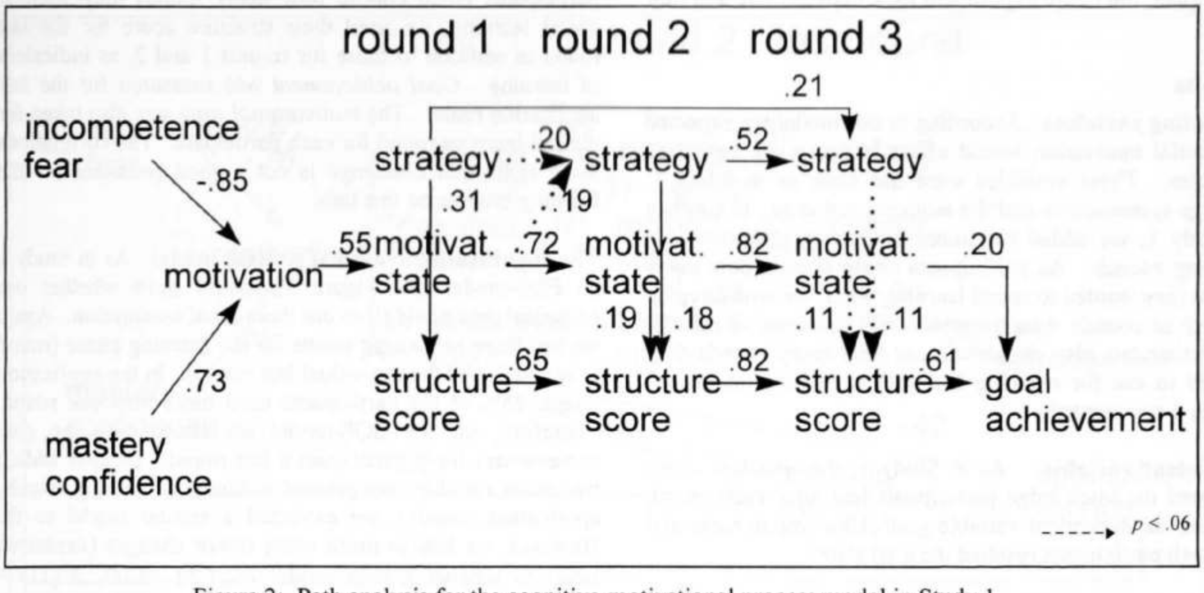

Figure 2: Path analysis for the cognitive-motivational process model in Study 1.

more about the structure of the system, perhaps because they put more effort into calculating the system's weights. The positive motivational state also helped participants reach the goal state more accurately in the application phase (motivational state –> goal achievement). This path analysis demonstrates how initial motivation affects learning (knowledge and application) via mediating variables (*motivational state* and *strategy systematicity*).

Summary

In the first study we constructed a questionnaire to measure the initial motivation that participants had after they read about a task. We found four factors: *mastery confidence*, *incompetence fear, interest,* and *challenge*. For our cognitive-motivational process model only two motivational factors (combined in a latent variable) were influential, these were *incompetence fear* and *mastery confidence*. These factors influenced motivation during learning. Participants with high scores on the motivational factors used a more systematic strategy. Therefore, initial motivation influenced learning in our task (knowledge and application) via mediating variables (motivation during the task, strategy systematicity), which was predicted by our model.

Study 2

Motivation theories propose that learning motivation influences time spent on a task. In Study 1 participants could not choose how many rounds they wanted to spend on learning or on trying to reach the goal states. Therefore, in a second study we allowed participants to choose how long they worked on the task. Our prediction was that motivation directly influences the number of learning and application rounds. The second aim was to replicate the empirical model we found in Study 1.

Method

Participants. Fifty one Psychology students at the University of Potsdam participated in the study and they received course credit for every hour they stayed.

Procedure. As in Study 1, participants were presented with the biology-lab system, which had the underlying structure shown in Figure 1. In contrast to Study 1, participants were told that they can use as many rounds (each round had six trials) as they liked to learn about the system. Also for the application phase participants were free to use as many rounds as they wanted to. The experimental session was fixed at two hours, however, if participants were motivated to continue longer than two hours they could come back a different time.

As in Study 1, all participants read the instructions explaining the task, and the good strategy for exploring the system. After the instructions they filled out the questionnaire measuring their initial motivation on the four factors: *mastery confidence, incompetence fear, interest*, and *challenge*. Then they started manipulating the inputs of the system to induce the underlying structure. After every round they filled out the structure diagram, showing which links and weights they already knew. Then they answered the motivational state questionnaire (see Table 1).

When the participants said they had learned enough, they were presented with the goal states. The application phase was finished when the participants decided that they were close enough to the goal states. Depending on the participant, the entire experiment took between one and four hours.

Results

Mediating variables. According to our model we expected that initial motivation would affect learning via mediating variables. These variables were the same as in Study 1: *strategy systematicity* and the *motivational state*. In contrast to Study 1, we added two more mediating variables. (1) *learning rounds*: As participants could choose how many rounds they wanted to spend learning about the structure, the number of rounds were counted. (2) *Application rounds*: As participants also chould choose how many rounds they wanted to use for reaching the goal states, the number of rounds were counted.

Dependent variables. As in Study 1, the *structure score* indicated the knowledge participants had after each round. The second dependent variable *goal achievement* measured how well participants reached the goal states.

Preliminary analyses. To analyze the initial motivation we constructed the same scales as in Study 1. The factors' intercorrelations can be seen in Table 3. Again it is evident that the constructs were not independent from each other. The highest correlation was between *incompetence fear* and *mastery confidence*, which is an argument for combining them into a latent variable.

Table 3: Correlations of the motivational factors and the dependent variables (N = 51).

	mastery confidence	incompet. fear	challenge	interest
incompetence fear	-.57**			
challenge	-.06	.32*		
interest	.48**	-.32*	.06	
motivat. state (last round)	.25	-.28	-.04	.39**
structure score (last round)	-.10	.14	-.20	.21
goal achieve. (last round)	-.01	.25	.07	.12
learning rounds	.32*	-.14	-.03	.36**
application rounds	.19	.30*	.12	.10

* p <.05 ** p < .001

On average, participants chose to spend about 5 rounds (M = 5.20, SD = 2.56) learning the structure of the system and about 4 rounds (M = 3.72, SD = 2.50) trying to reach the goal states in the application phase.

Before running a path analysis (using EQS) we looked at the correlations between the motivational scores and the mediating and dependent variables (see Table 3). As participants could choose how many rounds they want to spend learning, we used their structure score for the last round in addition to those for rounds 1 and 2, as indicators of learning. *Goal achievement* was measured for the last application round. The *motivational state* was also taken for the last learning round for each participant. The correlations show again that *challenge* is not a good predictor for the learning process on this task.

The cognitive-motivational process model. As in Study 1 an EQS-model (see Figure 3) should show whether our empirical data could fit to our theoretical assumption. Again we had three measuring points for the learning phase (round 1, round 2, and the individual last round). In the application phase, 25% of the participants used more than one round. Therefore, for the EQS-model we chose only the goal achievement for a participant's last round. Despite adding two more variables not present in Study 1 (learning rounds, application rounds), we expected a similar model to fit. However, we had to make some minor changes (explained later) to receive a high model fit, CFI =1.00, $X^2(71)$ = 67.02, p > .05. First we will describe what the models from Study 1 and 2 have in common and then the differences.

In Study 1 and 2 participants were instructed how to use a systematic strategy. If they used this strategy it led in both studies to better learning and, hence, to better solutions. We called this path a *cognitive* path. However, we were especially interested in the effects of initial motivation. *Interest* was again a worse predictor than the *motivation* latent variable (*mastery confidence* and *incompetence fear*). This initial motivation strongly affected how participants felt during learning: If they were more confident at the beginning of the task they had more fun and were more confident during the learning phase (*motivational state*). Similar to Study 1, the motivational state affected strategy systematicity and also knowledge about the system's structure (i.e., structure score).

In contrast to Study 1, there was no effect of motivational state on goal achievement. A possible explanation is that we changed the procedure as participants could choose the number of rounds for learning and application. With this procedure the motivational state in the last round might not be comparable to the third round in Study 1.

In Study 2 two new mediating variables were included: *learning rounds(LR)* and *application rounds(AR)*. The best predictors for learning rounds (LR) were the structure score and *mastery confidence*. Participants with confidence in their success tried for longer to discover the system's structure. Participants who had more knowledge in Round 1 stop learning about the system earlier. For application rounds (AR) the knowledge in Round 1 was a good predictor, and the motivational factor *incompetence fear* was also good. Participants who had more knowledge in Round 1 of the learning phase spent fewer rounds trying to reach the goal states and participants with *incompetence fear* tried longer to reach the goal states. This result demonstrated that initial motivation influences how long people work on a task.

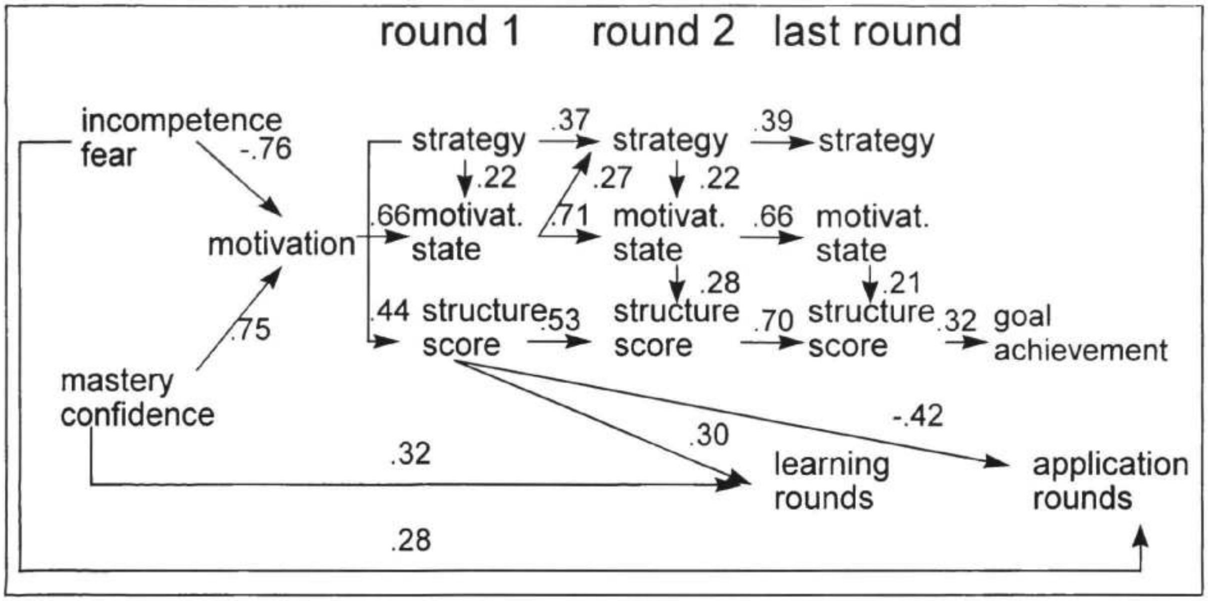

Figure 3: Path analysis for the cognitive-motivational process model in Study 2.

Discussion

The aim of our two studies was to demonstrate that motivational factors have an impact on cognitive processes and learning. We expected that initial motivation would affect performance (knowledge and application) via two mediating variables (strategy systematicity and motivational state during learning). This assumption was confirmed in two studies.

Simon (1967) assumed that motivation influences cognitive processes via the allocation of attention to a (learning-) goal. Following this idea, the next step in our research is to try to include attention in our process model.

Another challenge is to connect our motivational factors to already existing concepts, for example, what does Bandura's self-efficacy (1977) have to do with mastery confidence? Or our factor *challenge* with the concept of *flow-experience* (Czikszentmihalyi, 1975).

Acknowledgements

We would like to thank Bruce Burns and two anonymous reviewers for comments on this paper. This research was supported by DFG Grant Vo 514/5 to Regina Vollmeyer and Falko Rheinberg.

References

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological Review, 64*, 359-372.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavior change. *Psychological Review, 84*, 191-215.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*, 37-46.

Czikszentmihalyi, M. (1975). *Beyond boredom and anxiety*. San Francisco, CA: Jossey-Bass.

Funke, J. (1991). Solving complex problems: Exploration and control of complex systems. In R. J. Sternberg & P. A. Frensch (Eds.). *Complex problem solving: Principles and mechanisms*. Hillsdale, NJ: Erlbaum.

Locke, E. A. (1991). Goal theory vs. control theory: Contrasting approaches to understanding work motivation. *Motivation and Emotion, 15*, 9-28.

Neisser, U. (1963). The imitation of man by machine. *Science, 139*, 193-197.

Schiefele, U. (1991). Interest, learning, and motivation. *Educational Psychologist, 26*, 299-323.

Schiefele, U. & Rheinberg, F. (in press). Motivation and knowledge acquisition: Searching for mediating processes. In P. R. Pintrich & L. Maehr (Eds.). *Advances in motivation and achievement* (Vol. 10). Greenwich, CT: JAI Press.

Simon, H. A. (1967). Motivational and emotional controls of cognition. *Psychological Review, 74*. 29-39.

Vollmeyer, R., Burns, B. D., & Holyoak, K. J. (1996). The impact of goal specificity on strategy use and the acquisition of problem structure. *Cognitive Science, 20*, 75-100.

Vollmeyer, R. & Rheinberg, F. (in press). Motivationale Einflüsse auf Erwerb und Anwendung von Wissen in einem computersimulierten System. (Motivational influences on the acquisition and application of knowledge in a simulated system.) *Zeitschrift für Pädagogische Psychologie*.