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Computer-Based Science Inquiry: How Components of Metacognitive Self-Regulation Affect Problem-Solving

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Abstract

First, we sought to examine the effects of metacognitive self-regulation on problem solving across three conditions— an interactive, computer-based treatment condition, a non-interactive computer-based alternative treatment condition, and a control condition. Second, we sought to investigate which of five components of metacognitive self-regulation were important for scientific problem solving. We hypothesized that overall metacognitive self-regulation and its various components would predict success at content understanding and problem solving and that the treatment condition would be more effective in promoting learning outcomes than either the alternative treatment or control conditions.

Overall, 12 hierarchical linear models were produced. Results indicated that students in the treatment condition demonstrated significantly more Content Understanding and Problem Solving skill than students in the alternative and control classrooms. In regards to the treatment condition, of the five IMSR components, only Problem Representation was a significant predictor for success at Content Understanding. In contrast, within the alternative condition, students' Problem Representation had a significant inverse influence on Content Understanding. In terms of Problem Solving, Knowledge of Cognition and Problem Representation were found to be significant predictors.

These findings are especially noteworthy for science education and inquiry-based education. In particular, results indicate that metacognitive and self-regulatory constructs are important in teaching problem solving. Being able to identify and delineate these constructs further should allow our educational research and teacher professional development teams to begin providing teachers with a set of tools and training resources to help them target student self-regulation in their classrooms.

Introduction

<u>Self-Regulated Learning, Metacognition, and Problem Solving</u>

Many researchers would agree that an important goal of education is the development of intellectual independence— the ability to think critically and solve the every-day problems of life. Studies on the development of self-regulated learning offer important insights into the complex interrelationships between cognitive, metacognitive, and affective aspects of intellectual independence. Research conducted over the last 15 years on self-regulated learning has primarily focused on three core components: metacognitive awareness, strategy use, and motivational control (Bruning, Schraw & Ronning, 1995). In the present study we focused on the influence of metacognitive awareness for effective use of problem solving strategies.

Metacognition has been referred to as knowledge and regulation of one’s own cognitive system (Brown, 1978; Palincsar & Brown, 1987). Metacognition enables students to coordinate the use of current knowledge and a repertoire of reflective strategies to accomplish a single goal. Metacognitive awareness, therefore, serves a regulatory function and is essential to effective learning because it enables students to regulate numerous cognitive skills.

Studies of metacognition in academic settings has traditionally focused on two major components: <u>knowledge of cognition</u>— how much learners understand about their own memory organization and the way they learn,— and <u>regulation of cognition</u>— how well learners regulate their own memory and learning (Brown 1980; 1987). In an instrument development study, Howard, McGee, Shia, and Hong (2000) confirmed the existence of a knowledge of cognition factor and two regulation of cognition factors which they titled <u>subtask monitoring</u> and <u>evaluation</u>. They also found two additional self-regulatory constructs pertinent to problem solving, <u>problem representation</u> and <u>objectivity</u>.

The current work, therefore, examines five components of metacognitive self-regulation (Howard, McGee, Shia, & Hong, 2000):

- <u>Knowledge of Cognition</u>: understanding the extent and utilization of one’s unique cognitive abilities and the ways one learns best.
- <u>Subtask Monitoring (regulation of cognition)</u>: breaking the problem down into subtasks and monitoring the completion of each subtask.

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- Evaluation (regulation of cognition): double-checking throughout the entire problem-solving process to evaluate if it is being done correctly.
- Problem Representation: understanding the problem fully before proceeding.
- Objectivity: standing outside oneself and thinking about one's learning as it proceeds.

Metacognition and Problem Solving

In 1990 H. Lee Swanson presented a pivotal work linking metacognition to successful problem solving. Swanson set out to demonstrate the independence of metacognition and general aptitude on various problem-solving measures. He measured aptitude with standardized, cognitive ability and achievement tests and metacognitive ability using tape-recorded responses to a metacognitive questionnaire. His findings indicated that metacognition was more important for problem-solving success than aptitude. In situations where students had low aptitudes but high metacognitive levels, students performed as well as students of high aptitude.

Research in which students used a CD-ROM titled Astronomy Village®: Investigating the Universe™ provided evidence that students may not necessarily need nor use high levels of metacognition to solve every type of problem (Hong, 1998). This research indicated that metacognitive awareness was a significant predictor of success for ill-structured problem solving, but was not significant for solving well-structured problems. In addition, Howard, McGee, Hong and Shia (2000) found that three of the five factors (Knowledge of Cognition, Problem Representation, & Objectivity) were significant predictors of Content Understanding. In addition, four of five factors (Knowledge of Cognition, Evaluation, Problem Representation, & Objectivity) were significant predictors of Problem Solving. Results also showed that those with High Metacognitive Self-Regulation compensated for Low Aptitude on both Content Understanding and Problem Solving measures.

Some could argue that metacognition is innate and, therefore, largely unchangeable through instructional intervention. Research in science education, however, indicates that a variety of regulatory behaviors may be learned, and that such behaviors are beneficial for learning. For example, research has shown that certain behaviors lead to success in science education, such as identifying goals (Linn 1995), self-assessing (White & Frederiksen, 1995), planning (King, 1988; Scardamalia & Bereiter, 1991), self-explaining (Chi, Bassok, Lewis, Reimann, & Glaser 1989), self-questioning (King 1994), reflecting (Davis, 1998; Audet, Hickman & Dobrynina, 1996), and making concepts personally relevant (Linn, 1995).

Metacognitive training has been shown to be particularly effective for the acquisition of reading (Jacobs & Paris, 1987; Palincsar & Brown, 1984) and problem solving strategies (Delclos & Harrington, 1991) regardless of aptitude or achievement level. However, further evidence that metacognition affects variables that influence learning is scant. For instance Pintrich, Smith, Garcia, and McKeachie (1991) indicated that the use of metacognitive and cognitive strategies was not highly correlated with academic achievement. Pressley and Ghatala (1988) also found metacognition (in this case monitoring accuracy) to be unrelated to verbal ability.

Research Questions

We examined the effects of metacognitive self-regulation on problem solving across three conditions in 36 classrooms. In the treatment condition, students learned science using interactive, computer-based software. We hypothesized that metacognitive self-regulation would predict success at problem solving. In the alternative treatment condition, students used non-interactive computer-based materials, and completed associated worksheets. The control condition students completed pre- and posttests but did not complete any relevant instruction.

In this study, we also sought to investigate which of the five components of metacognitive self-regulation were important for scientific problem solving. The results would be important for creating a descriptive profile of the components of metacognitive self-regulation that are most necessary for problem solving. We hypothesized that overall metacognitive self-regulation and its various components would predict success at content understanding and problem solving and that the treatment condition would be more effective in promoting learning outcomes than either the alternative treatment or control conditions.

Method

Participants

Participants included 626 students, grades 5–12, from schools across the United States. They represented a cross-section of socioeconomic backgrounds and urban/suburban/rural categorizations. The ethnic breakdown of treatment and alternative treatment conditions included 65.5% Caucasian, 24.1% Asian American, 3.6% African American, 4.1% Hispanic or Latino, and 2.7% Other. By gender, the breakdown was 50% female and 50% male.

Procedure/ Materials

In the treatment condition, students used the Astronomy Village® Investigating the Solar System™ software. In the alternative treatment condition, students had access to the same content on the computer, but without the benefit of the Village interface and image analysis activities. Each group covered the material for an average of 20 instructional days.

Students were given pretest/posttest instruments that measured learning**:** One instrument measured Content Understanding, and the other measured Problem Solving (see McGee & Howard, 1999 for description of Astronomy Village).

Pretest scores were subtracted from the posttest scores to yield one score that represents the amount of learning gained from each student's instructional experience.

At pretest time students also took the Inventory of Metacognitive Self-Regulation (IMSR) which measures five factors related to awareness of learning processes and control of learning strategies: (1) Knowledge Of Cognition, (2) Subtask Monitoring, (3) Evaluation (4) Problem Representation, and (5) Objectivity (Howard, McGee, Shia, & Hong, 2000). The IMSR includes 32 items that use a five-point Likert scale. For each of the 32 items, students are instructed to circle the answer that best described "the way they are" when solving problems in math or science class (1=never, 2=seldom/rarely, 3=sometimes, 4=often/frequently, 5=always). The validation of the IMSR and a more detailed explanation of the five components is discussed elsewhere (Howard, McGee, Shia, & Hong, 2000).

<u>Hierarchical Linear Modeling</u>

We chose to use a data analysis technique known as hierarchical linear modeling (HLM), which has several advantages over ordinary least squares (OLS) regression, in that it allows analyses to be conducted simultaneously at multiple levels of data. Variables such as teacher effects, class period, and student ability or attitudinal levels can influence individual performance. When using OLS regression model, such variables modify the classroom or teacher-level outcomes, leaving unchanged the distribution of effects among individuals. In OLS analyses, only the intercept of a particular variable changes when predicting scores on a dependent variable.

To combat this problem, HLM uses a random-intercept model where the classroom or teacher-level effects modify both the classroom or teacher-level outcome and how these effects are distributed among individuals. HLM also reduces the chances of making a type I error. Measuring the effect of a variable at the student level ignores the fact that these students are nested within their classroom, resulting in an estimated standard error that is exagerratedly, thus inflating Type I errors (Altkin, Anderson, & Hinde, 1981). HLM also uniquely shows how variables at one level influence relations occurring at another level (Bryk & Raudenbush, 1992).

Results

Overall, 12 hierarchical linear models were produced. Student-level variables included Total IMSR and the five components of the IMSR. Classroom-level variables were coded as dummy variables to compare: 1) treatment vs. control, 2) alternative treatment vs. control, and 3) treatment vs. alternative treatment. Classroom-level variables were included in each model with each student-level variable in separate analyses for both dependent variables. Results for all analysis are included in Table 1.

Overall, results indicated that students in the treatment condition demonstrated significantly more Content Understanding and Problem Solving skill than students in the alternative and control classrooms (p=<.001). Experimental condition did not influence the effect of Total IMSR on Content Understanding or Problem Solving.

In regards to the treatment condition, of the five IMSR components, only Problem Representation was a significant predictor for success at Content Understanding, <u>B=</u>1.446, p=.047. In contrast, within the alternative condition, students' Problem Representation had a significant inverse influence on Content Understanding, <u>B=</u>-.885, p=.042.

In terms of Problem Solving, Knowledge of Cognition and Problem Representation were found to be significant predictors, <u>B=</u>4.363, p=.022 and <u>B=</u>3.847, p=.002 respectively. Though Monitoring abilities yielded a p value of .064, no other level-one variable was found to be significant.

Implications

These findings are especially noteworthy for science education and inquiry-based education. We hypothesized that overall metacognitive self-regulation and its various components would predict success at content understanding and problem solving and that the treatment condition would be more effective in promoting learning outcomes than either the alternative treatment or control conditions.

In particular, our results show that while the use of the software was a significant predictor in all analyses, in some instances metacognitive self-regulatory abilities yielded a higher intercept when predicting scores on the dependent variables. Knowledge of Cognition and Problem Representation lent more contribution to the intercept of gain in Problem Solving skills than did the effect of the software. It could be that such metacognitive self-regulatory skills are so important for individual students that even classroom-level variables such as the type of instruction received did little to take away from this effect.

In retrospect, we realize that two <u>non-significant</u> variables, Subtask Monitoring and Evaluation, may not have been important for either Content Understanding or Problem Solving because the software accomplishes such tasks for the learner (therefore clouding the overall effect). That is, the program breaks down problems into manageable chunks and helps students monitor and evaluate completion of those chunks. This finding is in line with our prior research which demonstrated that well-organized knowledge helps students apply their content understanding in solving novel science problems (Hong, McGee & Howard, 1999).

Knowledge of Cognition was not a predictor for Content Understanding, which is in line with prior research indicating that metacognition was a significant predictor for ill-structured problem solving, but not for well-structured problem solving (Hong, 1998). Problem Representation characterizes self-regulatory processes and, therefore, may be an important factor in predicting both Content Understanding and Problem Solving. Contrary to past research, Objectivity had no effect on the Content Understanding or Problem Solving. We suggest further investigation of the construct to verify its role in the learning process.

From this study it can be concluded that metacognitive and self-regulatory constructs are important in teaching problem solving. Being able to identify and delineate these constructs further should allow our educational research and teacher professional development teams to begin providing teachers with a set of tools and training resources to help them target student self-regulation in their classrooms.

Further, our analyses indicate that the constructs measured by the IMSR are independent, and therefore a student may show preferences or "styles" of metacognitive strengths and weaknesses. If these "styles" can be further understood and delineated, it might be possible to train students to habitually use particular regulatory behaviors.

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Table 1

Dependent Variable: Content Understanding

Monitoring

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-4.909050	3.815124	-1.287	32	0.208
SFL, G01	1.734110	0.358987	4.831	32	0.000
ALT, G02	1.155740	0.553560	2.088	32	0.045
MEANMON, G03	1.510761	1.079218	1.400	32	0.171
For MON slope, B1					
INTRCPT2, G10	-3.847425	2.751821	-1.398	32	0.172
SFL, G11	0.239203	0.257460	0.929	32	0.360
ALT, G12	-0.667177	0.430636	-1.549	32	0.131
MEANMON, G13	1.036966	0.780333	1.329	32	0.193

Objectivity

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	0.188978	2.465531	0.077	32	0.940
SFL, G01	1.759627	0.370861	4.745	32	0.000
ALT, G02	1.453101	0.530861	2.737	32	0.010
MEANOBJ, G03	0.072839	0.768097	0.095	32	0.926
For OBJ slope, B1					
INTRCPT2, G10	0.510136	1.882775	0.271	32	0.788
SFL, G11	-0.021789	0.260317	-0.084	32	0.934
ALT, G12	0.175300	0.365629	0.479	32	0.634
MEANOBJ, G13	-0.234533	0.585522	-0.401	32	0.691

Problem Representation

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-5.222349	2.741995	-1.905	32	0.065
SFL, G01	1.741450	0.345803	5.036	32	0.000
ALT, G02	1.234447	0.500079	2.469	32	0.019

MEANPR, G03	1.446173	0.699901	2.066	32	0.047
For PR slope, B1					
INTRCPT2, G10	-1.207206	2.354632	-0.513	32	0.611
SFL, G11	-0.123104	0.271155	-0.454	32	0.652
ALT, G12	-0.885255	0.419275	-2.111	32	0.042
MEANPR, G13	0.303082	0.604546	0.501	32	0.619

Knowledge of Cognition

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-4.869876	3.986891	-1.221	32	0.231
SFL, G01	1.818807	0.361432	5.032	32	0.000
ALT, G02	1.308773	0.521273	2.511	32	0.018
MEANKC, G03	1.460261	1.098323	1.330	32	0.193
For KC slope, B1					
INTRCPT2, G10	-4.553555	3.555771	-1.281	32	0.210
SFL, G11	0.417643	0.315763	1.323	32	0.196
ALT, G12	-0.312859	0.445340	-0.703	32	0.487
MEANKC, G13	1.200096	0.981385	1.223	32	0.231

Evaluation

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-0.403035	2.793633	-0.144	32	0.887
SFL, G01	1.780474	0.376876	4.724	32	0.000
ALT, G02	1.455396	0.522918	2.783	32	0.009
MEANEV, G03	0.228285	0.769138	0.297	32	0.768
For EV slope, B1					
INTRCPT2, G10	-2.786906	2.078226	-1.341	32	0.190
SFL, G11	0.366829	0.257337	1.425	32	0.164
ALT, G12	-0.017929	0.324394	-0.055	32	0.957
MEANEV, G13	0.713485	0.572524	1.246	32	0.222

IMSR Total

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-5.302700	4.184885	-1.267	32	0.215
SFL, G01	1.790998	0.358959	4.989	32	0.000
ALT, G02	1.267077	0.525256	2.412	32	0.022
MEANIMSR, G03	0.320462	0.233899	1.370	32	0.180
For IMSR slope, B1					
INTRCPT2, G10	-1.458798	0.835305	-1.746	32	0.090
SFL, G11	0.055245	0.067753	0.815	32	0.421
ALT, G12	-0.099846	0.100081	-0.998	32	0.326
MEANIMSR, G13	0.078208	0.046653	1.676	32	0.103

Dependent variable: Problem Solving

Monitoring

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
INTRCPT2, G00	-12.062297	6.466610	-1.865	32	0.071
SFL, G01	2.429504	0.608401	3.993	32	0.000
ALT, G02	0.009511	0.936053	0.010	32	0.992
MEANMON, G03	3.498272	1.829159	1.913	32	0.064
For MON slope, B1					
INTRCPT2, G10	2.150122	5.132644	0.419	32	0.678
SFL, G11	0.314674	0.480440	0.655	32	0.517
ALT, G12	0.670676	0.802395	0.836	32	0.410
MEANMON, G13	-0.527323	1.455362	-0.362	32	0.719

Objectivity

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	2.832060	4.284033	0.661	32	0.513
SFL, G01	2.500947	0.642692	3.891	32	0.001
ALT, G02	0.803968	0.918955	0.875	32	0.388
MEANOBJ, G03	-0.800098	1.334566	-0.600	32	0.553
For OBJ slope, B1					
INTRCPT2, G10	0.304703	3.778080	0.081	32	0.937
SFL, G11	-0.394071	0.527148	-0.748	32	0.460
ALT, G12	-0.616213	0.746763	-0.825	32	0.416
MEANOBJ, G13	0.049581	1.174865	0.042	32	0.967

Problem Representation

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-14.745530	4.371653	-3.373	32	0.002
SFL, G01	2.450103	0.543768	4.506	32	0.000
ALT, G02	0.150663	0.784310	0.192	32	0.849
MEANPR, G03	3.846521	1.114637	3.451	32	0.002
For PR slope, B1					
INTRCPT2, G10	-0.814542	4.342860	-0.188	32	0.853
SFL, G11	0.209900	0.500411	0.419	32	0.677
ALT, G12	-0.430160	0.773570	-0.556	32	0.582
MEANPR, G13	0.331775	1.115005	0.298	32	0.768

Knowledge of Cognition

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-15.526673	6.557085	-2.368	32	0.024
SFL, G01	2.663716	0.592373	4.497	32	0.000
ALT, G02	0.265533	0.851799	0.312	32	0.757
MEANKC, G03	4.363223	1.805930	2.416	32	0.022
For KC slope, B1					
INTRCPT2, G10	3.467956	6.556100	0.529	32	0.600
SFL, G11	0.805975	0.582297	1.384	32	0.176
ALT, G12	0.616278	0.821603	0.750	32	0.459
MEANKC, G13	-0.951491	1.809451	-0.526	32	0.602

Evaluation

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value

For INTRCPT1, B0					
INTRCPT2, G00	-2.968513	4.841117	-0.613	32	0.544
SFL, G01	2.578152	0.650535	3.963	32	0.001
ALT, G02	0.724443	0.902310	0.803	32	0.428
MEANEV, G03	0.895943	1.332981	0.672	32	0.506
For EV slope, B1					
INTRCPT2, G10	3.284108	3.781993	0.868	32	0.392
SFL, G11	-0.171948	0.467285	-0.368	32	0.715
ALT, G12	0.401901	0.587295	0.684	32	0.499
MEANEV, G13	-0.814299	1.041937	-0.782	32	0.440

IMSR Total

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	-13.464994	7.089037	-1.899	32	0.066
SFL, G01	2.560002	0.604966	4.232	32	0.000
ALT, G02	0.285799	0.882948	0.324	32	0.748
MEANIMSR, G03	0.769444	0.396145	1.942	32	0.061
For IMSR slope, B1					
INTRCPT2, G10	-0.307742	1.518043	-0.203	32	0.841
SFL, G11	0.024798	0.122839	0.202	32	0.842
ALT, G12	0.038854	0.181384	0.214	32	0.832
MEANIMSR, G13	0.023471	0.084781	0.277	32	0.784