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Board 333: Metacognitive Intervention to Improve Problem-Solving Skills in First-Year Engineering Students

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Work in Progress: Metacognitive Intervention to Improve Problem Solving Skills in First-Year Engineering Students

Introduction

Engineers are trained to solve problems with different levels of complexity. Jonassen defined problem solving as “a goal-directed sequence of cognitive operations” essential for everyday situations [1-3]. In engineering courses, problem solving is a multi-step process in which students need to understand the problem, determine which equations and principles are necessary to solve the problem, devise a plan to solve the problem, execute the plan, and verify that the solution is correct. Depending on the complexity of the problem, a problem can have one or multiple solutions. Story problems, also known as word problems, are the most common form of problem solving in formal education [2, 3]. Story problems contain a quantitative problem embedded in a narrative or story.

Metacognition refers to the processes used to plan, monitor, and assess understanding and performance. Zimmerman’s self-regulated learning (SRL) model is used as a framework in this study to understand self-regulation and metacognitive monitoring [4-9]. Seminal work has conceptualized metacognition and, in particular, monitoring, to comprise metacognitive knowledge, metacognitive experiences, goals, strategies, and interactions among these four phenomena [10, 11]. In this sense, both SRL and metacognition invoke environmental, personal, and behavioral influences, and learners must effectively regulate the reciprocal relations among these influences [12] to support strategic learning. For example, monitoring learning and performance in a task recruits one’s metacognitive knowledge, which supports the evaluation of their thought processes (personal factors) in relation to a standard (environmental and/or personal factors) [13, 14], and the outcome of such a comparison drives future cognition and behavior related to learning (behavioral factors).

Metacognitive monitoring – defined as a learner’s real-time awareness of their task performance [15] – is included as a component in most models of self-regulated learning, including Zimmerman’s [6, 16]. Research has shown metacognitive monitoring to be linked with higher academic performance and learning during problem-solving [17, 18] and, more generally, the development of domain expertise [19]. A developing body of research has indicated an important role of metacognitive skills and strategies in engineering problem-solving. Some efforts have been made to understand how students judge their learning; prominent findings indicate that a) students are often not very accurate in their monitoring, b) higher-achieving students tend to be underconfident, while lower-achieving students tend to be overconfident, and c) learners may draw on myriad sources when judging their confidence [14, 20]. Yet, the nature of these sources and the explanations learners provide for their metacognitive judgments are still largely not understood. More broadly, efforts to promote students’ metacognition during problem-solving - particularly through prompts to support accurate monitoring - are nascent in engineering education.

This work in progress paper summarizes the implementation of an intervention designed to promote students’ metacognitive monitoring during problem-solving. Specifically, the paper summarizes how metacognitive monitoring was incorporated in a problem-solving and reasoning course to improve students' ability to solve word problems. Implications of this work in the support of students that begin in engineering with deficiencies in math knowledge are discussed. Across two studies, we examined the effects of students' engagement in an introduction to engineering reasoning course on key metacognitive, social-motivational, and problem-solving outcomes based on two comparisons. In the first study (Study 1a), we conducted a between-group comparison based on students who did and did not complete metacognitive monitoring practice as part of the introduction to engineering reasoning course. We used this comparison to examine differences in students' metacognitive monitoring accuracy (as indicated by scores on a measure of calibration bias [21]) and problem-solving performance based on the metacognitive monitoring practice. Study 1a was guided by the following research question:

1a. Do students completing an introduction to engineering reasoning course with metacognitive monitoring practice obtain higher scores on course-embedded measures of metacognitive monitoring and problem-solving?

In the second study (Study 1b), to understand the degree to which the effects of the introduction to engineering reasoning course transferred to students' social-motivational outcomes, we compared students completing the introduction to engineering reasoning course with students (not enrolled in the engineering reasoning course) completing a first-year seminar in engineering. We used this comparison to examine differences in the following outcomes as students completed their first-year engineering coursework: social belonging, help-seeking motives, engineering efficacy, and mathematics efficacy. Study 1b was guided by the following research question:

1b. Do students completing an introduction to engineering reasoning course obtain higher scores on established measures of social belonging, help-seeking, engineering efficacy, and mathematics efficacy?

Study 1a

Method

Participants and Procedures

The study was conducted in a first-year engineering program at a land-grant institution in the Mid-Atlantic region. A total of 89 students (78 males, and 11 females) enrolled in and completed the introduction to engineering reasoning course. These students were enrolled in three course sections. We randomly assigned – at the course section level – one of these three sections (n=32) to a comparison condition; the other two sections (n=57) were assigned to an intervention condition based on strategy prompting and metacognitive monitoring practice. All students were enrolled in their first semester in college and began in engineering at the level of college algebra. Enrollment in the Introduction to Engineering Reasoning course occurred during the new student orientation events that were scheduled during the summer months prior to the beginning of the first school semester.

Metacognitive Intervention

The metacognitive intervention was based on three major components: a conceptual introduction to important concepts related to self-regulated learning, prompting of metacognitive monitoring during problem-solving, and reflection-on-learning activities. The design and implementation of the intervention work was based on Zimmerman's self-regulated learning model and established work prompting and promoting accurate metacognitive monitoring [21]. In the conceptual portion, three lectures were dedicated to introducing students to self-regulated learning, practice retrieval, and metacognition. Next, handouts with word problems were developed for the course to support the development of students' monitoring of and reflect on their problem-solving performance. Learning strategy prompts were embedded in these handouts and were designed to elicit students' judgments of confidence about their performance on each word problem, identification of specific questions students had about components of the problems, and reflection on the utility of specific problem concepts (e.g., the use of quadratic equations) in supporting their future work as an engineer. Students in the comparison condition were provided with handouts that sequenced the components of each word problem but did not contain the learning strategy prompts.

Materials and Measures

Problem solving. Students problem-solving performance was assessed using a word problem included in the final examination in the course. The following word problem was implemented:

> For a chemical reactor with a rectangular base, Torricelli's Law implies that the height h of a liquid in the reactor t second after it begins draining is given by:
>
> $$h = \left(\sqrt{h_o} - \frac{2\pi d^2\sqrt{3}}{lw}\, t\right)^2$$
>
> where l and w are the reactor's length and width, d is the diameter of the drain, and h_o is the liquid's initial height (all measurements in inches). You completely fill a reactor with the liquid.
>
> The reactor is 60 inches long and 30 inches wide by 25 inches in height and has a drain with a two-inch diameter. Find the time it takes for the reactor to go from being full to half-full. Find the time it takes for the reactor to go from being half-full to empty.

Students' performance on the word problem was assessed using an established grading scheme based on a total of three points (ranging from 0 to 3 points in half-point increments). This problem was selected as the focus of the present study because it represents a level of complexity that requires the use of multiple concepts learned in students' algebra-level coursework (e.g., rational expressions, radical expressions, quadratics).

Metacognitive monitoring. We obtained a metacognitive judgment of performance from students on the word problem and used this judgment to compute a measure of metacognitive monitoring accuracy. Specifically, students were provided with a confidence judgment based on the following: "How confident are you that you identified the correct time it takes for the reactor to go from being full to half-full? Draw a slash (/) through the line below to indicate your level of confidence.". Students were provided with a continuous scale ranging from *0-Not at all confident* to *100-Completely confident* to support their metacognitive judgments. Students' metacognitive judgments and performance on the word problem were converted to a decimal to facilitate the calculation of metacognitive monitoring accuracy. We computed calibration bias based on these judgments. The measure of calibration bias describes the direction and degree of students' error in judging their performance during problem-solving. Specifically, calibration bias was obtained by taking the signed difference between the average confidence judgment and actual performance on each item. Based on the measure, positive values indicated overconfidence while negative values indicated underconfidence [21, 22]. Values that approach zero (0) indicate metacognitive judgments that are accurate; that is, values that are calibrated with students' actual performance on the word problem. Values that approach ±1.00 indicate judgments that increasingly differ from students' problem-solving performance.

To describe and summarize students' metacognitive monitoring accuracy across the comparison and intervention conditions, we also categorized students' metacognitive monitoring accuracy based on three levels: inaccurate, somewhat accurate, and accurate using the absolute accuracy index. Absolute accuracy was obtained by taking the absolute value of the difference between the confidence judgment students provided on the word problem and their actual performance on the problem [22]. Absolute accuracy ranges from 0.00 to 1.00 and provides an assessment of students' precision in their metacognitive judgments. Using this index, we defined inaccurate, somewhat accurate, and accurate monitoring as follows: the confidence judgment expressed by the student was considered to be "accurate" if the judgment was close (within 25%) to the actual score obtained in the problem, "somewhat inaccurate" if the judgment was between 25% and 50% of the score obtained in the problem, and "inaccurate" if it was more than 50% off from the correct estimate.

Results

We first summarize students' metacognitive monitoring accuracy in terms of levels and based on whether students did or did not complete the metacognitive monitoring practice. As shown in Table 1, for that problem analyzed, most of the students in the group that received the metacognitive intervention (63.2% of the students) were "accurate" at predicting the accuracy of their solution, versus 37.5% of the students enrolled in the control group. Students that were trained on metacognition and self-regulation showed a better calibration in comparison with those students that were not trained on metacognition.

Table 1. Descriptive summary of students' metacognitive monitoring accuracy by condition

Metacognitive Judgement Accuracy	**% of students in Control Group n=32**	**% of students in Experimental Group n=57**
Accurate	37.5	63.2
Somewhat Accurate	25.0	21.1
Inaccurate	37.5	15.8

Additionally, a higher percentage of the students enrolled in the experimental group passed their college-level algebra class with a grade of C or better in the course, in comparison with the students enrolled in the control group.

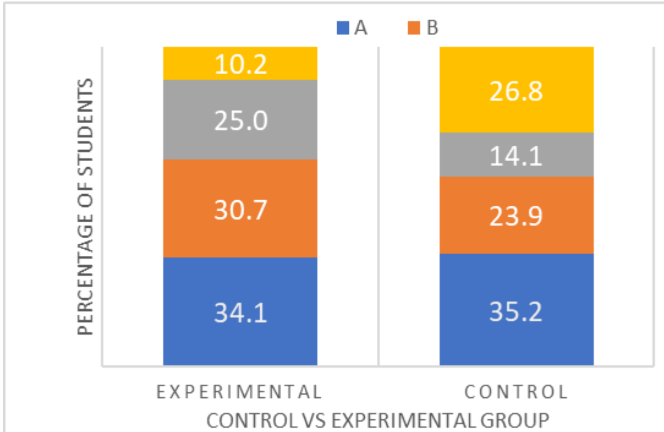

Figure 1. Distribution of grades in the mathematics course (college-level algebra) for the control and experimental groups (yellow: DFW)

In primary analysis, we implemented Bayesian methods to afford direct interpretation of the degree of support for the course in promoting students' metacognitive and problem-solving outcomes. Analyses were conducted using JASP (JASP Team, 2024). We implemented diffuse priors in model estimation. We report Bayes factor estimates as a relative measure of evidence supporting course effects (i.e., $BF_{10}>1.00$); we examine parameter estimates using the mean of the posterior distributions for the parameters we tested. We report and interpret 95% credibility intervals to demonstrate the range of values for the effects of the introduction to engineering reasoning course to further support inference about the significance of these effects [23].

To address the aim of Study 1b, we conducted Bayesian analysis of covariance to examine the effect of the introduction to engineering reasoning course on students' metacognitive monitoring accuracy and problem-solving performance. We conducted two models: in the first model, we examined differences in students' metacognitive monitoring accuracy – via calibration bias – on the word problem controlling for students' engineering efficacy and their problem-solving performance; in the second model, we examined differences in students' performance on the word problem controlling for their engineering efficacy and their average metacognitive monitoring accuracy.

Table 2. Descriptive statistics based on metacognitive and problem-solving outcomes

Measure	*M*	*SD*	*d*
Problem-solving performance			
ENGR 151: Comparison group	1.20	1.33	0.21
ENGR 151: Intervention group	1.47	1.28	
Metacognitive monitoring			
ENGR 151: Comparison group	-0.13	0.34	0.56
ENGR 151: Intervention group	0.05	0.30	

Note. *M*=mean. *SD*=standard. *d*=Cohen's *d* as a measure of effect size.

In the first model, students completing the metacognitive monitoring practice obtained scores on the measure of metacognitive monitoring that were more accurate (i.e., approached zero) and differed significantly from students who did not complete the monitoring practice. Compared with a null model that included both engineering efficacy and students' problem-solving performance as covariates, moderate evidence was obtained supporting the effect on students' calibration bias (BF=5.07). The effect of the course on students' metacognitive monitoring accuracy, based on the posterior mean, was 0.09 (95% CI: 0.02, 0.15). The model averaged R^2 was 0.15 (95% CI: 0.04, 0.27), indicating that the model explained moderate variance in students' metacognitive monitoring accuracy.

In the second model, students completing the metacognitive monitoring practice obtained higher scores on the problem assessing understanding of fluid dynamics. Compared with a null model that included both engineering efficacy and students' average metacognitive monitoring accuracy as covariates, moderate evidence was obtained supporting the effect on students' performance on the word problem (BF=4.89). The effect of the course on students' problem-solving performance, based on the posterior mean, was 0.33 (95% CI: 0.05, 0.61). The model averaged R^2 was 0.22 (95% CI: 0.09, 0.36), indicating that the model explained moderate variance in students' metacognitive monitoring accuracy.

Study 1b

Method

Participants and Procedures

To understand the effects of the introduction to engineering reasoning course on students' social-motivational outcomes, we compared all students completing the course with students completing a first-year seminar in engineering at West Virginia University. To do so, we matched students on measures of prior academic achievement (i.e., high school GPA, ACT/SAT scores), enrollment in an algebra-level mathematics course, and key demographic characteristics (i.e., gender and first-generation status). Students in both the introduction to engineering reasoning course and the first-year seminar completed the measures of social belonging, help-seeking motives, and engineering and mathematics efficacy at the conclusion of the fall, 2023 semester.

We matched students completing the same introduction to engineering course (from Study 1a) with students from a larger sample (N=637) that completed a general first-year seminar in engineering. We implemented propensity score matching, using priority for exact matches and a match tolerance of 0.01, to identify a close comparison sample of first-year engineering students. Based on the measures of prior academic achievement, enrollment in an algebra-level mathematics course, and select demographic characteristics, we identified a comparison sample of 68 first-year engineering students. The total analytic sample for Study 1a was 175; 107 students represented those completing the introduction to engineering reasoning course and 68 students represented the matched subsample. Based on the analytic sample, there were no differences in prior academic achievement, students' identification as low-income or a first-generation student, gender, or rates of algebra-level mathematics coursework based on whether students were or were not enrolled in the introduction to engineering reasoning course.

Using this comparison sample, we examined differences in students' end-of-semester social belonging, help-seeking, engineering efficacy, and mathematics efficacy based on their enrollment in the introduction to engineering reasoning course. Institutional review board approval was obtained for the study; ethical standards and principles as governed by the American Psychological Association were followed across study implementation.

Course Design and Implementation

The introduction to engineering reasoning course was developed with the support of an NSF IUSE grant (Award # 2236126). Components of the "Introduction to Engineering Reasoning" course have been summarized in previous publications [24-26]. The course is taught using the Paul-Elder framework of critical thinking. The course has a strong problem-solving component and each week students are introduced to engineering concepts that are associated with the topics discussed in their math course. The course is taught using problem-based learning.

Materials and Measures

Social belonging. We implemented four items assessing students' perceptions of their social belonging based on established work [27]. The items were applied to students' intended major in engineering (e.g. "I feel accepted in engineering"). Scores on the measure of social belonging demonstrated adequate internal consistency reliability based on McDonald's ω (ω=0.90).

Help-seeking motives. We administered seven items that assessed students' help-seeking motives [28]. The items were implemented using a 5-point scale (*1-Strongly disagree* to *5-Strongly agree*) and assessed both approach (e.g., "*If I needed help in my science classes, I would ask someone for assistance.*") and avoid (e.g., "*If I didn't understand something in my science classes, I would guess rather than ask someone for assistance.*") motives for seeking help. Items were contextualized to engineering and mathematics coursework. Items measuring help-seeking avoidance were reverse-coded prior to analysis. Scores on the measure of help-seeking motives demonstrated adequate reliability (ω=0.77).

Engineering efficacy. Six items assessed students' general engineering self-efficacy based on the work of Mamaril and colleagues [29]. Consistent with prior use of the scale, the items assessed students' perceived capability to master the content and coursework in engineering. Scores on the scale demonstrated adequate reliability (ω=0.94).

Mathematics efficacy. Adapted from the measure of general engineering self-efficacy, we assessed students' general mathematics efficacy using the item structure and approach in Mamaril and colleagues [29]. The items assessed students' perceived capability to master content and coursework in applied mathematics. Scores on the scale likewise demonstrated adequate reliability (ω=0.88).

Results

The overall analytical approach implemented in Study 1b was the same as that implemented in Study 1a. Specifically, to address the aim of Study 1b, we conducted Bayesian *t*-tests on each of the social-motivational outcomes: social belonging, help-seeking motives, and engineering and mathematics efficacy. Students completing the introduction to engineering reasoning course obtained higher scores on the measures of engineering efficacy (BF=2.37) and mathematics efficacy (BF=3.24) than students in the first-year seminar; analysis of Bayes factor robustness indicated moderate support for the effect of the introduction to engineering reasoning course in both models. Enrollment in the introduction to engineering reasoning course explained a small amount of the variance in engineering (*d*=0.36) and mathematics (*d*=0.39) efficacy. Effects of the course on students' social belonging and help-seeking were not observed, BF<1.00.

Table 3. Descriptive statistics for post-survey social-motivational outcomes

Measure	*M*	*SD*	*d*	*ω* 95% CI
Social belonging				
Comparison group	3.79	0.81	0.13	0.90 (0.87, 0.93)
ENGR 151	3.90	0.89		
Help-seeking motives				
Comparison group	3.68	0.76	0.26	0.77 (0.70, 0.83)
ENGR 151	3.87	0.73		
Engineering efficacy				
Comparison group	3.94	0.82	0.36	0.94 (0.92, 0.95)
ENGR 151	4.24	0.81		
Mathematics efficacy				
Comparison group	3.81	0.85	0.39	0.88 (0.85, 0.92)
ENGR 151	4.11	0.72		

Note. *M*=mean. *SD*=standard. *d*=Cohen's *d* as a measure of effect size. ω=McDonald's omega as an estimate of internal consistency reliability for each measure. 95% CI: 95% credible interval for the estimate of reliability.

Discussion

In the present work, we sought to examine the effects of a metacognitive monitoring intervention - embedded in an introduction to engineering reasoning course designed for non-calculus ready students - on students' metacognitive, social-motivational, and problem-solving outcomes. Students completing the metacognitive monitoring intervention in the course obtained more accurate estimates of metacognitive monitoring on an open word problem assessing knowledge of fluid dynamics. They also obtained higher scores, indicating stronger performance, on this problem implemented at the end of the course. These findings provide initial evidence of the possible benefits of incorporating structured opportunities for students to monitor their problem-solving performance.

We also examined the degree to which completion of the introduction to engineering reasoning course transferred to select social-behavioral outcomes in engineering. More broadly, students who completed the course also reported higher engineering and mathematics efficacy at the conclusion of the semester compared with students in a general first-semester engineering seminar. End-of-semester differences were not observed on measures of social belonging and help-seeking, suggesting specific effects of the problem-solving and metacognitive monitoring activities implemented in the course on the promotion of students' efficacy beliefs. Overall, the findings of this in-progress work suggest that an embedded and sequenced intervention designed to scaffold first-year engineering students' metacognition during problem-solving may promote shorter-term improvements in their monitoring and efficacy-related skills and beliefs. Existing research has demonstrated the importance of these skills in promoting longer-term achievement, persistence, and success in engineering. At the same time, existing work has documented the challenges associated with promoting students' metacognition in authentic and problem-based contexts [30].

Monitoring processes in metacognition have typically been examined using confidence ratings. Students rely on confidence judgments to determine if they want to double check a problem in an exam or to move on to the next problem. Therefore, proper metacognitive judgment is essential to support student success in problem solving, which is an important component of the training received by engineers.

Conclusion

To be a self-regulated learner, students must make proper and accurate judgments of their learning. Students must also use that information to make meaningful decisions about how to proceed when they are solving problems. This project shows that it is possible to improve students' metacognitive monitoring and performance during problem-solving and, in particular, in their work with open and complex problems. It also demonstrates the potential for curricula focused on engineering reasoning to promote stronger perceptions of efficacy in both engineering and mathematics, particularly among students who may be under-prepared for and are often under-represented in engineering.

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