

WIP: Students' metacognition and how it relates to their performance in conceptual problem-solving introductory Engineering courses.

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1 Introduction

Metacognition refers to the self-regulation process that learners can use to measure their own understanding and, thus, how effectively they are studying. Researchers have identified two levels of metacognition: knowledge and regulation. The level of Knowledge entails knowing facts about oneself and the demands of the task, procedural knowledge on strategies pertaining to the task, and knowing which strategies to apply in different situations. Regulation refers to students' ability to plan, monitor, and evaluate the effectiveness of their strategies as well as debug when facing difficulties[4, 11].

Metacognition skills have been shown to help students perform better academically[2, 3, 5, 6]. Moreover, lack of metacognitive knowledge has been shown to negatively impacts students' affect as well as harm the behaviors that impact their learning [5]. Yet instructors do not habitually refer to metacognitive skills to ensure that students develop them and researchers have been calling for more to be done to make students aware of these skills[5].

Recently, researchers found that it is possible to encourage improvements in student metacognition [9]. They measured students' metacognition using the Metacognitive Awareness Inventory (MAI), an instrument which was originally developed by Schraw and Dennison[11]. They found that students' scores on the instrument improved from the beginning of the semester to the end. These were students in their Junior year in an Engineering design course. In this paper, we ask whether these findings can be extended to first and second year students in required courses for their Engineering major: Discrete Math and Analog Signal Processing. We focus on these conceptual problem-solving required courses because they require new study strategies that students are not familiar with and often struggle with. We hypothesize that metacognitive skills would be particularly important for their success in these courses. To our knowledge, no work has been done on these courses, with most metacognitive work either focusing on non major CS programming courses, Eng 100 intro courses, or upper level design courses [1, 5, 7–10].

This paper also begin to explore what it takes to induce student improvement in metacognitive awareness. Is it enough to have the instructor introduce these skills in lecture? Or

do students need to spend more time on it by explicitly working on these skills in assignments [5, 9]. Instructors and students in required courses are often pressed for time and cannot add more assignments. Pushing these assignments to other courses such as ENG 100 often do not deal with the kind of metacognitive skills that are specifically needed for conceptual problem-solving courses such as the ones we study. Therefore, there is a clear advantage to have the instructor introduce metacognitive skills in the course and demonstrate which one they are using as they are solving problems. It is an open question whether this would be sufficient.

Our ultimate goal is to help students improve their metacognitive skills and, ultimately, improve their learning and course performance. In order to do that effectively, we need to establish if there are skills that students are more aware of and if there are skills that contribute more towards course performance. Prior work began to explore this and indicated that metacognitive regulation rather than metacognitive knowledge significantly related to high school students' and Eng 100 students' academic performance [1, 12]. In this paper we ask whether the same or different skills contribute to the performance of college students in our conceptual problem-solving courses.

Finally, we acknowledge that our courses comprise of different populations of students and that not all students enter university with the same preparation. It is possible that this also drives differences in students' metacognitive awareness. The Discrete Structures CS course in particular has vast population differences. It has students from the college of Engineering and from the college of Liberal Arts and Sciences. Therefore it is important to consider potential differences in population in our investigation.

We identified the following research questions:

RQ1: To what extent do we see improvement of metacognitive skills in courses that explicitly cover metacognitive strategies?

RQ2: In our classes, what do students report on the MAI and are there metrics where students are stronger or weaker?

RQ3: How does their self-assessment on the MAI correlate with course performance in our conceptual problem solving courses and which metrics contribute to course outcomes?

RQ4: Are there differences between the courses and groups of students with different preparations in their reports on the shortened MAI?

We surveyed students at the beginning and end of the semester, in two introductory Engineering courses that deal with conceptual problem solving: Discrete Math and Analog Signal Processing, first and second year required major courses in the School of Engineering at a large state University. We used a shortened version of the Metacognitive Awareness Inventory (MAI) originally developed by Schraw and Dennison[11]. The shortened version was developed by Harrison and Vallin[4] and assesses students along two dimensions: knowledge of cognition and regulation of cognition. Additionally, we introduced metacognitive strategies in our courses. The introduction was done in the lecture where metacognition strategies and metacognition regulation were discussed with students. The instructors reinforced these

strategies in lectures throughout the semester to remind students of the concepts and model the behaviors.

2 Methods

During Fall 2024 we surveyed over 1000 students in Discrete Math and Analog Signal Processing, first and second year courses in the School of Engineering at a large state University. We surveyed students using the shortened version of the Metacognitive Awareness Inventory (MAI) on metacognitive aspects such as declarative knowledge, procedural knowledge, conditional knowledge, planning, information management strategies, monitoring, evaluation, and debugging strategies. We surveyed students twice, once at the beginning of the semester, and once at the end of the semester. The instructors introduced the metacognitive measures that are included in our survey to the students.

2.1 The Courses

The Discrete Math course (CS) is a required course for Computer Science (CS) majors and CS+X majors. It has enrollment of many non-majors who are trying to switch into CS and is offered in both Fall and Spring. It is taken mainly by first year or second year students. The goal of the course is to introduce students to discrete mathematical structures frequently encountered in the study of Computer Science: sets, propositions, Boolean algebra, induction, recursion, relations, functions, and graphs.

The Analog Signal Processing course (ECE) is a required course for both electrical engineering and computer engineering majors. It is taken mainly by second year students and is offered in both Fall and Spring. The goal of the course is to introduce fundamentals of analog signal processing, with major emphasis on circuit analysis, differential equations, convolutions, Fourier methods, and applications in filtering and AM radio.

Both courses require conceptual understanding of the material which comes from an understanding of the material rather than rote memorization. The learning objectives of the courses expect students to solve problems that might be different in surface features from those they saw in practice, but share an underlying conceptual similarity. Successful students gain understanding through engaging with the problem solving process by working out many examples.

2.2 Participants

All students were asked to volunteer and answer two surveys during the semester, at the beginning and at the end. Students were given course credit for filling out the survey, regardless of whether or not they consented to their answers being used for the study. Both times students filled out the shortened Metacognitive Awareness Inventory[4, 11]. Only students who filled out the survey both times and consented to be included in the study were included. In Analog Signal Processing course (ECE), 195 students participated in the study out of the 386 students enrolled in the class. In Discrete Math (CS) 289 students

participated in the study out of 606 students in the class. In Discrete Math (CS) 399 students completed the survey at the end of the semester but not all of them completed the survey at the beginning of the semester.

2.3 The survey

The survey included 19 questions from the shortened Metacognitive Awareness Inventory[4, 11]. Students were asked to mark True or False for each of the questions. We assigned a score of 1 to students who responded True and 0 to students who responded False. We averaged the responses to all questions within one of the 8 categories described below. For example, the Declarative Knowledge category included the average of the scores over 4 questions, whereas the Monitoring category included the score of a single question.

- **Declarative knowledge (DK)** measures knowledge related to understanding oneself as a learner and what material needs to be learned.
 - I know what kind of information is most important to learn.
 - I know what the teacher expects me to learn.
 - I have control over how well I learn.
 - I am a good judge of how well I understand something.
- **Procedural knowledge (PK)** measures knowledge of strategies for studying and when to use them.
 - I am aware of what strategies I use when I study.
 - I find myself using helpful learning strategies automatically.
- **Conditional knowledge (CK)** measures knowledge of effective strategies for studying.
 - I can motivate myself to learn when I need to.
 - I know when each strategy I use will be most effective.
- **Planning (P)** measures knowledge of the importance of creating goals when studying
 - I think about what I really need to learn before I begin a task.
 - I set specific goals before I begin a task.
- **Information Management Strategies (IMS)** measures knowledge of the importance of processing information.
 - I try to translate new information into my own words.
 - I use the organizational structure of the text to help me learn.
 - I ask myself if what I'm reading is related to what I already know.

- **Monitoring (M)** measures knowledge of the importance of making connections between different concepts.
 - I periodically review to help me understand important relationships.
- **Evaluation (E)** measures awareness of the importance of evaluating one’s understanding.
 - I summarize what I’ve learned after I finish.
 - I ask myself if I learned as much as I could have once I finish a task.
- **Debugging strategies (DS)** measures knowledge of what to do to overcome obstacles in learning.
 - I change strategies when I fail to understand.
 - I reevaluate my assumptions when I get confused.
 - I stop and go back over new information that is not clear.

In our analysis, we also consider students’ Final Grade, which is the final calculated percent score that students were assigned at the end of the semester.

2.4 Introduction of Metacognitive Strategies

The instructors introduced the metacognitive measures that are included in our survey. They introduced these strategies at the beginning of the semester when the aggregated results of the first survey were presented. The instructors reinforced these strategies in lectures throughout the semester to remind students of the concepts and model the behaviors.

2.5 Data Analysis

We conducted a statistical analysis on the quantitative measures in our data set. We conducted a paired t-test between the scores of each student to the first and second survey to measure whether there was a change in students’ responses. To measure the contribution of each of the metacognitive categories towards final grades in each course, we fit an ordinary least squares (OLS) model. Additionally, the data was split into two sub-groups for comparison. A Mann-Whitney U test conducted to analyze the differences between the two sub-groups of students and a p-value cutoff of 0.05 was chosen as a cutoff for statistical significance. Calculations were carried out in a Jupyter Notebook using Python code and statistics were calculated using the package `scipy.stats`.

3 Results and Discussion

3.1 RQ1 and RQ2: Strong and Weak Metacognitive Skills

Towards RQ1, we wanted to know whether introducing students to metacognitive skills during lecture would help students increase their metacognitive awareness. As seen in Table 1,

Course	Survey	DK	PK	CK	P	IMS	M	E	DS
CS	1	.85	.79	.74	.71	0.83	.71	.59	.93
	2	.85	.82	.75	.75	0.86	.66	.63	.91
ECE	1	.90	.83	.77	.71	0.81	.74	.62	.92
	2	.91	.82	.78	.76	0.79	.73	.66	.89

Table 1: Average means for each category per course per survey. A score is marked with * if $p < .05$ for a paired T-test between the scores of Survey 1 and 2.

there was no difference for either course between Survey 1, which students answered at the beginning of the semester, and Survey 2, which they answered at the end of the semester, with the same list of questions. This suggests that introducing students to metacognitive skills during lecture as we did in our courses might not be sufficient in getting them to become more aware of metacognitive skills and more needs to be done.

Another possible interpretation for these results is that perhaps some of our students did improve but not all of them which results in insignificant differences. We reasoned that students who did well in the course might have also shown increases in their metacognitive scores. We divided the students into two groups, those who scored higher than average in their final grades and those who scored below the mean. Conducting the same analysis for a group of students whose final grade is above the mean, did not yield any significant differences between the two surveys. Similarly, there was no difference for the students who were below the mean in their final grades. In future work we will study whether there are other factors beyond final grades that yield improvement in metacognitive scores.

Could it be that students were already at ceiling in their answers to Survey 1 and there was not much room for improvement? As seen in Table 1, the scores of students are not at 100% indicating that there is some room for improvement. However, if we consider metacognitive scores that students received in prior work in the literature when completing the MAI, where students increased from one survey to the next, for example in [9], we see that students started out with a score of 75% on the MAI and ended up with a score of 85% on average. Our students received a score of 80 on the MAI in both classes on average, so it is possible that they are close to ceiling.

Still, it is possible that doing more instruction on metacognitive skills than was done in our courses could lead to getting students to improve their metacognitive scores. We plan to explore this in future work. Given that instructors have limited time, it is essential to know which are the metacognitive scores that are most essential to focus on in more detail. There are two ways to approach this. First, towards RQ2, we want to know which are the skills that students score lower on and which are the skills that they score high on. Instructors can choose to focus on skills students lack. As seen in Table 1, students averaged about .80 on most metacognitive categories. They scored highest on Declarative knowledge (DK) which measures knowledge related to understanding oneself as a learner and what material needs to be learned, and Debugging strategies (DS), which measures knowledge of what to do to overcome obstacles in learning. Students scored lowest on Monitoring (M), which measures knowledge of the importance of making connections between different

Course	Grade Group	DK	PK	CK	P	IMS	M	E	DS
CS	High	.88*	.81	.77	.73	.86	.65	.62	.92
	Low	.80	.83	.71	.76	.84	.67	.65	.88
ECE	High	.93*	.86*	.81	.75	.81	.77	.63	.90
	Low	.88	.77	.73	.77	.76	.69	.71	.88

Table 2: Average means for each category per course for Survey 2. A score is marked with * if $p < .05$ for Mann-Whitney U test between the group of students with final grades above the mean (High) and below the mean (Low) for that course

concepts, and Evaluation (E), which measures awareness of the importance of evaluating one’s understanding. This suggests that students either don’t understand the importance of Monitoring and Evaluating or don’t readily know how to implement these skills.

These results are different from prior work which found that students were low on the Knowledge categories such as DK and were higher on Regulation categories [1, 8]. This suggests that it is important to examine metacognition in different settings and in different student populations.

In the future, we plan to explore if the instructor focuses on M and E could result in improvement in these measures. But before concluding that these skills are essential to spend time on, we want to explore, towards RQ3, which skills contribute towards high final grades.

3.2 RQ3: Metacognitive Skills Contributing to Final Grades

Given that previous work demonstrates the important role metacognition plays in course performance, towards RQ3, we wanted to understand which measures contributed to better course performance.

To measure the contribution of each of the metacognitive category towards final grades in each course, we fit an ordinary least squares (OLS) model of the form

$$f_i = \beta_0 DK_i + \beta_1 PK_i + \beta_2 CK_i + \beta_3 P_i + \beta_4 IMS_i + \beta_5 M_i + \beta_6 E_i + \beta_7 DS_i,$$

where f_i is the final grade for student i , X_i is the score for metacognitive category X for student i . As Figures 1 and 2 show, DK, P and DS contribute to final grades in the CS course but not in the ECE course.

In order to understand these contributions better, we split the students into two groups: high grades (above the mean) and low grades (below the mean). We compared the scores of the two groups on each of the metacognitive categories. As predicted by our model, we found that there was a significant difference between the high grade group and low grade group in their metacognitive awareness in the Declarative Knowledge (DK) category for both CS and ECE courses, see Table 2.

This suggests that instructors might do well in focusing on introducing Declarative knowledge (DK) skills and making sure that students work on these skills for the CS and ECE courses.

Dep. Variable:	finalgrades	R-squared:	0.090
Model:	OLS	Adj. R-squared:	0.064
Method:	Least Squares	F-statistic:	3.452
Date:	Thu, 02 Jan 2025	Prob (F-statistic):	0.000823
Time:	14:17:27	Log-Likelihood:	-1062.8
No. Observations:	289	AIC:	2144.
Df Residuals:	280	BIC:	2177.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	76.9305	2.915	26.395	0.000	71.193	82.668
DK	6.8781	2.650	2.595	0.010	1.661	12.095
PK	-3.3657	2.185	-1.540	0.125	-7.667	0.935
CK	4.4634	2.366	1.886	0.060	-0.195	9.121
P	-4.0348	1.825	-2.211	0.028	-7.628	-0.442
IMS	-1.7384	2.840	-0.612	0.541	-7.329	3.852
M	-0.4348	1.428	-0.304	0.761	-3.247	2.377
E	-1.0090	1.759	-0.574	0.567	-4.471	2.453
DS	7.5879	3.160	2.401	0.017	1.367	13.809

Omnibus:	118.111	Durbin-Watson:	2.134
Prob(Omnibus):	0.000	Jarque-Bera (JB):	577.205
Skew:	-1.632	Prob(JB):	4.59e-126
Kurtosis:	9.106	Cond. No.	16.2

Figure 1: CS

Dep. Variable:	finalgrades	R-squared:	0.063			
Model:	OLS	Adj. R-squared:	0.023			
Method:	Least Squares	F-statistic:	1.574			
Date:	Thu, 02 Jan 2025	Prob (F-statistic):	0.135			
Time:	14:18:01	Log-Likelihood:	-746.80			
No. Observations:	195	AIC:	1512.			
Df Residuals:	186	BIC:	1541.			
Df Model:	8					
Covariance Type:	nonrobust					
	coef	std err	t	P> t 	[0.025	0.975]
Intercept	73.9766	4.796	15.424	0.000	64.515	83.438
DK	5.0902	5.180	0.983	0.327	-5.129	15.310
PK	3.3104	3.153	1.050	0.295	-2.910	9.531
CK	3.1703	3.058	1.037	0.301	-2.862	9.203
P	-3.4385	2.774	-1.240	0.217	-8.911	2.034
IMS	3.2330	3.591	0.900	0.369	-3.851	10.318
M	1.3422	2.124	0.632	0.528	-2.848	5.533
E	-4.3891	2.337	-1.878	0.062	-8.999	0.221
DS	-1.9164	4.066	-0.471	0.638	-9.939	6.106
Omnibus:	17.274	Durbin-Watson:	2.038			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	19.390			
Skew:	-0.763	Prob(JB):	6.16e-05			
Kurtosis:	3.238	Cond. No.	19.9			

Figure 2: ECE

These findings are counter to previous work where knowledge skills did not contribute to better exam scores[1]. In future work, we plan to explore whether these skills are particularly important to these conceptual problem solving courses or perhaps a population of students in required courses for their majors are more readily aware of certain metacognitive skills.

3.3 RQ4: Differences in Student Populations in Their Metacognitive Skills

We acknowledge that our courses comprise of different populations of students and that not all students enter university with the same preparation. It is possible that this also drives differences in students' metacognitive awareness. The Discrete Structures CS course in particular has vast population differences. It has students from the college of Engineering and from the college of Liberal Arts and Sciences. Therefore it is important to consider potential differences in population in our investigation.

In order to expand our population so that we have the most number of students, we included all students who consented to participate and filled out Survey 2, resulting in 399 students.

As shown in Table 3, there was no difference in final grades nor the scores of any of the metacognitive categories between females and males. There was a difference in grades between the Engineering (Eng) students and the College of Liberal Arts and Sciences students,

group	n	grade	DK	PK	CK	P	IMS	M	E	DS
F	103	83	.87	.83	.74	.75	.85	.66	.66	.90
M	296	85	.84	.80	.77	.76	.85	.70	.63	.91
Eng	232	86*	.86	.80	.78	.77	.85	.70	.62	.91
LAS	115	83	.83	.82	.75	.77	.86	.69	.71*	.89

Table 3: CS. Average means for each category for Survey 2. A score is marked with * if $p < .05$ for Mann-Whitney U test between the group of students Female (F) and Male (M) and between those in the College of Engineering (Eng) and College of Liberal Arts and Sciences (LAS).

but only a significant difference in the Evaluating category. This suggests that these differences in students populations do not contribute in a major way to differences in metacognitive skills.

As shown in Table 4, there are differences between the two groups of students that came in with different preparation. One group consists of students (J1) who entered the university and had sufficient AP credits to be considered Junior Standing and also were able to place out of CS1 prerequisites in order to take Data Structures in their first semester. This group is in the top row of Table 4. Another group of students (S3) at the bottom row of Table 4 are students who entered the university with Freshmen Standing and were not ready to take the Data Structures course until their first semester of their second year. As shown in the table, the group of the bottom row, S3 had significantly lower grades as well as lower scores on several of the metacognitive categories that our model found contributed to grades: DK, CK, and DS. The J1 group in the top row, had scores in the Monitoring category that were higher than all the other groups. They reported that they periodically review to help them understand important relationships more than the rest. This seems like a more sophisticated metacognitive skill. The other groups of students J3 and S1 in the middle and third row are somewhere in between the extreme groups in terms of their grades and scores. This suggests that having the preparation that the J1 group has also affords them with metacognitive skills that contribute to their success. This further demonstrates the importance of helping all groups of students learn metacognitive skills as they enter college.

4 Conclusions

Overall, students scored about 80% on the MAI. This indicates that students are metacognitively aware. We found that students scored highest on Declarative knowledge (DK) which measures knowledge related to understanding oneself as a learner and what material needs to be learned, and Debugging strategies (DS) which measures knowledge of what to do to overcome obstacles in learning. Students scored lowest on Monitoring (M) which measures knowledge of the importance of making connections between different concepts, and Evaluation (E) which measures awareness of the importance of evaluating one’s understanding. This suggests that students either don’t understand the importance of Monitoring and Evaluating or don’t readily know how to use implement these skills.

Semesters	Standing	n	grade	DK	PK	CK	P	IMS	M	E	DS
1	Junior	39	91	.90	.82	.82	.83	.86	.90*	.72	.97
3	Junior	118	85	.86	.81	.76	.77	.86	.65	.62	.91
1	Sophomore	72	.90	.87	.81	.81	.72	.85	.65	.61	.93
3	Sophomore	73	81*	.77*	.76	.70*	.71	.80	.60	.65	.83*

Table 4: CS. Average means for each category per course per survey, a score is marked with * if $p < .10$, and ** if $p < .05$ for Mann-Whitney U test between the group of students. Semester refers to the number of semesters they are in college when taking the course. Standing refers to the amount of credit they have. So in the top row, Semester 1 and Junior Standing (J1), means the student just entered college in Fall 2024 and had enough credit to be considered a Junior. In the bottom row, Semester 3 and Sophomore Standing (S3), means the student is currently in their second year and when they entered the previous year they did not have extra credits and entered with Freshmen Standing

However, students did not significantly improve from the beginning of the semester to the end of the semester. This suggests that introducing students to metacognitive skills during lecture as we did in our courses might not be sufficient in getting them to become more aware of metacognitive skills and more needs to be done. It is also possible they might have overestimated their self-regulation abilities or were already at the ceiling for some measures.

We found that Declarative knowledge (DK) skills contribute to final grades. This suggests that instructors might do well in focusing on introducing Declarative knowledge (DK) skills and making sure that students work on these skills for our CS and ECE courses. This result is different than what was found in prior work where knowledge skills did not contribute to exam scores. In future work, we plan to explore whether these skills are particularly important to these conceptual problem solving courses or perhaps a population of students in required courses for their majors are more readily aware of certain metacognitive skills. We plan to use this to design future interventions specifically tailored to our courses. We found that the preparation of some students before they enter university also affords them with metacognitive skills that contribute to their success. This further demonstrates the importance of helping all groups of students learn metacognitive skills as they enter college. Our future work is also planned to explore ways to design interventions that help students with different levels of preparation.

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