A Study of Metacognitive Problem Solving in Undergraduate Engineering Students

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Abstract. One of the key challenges in engineering education is the problem of teaching future engineers' professional skills. Engineering students need to know what they do and do not know. This is termed metacognition. There is still quite a bit that we do not know about how metacognition develops in classroom settings. In this study, we discuss an exploration of these issues using both physical and virtual reality (VR) simulations of manufacturing systems; which are performed by student teams. We discuss the incorporation of measures of metacognition into a model of conflict and error to predict what types of experiences may be most helpful to produce improved metacognition in engineering students.

Keywords: Metacognition · Engineering Education · Virtual Reality

1 Introduction

Two million manufacturing jobs may go unfilled in the next decade because of a skills gap and a decline in education in areas such as engineering [1] [2]. One such skill, problem solving, is most critical. Engineers are required to have both technical skills, which are part of the traditional engineering curriculum, and non-technical skills which are often not taught or fostered. These non-technical skills can determine a future engineer's success when working in teams, deriving novel solutions to ill-defined problems, and determining the viability of any solution. In most cases, engineering students are taught structured strategies for solving problems. These steps include: 1) defining the problem, 2) understanding the process, 3) identifying root causes, 4) developing solutions and sustaining the improvement. In addition, several methodologies help problem solving such as Lean, Six Sigma, Design for Six Sigma, and Business Process Re-Engineering [3]. However, when the problem is ill-defined, the process muddled, or solution is unclear, problem solving strategies need to be redeveloped and reassessed. Regardless of the methodology or strategy, engineers must know what questions to ask, when to ask them, and how to convey the proper information to other engineers on their teams as well as other stakeholders.

When working in teams, engineers face challenges. Within the team, there must be a shared understanding within and between each team member.

Knowing what is known within themselves and each other is termed metacognition [4]. Developing this skill in new engineers is a key component of the emerging engineering curriculum as demanded by employers. Training engineering students to understand this concept is key to deriving the best solution for a problem [5].

Physical drawings and models that engineers are accustomed to working with are explicit. They can be viewed, manipulated, and easily discussed. Metacognition is implicit and involves the construction of a mental representation by the problem solver [6]. This makes metacognition particularly difficult to teach and examine. In the engineering curriculum, many solutions are possible for a given problem. However, with given affordances and constraints, only one optimal solution exists. It is up to the curriculum to instruct students in ways of finding that one optimal solution. While there are explicit methods, if an engineer does not use implicit methods and think critically, a less than optimal solution is easily chosen. In psychology, research has suggested that one of the reasons for choosing a less than optimal solution and believing it to be the optimal solution is the lack of a proper mental representation constructed through a good understanding of what is known and what needs to be known. To date, there is little research on how design and manufacturing solutions are determined when students solve problems in class and how their teamwork and questions contribute to their mental representations are made during the classroom exercise [7].

Knowing what is known and what needs to be known guides the students' decision of when they are ready to solve a problem. Flavell defined this idea in a study of school children under the age of 12 years old who were asked to study a set of items until they could recall them without error (i.e., the problem) [8] [9]. In this study, older students were able to accurately assess when they knew the items perfectly. When tested, they were able to recall the items without any errors. Younger children thought that they were able to accurately assess when they knew the items perfectly. When tested, the younger children's performance was less than perfect.

In a subsequent study by Markman [10] in children under the age of 12, they were asked to evaluate instructions and detect any errors in the simple instructions. The researchers incorporated obvious errors and omissions. The younger students were surprisingly poor at detecting the errors and thought that they understood the instructions until they started the procedure. In both cases, students believed that they had memorized and understood, but they had not. The monitoring of their own memory and comprehension was flawed as they built mental representations of the problem space.

Understanding how knowledge is integrated and monitored is termed metacognition. According to Flavell, metacognition plays an important role in communication, comprehension, writing, attention, memory, problem solving, and social cognition as well as self-control, self-instruction. social learning, personality development, and education (p. 906) [5]. In education, we see that educators need additional tools developed to help engineering students improve this process as they solve complex and multi-layered problems. The parts of metacognition are complex. In Flavell's model, there are four subcategories of metacognition: knowledge, experiences, goals, and actions. Metacognitive knowledge is the idea that other people are those with separate thoughts, tasks, and experiences. For example, you may believe that another person is better or worse at a particular task (i. e. Jeff is better at algebra than I am). Metacognitive goals are the objectives to be attained in the problem space. Metacognitive actions are the behaviors to attain the goals.

Within this framework exists a person's thoughts about themselves and other persons, their opinions, understanding, and beliefs about the task, and their approach in using these resources to attain the goal with strategies that have worked in the past, what they have learned currently, and what they can adapt from similar situations. Metacognition is an interaction of all of these moving parts: understanding of self and other persons, tasks, strategies, metacognitive knowledge, metacognitive experiences, goals, and actions of the self and others [5]. Metacognition can be acquired, it can fail, and it can be inaccurate. The lack of metacognition can lead a person to believe that they have all the knowledge that they need to solve a problem, when they do not. This would lead someone to select one course of action over another better course of action. It can influence your communication style, critical thinking, decision making, and problem solving [12].

Garrison and Akyol [13] discuss the role of metacognition in collaborative environments such as engineering in which self-regulated learning plays a role. Metacognition mediates knowledge construction and collaboration. Students must be aware of each other's metacognition in order to construct meaning. In this case, students as co-learners constantly assess internal and external conditions. They may ask for help or provide help to realize the learning goal.

Zohar and Lustov [14] recognize that teaching metacognition leads to teaching higher order thinking which establishes ideas about causation in problem solving. However, teaching strategies require a learners' self-knowledge of their own judgment of learning and feeling of knowing. Back to the two studies with the children by Flavell [8, 9] and the one by Markman [10]. It was clear that the younger children had not yet developed an accurate judgment of learning which caused them to make errors in both the memory recall task [8, 9] and the detecting errors in instructions task [10].

Judgment of learning and feeling of knowing are impacted by the limited resources in working memory [15]. Working memory integrates the current state with past, regulates attention, and allocates cognitive resources during learning. When a student is learning something for the first time, their working memory may allocate full attention to the task as they integrate the instructions with strategies, tasks, goals, and previous experience. As they begin to learn the task, students with good metacognitive strategies will monitor for uncertainty in an uncertainty monitoring state. This type of monitoring requires intensity in attention and good self-regulation. As this is an internal and implicit process, it is difficult to verbalize what mental representations are being constructed, how, why, and when. Often, it is only when an important component is lacking, that individuals know their representation is lacking. Because of the internal implicit nature of metacognition, observation and some self-report has been the primary way to measure it [11]. For this study, we will have students engage in a manufacturing exercise individually and in teams in such a way that metacognition increases within and between students. We will integrate an improved measurement paradigm to detect changes during the exercise.

2 Simulations

We expect that up to ten teams of four students in each team will participate in this study. We are using physical and virtual reality simulations of two different manufacturing systems, craft production and mass production, as a framework. In both manufacturing processes, the students manufacture a car made of Legos building blocks from a larger Lego kit. Students will start individually in the craft production exercise in either the virtual reality or physical simulation. In this portion of the task, they will learn their role, expectations, and overall goals of the task. Following this, students will then come together to take part in the mass production exercise. During each exercise, we will be observing the participants' interactions including the questions that they ask and answer and how their knowledge base and overall metacognition changes from the beginning to the end of the simulation. Then, they will report their own understanding of the exercise and their perception of others'. During the virtual reality part of the exercise, we will use eye-tracking to model their knowledge change. The use of eye-tracking in this type of study is novel.

Within the virtual reality simulation, an eye-tracker will record fixation points, latencies, and saccades. The latencies and fixations points will add to our ability to model attention and tie it to their answers on the metacognitive measures as shown in Van Gog and Jarodzka [16]. As participants use the virtual reality game, we expect that their performance will begin to approach an expert's performance in the same game as their metacognition improves as measured by the Engineering Design Metacognitive Questionnaire (EDMQ) developed by Lawanto [17] as well as the Metacognitive Awareness Inventory (MAI) [13] and Group Style Inventory (GSI) [18]. Other questionnaires such as Flow State Scale (FSS) will also be used [19].

Fig. 1. Student in the virtual reality engineering simulation.

3 Analysis

We are incorporating the raw eye tracking data as a measure of metacognition into a model of conflict and error to predict what types of experiences are most beneficial when training metacognitive skills. The raw eye tracking data analysis using signal detection theory (SDT) [20] as an approach to differentiating stimuli and quantifying a student's performance as it approaches expert performance over the course of the simulation. For example, initially we expect that the student will survey the Lego car parts that are available and focus on one or two options to use to manufacture their car. As the student considers the affordances and constraints of each choice, he will vacillate between the choices eventually settling on one and choosing that one. Expert performance is similar, but the vacillation time is less as the expert knows which choice is optimal.

Through comparing the student data to the expert data, we obtain a more accurate estimate of what the student is considering and how the metacognition is developing in terms of sensitivity (an observer's ability to discriminate stimuli) and response bias (an observer's standards for producing different behavioral responses) [20]. As the virtual reality simulation progresses, they view and choose items to construct the car. It is during this viewing of items that they attend to, the amount of time that they attend to them, the order in which they attend to them and their choice of attention to each of the items. Let us discuss the details of how that score will be derived.

Eye-tracking and gaze-tracking tools have made tremendous strides in providing information on a number of perceptual and cognitive processes, including focus and attention, information processing, and cognitive workload [21]. An eye-tracker is a device that measures eye movements, pupil size, focus, and other characteristics of one or both eyes while engaged in a given task. Through the measurement of these characteristics, an eye tracker enables researchers to track an individual's eye movement patterns across an entire task. In this study, participants were equipped with a virtual reality headset outfitted with an eye-tracker within the mark. This eye-tracker model utilizes a scene camera to record the direction in which the participant is looking, and a second camera pointed at the participant's eye is used to examine fixations. The information from the eye-tracker collects two basic measures: gaze fixation and saccade. Previous literature has established that these measures are sufficient measures of attention and information processing as it relates to learning in knowledge change and metacognition [22]. The Fixation will measure the amount of attention in terms of location (area of interest- AOI) and in terms of time [23] and the Saccade will measure the length of time for which items on the screen are attended to [24]. Within these two measures, there is spatial and temporal information as seen in Table 1.

Table 1. Measures of eye-tracking.

	Spatial Measure	**Temporal Measure**
Fixation (attention-correct item)	Gaze Point- as an X,Y coordinate as the center of the optimum Area of Interest/AOI (attention to correct item)	Time stamp of gaze point – gathered each 16.7 millisecond
Saccade (order of processing, correct length of time)	Order of gaze points- what the participant looks at first, second, third, and so forth	Loiter of fixation- the amount of time the participant gazes before the next saccade (attention- correct length of time)

Calculating these measures alone for each participant would be helpful but not as useful as when the measures are compared to the performance of an expert with knowledge of the optimal solution and a complete and accurate mental representation of the problem space (i. e. the subject matter expert or SME). We want the participant performance to approach expert performance as their information processing behavior starts to match the behavior of the SME in the same virtual reality exercise. The SME sets the optimum areas of interest (AOI) and benchmarks the gaze points and optimum loiter. The eye tracking data will be segregated into the following categories and processed as described in A – D.

A. Attention Location Difference Score- ALDS

The root mean square or RMS value from the center of the SME's AOI for each salient item will be calculated. The RMS value from the center of the participant's AOI for each salient item will be calculated. The difference between the two scores will be calculated to derive the Item Location difference score or ALDS.

B. Attention Time Difference Score- ATDS

The amount of time that the SME loiters on a particular item before moving onto the next item indicates the amount of information processing time needed to incorporate the item and decide. This loiter time between large saccades will be calculated and then each participant's loiter time will be subtracted from the SME's ideal time to find the attention time difference score or ATDS.

C. Number of Fixations difference-Fxd

As outlined in the original document, the number of fixations also plays a factor and can moderate duration time by distraction. The number of fixations difference before a major saccade will be Fxd.

These measures will comprise the individual's eye tracking performance.

$$\textit{Participant Individual Eye Tracking Performance} = ALDS + ATDS + Fxd$$

We expect that this performance equation will change as the participant engages in continued game play and will begin to approach the SME model of performance. For example, a very good model of performance in the game may be an ALDS of 13 (the center of the AOI was within thirteen pixels of the center of the expert AOI), ATDS = 53 (fixated about 53 ms longer than the expert), Fxd = 2 (two additional fixations than the expert). The score for this participant would be 68 (13 + 53 + 2). This would be a fairly good score as earlier in the exercise the same participant had a farther AOI (139 pixels) and a longer difference in fixation ATDS = 106, with more 18 more fixations Fxd = 18. This score of 163 (39 + 106 + 18) essentially described performance more distant from the ideal of 68 and could be described as a 95-point improvement. With this model, participant's micro- improvement in the tasks can be observed over individual items and over sections of the game temporally.

When we incorporate this into a Conflict (C) and Error (E) model we can predict the team performance by examining the divergence of acceptance of a specific task, the task time to solve the problem, the disparity between the expected state and the actual state. Conflicts and errors are very common and can occur in any problem solving process. We will focus on conflicts occurring during the problem solving process among collaborative undergraduate engineering student teams. Such C & Es can impact team performance and lead to ineffective solutions. Suppose that there is a conflict between two collaborative engineering teams working to solve a given problem related to a manufacturing process in product design. Error is the deviation between intentions and actions. We define the conflict as the competition between two or more simultaneously activated response tendencies represented by the difficulty level of the problem. If a student considers a given task easy whereas another student considers it difficult, a conflict, will occur. An error, will occur if a student did a task wrong, reflected by his/her performance certainty. If an error is not caught during the problem solving process, the error can lead to wrong or ineffective solutions. We will be measuring the flow of information between the collaborating team members, the probabilities of the perception of difficulty and the conflicts. We expect that this model will predict collaborative problem solving and an improvement in metacognition between and within team members.

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4 Reference

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