CWSEI – PHYS & ASTRO Newsletter

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Our department has always been committed to high standards in education. Recently, with support and leadership from the CWSEI, we have made increasing progress in successfully implementing research based educational methods in our classrooms. An increasing number of our faculty are showing keen interest in these developments. In response, we distribute this newsletter to keep you up-to-date with the latest CWSEI efforts.

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Invention as Preparation for Learning (IPL) involves asking students to invent solutions to challenging problems, prior and in addition to being taught the canonical solution through tell-and-practice methods (direct instruction followed by opportunities to practice the domain). It has been shown that students who engage in IPL perform better on domain-level transfer tasks than students who receive tell-and-practice methods alone (Schwartz & Martin, '04; Roll, Aleven & Koedinger, '09). It is unknown, however, through what cognitive processes these learning gains occur.

A study was thus carried out to answer the following research questions:
-How does metacognitive scaffolding, which guides students to noticing the deep features in the data, affect the quality of students' inventions?
-How does metacognitive scaffolding affect students' use of unsupported inquiry strategies, such as self-explanations?

Method

Students in each section of the Phys 109 labs were presented with an identical introduction and then worked through individual worksheets in randomly assigned pairs, with access to a spreadsheet program with which to implement their methods. Domain-level prompts were identical between groups, but two lab sections received "Guided Invention" activities with metacognitive scaffolding as outlined in Table 1. Contrasting cases were provided as in Figure 2 to highlight particular features of the domain, which was regarding uncertainty in the slope of a linear best-fit line that goes through the origin (Figure 1).

$$\sigma_m^2 = \frac{1}{N}\,\frac{\overbrace{\frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))^2}^{\text{Higher variability -> Higher uncertainty}}}{\underbrace{\frac{1}{N}}_{\text{More points -> Lower uncertainty}}\underbrace{\sum_{i=1}^{N}x_i^2}_{\text{Higher range -> Lower uncertainty}}} = \frac{1}{N}\,\frac{\sum_{i=1}^{N}(y_i - f(x_i))^2}{\sum_{i=1}^{N}x_i^2}$$

Figure 1: Formula to calculate the uncertainty in the slope of a linear best-fitting line that goes through the origin.

Invention stage	Instructions (given to all students)	Scaffold (given to Guided Invention only)		
		Exploratory data analysis	Self explanation	Peer critique
Task definition	Story problem: compare contractors			
Analysis		Engage in pair-wise comparisons; Rank all data sets	Explain comparisons	Discuss with peers
Plan & design	Write down a formula for calculating s_m			
Implementation & prediction	Calculate the uncertainty for each data set; Rank all data sets based on the invented methods			
Evaluation				

Table 1 : Metacognitive scaffolding through domain-independent prompts characterized the Guided Invention (treatment) and Unguided Invention (control) groups.

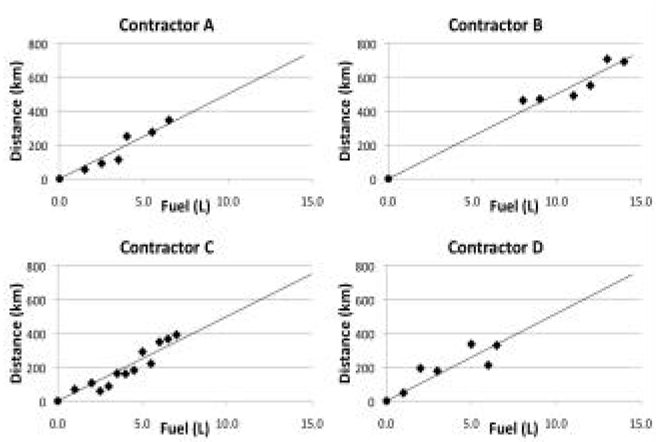

Figure 2 "Contractor Data" provided to the students during the invention task.

A vs B: Large range, gives low uncertainty
A vs C: More measurements lowers uncertainty
A vs D: High residuals increases uncertainty

Students in the Guided Invention condition were 3 times more likely to include new features (Sample Size) in their invented methods, and also made correct prediction more often (Table 2). While there was no significant difference in the technical, mathematical qualities of inventions, fewer students in the Unguided Invention

	Guided Invention	Unguided Invention
Included features		
- Sample Size	42% (.50)	14% (.35) ***
- Residuals	99% (.11)	98% (.13)
- Leverage	65% (.48)	71% (.46)
Correct predictions	69% (.25)	57% (.28) **
High-level comments		
- Any	56% (.50)	39% (.49)
- Focusing on features	56% (.50)	28% (.45)**
Multiple methods	13% (.34)	3.4% (.18)*
	* - p < .05; ** - p < .01; *** - p < .001	

Table 2: Percentage of students who included each of the three features of the domain in their inventions, and whose inventions resulted in correct rankings of uncertainties in the cases.

condition produced formulae that could accurately predict the rankings of slope uncertainties for each case (i.e., $dm_A > dm_B$, $dm_A > dm_C$, and $dm_A < dm_D$). While most students included unprompted self-explanations with their solutions regardless of condition, students in the Guided Invention condition included more deep-reasoning comments that focused on key features of the data (Figure 3, Table 2). Metacognitive prompts, therefore, improve the invention process and exploratory data analysis behaviors.

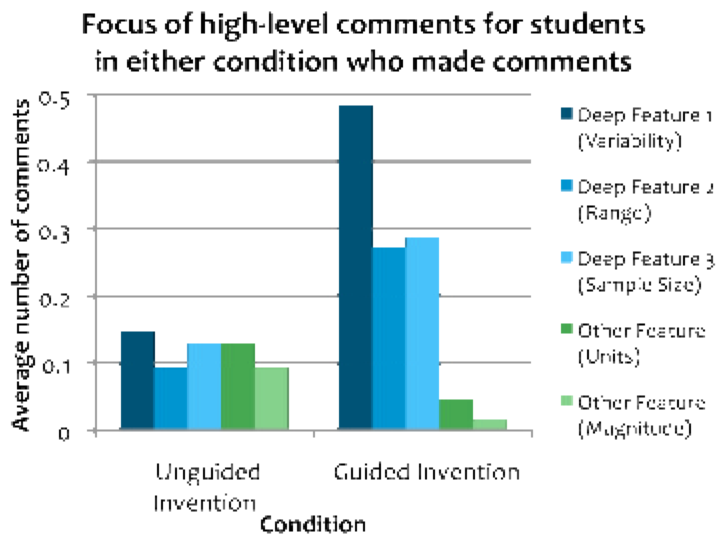

Figure 3: Distribution of student comments across surface and deep features.

Current Work

We are currently examining the effect of faded metacognitive scaffold across 5 invention activities. In addition, we have implemented these tasks using intelligent tutoring systems. Figure 4 shows the Fuel Consumption activity as presented to students using the "Invention Lab 2.0."

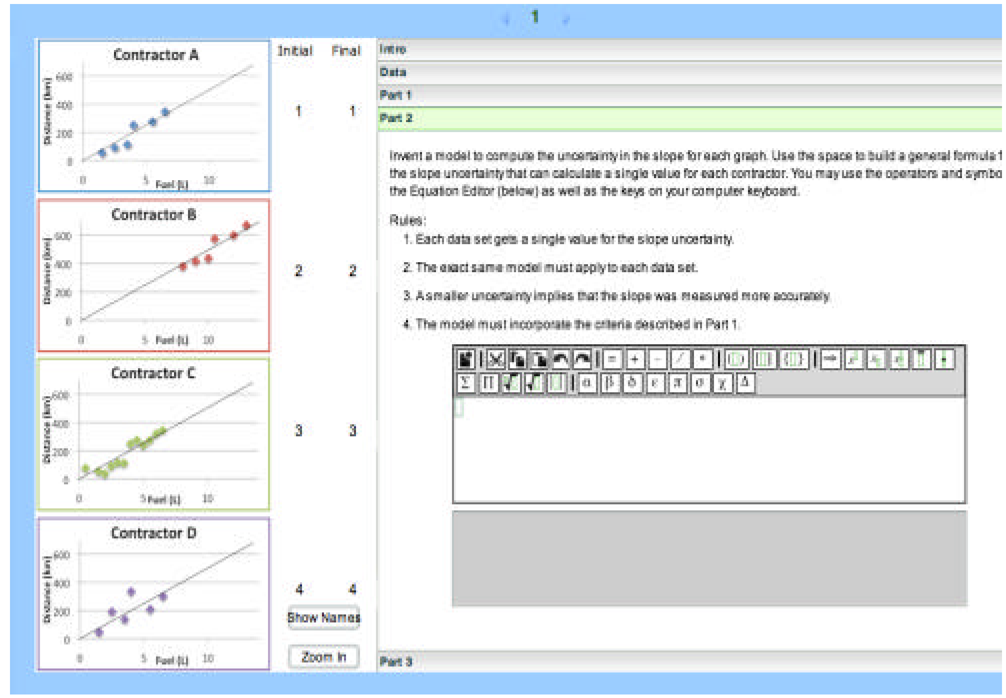

Figure 4: Screenshots of the "Invention Lab 2.0" demonstrating the equation editor and self-explanation space.

Scientific reasoning skills will be assessed through several methods:

• Quality of reasoning and methods on invention tasks
• Throughout the term's invention activities
• On transfer activities
• Performance on evaluation (or debugging) activities
• Recreating data from a previous task

Domain-level knowledge will be assessed through a statistics assessment as developed by the researchers.

This work was recently submitted to a special issue of Instructional Science.