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Students' Concept-Building Approaches: A Novel Predictor of Success in Chemistry Courses

Regina F. Frey,*,†,§ Michael J. Cahill,§ and Mark A. McDaniel‡,§

†Departments of Chemistry, ‡Psychological & Brain Sciences, and §The Center for Integrative Research on Cognition, Learning, and Education (CIRCLE) Washington University in St. Louis, St. Louis, Missouri 63130, United States

Supporting Information

ABSTRACT: One primary goal of many science courses is for students to learn creative problem-solving skills; that is, integrating concepts, explaining concepts in a problem context, and using concepts to solve problems. However, what science instructors see is that many students, even those having excellent SAT/ACT and Advanced Placement scores, struggle in the introductory science courses. As faculty work to adopt more evidence-based teaching methods, the question arises of how to determine early on who may have difficulty in these introductory courses. Recent basic cognitive science research suggests that there are individual differences in how learners approach conceptual tasks: some learners tend toward rote concept-learning (exemplar learners), whereas other learners tend to use abstraction concept-learning. We explored the possibility that this individual difference in concept-building might have consequences for classroom learning. In the current study, using an online concept-building task, we differentiated students based on their concept-building approach and then tracked their exam grades in general chemistry and organic chemistry courses. Abstraction learners demonstrated advantages over exemplar learners even after taking into account preparation via ACT scores and prior chemistry performance. Further, these performance differences grow even more pronounced in Organic Chemistry 2. Our results suggest that individual differences in how learners acquire and represent concepts persist from laboratory concept learning to learning complex concepts in introductory chemistry courses.

KEYWORDS: *First-Year Undergraduate, Second-Year Undergraduate, Chemical Education Research*

FEATURE: Chemical Education Research

INTRODUCTION

Over the years, there has been much interest in variables that could be used to predict student success in university lower-level chemistry courses because unsatisfactory grades obtained in these courses are one of the reasons students migrate out of STEM. Hence, being able to predict which students might struggle in these courses would allow instructors to modify their curriculum to help those students most at risk. There have been numerous studies that have examined various factors to determine their predictive ability such as general math ability,[1−5] formal thought,[6] scientific reasoning ability,[7] affective characteristics,[8−10] and language comprehension.[11] In addition, chemical education researchers over many years have been examining how students solve problems and whether students are understanding the concepts behind the problems or just solving the problems algorithmically.[12−14] Also, even some students with excellent preparation and high ability (based on standard preparation exams) can struggle in these lower-level chemistry courses.[15−17] Thus, there remains intense interest in identifying which students will struggle in these key introductory science courses.[18]

In this paper, we propose that students' individual differences in concept building is one potentially crucial factor in explaining these differing outcomes of otherwise similar students and examine how this individual difference in concept building might predict course performance in lower-level chemistry courses. In addition, following previous analyses that organic chemistry is typically more process-oriented than general chemistry,[19] we test the hypothesis that the association between concept-learning tendencies (assessed by the concept-building task) and course performance is amplified in organic chemistry relative to general chemistry.

Individual differences in concept-building approach were demonstrated initially in cognitive psychology laboratory experiments conducted by two of the coauthors (M.A.M. and M.J.C.).[20] Using the concept-building task (termed a function-learning task in McDaniel et al.),[20] which involves learning input−output relationships (described in detail below), learners were classified as having one of two distinct concept-building approaches. One set of students (abstraction learners) focused on learning the functional relationship among points and used this information to solve novel inputs. Therefore, abstraction learners may orient toward extracting underlying principles, encouraging a relatively deep understanding of content. In contrast, other students (exemplar learners) focused on learning the individual input−output pairs, thereby failing to learn the functional relationship; consequently, these students could not successfully solve novel inputs. That is, exemplar learners may instead develop conceptual representations based on memory of studied examples and algorithms rather than abstractions that summarize and relate particular examples. In a recent study,[21] we showed that individual concept-building approaches persist from laboratory-concept learning (the concept-building task) to learning complex concepts in a

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general chemistry course by examining performance differences on retention and transfer questions on the final exam. We found that abstraction learners performed better than exemplar learners on the transfer questions even after controlling for ACT Math, but the two groups had equivalent performance on retention questions. Hence, in that recent study, we showed that individual concept-building approaches persist from laboratory-concept learning (the concept-building task) to learning complex concepts in a general chemistry course.

In the present study, we expand upon the previous classroom study to examine whether the students' concept-building approaches affect their exam performances in general chemistry and organic chemistry courses and whether this effect is different across these courses. We suggest, based on instructors' observations in the classroom, the chemical-education literature on problem solving, and the cognitive psychology literature, that there are some key commonalities in a student's concept-building approach and how students approach their chemistry and possibly other science courses.

■ RESEARCH QUESTIONS

Because of the focus on complex problem-solving in most science courses, we hypothesize that it is the exemplar learners who have difficulty succeeding in these courses and are consequently the ones who are likely to perform poorly. Anecdotally, this is also the belief of many science instructors, also reflected in the chemical education literature,[12−14] that students who memorize studied examples and algorithms (exemplar learners) are the ones who struggle in science courses. Therefore, we hypothesize that exemplar students will fare more poorly in these chemistry courses than the abstraction learners. Further, we posit that this difference might be greater in organic chemistry compared to general chemistry given the different demands of organic chemistry relative to general chemistry. A recent review of the research on student problem-solving in organic chemistry[19] suggests that because the use of mechanisms is essential in organic chemistry, students need to modify their thinking from a product-oriented thinking (used primarily in general chemistry) to a process-oriented thinking (used primarily in organic chemistry). The use of combinations of reaction-types required to design mechanisms requires in-depth chemical reasoning and conceptual understanding; hence, mechanistic problems cannot be easily solved by using memorized patterns.

Assuming that in many chemistry classes (including those involved in the present research), the course assessments (exams) focus on testing new problems not covered in class and homework, abstraction learners would be expected to generally outperform exemplar learners on the course exams. To explore this possibility, in the current study, we examined the relation between concept-building tendency and exam performances. In addition, because Math ACT scores and general math ability consistently correlate with performance in general chemistry, we included ACT Math as a covariate in our analyses for the general chemistry courses.[1−5] For organic chemistry, there seems to be little correlation between organic chemistry performance and the standard student measures,[22−25] but instructors have seen correlation with general chemistry performance.[23−25] Therefore, ACT Composite and general chemistry performances were included as covariates in the organic chemistry analyses.

Our hypotheses are:

1. Students' concept-building approaches will predict performances on examinations in general and organic chemistry such that students identified as abstraction learners will outperform those identified as exemplar learners.
2. Concept-building approach will be a unique predictor of exam performance; that is, it will remain as a predictor when ACT math, composite, and other achievement variables are included in the analyses.
3. Concept-building approach will be a more robust predictor for organic chemistry performance than general chemistry performance such that performance advantages for abstraction learners relative to exemplar learners will be magnified in organic relative to general chemistry.

If these hypotheses are correct, then the concept-building assessment could be a fruitful tool for anticipating which students might fare more poorly in chemistry classes. Further, this assessment would directly shed light on the cognitive underpinnings of these students' difficulty.

■ BASIC CONCEPT-LEARNING THEORIES AND CONCEPT-BUILDING APPROACH

Cognitive psychologists have attempted to characterize human concept-learning with two competing classes of models: exemplar models[26−28] and abstraction models.[29−31] Exemplar models assume that individuals learn concepts by storing specific instances and features of those instances, and they respond to new stimuli based on how similar the new stimuli are to stored instances. For instance, according to these exemplar models, in a category-learning task, a new stimulus is assigned to the category for which the stored instances of the category are more similar to the new stimulus than are stored instances of other categories. In contrast, abstraction models assume that learners extract underlying principles that govern the instances rather than storing specific instances and that they respond to new stimuli by applying the learned principles to them. Thus, in a category-learning task, a new stimulus is considered in terms of the underlying abstract features (or principles) that determine membership in a category (not in terms of particular category members). These theoretical approaches have been viewed as competitive because both can successfully characterize learning across a number of conceptual tasks.[27,32,33]

However, recently, in a range of conceptual tasks (category learning,[34,35] function learning,[20] multiple-cue prediction learning,[36,37] and skill learning[38]), studies have integrated these two existing approaches by suggesting that for conceptual tasks, some learners tend toward rote concept-learning (exemplar learners), whereas other learners tend to use abstraction concept-learning. In the function-learning studies by McDaniel et al.,[20] a participant's concept-building approach was assessed with a computer-based concept-building task, described below, in which they had to learn to predict an output variable based on input-variable values. It is important to note that the concept-building task is independent of course-domain knowledge. More generally, these laboratory studies showed that the tendency to be an abstraction versus exemplar learner remained relatively stable across different types of concept-learning tasks, suggesting that concept-building approach may exert influence in a wide range of learning contexts, perhaps including classroom settings.

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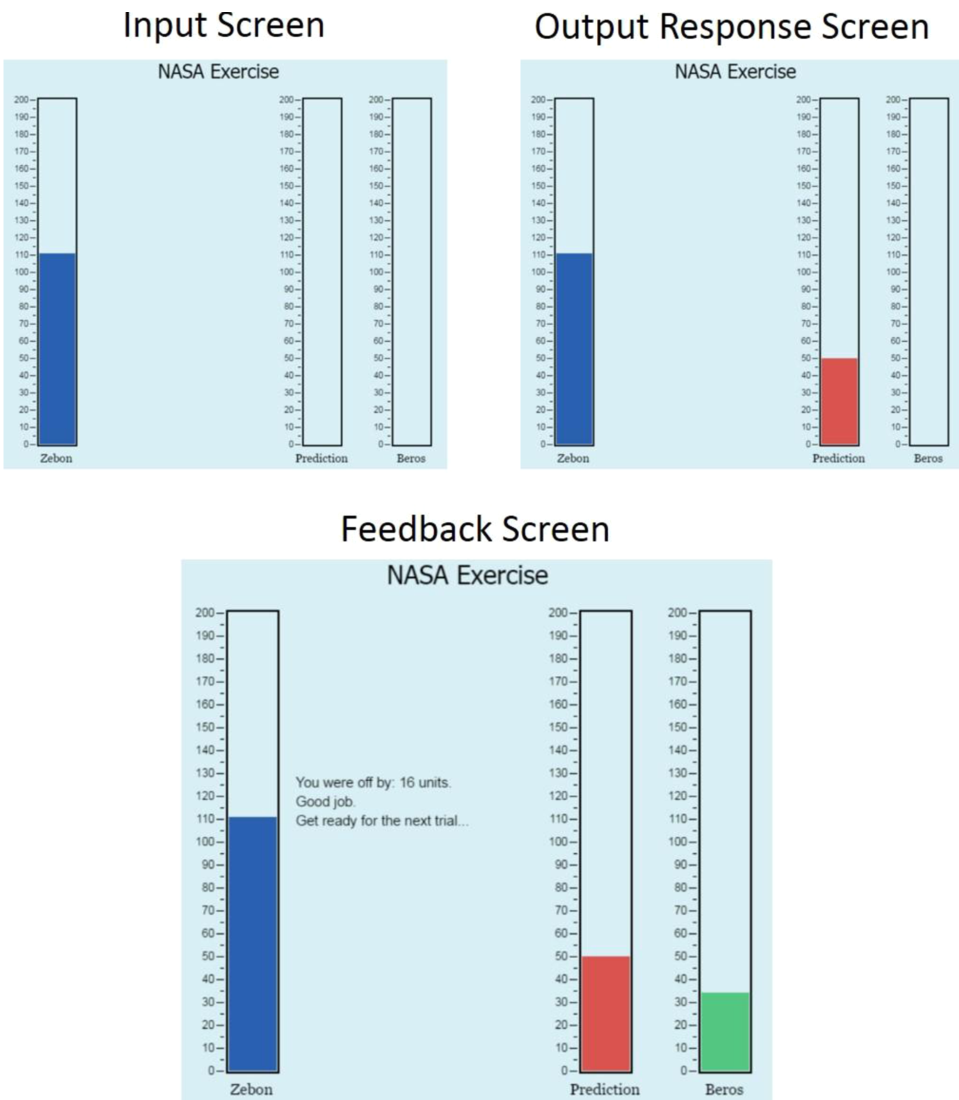

Figure 1. Screen shots from the concept-building task, adapted from Figure 2 in McDaniel, M. A.; Cahill, M. J.; Robbins, M.; Wiener, C. Individual differences in learning and transfer: Stable tendencies for learning exemplars versus abstracting rules. *J. Exp. Psych.: Gen.* **2014**, 143, 668−693, Publisher: American Psychological Association, adapted with permission.[20]

■ METHODS

Concept-Building Task

The task involves a fictional organism and two fictional elements, so students have no prior knowledge about the task. Unknown to the students, these input−output points follow a particular function form (i.e., a V function or an inverted-V function). During a training phase, students make output predictions on training inputs and learn the true outputs via feedback.

Students are given instructions on a computer monitor that ask them to pretend they have just been hired by NASA. On Mars, NASA discovered two completely new elements and one organism that absorbs an element Zebon and releases an element Beros. Their job is to determine how the absorption of Zebon and the release of Beros are related; that is, they need to determine how much of Beros is excreted after absorbing a certain amount of Zebon.

After students read this cover story, they are presented with training trials consisting of 10 blocks of 20 training points. As seen in Figure 1, the students are presented with three vertical bars. The leftmost bar gives the input value, and students make their output predictions by moving the middle bar. Three forms of feedback are then given: the rightmost bar shows the correct output value, the exact number of units of error is displayed in text, and an encouraging message is displayed. The training points are selected within a training range of a bilinear function (see Figure 2). After the training trial, all students are given a test block; note that the students are not told about the test block until after the training is complete. They see new inputs inside (interpolation trials) and outside (extrapolation trials) the range of the training inputs and make predictions, this time without receiving feedback. Figure 2 shows the mean predicted values (outputs) using both the V function and the inverted-V function for the students in this study. Note that these output graphs are not seen by the students. These graphs result from the analysis of the data set containing the output results from all of the students in the study.

Students who are able to make accurate extrapolation predictions are classified as abstraction learners. Students who learn the training points but give extrapolation points that are consistent with an exemplar model (for the V-shaped functions,

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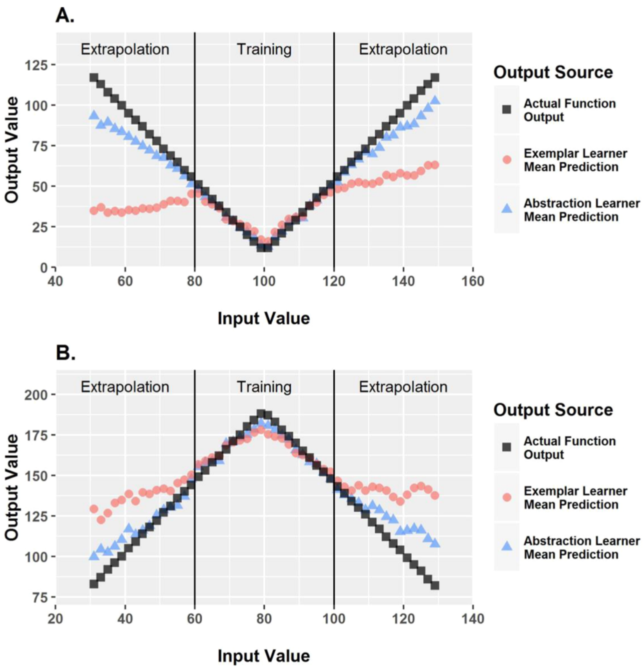

Figure 2. Input and mean output values from the training and extrapolation components of the concept-building function for the students in this study. Graphs A and B show the mean output values for the V and inverted-V functions, respectively.

this is relatively flat extrapolation extending from the training point that is just inside the extrapolation range; Figure 2) are classified as exemplar learners. The classification procedure for the concept-building task utilizes the mean absolute error (MAE) between a student's predictions and the correct outputs based on the function. In other words, abstraction learners were those students who performed statistically significantly better than an exemplar model, suggesting that they extracted some rule-based information from the training points that helped them make predictions on extrapolation trials (additional details of the classification procedure are given in the Supporting Information). Consistent with exemplar models of concept-learning, the exemplar learners apparently learned specific input−output associations but did not extract the function rule necessary to make predictions on the novel test inputs.[20,21] In addition, the concept-building approach only modestly relates to traditional measures of cognitive ability (e.g., working memory capacity, fluid intelligence)[20] and achievement (e.g., ACT/SAT),[21] suggesting that it taps a unique cognitive characteristic. The validity of the concept-building task is demonstrated by findings that on different category tasks students continued to show different underlying representations for the two concept-building approaches.[20]

Setting of Study

This research was performed at a medium-size selective research university in the Midwest United States. There are approximately 7500 undergraduates, and the average ACT composite score is 33. Our study focused on three large introductory courses (General Chemistry 1 and 2 and Organic Chemistry 2). General Chemistry 1 is taught in the fall semester, and General Chemistry 2 and Organic Chemistry 2 are taught in the spring semester. Both general chemistry courses enrolled 650−800 students, had weekly subsections taught by graduate students, and had a separate, independent laboratory course. Each general chemistry course had multiple sections that were taught by different instructors, but the overall course was managed as a single course with the same content, homework assignments, quizzes, and exams across sections. In the subsections, students were mixed from all of the sections. The Organic Chemistry 2 course enrolled about 200 students, had no weekly subsections, had the laboratory included as part of the course, and was taught by a single instructor. Both general chemistry courses had three midterm exams, quizzes, and a cumulative final; the majority of the students were first-year students. The Organic Chemistry 2 course had four midterm exams and a cumulative final; the majority of the students were second-semester sophomores.

Procedure

For academic years 2012−2013, 2013−2014, and 2014−2015, students in General Chemistry 1 and 2 were asked to take the online concept-building task in the first part of the fall semester and in the middle of the spring semester, respectively. For spring 2014, students in Organic Chemistry 2 were asked to take the online concept-building task in the middle of the spring semester. The average amount of time taken on the online concept-building task was approximately 33 min. In each case, the students were offered a small amount of extra credit in the corresponding chemistry laboratory courses (6 points out of a total of 1200 laboratory course points) to participate in taking the concept-building approach task (approved by the university's IRB). The study included two different versions of the task; the two versions were identical except different functions were used. The two functions were a V function and an inverted-V function (see Figure 2).

We collected three years of data for the two general chemistry courses and two years of data for the Organic Chemistry 2 course; hence, we examined the relation between concept-building tendency and exam performances for over 10 chemistry classes. During the study, for each course, there were different instructors and variations in the exams. Our outcome measure for each course was the exam average, as calculated by the course grading structure; we did not use course grade as that contained homework, quizzes, or laboratory reports. For the general chemistry courses, the exam-average score is the weighted average of the two highest midterm exams and the cumulative final. For the Organic Chemistry 2 course, the exam-average score is the weighted average of the four midterm exams and the cumulative final.

Out of the multiple assessments using both versions of the function, preliminary analyses showed that the inverted-V function is more robust in the correlation with exam performance. The results using the V function still show the abstraction learners outperforming the exemplar learners in all of the courses, but the differences were not always statistically significant after taking into account the appropriate ACT score. These results are shown in the Supporting Information. We acknowledge that the emergence of using the inverted-V function is post hoc and have no theoretical reason for it being more robust than the V function. However, we are interested in using the concept-building approach as a tool for anticipating which students might fare more poorly in chemistry classes. Thus, we identified that one particular function (the inverted-V) is most useful in predicting classroom performance. Therefore, in future work, we will use the inverted-V function and not the original V function.

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Table 1. Sample Sizes for the Analyses

Courses	Full Sample Abstraction Learners (N)	Exemplar Learners (N)	% of Class in Sample[a]
Gen Chem 1 (Fall 2012−2014)	306	163	20
Gen Chem 2 (Spring 2013−2015)	293	156	23
Orgo Chem 2[b] (Spring 2014−2015)	80	30	24
	Common Sample Abstraction Learners (N)	Exemplar Learners (N)	% of Class in Sample
All 3 courses (Gen Chem 1, Gen Chem 2, and Orgo Chem 2)	80	29	5, 6, and 24, respectively

[a]Includes everyone who completed the course (consenters and nonconsenters). 94% of the students in General Chemistry 1 and 2 consented, and 95% of the students in Organic Chemistry 2 consented. [b]There was one student in the organic sample who did not take General Chemistry 1 but took General Chemistry 2 and Organic Chemistry 2; hence, there is a difference of one student between the full and common samples in Organic Chemistry 2.

Table 2. Proportion of Sample and Nonsample Binned in Quintiles by Exam Average[a]

	General Chemistry 1		General Chemistry 2		Organic Chemistry 2	
Percentiles for Exam Average	Proportion of Sample, % (N)	Proportion of Nonsample, % (N)	Proportion of Sample, % (N)	Proportion of Nonsample, % (N)	Proportion of Sample, % (N)	Proportion of Nonsample, % (N)
Below 20th	11.73 (55)	22.20 (395)	13.81 (62)	22.14 (312)	14.55 (16)	22.22 (72)
20−40th	13.86 (65)	21.59 (384)	17.37 (78)	20.87 (294)	20.91 (23)	19.44 (63)
40−60th	21.32 (100)	19.67 (350)	19.15 (86)	20.37 (287)	21.82 (24)	19.44 (63)
60−80th	24.95 (117)	18.94 (337)	23.39 (105)	18.59 (262)	16.36 (18)	20.99 (68)
Above 80th	28.14 (132)	17.49 (313)	26.28 (118)	18.03 (254)	26.36 (29)	17.9 (58)

[a]The nonsample students are students who consented but either (1) did not take either version of the concept-building task, (2) took the V-function task, or (3) was a nonlearner in the inverted-function task.

Table 3. Exam Averages of Abstraction and Exemplar Learners Across Courses Using the Full Sample[a]

		Unadjusted Means		Adjusted Means		p-Value, η_p^2	p-Value, η_p^2
Course	Semester	Abstraction (SE, N)	Exemplar (SE, N)	Abstraction (SE)	Exemplar (SE)	For concept-building approach	For ACT score[b]
Gen Chem 1	Fall 2012−2014	72.40 (0.61, 306)	68.08 (0.91, 163)	71.97 (0.59)	68.88 (0.81)	0.002, 0.02	0.001, 0.13
Gen Chem 2	Spring 2013- 2015	71.22 (0.81, 293)	64.24 (1.15, 156)	70.54 (0.75)	65.51 (1.04)	0.001, 0.03	0.001, 0.16
Orgo Chem 2	Spring 2014−2015	71.29 (1.49, 80)	57.57 (3.47, 30)	71.07 (1.69)	58.15 (2.77)	0.001, 0.13	0.18, 0.02

[a]p-Value and η_p^2 are from an ANCOVA with ACT Math or ACT Composite included as a covariate. [b]ACT Math score was used for general chemistry courses, and ACT Composite was used for the Organic Chemistry 2 course.

■ RESULTS

Having identified students' concept-building approaches using the inverted-V function, we examined the effect a student's concept-building approach has on their performances in these three courses in a series of analyses. We took into account prior preparation based on ACT Math (for general chemistry) and ACT Composite (for Organic Chemistry 2). In Organic Chemistry 2, we also performed an additional analysis taking into account prior general chemistry grades. For each course, we first examined the effect using all of the students in that course who consented and completed the inverted-V function concept-building task (i.e., the full sample); hence, the analyses for General Chemistry 1 and 2 and Organic Chemistry 2 include different (but overlapping) samples. See Table 1 for sample sizes for all of the analyses.

To compare the students in the sample to the students in the rest of the class who consented (94% of students in General Chemistry 1 and 2, and 95% of students in Organic Chemistry 2 consented), we compared the ACT Math and ACT Composite means for the sample and nonsample students for each of the courses. Note: the nonsample students are students who consented but either (1) did not take either version of the concept-building task, (2) took the V-function task; or (3) was a nonlearner in the inverted-V-function task. In General Chemistry 1 and 2, the ACT Math means were not statistically different ($p > 0.05$, for both courses). In General Chemistry 1 and 2, the ACT Composite means were statistically different ($p < 0.05$, for both courses); however, the differences (0.23 of the means) were not of practical difference. In Organic Chemistry 2, both the ACT Math and ACT Composite means were not statistically significant ($p > 0.05$). We also binned the students into quintiles by exam averages and compared the proportion in each percentile bin of the students in the sample with students in the rest of the class for each course. Table 2 shows the proportion of students in each bin for the three courses. For General Chemistry 1 and 2, the distributions of students across quintiles significantly differed between the sample and the rest of the class ($p < 0.05$), though the largest difference in the proportion of students in any particular quintile was 10%. For Organic Chemistry 2, the distributions of students across quintiles between the sample and the rest of the class was not statistically significant ($p < 0.05$). Hence, the students in the sample are not dramatically different in terms of their distribution of exam performances relative to the rest of the class for all three courses.

In all of these analyses, we compared the ACT Math and ACT Composite means for the abstraction and exemplar learners (these results are shown in the Supporting

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Information). In almost all cases, the means of the two groups (abstraction vs exemplar) were statistically different. However, for the statistically different cases, there was not a practical difference in the means of the two groups. The largest difference in the means of the two groups for either ACT Math or Composite was 0.87. Hence, there is no difference in ability (at least as determined by ACT Math or ACT Composite) between the abstraction and exemplar learners in any of these analyses. Even though there is not a practical difference in the ACT scores between the abstraction and exemplar learners, our calculations included either ACT math or ACT composite as a covariate, as described below.

For each course, an analysis of covariance (ANCOVA) was conducted in which the concept-building approach was an independent variable, and ACT scores (ACT Math for General Chemistry 1 and 2; ACT Composite for Organic 2) were included as a covariate. To combine exam averages across different semesters of the same course, exam scores were *z*-scored within each semester and then combined. These *z*-scores were used as the dependent measure in the ANCOVAs. The results are shown in Table 3. For presentation purposes, untransformed exam-average means are shown in Figure 3,

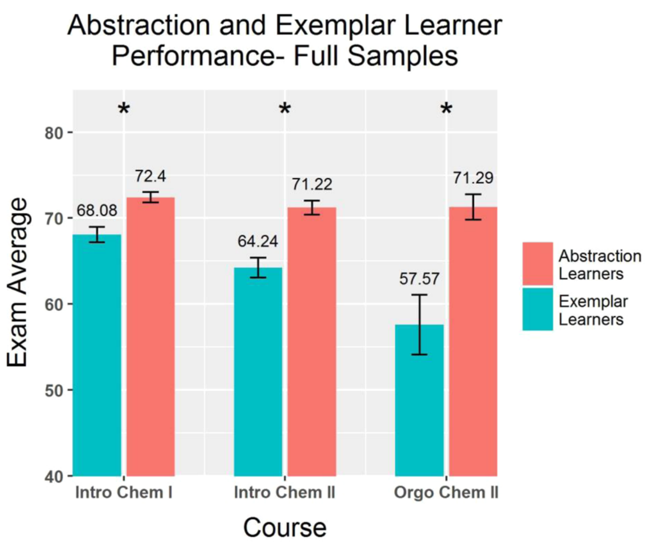

Figure 3. Unadjusted means for the exam averages for each course using the full sample; * represents $p < 0.05$ after accounting for ACT score.

which display the performances of abstraction and exemplar learners across the three courses. Asterisks denote statistically significant differences between groups for the course (i.e., $p < 0.05$), as determined by the ANCOVAs on *z*-scored exam averages described above.

Both ACT Math and the concept-building approach were significantly associated with General Chemistry 1 and 2 exam scores: abstraction learners performed significantly better than exemplar learners with the average exam differences being 4.32 ($\eta_p^2 = 0.02$) and 6.98 ($\eta_p^2 = 0.03$), respectively. Higher ACT Math scores were associated with better exam performance with large effect sizes ($\eta_p^2 = 0.13$ and 0.16, respectively). By contrast, in Organic Chemistry 2, ACT (Composite) was not significantly associated with exam performance, but the advantage for abstraction learners relative to exemplar learners was robust with an average mean difference of 13.72 ($\eta_p^2 = 0.13$; approaching a large effect size). Hence, on overall performance (exam average), we found consistent advantages for abstraction learners across the three courses even after accounting for preparation in terms of ACT Math and ACT Composite.

Recall that the full sample analyzed everyone in that course who consented and completed the concept-building task; therefore, the samples for each course were slightly different, although overlapping. Hence, the large difference in performance in Organic Chemistry 2 between the abstraction and exemplar learners could be due to that particular sample of students. Therefore, our second set of analyses used a common sample of students. In the common-sample analyses, students were included only if they were in General Chemistry 1 and 2 and Organic Chemistry 2 and successfully completed the specific concept-building task. Hence, in the common-sample analyses, the exact same students were used in the analyses for all three courses, which allowed us to follow the effect on performance on the same students as they progressed through the course series. The sample sizes are shown in Table 1.

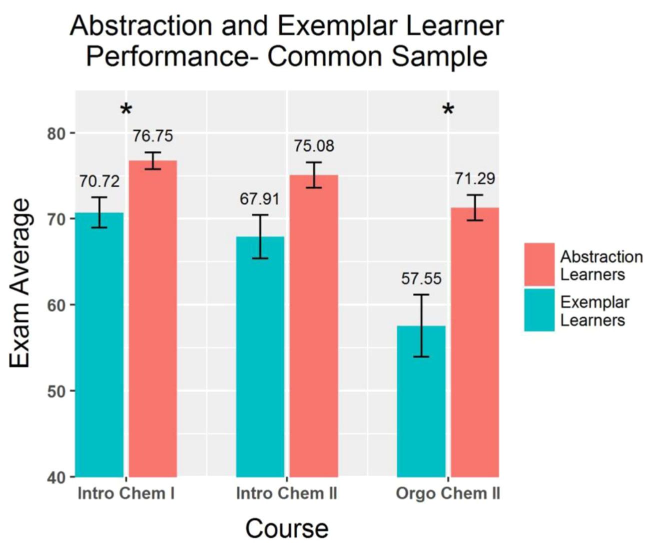

Figure 4. Unadjusted means for the exam averages for each course using the inverted-V function and the common sample; * represents $p < 0.05$ after accounting for ACT score.

As shown in Figure 4 and Table 4, following the same students through these three major STEM courses, abstraction learners again consistently outperformed exemplar learners in all three courses. The effect of concept-building approach in General Chemistry 2 just misses significance ($p = 0.06$); this is likely because ACT Math accounts for more variance in General Chemistry 2 (which is more quantitative than General Chemistry 1), and the standard error of the means is higher in General Chemistry 2 than in General Chemistry 1. Hence, the concept-building approach seems to be capturing a unique characteristic of the student with the largest effect being seen in Organic Chemistry 2 even taking into account prior preparation ($\eta_p^2 = 0.06$ for General Chemistry 1 and $\eta_p^2 = 0.13$ for Organic Chemistry 2).

Recall that in some studies, performance in organic has been correlated with prior chemistry performance.[23−25] Hence, to see if the concept-building approach was still important in Organic Chemistry 2 after taking into account ACT composite and General Chemistry 1 and 2 performance, we ran an

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Table 4. Exam Average of Abstraction and Exemplar Learners Across Courses Using the Common Sample[a]

Course	Semester	Unadjusted Means: Abstraction (SE, N)	Unadjusted Means: Exemplar (SE, N)	Adjusted Means: Abstraction (SE)	Adjusted Means: Exemplar (SE)	p-Value, η_p^2 For concept-building approach	p-Value, η_p^2 For ACT score[b]
Gen Chem 1	Fall 2012–2014	76.75 (0.97, 80)	70.72 (1.76, 29)	76.53 (0.98)	71.33 (1.65)	0.008, 0.06	0.03, 0.04
Gen Chem 2	Spring 2013- 2015	75.08 (1.48, 80)	67.91 (2.52, 29)	74.59 (1.43)	69.24 (2.40)	0.06, 0.03	0.001, 0.09
Orgo Chem 2[c]	Spring 2014–2015	71.29 (1.49, 80)	57.55 (3.60, 29)	71.10 (1.69)	58.06 (2.82)	0.001, 0.13	0.17, 0.02

[a]p-Value and η_p^2 are from an ANCOVA with ACT math or ACT Composite. [b]ACT Math score was used for General Chemistry courses, and ACT Composite was used for Organic Chemistry 2 course. [c]There was one student in the organic sample who did not take General Chemistry 1 but took General Chemistry 2 and Organic Chemistry 2; hence, there is a difference of one student between the full and common samples in Organic Chemistry 2.

Table 5. Exam Average of Abstraction and Exemplar Learners in Organic Chemistry[a]

Unadjusted Means for Abstraction Learners (SE, N)	Unadjusted Means for Exemplar Learners (SE, N)	Adjusted Means for Abstraction Learners (SE)	Adjusted Means for Exemplar Learners (SE)	p-Value, η_p^2 for Concept-Building Approach	p-Value, η_p^2 for Gen Chem 1 Performance	p-Value, η_p^2 for Gen Chem 2 Performance	p-Value, η_p^2 for ACT Score
71.29 (1.49, 80)	57.57 (3.47, 29)	69.92 (1.47)	61.31 (2.49)	0.004, 0.08	0.005, 0.07	0.07, 0.03	0.17, 0.02

[a]p-Value and η_p^2 are from an ANCOVA with average exam performance in General Chemistry 1, 2, and ACT Composite used as covariates.

additional analysis on these data using the average exam scores in General Chemistry 1 and 2 as covariates. As seen in Table 5, we found that average exam performance in Organic Chemistry 2 was dependent on performance in General Chemistry 1 (medium effect size, $\eta_p^2 = 0.07$) but not General Chemistry 2 ($p > 0.05$). Most importantly, concept-building approach remained significantly associated with Organic Chemistry 2 performance (medium effect size, $\eta_p^2 = 0.08$). It seems that the concept-building approach captures something in students' learning of Organic Chemistry 2 that is not represented in ACT Composite or in general chemistry performance.

One possible interpretation of the difference in course performances between abstraction and exemplar learners is that the exemplar learners are less motivated or less able students. There was little difference in ability, however, according to the ACT Math and ACT Composite scores. Table 1 in the Supporting Information shows comparisons of abstraction and exemplar learners across all samples (all General Chemistry 1, all General Chemistry 2, all Organic Chemistry 2, and common sample), classification functions (Inverted-V and V), and ACT scores (Math and Composite). Although most of these comparisons show a statistically significant advantage for abstraction learners, the differences between groups are small and unlikely to hold practical significance. These differences ranged from 0.38 to 0.87 with a mean of 0.60. Further, we accounted for this difference by adding ACT Math and ACT Composite scores into the analyses.

The interpretation that the exemplar learners are less motivated students is disfavored by several observations. First, note that this concept-building task is a difficult task; therefore, the exemplar learners displayed as much motivation as the abstraction learners in completing the task to a stringent learning criterion. Still, they were not as successful in the chemistry courses because of their concept-building approach. Second, there is a set of students (nonlearners, approximately 49% of participants) who start the concept-building task and do not reach learning criterion at the end of the training period. Upon close examination of these nonlearners, many of them did not take the task seriously. Third, it turns out that in this study, many students consented to participate but did not actually participate in taking the concept-building task (we are denoting these students as nonparticipants). The percentages of nonparticipants are 53, 53, and 45% for General Chemistry 1 and 2 and Organic Chemistry 2, respectively. Hence, there is a large number of students (i.e., the nonlearners and the nonparticipants) who are less motivated than the exemplar learners. Certainly, the students who were not motivated to take the concept-building task may have been motivated in chemistry, but we have no reason to believe that the exemplar learners would have been less motivated than these students to learn chemistry.

It is interesting to compare the Organic Chemistry 2 performances for these four groups (i.e., abstraction learners, exemplar learners, nonlearners, and nonparticipants). As seen in Figure 5 below, it turns out that the abstraction learners (M = 71.29) and the nonlearners (M = 67.37) outperform exemplar learners (M = 57.57). Even after adjusting for ACT Composite scores, least square mean pairwise contrasts (Tukey-adjusted for multiple comparisons) reveal statistically

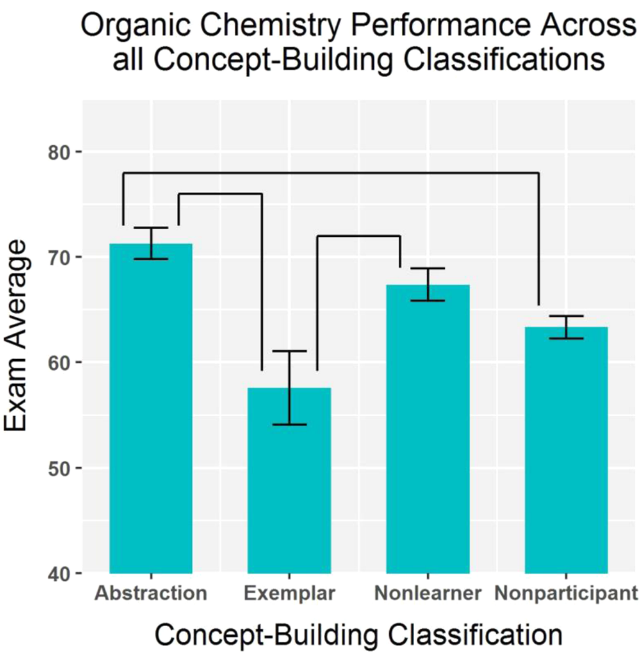

Figure 5. Unadjusted means for the exam averages for Organic 2 using the inverted-V function; connected bars represent significant ($p < 0.05$) pairwise comparisons, even after accounting for ACT score.

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significant advantages for both abstraction learners, $t(383) = 4.06$, $p < 0.001$, and nonlearners, $t(383) = 3.17$, $p < 0.01$, over exemplar learners. In addition, the abstraction learners have a statistically significant performance advantage over nonparticipants ($M = 63.34$), $t(383) = 3.62$, $p < 0.01$. Hence, the exemplar learners have the lowest performance. It seems that, for Organic Chemistry, the types of mental representations that exemplar learners have result in poorer performance even relative to the presumably less motivated students.

■ LIMITATIONS

There are several limitations to this study that should be noted. One limitation is that completing the task online in an unstructured environment resulted in more nonlearners than has been observed in the structured psychology laboratory environment. Previous laboratory studies have reported a nonlearner rate of ~15%[20] compared to the 45% (inverted-V) and 32% (V) nonlearner rates in the current data collected online. In this study, the nonlearner rates for the full sample are 45, 45, and 49% for General Chemistry 1 and 2 and Organic Chemistry 2, respectively; for the common sample, the nonlearner rate is 49%. Perhaps, in the unstructured, unproctored online environment, students take the task less seriously. In fact, upon close examination of a sample of 170 nonlearners, we found that approximately 73% these online nonlearners demonstrate at least one of the following markers of nonsustained effort on the task: (a) averaging <2 s per trial (the average for a learner is approximately 8 s per trial, (b) repeatedly using only one or a handful of prediction values for multiple training blocks, and (c) resulting increases in training error across blocks. It might be that students would likely take this task seriously if it were linked to a course and potentially had a practical impact like being part of their course grade or determining if they may participate a given supplemental program. Also, some students may have a more difficult time concentrating in an unstructured online environment. However, the advantage of giving the task online instead of in a structured setting is that the students can take this task at their convenience and before they arrive on campus.

Another potential limitation is that a student's concept-building approach might change over time. To inform this possibility, we did a preliminary study on the stability of a student's concept-building approach with respect to time. We checked the change across time by comparing the results using the V function that students took both in General Chemistry 1 (fall 2012) and Organic Chemistry 2 (spring 2014), which is one and half years apart. The results showed that 85% of the 41 students who successfully completed both tests were identified with the same concept-building approach both times. The other 15% of these students changed to the other concept-building approach. Hence, it seems that a student's concept-building approach does not necessarily change across time (at least over 1.5 years). Thus, we are able to identify the concept-building approaches of students outside of the structured cognitive science laboratory, using the online concept-building task, and it seems that students' approach to concept learning does not change over time (at least, if no intervention occurs).

A third potential limitation is the use of course exam average to evaluate student learning instead of standardized instruments such as the ACS exams. However, standardized exams are problematic if the exam is not one that is used in the course for a grade, as students may not try their best. Because the courses that we studied do not use standard exams in their courses to evaluate learning (the instructors write the exams), we opted not to use standardized exams. Still, one concern about using course exams is that the psychometric properties of the course exams are unknown. To establish provisional reliability of the exams, we reasoned that because the midterms and the cumulative final exams were assessing similar constructs, performances should be correlated. Therefore, we correlated the midterm exam performances with the cumulative final exam performances in each course for all years. We found that for each course, all of these correlations were statistically significant ($p < 0.001$). For all of the courses, the average correlation between the midterms and the cumulative final exam was 0.63 with the lowest correlation being 0.49 and the highest correlation being 0.79. Thus, this is some evidence that the exams reliably assessed student performance on acquiring chemistry content and skills in all three courses.

A final limitation is that the sample in this study consisted of students from a highly selective private university who volunteered to participate and where students in the study average between the 98th and 99th percentile on math and verbal achievement (ACT or SAT). Nevertheless, these volunteers show a similar distribution of exam grades to the rest of the students in each class, which shows they are representative of these courses. There was no difference in exam grade distribution for Organic Chemistry 2, where we found the most robust effect of concept-building approach with performance. In General Chemistry 1 and 2, where the distribution of the sample tended to be more skewed toward higher exam performances than did the rest of the class, we still find that concept building is associated with exam performance. However, students in this study would be considered in the very high range of ability on standard measures. Accordingly, the results in this study could be limited in generalizing to students reflecting a broader ability profile. We are currently working with a range of institutions to determine how the concept-building approaches of students with a broader range of ACT/SAT scores affect their performance in lower-level chemistry courses.

■ DISCUSSION

In this paper, we examined the "extension" of cognitive science laboratory results in identifying students' concept-building approaches to the classroom. The cognitive psychology experimental work identified two concept-building approaches: abstraction (learns to extract more abstract ideas and underlying concepts) and exemplar (focuses on memorizing facts and algorithms) learners. Because science courses focus on complex problem-solving, we hypothesized that the exemplar learners have a more difficult time succeeding in these courses and are therefore the ones who are likely to perform poorly. There is a need to find a measure that can determine early on students who are likely to struggle in these introductory science courses. In this study, we presented this novel measure (the concept-building task) that seems to be associated with course performance above the standard preparation ACT tests. In addition, this task is domain-independent, can be easily given online, and therefore it can be given outside of class time and before students arrive on campus.

We determined that there was a correlation with chemistry course performance, and the task using the inverted-V function resulted in higher correlation with chemistry course performance. Using either the full sample or the common sample, we found a consistent advantage for the abstraction learners over

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the exemplar learners. For general chemistry, ACT Math was statistically associated with course performance with a large effect size, but the concept-building approach was still significant albeit with a small effect size. However, in Organic Chemistry 2, ACT Composite was not found to be statistically related to course performance among the concept-building-task learners, but the concept-building approach was statistically related, approaching a large effect size (0.13 for both samples). This large effect is reflected by large differences in the means at 13.72 and 13.74 percentage points (for full and common samples, respectively). Just as importantly for purposes of using this measure to predict student success in an Organic Chemistry 2 course, the concept-building test was administered 1−1.5 years prior to taking Organic Chemistry 2.

Because prior chemistry course performance has been found to correlate with Organic Chemistry course performance, we also conducted analyses using general chemistry course performance. We found that average exam performance in Organic Chemistry 2 was dependent on performance in General Chemistry 1 with a medium effect size of 0.08. Still, Organic Chemistry 2 was dependent on the concept-building approach with a medium effect size of 0.07. Thus, it seems that the concept-building approach captures something in the student learning that is not represented in ACT Composite for Organic Chemistry 2 or in prior chemistry course performance.

Having determined that abstraction learners are outperforming exemplar learners in general and organic chemistry, what might we do as instructors to help students who are exemplar learners? We are starting to examine the effect of active learning in the form of the peer-led team learning approach (PLTL) on the different learners' performances in general chemistry. In our sample, we are finding that there is a consistent advantage for student participating in PLTL versus students not participating in PLTL even after accounting for ACT Math. These findings are consistent with our earlier PLTL study[39] and other studies nationally.[40−42] More interestingly, preliminary data show that a certain subset of exemplar learners seem to receive a tremendous benefit from PLTL and really struggle without this active learning support. We are currently attempting to better classify this subset of learners and the effect that PLTL has on their performance in general chemistry.

In summary, a student's concept-building approach may be a possible domain-independent indicator of student performance in the lower-level chemistry courses such as general chemistry and organic chemistry. Our results indicate that the student's concept-building approach captures a characteristic of student learning that is not captured by preparation or prior performance. Preliminary data in general chemistry seems to indicate that active learning, at least in the form of PLTL, helps a subset of the exemplar learners. Hence, this is an additional reason for instructors to incorporate more active learning into their courses. Also, this concept-building task is an online test; therefore, students could take it on their own time (outside of class) and even before arriving on campus. The online setting also allows us to easily disseminate this concept-building task to other institutions. To see if these results emerge in other introductory STEM courses and institutions, we are currently studying these effects in different STEM courses and at different institutions.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available on the ACS Publications website at DOI: 10.1021/acs.jchemed.7b00059.

Classification procedure details for the concept-building task, ACT Math and Composite results for all of the analyses using both the inverted-V and V-functions, and complete analysis using V-function results (PDF)

■ AUTHOR INFORMATION

Corresponding Author

*E-mail: gfrey@wustl.edu.

ORCID

Regina F. Frey: 0000-0003-2270-2030

Notes

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