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Measuring Students' Approach to Learning

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Abstract

Function learning tasks are widely used in cognitive science to explore the mechanisms involved in learning. Recently, these tools have been deemed useful in probing different approaches to problem solving widely found in university-age students. We use the labels "exemplar (or rote) learners" and "abstraction (or theory-based) learners" to distinguish students who principally solve problems by learning a spectrum of examples from those who connect underlying rules to a category of problems. Through collaboration with a consortium of institutions, we have employed an on-line instrument to evaluate the learning approach of first-year chemistry students and compare their learning approach to their academic performance. This paper describes the on-line assessment instrument used and reports on three years of data. In conjunction with this study, the same students completed entering and exit surveys that were designed to assess students' attitudes towards learning chemistry. Correlations between the student learning approach and their attitudes are reported. Going forward, this tool can be used to assess the effectiveness of different learning interventions that will attempt to help exemplar learners develop into abstraction learners.

Keywords: function learning task, exemplar learner, abstraction learner, attitudinal survey, learning approach

Introduction

Function learning tasks have been developed as instruments to investigate the cognitive process of learning (Koh & Meyer, 1991). They are characterized by a function that maps some input stimulus to an output action. Understanding functions is clearly an important component of success in STEM disciplines, but the meaning here is somewhat broader. Function tasks are an integral part of our daily lives. For example, we use knowledge about traffic patterns to make decisions about when to leave work at the end of the day. We routinely consult weather reports to decide what to wear that day. Function tasks are viewed as one approach used in our overall cognition tool kit. As they map continuous input signals onto continuous output decisions, they are distinguished from category learning tasks (Ashby & Maddox, 2005), which map input stimuli into categories, such as, "is this person a friend or a danger?" Other learning tasks might further include vocabulary recall or fine art analysis, as an example of a concept learning task (Kornell & Bjork, 2008). A function learning task in not so much about training a subject to learn how a particular mathematical function behaves, but rather it is an attempt to understand how the brain assesses the input from some continuous variable and maps the output to another continuous variable.

Function learning tasks generally consist of a training phase and a testing phase. A response model is hypothesized and data selected to train the subject appropriately. New data are selected and the responses are assessed for accuracy. Various models have been explored, including polynomial (Brehmer, Kuylenstierna, & Liljergren, 1974) and log-polynomial (Koh & Meyer, 1991). Other work involving exponential, Fourier, and logistic functions (McDaniel & Busemeyer, 2005) and even sinusoidal functions (Bott & Heit, 2004) have also been undertaken. Most of the early studies explored how well subjects were able to recall the training and to interpolate between training points. Later work found that analyzing a subject's extrapolation (testing into regions not covered

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during training) behavior was more illuminating (DeLosh, Busemeyer, & McDaniel, 1997) as it probes a participant's ability to transfer their learning to new situations rather than to only measure their accuracy at recalling information.

Within extrapolation studies, different subjects demonstrated divergent response patterns during the extrapolation aspect of the learning task (McDaniel, Cahill, Robbins, & Wiener, 2014). It has been suggested that learners can be categorized based upon their contrasting performance. Subjects who successfully connect training stimuli with an output response, but are less successful in transferring this behavior to a non-training regime, can be classified as "rote learners" or "exemplar learners." These labels emphasize the repetitive aspect of the training, where some learners see the training points as a collection of input-output examples to be memorized (Erickson & Kruscke, 1998). By contrast, those who demonstrate success in transferring the function rule to the extrapolation regime can be termed "rule learners" or "abstraction learners," as they have successfully "abstracted" the underlying rule that governs the function.

An instrument has been developed to identify these two learning types (McDaniel et al., 2014). It has been tested successfully in a psychology laboratory environment on small groups of subjects and its results have proven to be quite robust. A much larger study to extend the instrument's applicability into "the wild" and test larger groups of students to assess its value of binning students into these two categories was undertaken. This research was part of that larger study and involved a large first-year chemistry class with an annual enrollment approaching ~2400 students. The instrument was applied to this group in the fall and winter semesters over a three-year period and correlated course grades with learning approach.

An equally important correlation to explore is if these learning approaches also correlate with differences in students' affective perspective – how they view their personal abilities and interest in the discipline of chemistry. While many instruments have been developed to assess student attitudes (Bauer, 2008; Brandriet, Xu, Bretz, & Lewis, 2011; Brown et al., 2014; Dechsri, Jones, & Heikkinen, 1997; Glynn, Taasoobshirazi, & Brickman, 2007; Hazari, Tai, & Sadler, 2007) towards their abilities and perspectives towards a discipline, this is a new approach that attempts to see if their learning approach may correlate with these attitudes.

In this paper, the learning approach instrument and the attitudinal survey instrument are described. Results arising from the data acquired over three years are then discussed with some plans for future work in this area provided.

Instrumentation

Function Learning / Learning Approach Instrument

Over many years, the McDaniel group at Washington University has developed numerous versions of a similar instrument to explore function learning in students (DeLosh et al., 1997). The most recent version was used during this study (McDaniel et al., 2014) and is described herein. Students individually logged on to the testing site remotely and, after providing informed consent, were provided with a cover story. They had been hired by NASA to investigate a Martian organism. This organism absorbed a newly discovered element, Zebon, and released a new element, Beros. Their task was to interpret read-outs and determine how the amount of Zebon absorbed related to the amount of Beros released.

Students enter the training phase where they are shown three vertical bars (Figure 1).

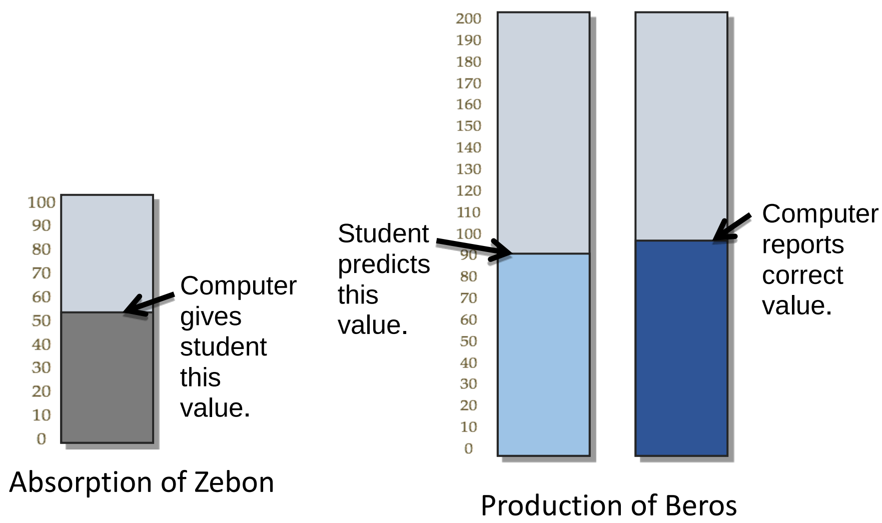

Figure 1. Students are presented with a screen similar to this when participating in the function learning task. They are first given a value for the Absorption of Zebon by the program. They then submit their estimate for the Production of Zebon. The program responds with the correct answer and informs the student how far they were from that answer. It then proceeds to the next test point. It does this 200 times during the training phase.

The first provides the program-controlled input value indicating the amount of Zebon absorbed. Students were instructed to predict the amount of Beros produced by adjusting the height of the second bar, which initially sat at zero. Upon submitting their answer, the program provides immediate feedback through the third bar. Both the amount of Beros released and the number of units the prediction was off are displayed. Students acknowledge the feedback before the next trial automatically appears. They are instructed not to write anything down.

Students are not told the functional relationship between the input and output variables, which consists of a bilinear V-shaped function (Figure 2). During the training phase, 20 equally spaced points in the central region of the function are presented in a randomized order. The presentation of all 20 points constitutes one training block.

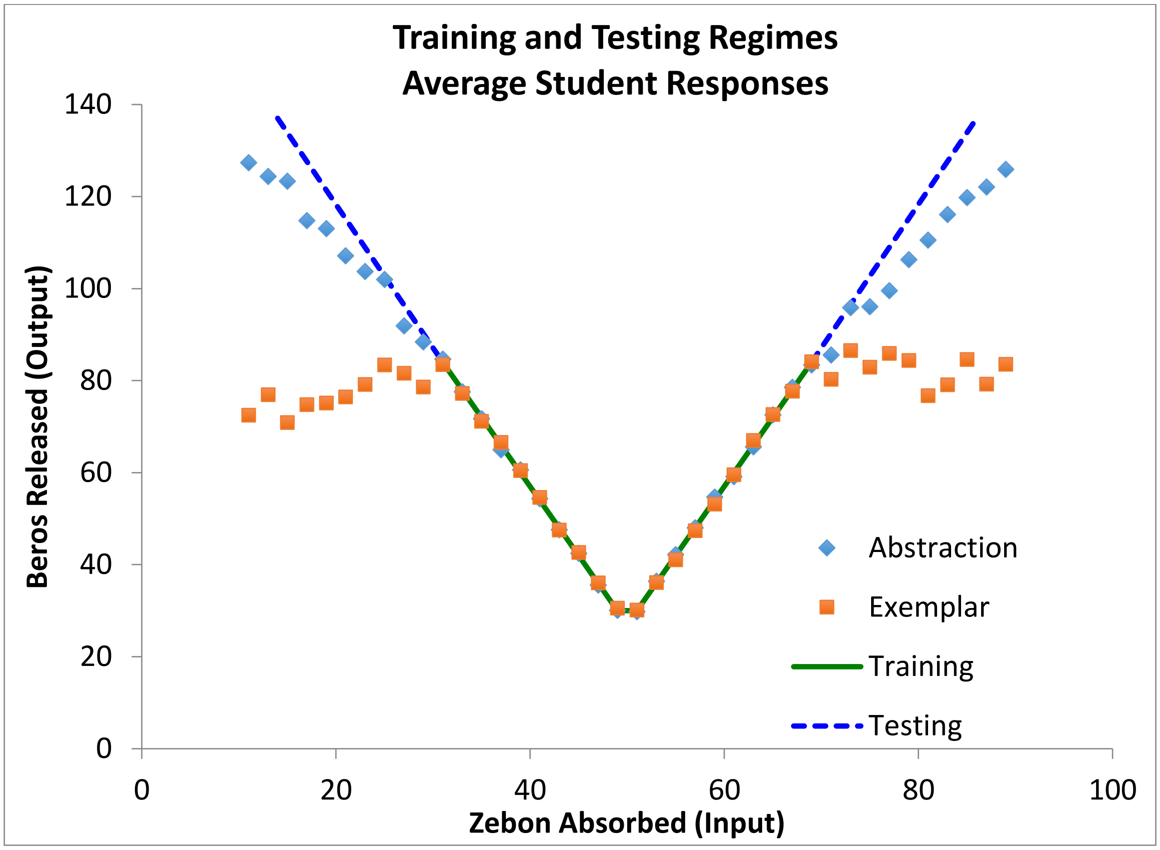

Figure 2. The underlying functional association used by the instrument is this bi-linear relation. Twenty equally spaced data points are selected for the training phase (solid line, input between 30 and 70). The data points are randomized into ten training blocks (each block has each data point presented once). When all ten blocks have been presented, that is, each data point has been presented ten times, the training phase is complete. The testing phase extends beyond both endpoints of the training phase (dashed line, input between 10 and 30 and 70 and 90). Typical average student data is shown. A student whose results most closely follow the square data points is identified as an exemplar learner. The diamond data points characterize an abstraction learner. Note how both exemplar and abstraction learners perform equally well in the training regime, but their differences are manifest in the extrapolation portions of the testing region.

The training phase consists of a total of 10 training blocks (i.e., 200 predictions) that takes most students approximately 30 minutes to complete. Previous work by the McDaniel group has demonstrated that the 10 training blocks are necessary and adequate for effective training and that additional blocks do not improve student performance (McDaniel, Griego, Dimperio, & Busemeyer, 2009).

Immediately following training, students begin the testing phase. They are given the same instructions as before, but they are told they will not receive feedback this time. Each trial consists of only the input bar ("Zebon Absorbed") and their predicted response. Students are presented with 30 novel input values falling outside the training range (extrapolation). Figure 2 includes typical average student data. When students are tested on values inside the training region (solid line), all students perform comparably well and accurately map out the training function. However, when testing points are presented, which are extrapolated beyond the training region (dotted lines), students tend to fall into two response groups. Those whose data most closely resemble that of the diamond marker data are identified as abstraction learners while those following the square marker data are identified as exemplar learners. The interpretation is that students who have perceived the bi-linear relationship can extrapolate beyond the training regime. Conversely, exemplar learners have been simply memorizing input-output pairs and when an input outside their training experience is presented, they are unable to do more than guess, which after many trials averages to an approximate flat-line response. Following the testing phase, the assessment concludes.

A student's learning approach is based on the analysis of the extrapolation profiles, and as such, only students who successfully learned the function can be analyzed. A cumulative error of less than 10 in the last training block is used to decide who has been trained and around half of the students achieve this level. Failure is due to a number of factors, including testing fatigue and casual inattention.

Student Attitude Survey

A student attitude survey was given in a pre-post format in both the fall and winter semesters. Before completing the learning approach task, students completed the survey within the first three weeks of the semester. Students completed the same survey again during the last two weeks of the course.

The survey was designed to explore student attitudes in three general areas: (a) their attitudes towards the discipline of chemistry, (b) their self-assessment of their efficacy in chemistry, and (c) their views on what might be termed "chemical intelligence." All three are assessed using a Likert scale (see Appendix A). The first uses a semantic differential format on a 7-unit scale and consists of eight questions; the second area is assessed on a 9-unit scale ("very poorly" to "very well") and consists of 21 questions; and the last area is measured using a 6-unit scale ("strongly disagree" to "strongly agree") and consists of four questions. The complete survey questions are included in Appendix A.

Results and Discussion

Courses Involved and Population in Study

The instruments described were employed in a wide-ranging study involving a consortium of several institutions in Canada and the United States. The consortium focused on students in Introductory Chemistry courses at the respective institutions. Researchers in this study included two general chemistry courses with features as described in Table 1. Only the Guelph data is discussed in this paper.

Table 1
Courses Involved in the Study at the University of Guelph.

Course	Semester	Content Description	Average Enrollment
General Chemistry I	fall	Stoichiometry, Bonding, Equilibrium, Acid/Base, Organic Chemistry	~2200
General Chemistry II	winter	Thermodynamics, Electrochemistry, Reaction Kinetics	~1700

Students from these courses were recruited to participate in the study through two methods. In 2012-2013, fifty $100 university gift certificates were offered through random draw to participants who completed all three tasks (pre- and post-attitudinal surveys and learning task). This offer resulted in poor participation rates, as shown in Table 2. Consequentially, the next two years participants were offered 2% on their course grade for successfully completing the three tasks. If they elected not to fully participate, the weight was applied to their exams. This approach was dramatically more successful. Even though the grade weight of participation had minimal meaningful influence on their final grade, it nevertheless was widely seen as worth the 65 minutes (one 45 minute session plus two 10 minute sessions) required by the activities.

Table 2
*Participant Numbers and Learning Approach Classification by Semester**

Semester	Pre-Survey	Learning Task	Post-Survey	Completed All Three Activities	Total Learners	Abstraction Learners	Exemplar Learners	Percent Abstraction
Fall 12	269	110	155	107	71	35	36	49%
Fall 13	1406	1071	986	967	576	206	370	36%
Fall 14	1311	1063	1013	950	548	180	368	33%
Winter 13	174	94	121	78	60	44	16	73%
Winter 14	991	903	852	822	484	276	208	57%
Winter 15	1127	989	908	866	396	220	176	56%

Note. *"Total Learners" are those who successfully learned the learning task function, as indicated by a cumulative error of less than 10 in the last training cycle.

Table 2 shows the number of students who completed each of the three tasks by semester, as well as those who completed all three tasks. Invariably, some students only completed a subset of the tasks and so their work could not be correlated across all measurement outcomes. Additionally, of those who completed the tasks, only those who achieved the necessary accuracy in the final training block, were retained for analysis in the study. These participants are identified in the column labeled "total learners."

Learning Task Outcomes

Perhaps the first outcome to note is the proportion of students (as represented by the subset which achieved total learner status) who are classified as abstraction learners. As pointed out earlier, these students successfully abstracted the functional behavior underlying the learning task and applied it in the extrapolation testing phase. The winter cohort is the same group of students who took the fall course previously (having successfully completed their first semester course). For example, winter 2014 students come from the same pool as fall 2013 students.

The fraction of abstraction learners almost doubles in moving into the second semester. This could be a result of the success of the first-semester chemistry course alone, an effect of all the first semester courses taken or simply the maturation of students as learners in higher education. Following the cohort into higher years could prove informative, though challenging experimentally as the cohort disperses into a wide range of courses based on their chosen majors.

Of greatest concern is how these groups of students perform in an examination environment. In Table 3, final exam averages are provided based on learner type. A surprising dichotomy very clearly arises in this data. The fall class shows a significant difference in course performance between the two learner groups ($p < 0.001$), the abstraction learners having about a 6% advantage. By contrast the winter class shows no significant difference between the performances of the two groups, with p-values well in excess of the commonly used 0.05 criterion.

Table 3
Exam Performance for Abstraction and Exemplar Learners

Semester	Abstraction Learners		Exemplar Learners		Exam Grade Difference (%)	p-value
	Exam Average					
	%	N	%	N		
Fall 2013	65.61	206	60.49	370	5.12	<0.001
Fall 2014	64.72	180	57.11	368	7.61	<0.001
Combined F13/F14	65.19	386	58.80	738	6.39	<0.001
Winter 2014	67.79	276	67.11	208	0.68	0.60
Winter 2015	66.53	220	64.91	176	1.62	0.25
Combined W14/W15	67.23	496	66.10	384	1.13	0.24

The fall data are consistent with findings from other members of the consortium with an average performance difference of about 5% (or about half a letter grade) in the mid-range of the grading scale. The clear discrepancy for the same group in their second semester – which includes an even larger proportion of abstraction learners – wherein the performance of both groups is the same, is not fully understood, though we do suggest here a hypothesis.

We note that during the learning task, both abstraction and exemplar learners performed equally well at the end of the training phase. The difference in the two groups only became evident during the extrapolation phase. We are considering if the similarity in exam performance between the two groups suggests that the structure of the exam for the winter course does not provide enough opportunity for the abstraction learners to demonstrate an advantage over the exemplar learners. If the exam was not really testing their performance "in extrapolation," then we would expect the two groups to perform equally well. We have reviewed and compared the exams and it is not immediately obvious that the fall course exam questions require more abstraction than the winter. The winter course is considered more mathematical (thermodynamics and electrochemistry as compared to stoichiometry and organic chemistry, for instance). While the exams are individually prepared each year, the types of questions and the exam structure are repeated. While this is true for both courses, these results may be revealing that the winter exam design approach has evolved over the years into a format that allows both groups to perform equally well. Another possible explanation is that since the winter class had previously taken the learning task activity (although an inverted V function was used) it is possible that they had decoded the task. This resulted in participants more successfully demonstrating the behavior identified as abstraction and the instrument was therefore not accurate in assessing the learning approach. Studies on student groups throughout their time in university, ensuring that the students were correctly assessed by the tool, would help to clarify the nature of the evolution of students' learning from a primarily exemplar approach towards a more expert view of the world reflected in a more abstraction approach to problem solving. A study testing groups in semesters two, four, six, and eight would help to clarify the situation.

A successful exam will consist of questions that span the abilities of the students taking it and yet we expect to see a differentiation in performance between exemplar and abstraction learners principally with questions that require students to extrapolate their problem solving skills beyond what has been practiced to that point. This skill is often referred to as "transfer" in the literature (McDaniel, Fadler, & Pashler, 2013), referring to the ability of a student to transfer their skills developed in one context into a related but notably different context. The exams in the fall semester course were analyzed by the course instructor, and questions were categorized as being either "near-transfer" or "far-transfer." The same analysis has not been done for the winter semester course.

Once question types were identified, an analysis of variance (ANOVA) attempted to compare student learning groups and overall performance. Figure 3 shows the performance of both student groups on questions categorized as either near- or far-transfer based on the Fall 2014 final exam.

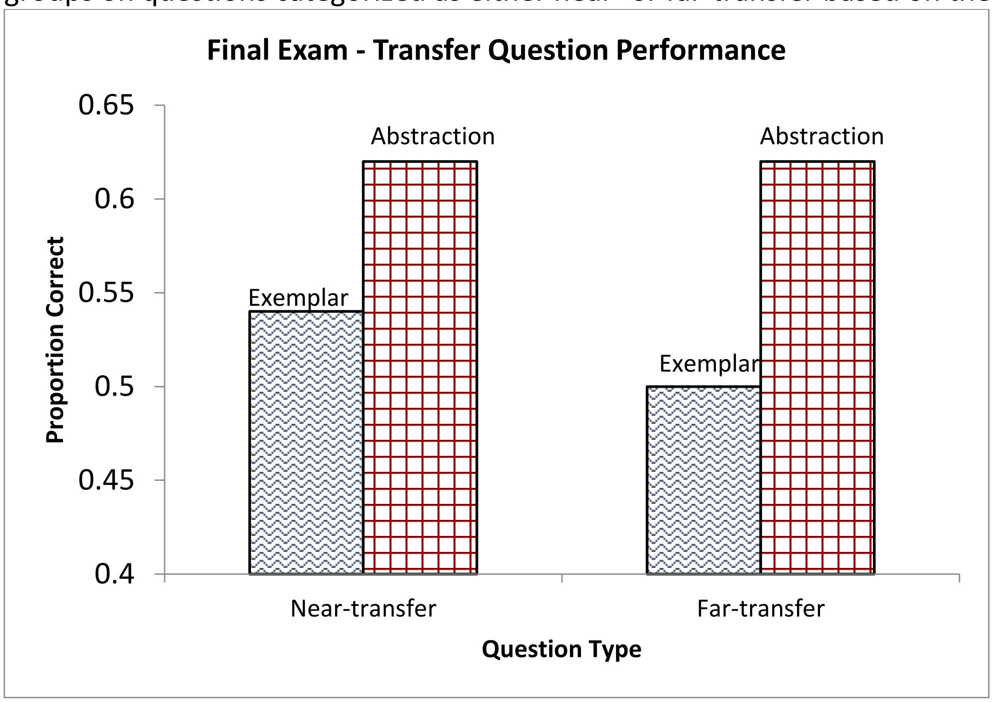

Figure 3. A comparison between the performances of both learner groups on the final exam depending upon the transfer nature of the question involved. Abstraction students (n = 179) out perform their exemplar peers (n = 370) on both categories of questions. A significant difference is observed between learner type ($F(1,547) = 25.2$; $p < .001$) and question type ($F(1,547) = 7.71$; $p = 0.01$).

Note that a substantially greater proportion of abstraction learners correctly answered both types of questions, and the gap between the abstraction and exemplar learners increases for the far-transfer questions, with differences of 7.5% and 12.0% respectively. A significant difference was observed between learner type ($F(1,547) = 25.2$; $p < .001$) and question type ($F(1,547)=7.71$; $p = 0.01$). Figure 4 compares the performance of both groups on the near-transfer questions on the mid-term exam and the final exam.

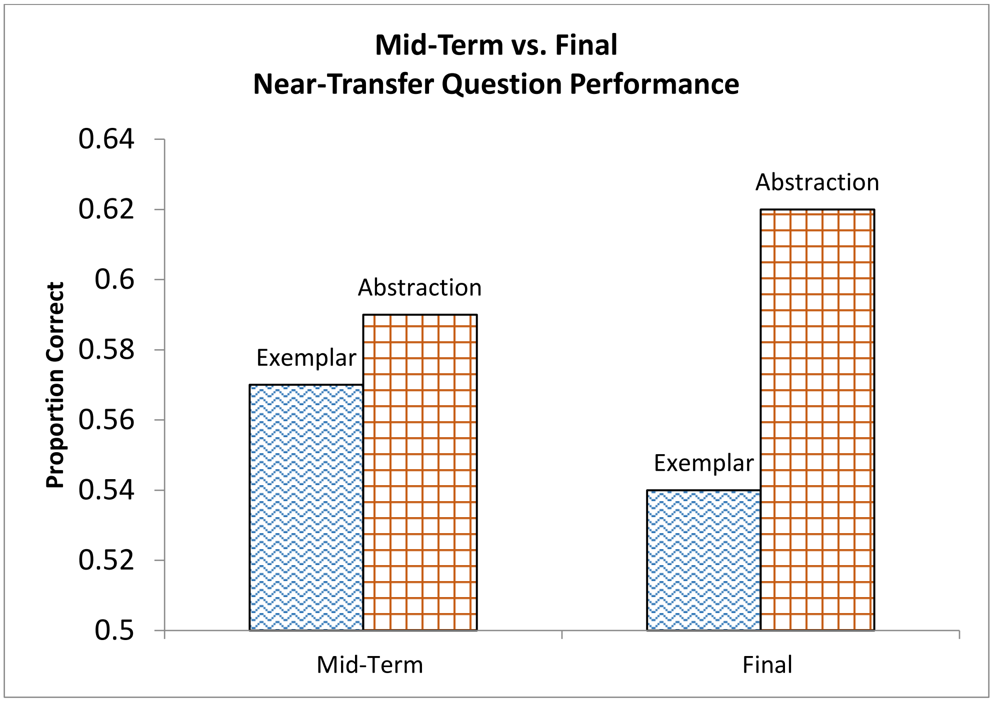

Figure 4. A comparison of near-transfer question performance on the mid-term exam and the final exam. The abstraction students (n = 179) are again out-performing the exemplar students (n = 370), leading to wide performance gap on the final. This suggests the performance gap between the two groups actually widens during the course. A significant difference is observed between the learner type ($F(1,547) = 16.3$; $p < .001$) but not between question type ($F(1,547) = 0.03$; $p = 0.87$).

A significant difference was not observed between question type ($F(1,547) = 0.03$; $p = 0.87$). However, for both exams, the abstraction students performed better than the exemplar students ($F(1,547) = 16.33$; $p < .001$) and the gap widens on the final exam compared to the mid-term; the abstraction learners are becoming more successful and the exemplar learners are becoming less successful.

Student Attitude Survey Outcomes

The Likert scale survey questions were grouped into the following six areas (an example question is included for each category):

1. Self-efficacy for cognitive skills (e.g., How well can you interpret chemical equations?)
2. Self-efficacy for psychomotor skills (e.g., How well can you use the equipment in the chemical laboratory?)
3. Self-efficacy for everyday application (e.g., To what extent can you explain everyday life using chemical theories?)
4. Emotional satisfaction (e.g., Chemistry is…frustrating or satisfying?)
5. Intellectual accessibility (e.g., Chemistry is…confusing or clear?)
6. Growth mindset (e.g., Indicate your level of agreement with this statement: 'Your chemistry intelligence is something about you that you can't change very much.')

Pre- and post-survey results were analysed for Fall 2013, Winter 2014, Fall 2014, and Winter 2015, noting that the first two semesters and the latter two semesters are made up of the same cohort of students. Table 4 presents the average response for the questions in each of these six categories for students in both learner approaches over the four semesters.

Table 4
*Attitude Survey Results**

Category	Learner Type	Fall 2013						Winter 2014					
		Pre	Post	Pre-Post Statistics		Learner Type Statistics		Pre	Post	Pre-Post Statistics		Learner Type Statistics	
				F	*p*	*F*	*p*			*F*	*p*	*F*	*p*
Cognition	A	6.28	6.48	(1,549) = 23.4	<0.001	(1,549) = 15.5	<0.001	6.12	6.22	(1,435) = 1.14	0.29	(1,435) = 0.54	0.46
	E	5.96	6.18					6.12	6.08				
Psychomotor	A	6.30	6.68	(1,549) = 45.9	<0.001	(1,549) = 0.01	0.92	6.54	6.84	(1,435) = 14.0	<0.001	(1,435) = 0.36	0.55
	E	6.28	6.64					6.58	6.66				
Everyday	A	5.72	5.94	(1,549) = 16.9	<0.001	(1,549) = 13.4	<0.001	5.62	5.75	(1,435) = 0.63	0.43	(1,435) = 0.001	0.98
	E	5.40	5.58					5.71	5.65				
Emotional Satisfaction	A	3.73	3.69	(1,549) = 1.76	0.19	(1,549) = 14.3	<0.001	4.08	4.09	(1,435) = 5.22	0.02	(1,435) = 0.99	0.32
	E	3.98	4.14					4.10	4.27				
Intellectual Accessibility	A	3.76	3.83	(1,549) = 2.6	0.11	(1,549) = 6.15	0.01	3.74	3.72	(1,435) = 0.09	0.77	(1,435) = 0.98	0.32
	E	3.57	3.65					3.62	3.67				
Growth Mindset	A	4.69	4.53	(1,549) = 8.64	0.003	(1,549) = 1.11	0.29	4.49	4.55	(1,435) = 0.04	0.84	(1,435) = 5.09	0.03
	E	4.58	4.50					4.37	4.29				
Category	**Learner Type**	**Fall 2014**						**Winter 2015**					
		Pre	**Post**	**Pre-Post Statistics**		**Learner Type Statistics**		**Pre**	**Post**	**Pre-Post Statistics**		**Learner Type Statistics**	
				F	*p*	*F*	*p*			*F*	*p*	*F*	*p*
Cognition	A	6.18	6.17	(1,455) = 0.85	0.36	(1,455) = 4.86	0.03	6.08	6.02	(1,310) = 0.04	0.84	(1,310) = 0.52	0.47
	E	6.02	5.95					6.11	6.15				
Psychomotor	A	6.36	6.56	(1,455) = 10.43	<0.001	(1,455) =0.004	0.95	6.46	6.64	(1,310) = 27.21	<0.001	(1,310) = 0.79	0.38
	E	6.24	6.42					6.50	6.84				
Everyday	A	5.67	5.50	(1,455) = 5.64	0.02	(1,455) = 0.2	0.66	5.58	5.53	F(1,310) = 2.39	0.12	(1,310) = 0.84	0.36
	E	5.58	5.50					5.57	5.76				
Emotional Satisfaction	A	3.77	4.13	(1,455) = 51.24	<0.001	(1,455) = 2.75	0.10	4.15	4.29	(1,310) = 2.66	0.1	(1,310) = 0.11	0.74
	E	3.94	4.32					4.16	4.20				
Intellectual Accessibility	A	3.72	3.54	(1,455) = 10.93	0.001	(1,455) = 0.58	0.45	3.58	3.48	(1,310) = 0.76	0.39	(1,310) = 0.21	0.65
	E	3.66	3.47					3.57	3.58				
Growth Mindset	A	4.68	4.46	(1,455) = 25.8	<0.001	(1,455) = 0.45	0.50	4.42	4.42	(1,310) = 0.23	0.63	(1,310) = 0.06	0.81
	E	4.61	4.41					4.41	4.38				

Note. *The attitude survey results are categorized in six general areas, separated by learner group, where A = Abstract and E = Exemplar. Data is presented for four classes over two years. The student cohort in Fall 2013/Winter 2014 is essentially the same. The same is true for the cohort in Fall 2014 and Winter 2015.

From the ANOVA, *F* and *p*-values for pre-post and learner type comparisons are provided. Although the dispersion in the data is not large, the sample size is large enough that statistically significant conclusions can be drawn. We are able to consider questions about whether or not each learner type demonstrated any change, positive or negative, during the course or between cohort groups and if the learner groups exhibited any attitudinal differences. While not all data showed statistically significant differences either between learner groups or in providing evidence of change during the course, there are nonetheless some statistically relevant conclusions that we can make.

Self-efficacy of cognitive skills. The abstraction learner group is slightly but consistently higher than the exemplar learner group within the fall data. On the other hand, we do not observe a measureable change in their perception of their own learning ability during the course of the year. Figure 5 shows data for the Fall 2013 class as an example, where significant pre-post ($p < 0.001$) and learning type ($p < 0.001$) effects were observed for this particular semester.

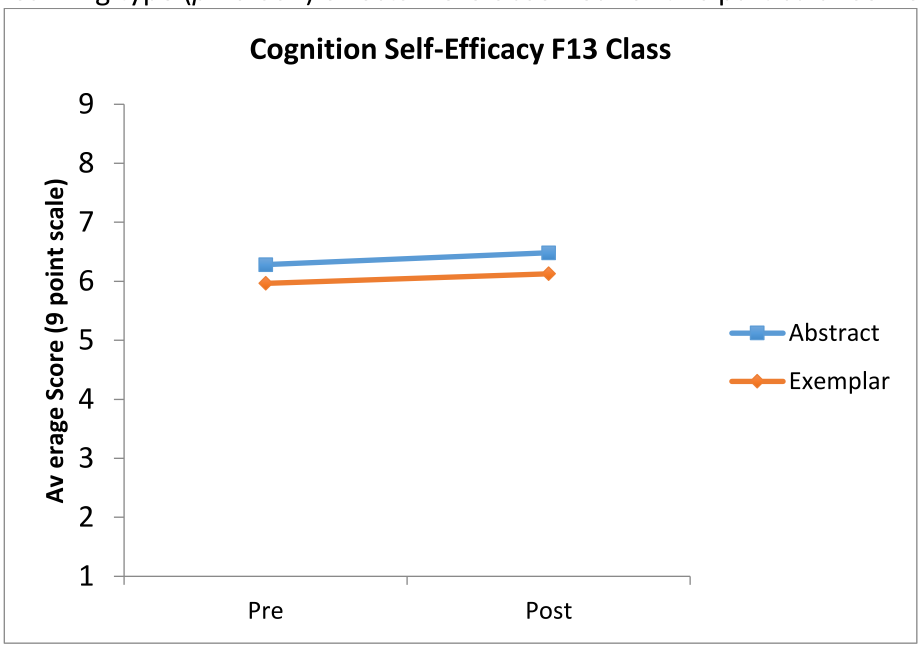

Figure 5. Graph of data for the Fall 2013 class on questions related to their self-perceived efficacy in understanding chemistry. The "pre" assessment was taken during the first two weeks of the course while the "post" assessment was taken in the last week of the course. Significant pre-post ($p < 0.001$) and learning type ($p < 0.001$) effects were observed (df2 =549).

Self-efficacy of psychomotor skills. This area showed a consistent and significant increase during the course of the year for both learner groups ($p < 0.001$); they seemed to find the laboratory experience to have improved their technical skills. However, no difference between learner groups was measured. Figure 6 shows data for the Fall 2014 class as an example.

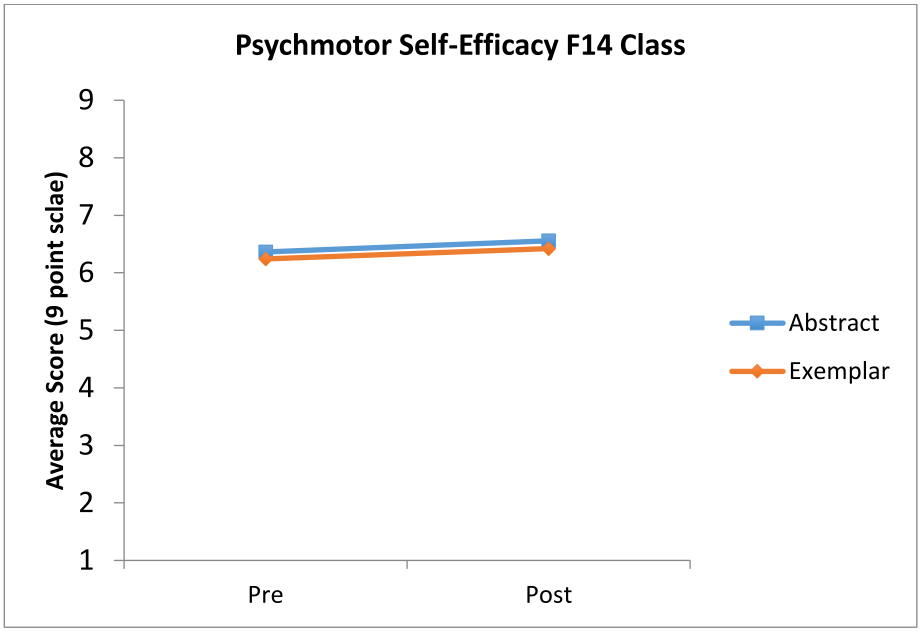

Figure 6. Graph of data for the Fall 2014 class on questions related to their self-perceived efficacy in manipulating chemical equipment. The "pre" assessment was taken during the first two weeks of the course while the "post" assessment was taken in the last week of the course. Significant pre-post ($p < 0.001$) effects were observed (df2 =455).

Self-efficacy of everyday application. Neither changes during the course nor differences between the learner groups could be significantly observed. There was more scatter in the observations which may imply students had a difficult time evaluating this category.

Emotional satisfaction. Both learner groups showed improvement during the course, however, the exemplar learners generally measured higher on this category. Figure 7 shows data for the Fall 2014 class as an example.

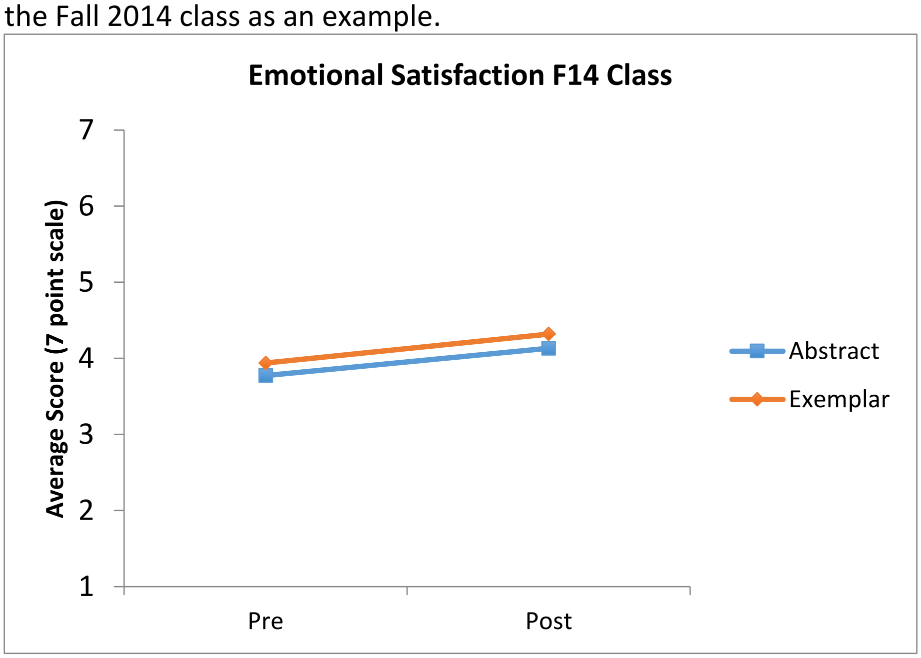

Figure 7. Graph of data for the Fall 2014 class on questions related to their emotional satisfaction with studying chemistry. The "pre" assessment was taken during the first two weeks of the course while the "post" assessment was taken in the last week of the course. Significant pre-post ($p < 0.001$) effects were observed (df2 =455).

Intellectual accessibility and growth mindset. Both showed little difference between the two learner groups over the course. Figure 8 shows data for the Growth Mindset for the Fall 2014 data, the only semester where a significant pre-post effect was observed in both categories ($p < 0.001$).

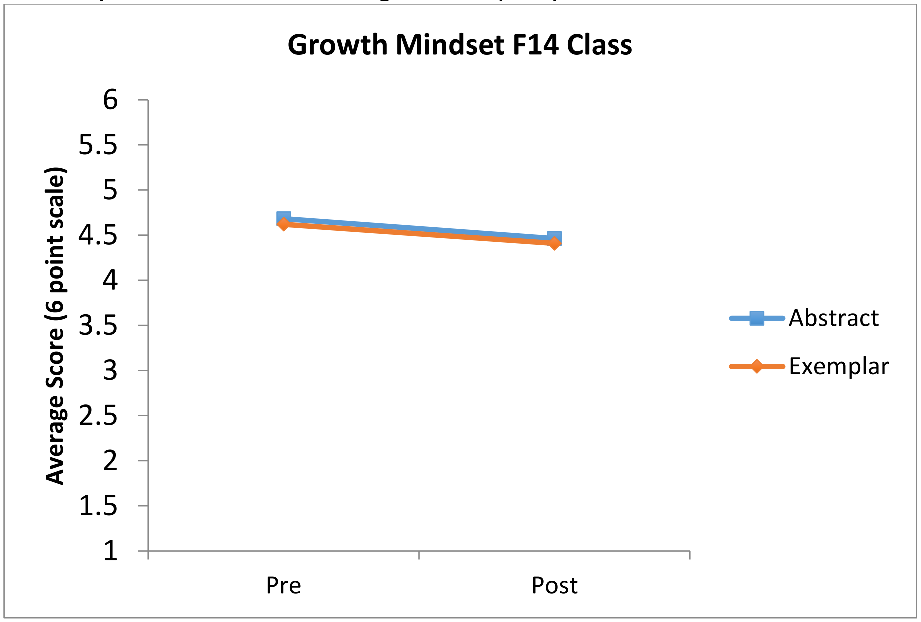

Figure 8. Graph of data for the Fall 2014 class on questions related to the mindset they have regarding their ability to change their chemical aptitude. The "pre" assessment was taken during the first two weeks of the course while the "post" assessment was taken in the last week of the course. Significant pre-post ($p < 0.001$) effects were observed (df2=455).

One might suggest that the students from this particular semester ended up feeling that chemistry was less approachable intellectually and more convinced that there is nothing they can do to change that. This attitude holds in spite of the fact that they seem to come away with a positive experience, as evidenced by the improvement in emotional satisfaction. However, the students' average response still shows a growth mindset, even at the end of the semester. Other disciplines have studied perceptional shifts, such as introductory physics courses (Adams et al., 2006), to find negative perceptional shifts for both traditional and non-traditional instructional approaches.

Summary and Conclusions

A function learning task tool was used to assess students' learning approach. One student group was classified as having an abstraction approach to learning, wherein they were able to identify an underlying function and successfully make extrapolative predictions. The other was identified as exemplar learners or rote learners. This group seems to learn by developing a catalogue of examples and solving challenges by comparing the new situation with their bank of stored examples. Novel situations, modeled through extrapolation in this particular function learning task, are not handled as well by the exemplar learner since none of their examples fit the new situation and they are left to only guess at a solution.

This study was performed on general chemistry courses (both fall and winter semesters) over three years. The study was part of a larger consortium of institutions in the United States led by two groups at Washington University in St. Louis. Only the Guelph data are discussed herein.

About one third of the students were identified as abstraction learners upon arrival at university from high school. In the second semester, about one half of the students were classified as abstraction learners. We cannot conclude whether this is a result of the first general chemistry class successfully transforming students from exemplar learners into abstraction learners, or if this is simply a result of their overall university experience. It can be suggested that students' abstraction skills are discipline specific (we all seem to adopt an exemplar approach at first when exploring a new field) so it might be tied to the course, but this is not clear from this study. Also, we are uncertain as to how the effect of having completed the task previously may affect the result the second time. The development of more diverse function learning instruments may help to elucidate these issues.

A strong correlation between student achievement and being an abstraction learner was found in the first semester course. Surprisingly, correlation for improved grades was non-existent in the second semester course. The source of this difference may be related to the nature of the exams. Abstraction learners can only demonstrate their learning skills compared to the exemplar learners when tested in an extrapolation or far-transfer manner. The winter course exams may have developed over the years into a format that caters to exemplar learners and, if so, would not show a difference in performance between the two groups. Further analysis of the transfer characteristics of the course exams will help to guide future studies in this area.

In conjunction with this function learning task, the same students completed an attitudinal survey at the beginning and the end of each course. The survey results were categorized into six affective domains. Pre-post changes within each domain were small, but in half the cases were statistically significant. Also, the differences between learners groups was equally small but statistically significant in a quarter of the cases. Most changes were not consistent between semesters, with the exception that students widely felt that the laboratory experience improved their ability to handle chemicals and chemical instrumentation. Further work is being planned to probe attitudinal changes as they correlate with different educational interventions.

Other specific future work includes exploring why so many students (about half) did not successfully complete the training phase of the function learning task when a much larger portion (93%) succeeded under controlled laboratory conditions (McDaniel et al., 2014). Developing an approach that improves the training success would ensure our ability to identify most if not all students in the exemplar category and provide them with targeted interventions to help them make the transition to being more abstraction learners in their problem solving approach.

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The human subject nature of this work was approved by the University of Guelph Research Ethics Board under certificate #12JL002.

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Appendix A
The Attitudinal Survey

Below are the survey questions given to students at the beginning and end of each course. All responses were recorded on a Likert scale. Both the category title and scale size for each group of questions is provided according to the six areas of analysis for the convenience of the reader. In practice students were not aware of the categorization as the presentation sequence was shuffled.

Emotional Satisfaction (7 point scale, semantic differential format)

"Chemistry is …"

1. Hard … Easy
2. Uncomfortable … Comfortable
3. Frustrating … Satisfying
4. Unpleasant … Pleasant

Intellectual Accessibility (7 point scale, semantic differential format)

"Chemistry is …"

5. Complicated … Simple
6. Confusing … Clear
7. Challenging … Unchallenging
8. Chaotic … Organized

Self-Efficacy for Cognitive Skills (9 point scale; Very Poorly to Very Well)

9. To what extent can you explain chemical laws and theories?
10. How well can you choose an appropriate formula to solve a chemistry problem
11. How well can you establish the relationship between chemistry and other sciences?
12. How well can you describe the structure of an atom?
13. How well can you describe the properties of elements by using the periodic table?
14. How well can you read the formulas of elements and compounds?
15. How well can you interpret chemical equations?
16. How well can you explain the particulate nature of matter?
17. How well can you interpret graphs/charts related to chemistry?
18. How well can you interpret data during the laboratory sessions?
19. How well can you write a laboratory report summarizing main findings?
20. How well can you solve chemistry problems?

Self-Efficacy for Psychomotor Skills (9 point scale; Very Poorly to Very Well)

21. How well can you work with chemicals?
22. How well can you construct laboratory apparatus?
23. How well can you collect data during the chemistry laboratory?

24. How well can you use the equipment in the chemistry laboratory?
25. How well can you carry out experimental procedures in the chemistry laboratory?

Self-Efficacy for Everyday Application (9 point scale; Very Poorly to Very Well)

26. To what extent can you propose solutions to everyday problems by using chemistry?
27. To what extent can you explain everyday life by using chemical theories?
28. How well can you understand the news/documentaries you watch on television related to chemistry?
29. How well can you recognize the careers related to chemistry?

Theories of Chemistry Intelligence (6 point scale; Strongly Agree to Strongly Disagree)

31. You have a certain amount of chemistry intelligence, and you can't really do much to change it.
32. Your chemistry intelligence is something about you that you can't change very much.
33. To be honest, you can't really change how intelligent you are in chemistry.
34. You can learn new things, but you can't really change your basic chemistry intelligence