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Studying student chemistry skills using browser-based tools and eye-tracking hardware

Estudiant les habilitats químiques de l'estudiant amb l'ús d'eines basades en la navegació i el maquinari de seguiment de la mirada

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abstract

Browser-based tools collected quantitative data from students in introductory chemistry at the tertiary level. A word-problem tool used a set of variables generated by an algorithm. A second tool was for drawing Lewis dot structures, including atoms, electrons, bonds and charges. The third tool examined the particulate nature of matter in which spheres represent atoms, ions or molecules. In addition, eye-tracking hardware examined proton NMR problems and finding structural features.

keywords

Student problem solving, solving word problems, drawing Lewis structures, browser-based tools, eye tracking.

resum

Es recullen dades quantitatives d'estudiants de química introductòria de l'àmbit universitari amb eines basades en un navegador. Una eina de problemes de paraules utilitza un conjunt de variables generades per un algoritme. Una segona eina dibuixa estructures de Lewis amb punts, incloent-hi àtoms, electrons, enllaços i càrregues. La tercera eina examina la naturalesa de partícules de la matèria en què les esferes representen àtoms, ions o molècules. A més, s'utilitza el programari de seguiment ocular per analitzar problemes d'RMN de protó i per trobar funcions estructurals.

paraules clau

Resolució de problemes, resolució de problemes de paraules, representació d'estructures de Lewis, eines basades en un navegador, seguiment ocular.

Introduction

In addition to providing basic evidence, studies in chemistry education research enable application of the research findings into improvements to the teaching and learning of chemistry. Introductory science or chemistry classes at the tertiary level have elicited a persistent set of questions: do we try to teach too much? Should we stress theory or facts, and in what order? How does content deliver (*i.e.*, pedagogy) come into play? Although current educators might find these questions relevant, they appeared in a paper that collected data from twenty-eight universities in the US in 1924 (Cornog & Cobert, 1924). For example, a characterization of the contemporary content of college chemistry texts appears in fig. 1. Although this might serve as an early example of discipline-based education research, more refined research questions and methods have been applied in this work. Several tools and methods were

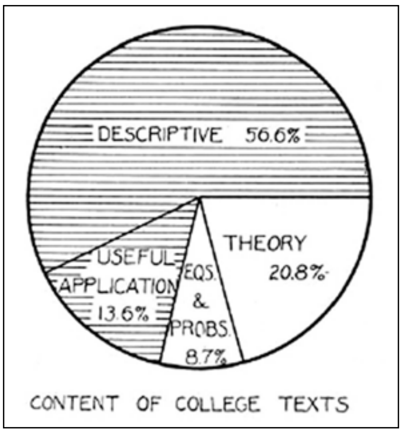

Figure 1. College chemistry text content, circa 1924 (Cornog & Cobert, 1924).

utilized to examine student approaches and steps in solving word questions and in drawing or interpreting chemical structures.

Solving word problems

Educators employ questions to assess student knowledge about content and about their ability to formulate a strategy to solve them. Many instructors would consider questions about the application of an ideal gas law (*i.e.*, what is the final volume at the final temperature if the initial volume and temperature are given) as simple exercises rather than problems. These questions apply a small amount of conceptual knowledge but a set of skills to solve a numerical version. Nonetheless, the question form allows one to examine the role of cognitive or memory load, especially because the software could generate a large number of variants based on a small number of variables. Cognitive load was first described by Miller (1956) and refers to an adult's ability to store seven plus or minus two items in short term memory. Thus, a learner can «collect» a set of separate items that are treated as such in memory until that person processes them into longer term memory or existing knowledge. This processing of disparate items into an outline or model (often called *schema* in cognitive science) requires that the learner have some previous knowledge to do so. These phenomena have been extensively characterized including examples of mathematics or science learning (Sweller, Ayres & Kalyuga, 2011; Plass, Moreno & Brünken, 2010). Johnstone (2006) provides evidence from chemistry questions that shows a precipitous drop in student success when those questions exceed seven memory components.

A browser-based tool with Flash™ scripting language was designed and implemented to examine student performance on word questions (Schuttlefield *et al.*, 2012; Tang & Pienta, 2012; Tang, Kirk & Pienta, 2014). The first such tool creates questions about the ideal gas law in which the student is asked to determine the final volume of a gas at a final temperature if the gas was originally at a different volume and temperature. An example is given here:

> An ideal gas occupies an initial volume of 6.22 L at a temperature of 262 K. What is the final volume in units of L if the temperature is changed to 289.6 K while the pressure of the system is maintained at a constant value? Assume that no chemistry occurred and there is no change in the amount of material.

The software generates the questions using five factors shown in table 1: gas identity, format of numbers used, initial and final temperature units, initial and final volume units, and a value for the constant pressure.

Thus, each question contains one of the possible variants for each of the five factors, randomly selected by the software. In addition, the numerical values for each item was also randomly selected by the algorithm. For the volume-temperature VT questions, there are 432 unique possibilities that could be assigned, based on individual options for each factor. The browser-based nature of the tool allowed the collection of > 3 000 individual attempts over two populations at the college level: the students in the first semester of a two-semester general chemistry sequence or students in a one-semester preparatory chemistry course. Logistic regression was used to analyze the results (Legg, Greenbowe & Legg, 2001). The log-odds function is given in the equation: p is the fraction of answers that are correct, and the dependence β (*i.e.*, β_0, β_1, β_2, etc.) is determined for each variable (*i.e.*, X_1, X_2, etc.):

$$logit\,(p) = ln\frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$$

Table 1. Factors and possible variants for gas law questions

Gas identity	
— An ideal gas. — A mixture of ideal gases…	— An unknown gas with a MW of 44…
Volume numbers	
— 1.23 (general). — 1.23E6 (scientific notation).	— 0.0012 (decimal).
Volume units	
— L to L. — mL to mL.	— mL to L. — L to mL.
Temperature units	
— K to K. — °C to K.	— K to °C. — °C to °C.
Pressure units and value	
— Blank. — atm.	— torr.

Fig. 2 contains the data from the logistic regression of the data divided by population, *prep chem* and *gen chem*. The values of β come from the logistic regression function, while *sig* refers to the statistical significance of each of the entries (*i.e.*, significance at < 0.05 at the 95 % confidence level). For each factor, a negative β means that the problems are more difficult (*i.e.*, lower success). Bolder entries are statistically significant, while the gray entries are not.

The questions with the scientific notation number format apparently are solved at a lower success rate. The questions with a temperature conversion from °C to °C are more difficult either because students are unable to make two conversions from °C to K or more likely because they forgot to do so. In cases where both units appear in the question, the users are likely reminded to change units. The volume dependence is quite interesting. Compared to the default conversion of L to L, mL to mL conversions are more difficult. However, mL to L problems are completed at different success rates than ones with L to mL, with the latter ones apparently being much more difficult. (Please note that the function is logarithmic.) The expectation that students would simply use algorithms like dimensional analysis would lead to identical β values, but this was not the case. Although many educators would agree that these are simple exercises, but the inclusion of several «distractors» in the questions greatly reduces student success. Although numerical values were not ascribed to the short-term memory load, cognitive load is most likely an underlying cause. It should also be pointed out that this experiment represents a general method for investigating a series of factors; it would be a great challenge to simultaneously examine 432 possibilities using paper quizzes or assignments.

		Prep Chem		Gen Chem	
Factor	**Variable**	**β**	**Sig**	**β**	**Sig**
Intercept		0.852	0.000	1.770	0.000
Gas identity	"ideal gas"	0.028	0.804	-0.067	0.599
	"mixture…"	-0.093	0.428	-0.047	0.716
	"unknown… MW"	0.000	---	0.000	---
Number format	decimal (0.0012)	-0.121	0.284	-0.081	0.530
	scientific notation	-0.234	0.016	-0.322	0.011
	general (1.23)	0.000	---	0.000	---
Volume Unit	mL to mL	-0.495	0.003	-0.494	0.002
	mL to L	-0.405	0.001	-0.831	0.000
	L to mL	-0.894	0.000	-1.362	0.000
	L to L	0.000	---	0.000	---
Temp unit	K to K	-0.019	0.889	-0.029	0.850
	C to C	-0.223	0.076	-0.380	0.009
	K to C	-0.044	0.726	-0.071	0.630
	C to K	0.000	---	0.000	---
Pressure	torr	-0.169	0.134	0.152	0.227
	atm	-0.053	0.607	0.267	0.035
	(blank)	0.000	---	0.000	---

Figure 2. Outcomes from logistic regression analysis of ideal gas questions (Schuttlefield et al.*, 2012).*

Table 2. Factors and variables in the stoichiometry questions

Alumina identity
— Blank. — «Aluminum oxide occurs naturally as the mineral corundum». — «Aluminum oxide is the main component of the gemstone…».
Equation
— Balanced *eqn* given. — Word *equation*: «Synthetic aluminum oxide is formed by…». — Unbalanced *eqn* given.
Numbers
— *Gen* number (1.23). — Scientific notation (1.23E6). — Decimal (0.012).
Units
— Mol to mol. — g to mol. — Mol to g. — g to g.
Stoichiometry / substance: «Find…»
— Amount of aluminum oxide formed from aluminum hydroxide. — Amount of water formed from aluminum hydroxide. — Amount of aluminum hydroxide needed to form aluminum oxide.

In addition to the observations from the ideal gas questions, a similar experiment was conducted with some stoichiometry problems. Based on a chemical reaction equation (*i.e.*, a balanced equation, unbalanced equation or equation only given as words), students were asked to determine the amount of material produced or consumed based on the another amount of material in that equation. The factors are given in table 2: there are six factors accounting for 324 unique questions formats.

The numerical values were again generated by the algorithm. The > 2000 attempts were again collected from general chemistry and preparatory chemistry students and are shown in fig. 3.

		Prep Chem		Gen Chem	
Factor	Variable	β	Sig	β	Sig
Intercept		1.096	0.000	1.397	0.000
Alumina identity	mineral corundum	-0.215	0.285	-0.081	0.505
	gemstone	0.024	0.908	-0.038	0.759
	blank	0.000	---	0.000	---
Number format	scientific notation	-0.486	0.019	-0.255	0.038
	decimal	-0.035	0.859	-0.163	0.170
	general	0.000	---	0.000	---
Equation	no eqn	-0.030	0.884	-0.395	0.001
	unbalanced eqn	-0.064	0.746	-0.366	0.002
	balanced eqn	0.000	---	0.000	---
Unit	mol to g	-1.340	0.000	-0.857	0.000
	g to g	-1.083	0.000	-0.659	0.000
	g to mol	-1.130	0.000	-0.490	0.001
	mol to mol	0.000	---	0.000	---
Substance	aluminum hydroxide	-0.130	0.140	-0.114	0.350
	water	-0.082	0.163	-0.108	0.375
	aluminum oxide	0.000	---	0.000	---

Figure 3. Outcomes from logistic regression analysis of stoichiometry questions.

Neither the alumina identity or substance for which the target calculation must be performed showed any differences that were statistically significant. As in the case of the ideal gas questions, those items with scientific notation led to lower success rates. Among the preparatory chemistry cohort, the questions with unbalanced equations or the word version of the equation prove to be a challenge. The general chemistry students were not distracted by those differences. Again, the unit conversations provided the largest effects: all three alternatives to conversions of mol to mol were significantly more difficult. Overall, additional complexity in the problems led to lower success, results that are once again explainable based on cognitive load.

Additional studies on the student approaches to word problems were conducted using eye-tracking methods. A Tobii Technology eye-tracking device employs an infrared source to generate reflection patterns from the dark portion of the pupil of the eyes (*Tobii Technology eye-tracking hardware*, 2017). The eye-tracking hardware is contained in the base of a 17-inch LCD monitor that is connected to a computer that collects the 3-D position of each eye and pupil size; analysis of these data enable detection of the gaze position, gaze duration and, over time, a pattern of locations. Eye-tracking methods have found many applications in cognitive science and in applications in various content disciplines (Duchowski, 2007).

For the gas law and stoichiometry questions, eye-tracking data were collected from a somewhat modified screen compared to the browser-based tool alone. Thus, the word-problem tool, a calculator and a white board were all placed on the same screen. The «white board» drawing area was intended to capture student work without the need for them to look away from the data collecting monitor (using paper and pencil would interrupt the continuous monitoring of the test subjects). Sample gaze data appear in fig. 4, in which the gaze duration is integrated into a «heat map». The brighter the colors (*i.e.*, red), the longer the duration of the subject. Note that the test subject either spent longer times looking at certain words or returned to those words more often within the word-problem tool. The calculator and drawing/planning tool also appear to be used extensively.

The eye-tracking data was used to compare the behavior of students who were more and less successful at solving the ideal gas law and stoichiometry problems. The total time used to read the word questions the first time is defined as the *reading phase*. The time between the reading and the use of the calculator was designated as the *planning phase*. The time using the calculator is the third measured value. Overall times are the sum of the three individual ones. Fig. 5 shows a comparison of each user group for all of the analysis times, while table 3 compares the p value for statistical significance.

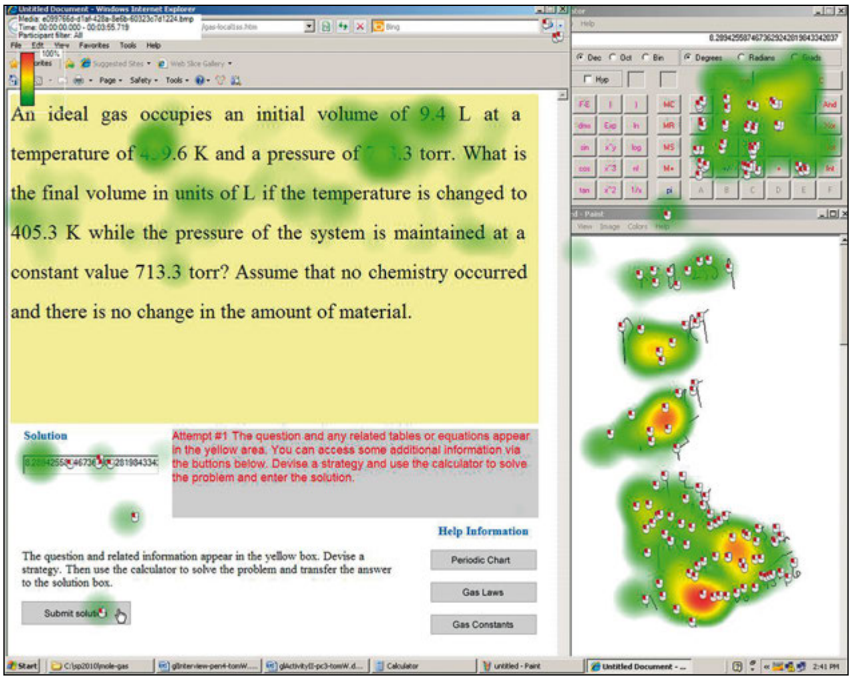

Figure 4. Overall gaze duration (a.k.a. heat map) for one subject's use of the word-problem tools (Tang & Pienta, 2012).

stoichiometry comparison, the overall time is statistically significant. For both tools, the reading phase shows no difference, a result that serves as a control experiment at least for that portion of the activity. Thus, the eye-tracking data is an alternative method to gather information about cognitive issues related to solving the word problems. In addition, for the stoichiometry questions, students who participated in the eye-tracking portion could «think aloud» while they solved the problems simultaneous with the measurement of the gaze data. In general, the more successful students had better strategies or had better plans to answer the questions.

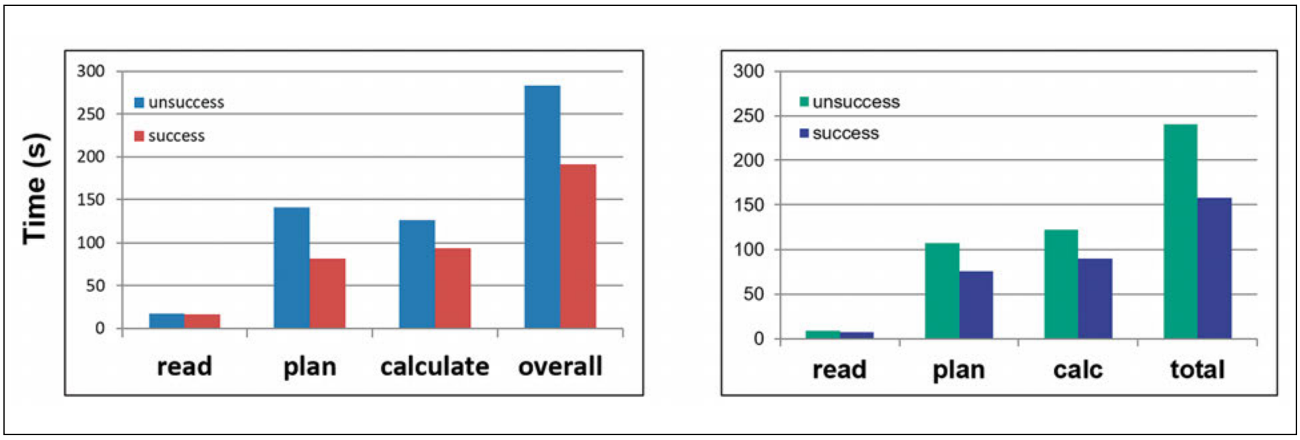

Figure 5. Average time for each phase in successful and unsuccessful students using the word-problem (left) and stoichiometry-problem (right) tools (Tang & Pienta, 2012; Tang, Kirk & Pienta, 2014).

Table 3. Statistical comparison of average time of phases using the word and stoichiometry questions

	Ideal gas	*Stoichiometry*
Phase	*Significance (p)*	*Significance (p)*
Read	0.867	0.465
Plan	0.019	0.100
Calculate	0.414	0.100
Overall	0.084	0.018

For the ideal gas law questions, the planning phase is statistically significant between the successful and less successful students. The overall time is approaching significance. In the

Drawing Lewis structures and molecules

Another two browser-based tools collect information related to student-drawn representations. A Lewis dot structure drawing tool provides a drawing area into which the user can drag and drop atoms, electrons (*i.e.*, as a dot or series of dots), bonds (*i.e.*, lines or set of lines) and charges. The tool is «free-form» allowing the student to place those items anywhere in the drawing area. (Some guidance is provided about appropriate spacing to have the tool recognize the work correctly.) The tool also allows the components to be moved and deleted; a view of the interface and a partially drawn structure is shown in fig. 6.

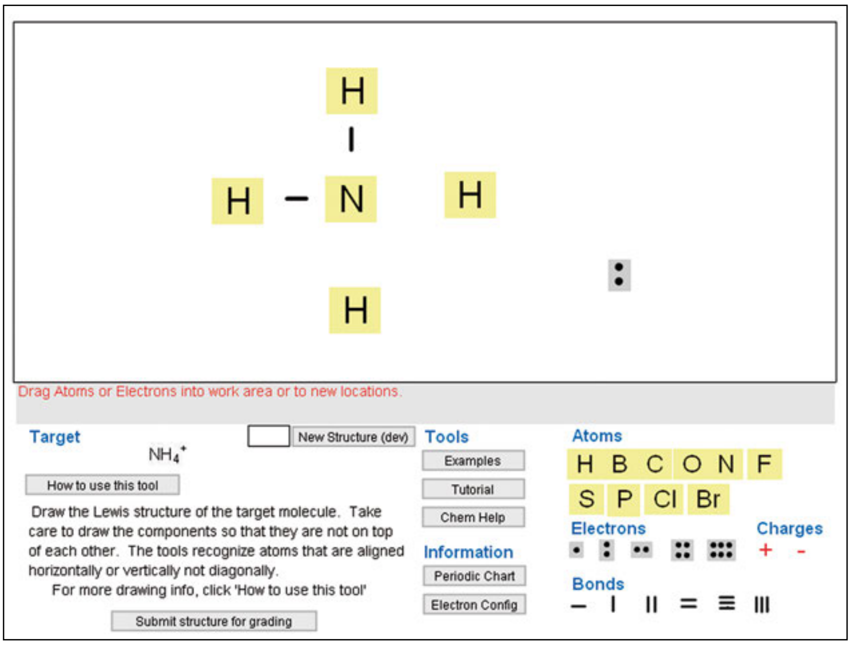

Figure 6. Lewis structure drawing tool with partial structure of ammonium ion.

The Lewis structure drawing tool randomly assigns a structure from one of twenty-four possibilities: BF_4^-, BH_3, BH_4^-, CH_2Cl_2, CH_2ClF, CH_3Cl, CO_2, CO_3^{2-}, CS_2, H_3O^+, HCN, HNO, N_3^-, NH_3, NH_4^+, NO_2, NO_3^-, O_3, $OCCl_2$, OCH_2, OCN^- PCl_3, SCN^-, and SO_3 (Pienta, 2017). The tool tracks each step taken by user, and when submitted, provides feedback about whether the structure appears to be correct. (A few structures can be represented by resonance structures and common versions are recognized by the software.) Reasons for being incorrect can include: wrong atoms, wrong number of electrons, wrong electron locations and missing charges. Three cohorts of students (*i.e.*, preparatory chemistry, general chemistry, organic chemistry) are compared based on their percentage correct of each structure and the percentage of errors for incorrect structures (Pienta, 2017). Some comparisons are more easily understood than others: for example, BH_3 is completed at the highest rate; BH_4^- is more difficult because of the charge, and BF_4^- has the lowest rate of success because of the charge and large number of lone pair electrons. Some of the variation in user success appears to be related to the method and degree of instruction. Efforts are underway to examine the series of steps or paths using pattern analyses.

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A second tool called Spheres has a similar drag-and-drop interface, but in this case each type of sphere represents a different atom in representations of particulate nature of matter drawings. Overlapping spheres denote atoms in these simple 2-D representations.

The example (fig. 7) shows the reaction: $H_2 + Cl_2 \rightarrow 2\ HCl$. Again, the spheres can be dragged anywhere in the drawing areas (*i.e.*, start and finish), moved and deleted. Currently,

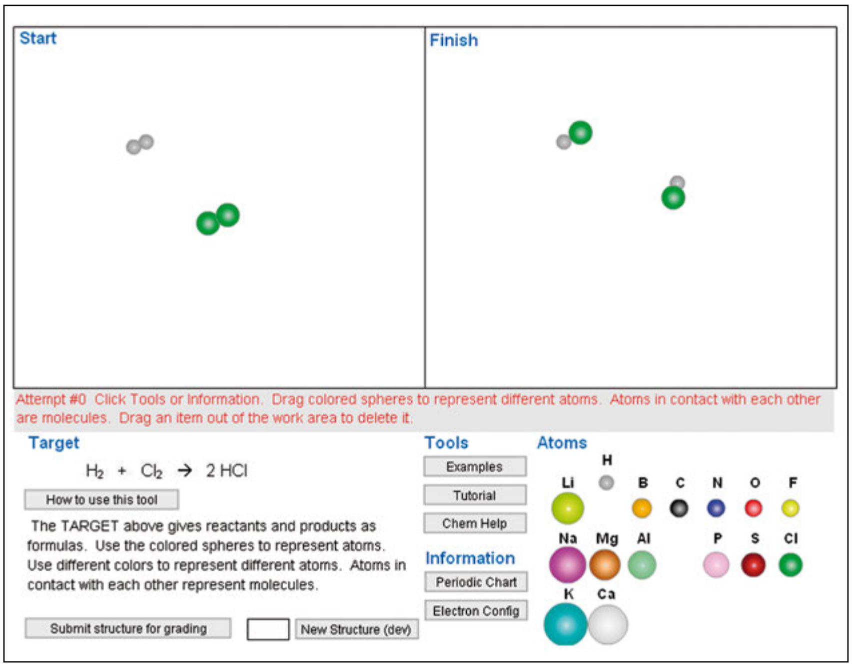

Figure 7. Spheres drawing tool showing a reaction.

Additional eye-tracking experiments have been used to examine students' interpretation of proton NMR spectra

the Spheres tool is not able to provide feedback about whether a drawn representation appears to be correct. However, the drawing tool does provide the means to operate in a tutorial mode. Thus, the user is asked to draw a physical or chemical change. When the structure is submitted, the user is asked whether the equation is balanced and then asked to balance the equation, if appropriate. Finally, the student is asked to draw a scenario where there is a limiting reagent. Fig. 8 shows some student-drawn representations from an example of the latter. The student was asked how the reaction would look on the molecular level if four mol of NO react with three mol of O_2 according to the equation: $NO + O_2 \rightarrow NO_2$. The expectation is that the drawing would contain these components: $4\ NO + 3\ O_2 \rightarrow 4\ NO_2 + O_2$. In this example, the submitted solution does not connect the atoms to make molecules and the atom count is not correct.

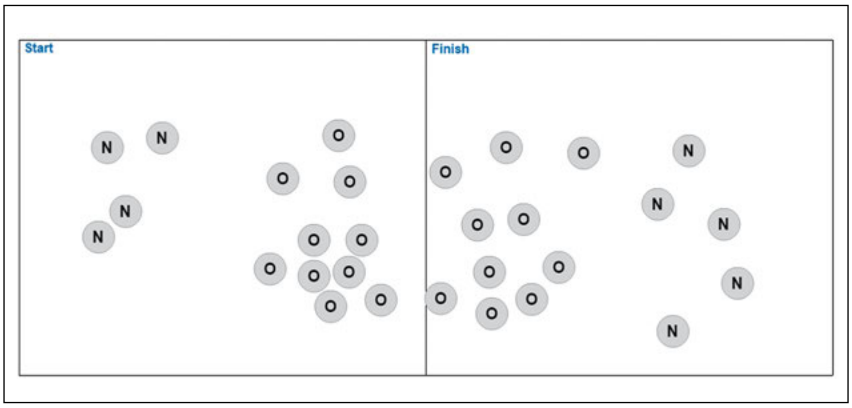

Figure 8. Student solution to drawing a limiting reagent (Pienta, 2017).

Additional examples (*i.e.*, correct molecular structures without the excess reagent and completely correct solutions) have been reported (Pienta, 2017). Currently, extensive experiments using the tools are still underway (Atkinson & Pienta, 2017).

Relating proton NMR spectra to structures

Additional eye-tracking experiments have been used to examine students' interpretation of proton NMR spectra (Topczewski *et al.*, 2017; Tang *et al.*, 2012). Students were shown a H-NMR spectrum and a set of structures, one of which is the correct match to the spectral data. Each student is given 1 min to match the data with the structure, after which the computer goes to the next example. A representative example appears in fig. 9 and the gaze locations can be designated into areas of interest (AOIs) for analysis as shown in fig. 10.

Data were collected from two groups: undergraduate students enrolled in the second semester of organic chemistry, who were designated as *novices*, and second and third year graduate students who were conducting research in organic chemistry, who were designated as «experts». Differences were found between the groups for several criteria (*i.e.*, percent correct, gaze duration and search patterns). The search patterns were based on the AOIs in fig. 10. Each of the «boxes» are defined as an AOI so that all gaze locations within that area can be integrated. Then the AOIs were assigned a number so that string patterns represented a series of digit corresponding to those AOIs. For all questions: 1 = correct structure; 2, 3, 4 = incorrect structures; 5 = question; 6, 7, 8, (9) = spectral parts, and 0 = remaining white space. Algorithms and analytical techniques were developed for the search protocol (Tang *et al.*, 2012). Search patterns were identified for cases that involved > 25 % of the population. Fig. 11 shows that the longest search patterns were only three AOI locations, a result that was somewhat surprising.

The search patterns are three-digit numbers that correspond to a sequence of locations, but the coding for the locations is the same among all six questions. The six questions are grouped into two sets because three of them have one more spectral area than the others. The search patterns are very different for the two groups. Among the experts, eight out of nine patterns have the correct structural answer and resonance feature. However, among the novices, only one out of nine patterns do the same. Clearly, the former group has a significantly different strategy and method. Efforts continue at further elucidating the different strategies and at understanding what interventions can move students from the novice to the expert group.

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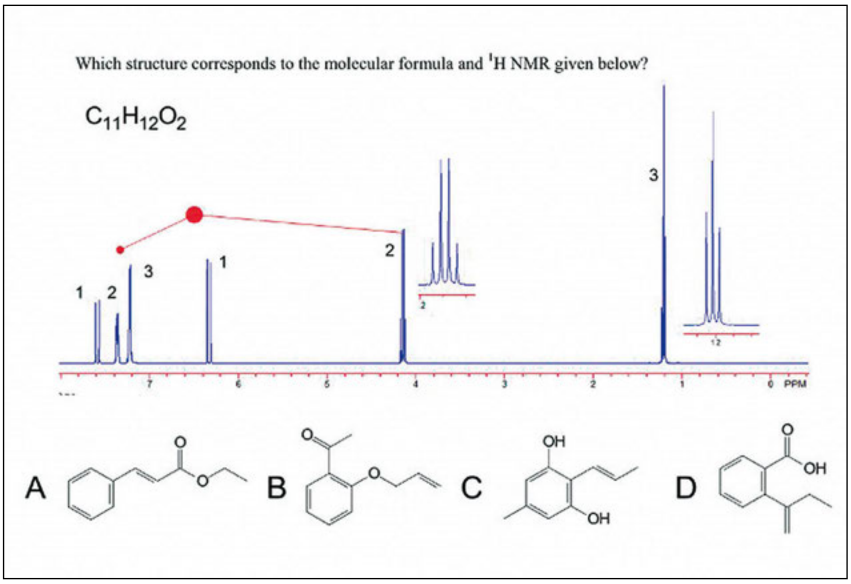

Figure 9. Relating H-NMR spectra and structures of organic molecules (Topczewski et al., *2017).*

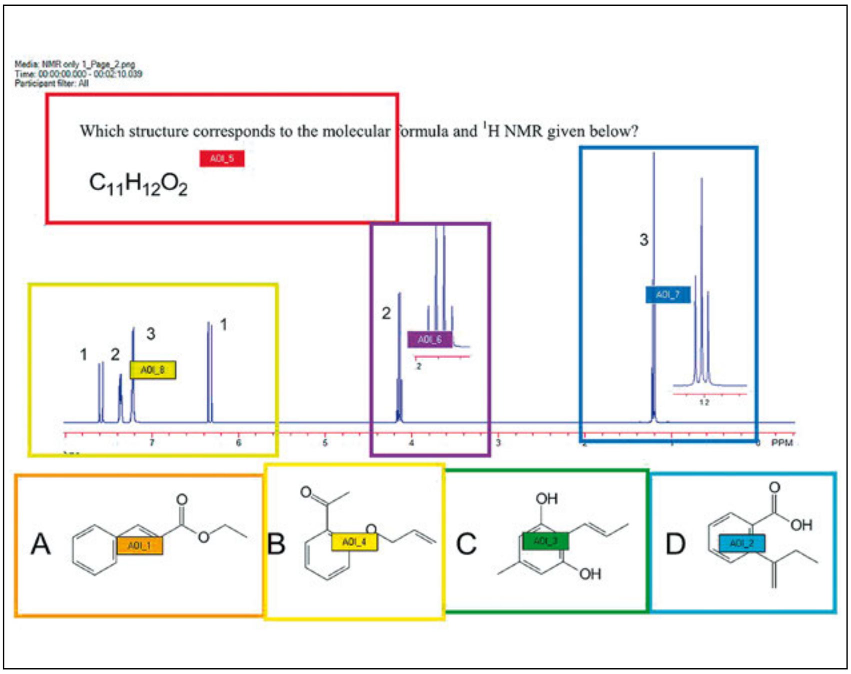

Figure 10. H-NMR spectral question divided into areas of interest (AOIs) for analysis (Topczewski et al., *2017).*

Questions 1, 2, and 6		Questions 3, 4, and 5	
Experts	Novices	Experts	Novices
181	505	818	431
818	323	181	121
186	186	717	505
681		171	312
101			050
			707

For all questions…

AOI	Feature
1	Correct answer
2,3,4	Incorrect answer
5	Question
6,7,8,(9)	Spectral parts
0	White space

Figure 11. Search patterns for series of location within areas of interest found in > 25 % of users (Topczewski et al., *2017).*

An important aspect related to the teaching and learning of chemistry for undergraduate students involves the ways that instructors assess or evaluate them

Summary

An important aspect related to the teaching and learning of chemistry for undergraduate students involves the ways that instructors assess or evaluate them. In order to better understand students' approach to problem solving, basic research has been conducted using several different methods. Browser-based tools enable researchers to collect quantitative data from large numbers of students across different courses and institutions. In turn, this enabled the examination of a large number of variables and factors among some ideal gas law and stoichiometry questions and to investigate the role of cognitive load. Two different tools for examining student-drawn representations provide information about their success and approaches. Thus, drawing Lewis structures or representations of the particulate nature of matter provides insight into their misconceptions and approaches, again from the analysis of large numbers of attempts across different courses. The use of eye-tracking hardware in a series of different experiments established other methods for examining problem solving. Gaze-duration differences among more and less successful students attempting the word problems suggests a means of characterizing or identifying them. Search patterns from experts and novices at relating H-NMR spectral data to

The use of eye-tracking hardware in a series of different experiments established other methods for examin in problem solving. Gaze-duration differences among more and less successful students attempting the word problems suggests a means of characterizing them

appropriate chemical structures gives insights into strategies and provides a mean to test interventions to help the novices become more successful. All of these technology-based approaches suggest a wide variety of additional experiments relevant to chemistry education research.

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