

Chapter 12

A Short History of the Use of Technology To Model and Analyze Student Data for Teaching and Research

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The use of technology for teaching, learning and research has become almost ubiquitous in the chemistry classroom from student response systems, simulations and virtual environments, to online courses complete with assessments. The data generated by such activities can provide insight into how students learn and how we might provide environments that support learning. However, to take full advantage of the affordances of technology, the activities that students perform must be meaningful and must generate useful data that can shed light on student learning and trajectories towards competence. In this paper we present examples from our work describing how we have used technology to investigate and assess student learning with large enrollment courses.

Introduction

Over the past few decades, technological approaches to teaching and learning have led to the development of a wide range of approaches to support learning including online homework systems (1–3), simulations (4), games (5), class response systems (6, 7) and even whole online courses where all of the readings, assignments, and tests are completed online (e.g. massive, open online courses – MOOCs) (8, 9). For the researcher, these technologies can provide a trove

of data, that, if properly analyzed, could provide insights into a wide range of research questions.

Most of the work to date has been focused on whether the use of a particular technology improves learning outcomes for students. For example, studies have compared the use of online homework systems with traditional homework (10–13), how the use of clickers affects learning (14, 15), whether simulations improve conceptual understanding (5), and have compared online and blended courses with face-to-face courses (16). What is interesting about all these works is that the results are not conclusive; as was noted in the NRC DBER report (17) and in an extensive literature analysis (16), there is little strong evidence that technological aids to learning are effective in themselves. That is, “*The use of learning technology in itself does not improve learning outcomes. Rather, how technology is used matters more*” (NRC DBER report) (17). This is not to say that technological approaches to learning have no promise, but rather that the studies to date have not provided strong evidence. For example, there are almost no randomized control treatment studies on the effects of online vs face-to-face courses (16). As has been previously noted (16), many studies of online learning systems are conducted by parties who have something to gain from their findings, making any claims somewhat suspect (we would certainly not accept the claims of drug manufacturers without well designed clinical trials). It appears that merely incorporating technology into the classroom is not a guarantee of improved learning. For example, studies on the use of class response systems seem to indicate that it is implementation – to promote socially mediated learning – rather than the actual use of the technology that improves learning (15). Clearly, if we are to embrace the opportunities (and avoid the pitfalls) offered by online learning, it will become ever more important to learn how to assess student learning in technological settings. At the moment, the evidence required to make such decisions is lacking.

A second, much less investigated, area of research using technology involves its use to collect data that captures students’ approaches as they answer questions and work through tutorials or simulations. That is, rather than investigating whether technology supported learning is more effective or efficient than traditional face-to-face instruction, it could be argued that an equally important use for such technologies is to investigate **how** students learn, how they solve problems, construct models and arguments, and how their trajectories to competence arise (18). This kind of analysis requires that we encourage students to answer questions that require them to construct responses, rather than being asked to choose from among a set of preconstructed responses. Constraining student actions by providing answers from which to choose, imposes conditions that may (almost certainly will) affect the questions we can ask about learning, and what we learn from those questions.

Although the promise of “big data” (19) may be highly seductive, it is important to understand that the nature of the online activity must be one in which students construct artifacts, rather than simply recognize them. No matter how many data points are collected, using commonly available, easily graded, types of assessments such as simple multiple choice questions cannot provide a particularly illuminating picture of student understanding. So, while a great

deal of time and effort has been spent on developing intelligent systems that can provide each student with a customized set of assessments of increasing difficulty (20, 21), there is still a great need for technological systems that help students go beyond recognizing facts and using algorithms. These systems need to help students integrate ideas into conceptual understanding and construct models (diagrams, pictures and structures), arguments and explanations (22). The truism that assessments drive the enacted curriculum indicates that if assessments are unable to probe important skills and concepts, then what is assessed will become what is learned.

Systems That Allow Data Capture for Later Analysis

Technological supports to research data collection have been a mainstay of many studies for many years. For example, researchers routinely record both audio and video of student interviews or teaching activities for further analysis. See Herrington and Daubemire's Chapter 3 as an example (23). More recently, it has become possible to record and replay students' writing with implements such as a Livescribe pen (24). In practice however, all of these qualitative data collection techniques are very time consuming to analyze and requires considerable expertise. In a typical study using recorded audio, video or drawings, only a few (usually less than 30) students' or teachers' data are analyzed. While these studies have provided important insights about teaching and learning, they are not as feasible for large numbers of study participants. Examples of the qualitative analysis process can also be found in Talanquer's Chapter 5 (25).

This chapter provides an overview of systems that use technology to investigate how data from large numbers of students can be used in a meaningful way to investigate how students develop scientific practices and skills. That is, the use of knowledge rather than the acquisition of knowledge.

Interactive Multi-Media Exercises (IMMEX)

There are a growing number of studies where technological approaches have been used to study teaching and learning for larger groups of students. One of the first such systems was *Interactive Multi-Media Exercises* (IMMEX) software, which allowed students to solve problems by choosing menu items that were tracked and stored in a database for further analysis (26). While the actions of the students were predicated on the menu items available, a typical problem required that students choose a sequence of as many as ten items to solve the problem, and the possible permutations were very large. These problems were "knowledge rich" and complex, and could not typically be solved by use of a heuristic or algorithm. There was not one way to solve the problem, meaning that there were multiple approaches to the solution. The sequences of students' actions were then clustered using data mining techniques (27, 28), which produced a number of problem solving strategies or models. This process is shown in Figure 1.

A typical IMMEX problem scenario for general chemistry (Hazmat) required students to identify an unknown compound by performing (virtual) tests (29). For

example, students could perform a solubility or conductivity test to determine the properties present and identify the unknown compound. Ideally, students would use the results from each test to determine how to proceed, rather than randomly performing tests. Using the hidden Markov models (30) produced by the IMMEX analysis system, the students' strategies were determined and could be used to investigate how student problem solving abilities and strategies changed over time, and after interventions (31).

In our studies, we found that student's problem solving strategies stabilized after solving five problems (31–33). No amount of extra practice, even with targeted feedback, produced further improvements. However, if students were paired in problem solving dyads, where they were able to discuss their actions and had to jointly decide on how to proceed, most students significantly improved both their problem solving strategy and their ability (as measured by Item Response Theory – IRT) by about 10% after one group session. Moreover, these improvements were retained even after students returned to individual problem solving sessions (31). A more detailed discussion of the background and use of Hidden Markov modeling are provided in the original paper (31).

While almost all students improved equally in problem solving ability, there were two exceptions to this finding (31). Prior to the problem solving activity, students were given a test of logical thinking (specifically the Group Assessment of Logical Thinking – GALT (34)) and assigned to one of three groups: high (formal), medium (transitional) and low (concrete). If two students from the lowest category (i.e. those who had difficulty with such tasks as proportional reasoning or using data to make inferences) were paired, there was no improvement in problem solving – not a surprising finding. However, we also found that female students from the medium (transitional) group who were paired with a student in the lowest group improved significantly more than any other group, and ended up in the same problem solving category (i.e. with the same ability, and effective, efficient problem solving strategies) as students in the highest ability (see Figure 1, state 5). While much has been written on the advantages of collaborative learning, there are few examples like this study involving large numbers of students (around 800) showing how and where collaborative grouping can improve problem solving.

Unfortunately, the IMMEX software is no longer available for use and its discontinuation is a reminder of how many resources are needed to operate such software for research purposes. There are currently no other programs similar to IMMEX that are commonly available. The development of systems such as IMMEX require a great deal of expertise across a wide range of domains, from computer science to cognitive science. Disciplinary expertise and an understanding of psychometric techniques is also necessary. The inter- and cross-disciplinary teams required to construct and maintain a complex system such as IMMEX are few and far between, and the funding to support these systems is also difficult to maintain. Our intent here by including a discussion of IMMEX is to show what kinds of systems are possible.

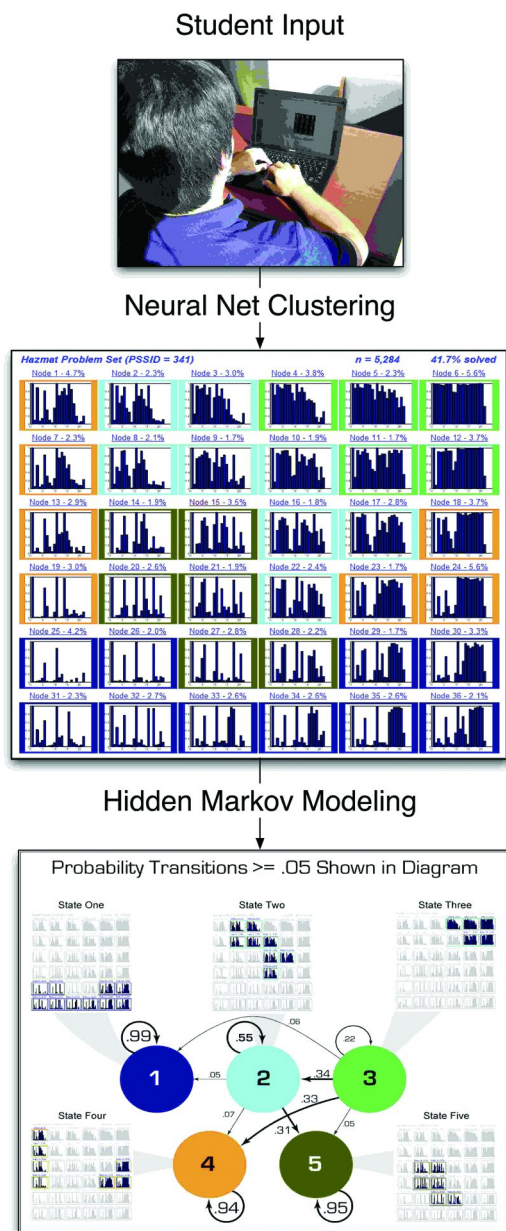


Figure 1. Process for data collection and analysis using IMMEX. Adapted with permission from reference (31). Copyright 2008 American Chemical Society.

Moving from IMMEX to *OrganicPad*

While the IMMEX system provided a way to investigate how students solved quite complex problems and allowed the researcher to track and model student inputs, it was still somewhat limited in that all the possible actions had to be pre-programmed into the problem space. That is, using the Hazmat IMMEX example, each of the different unknowns must also contain pre-programmed results for the various simulated tests that students could perform (e.g. litmus paper testing, flame tests, solubility tests, and conductivity tests). While students had a great deal of choice, it was not possible to allow them to construct their answer “from scratch”. The advent of tablet PCs, and even more so iPads and other tablets, has provided a more flexible interface on which students can write and draw directly. Our first foray into completely open-ended input was the development of a chemical structure drawing tool: *OrganicPad* (35).

OrganicPad is tablet PC software that can recognize and respond to free-form input of chemical structures; it has since morphed into a web-based cross-platform system as part of *beSocratic* (see discussion below). This system provides a natural environment in that students can construct *their* structural representations using a stylus, slate, or trackpad (35). *OrganicPad* can be used in a number of ways for teaching and research purposes: as a classroom response system to automatically grade and respond to students’ structures (using its teacher-student interaction feature); as a formative assessment system where the system collects and grades students’ structural drawings (using its quiz feature); or as a tutorial with multi-tiered assistance (using its pre-programmed contextual feedback feature) (36, 37). *OrganicPad* can recognize and respond to students’ structural drawings in addition to providing feedback based on the students’ input, as it was designed to guide students as they work to produce a reasonable structure (36). This feedback is multi-tiered in that initial feedback may be more general, but if a student does not respond with a correct action the feedback becomes increasingly more specific. For example, if a student’s structure contains a carbon with six bonds, he/she might first be prompted to reflect on the number of valence electrons present for the structure. If the student continues to struggle, he/she would receive more specific feedback that carbon typically forms 4 bonds. A thorough description of *OrganicPad*’s various features are found in the user manual for the program (37). In all of these modes (in addition to recognizing and responding to student free-form structures), the students’ input data are recorded and stored for later analysis. Using this replay feature, we were able to investigate the development of skills associated with drawing and using chemical structures.

For example, we used *OrganicPad* to record and analyze how students enrolled in organic chemistry developed Lewis structure drawing skills (38). We determined that students had great difficulty constructing any structure unless they were presented with structural cues (for example CH₃OH instead of CH₄O). Even with such cues, the success rate fell from around 80% to around 30% correct, when the number of carbon atoms increased from one to two (38). After supplementing this data with interviews and open-ended responses, we believe that the reason students have such difficulty with this task is that the “rules” for drawing structures are not based on any theoretical framework for learning.

Constructing Lewis structures is often seen (at least by students and sometimes by faculty) as an activity that has no meaning or purpose (for example, over half of all students at all levels did not report any use for Lewis structures beyond representing structural information) (38). That is, students were unable to see that the reason for learning to draw such structures is to use them as a predictive tool for how that substance may behave.

It should be noted that students can be quite successful in chemistry courses, even organic courses where structure-property relationships are central, by using heuristics instead of reasoning (39). That is, if students do not have a basic understanding of these ideas, they cannot use reasoning to predict answers, and must resort to heuristics and memorization.

In order to test this hypothesis, we designed a learning progression (40–43) for structure and properties, as part of a new curriculum – Chemistry, Life, the Universe and Everything (CLUE) (44, 45). Again we used *OrganicPad* to record and analyze how students constructed their representations of Lewis structures. Using the tagging feature for analyzing students' structures we were able not only to code the types of errors that were present in each student's structure, but also to develop a timeline for the actions of each student. For example, we could identify if the student was able to correctly connect the atoms to form a viable structure or if their structure contained too many bonds or electrons on carbon. We could analyze the order students constructed their structures, and whether this process was coherent or random. Using pre-programmed coding allowed us to analyze large numbers of students' structures since the program could recognize and compile identical structures. For example, 100 responses might be collapsed into 10 unique structures. This would give the researcher fewer representations to analyze and would help in the process of coding large data sets. In addition to coding students' common mistakes, we were also able to model the sequence of students' actions during this construction process. Markov modeling (37, 46) tracked each student's steps through the construction process. Based on similarities among structures, the user can determine which paths are most commonly taken for constructing structures. Again the reader is directed to the original literature for more details on how the modeling was performed.

These methods allowed us to compare students in the CLUE curriculum with a matched cohort. We found that the CLUE students were significantly more likely to construct reasonable Lewis structures than their traditional counterparts (44). It should be noted that without this technology we would have been unable to do this kind of comparison, not only because of the large numbers of students involved, but also because *OrganicPad* allowed us to track and model the students' input data.

In a similar manner, we used *OrganicPad* to investigate how students develop competence in constructing mechanisms in organic chemistry. Using the program's replay feature allowed us to create Markov models to identify the sequence in which students wrote mechanisms (for example, about 20% of students put the mechanistic arrows onto the reaction scheme after they had drawn it – that is, they did not use mechanisms for predictive purposes) (47). We were also able to determine that use of mechanisms did not affect the correctness of common reaction products, but when students were faced with a problem

in which they did not know the answer, the students who used mechanistic reasoning were more likely to produce a reasonable product (48). Once again, it is important to emphasize that it was the data collection and analysis tools provided by *OrganicPad* that allowed us to do this research with large numbers of students, to model trajectories over time, and to compare students in different courses and stages in their development.

Moving beyond *OrganicPad*: The Development and Assessment of Science Practices

While *OrganicPad* has been useful in providing information that was previously unavailable, it is limited to concepts and skills associated with chemical structure drawing. We wanted to use the kinds of data collection and modeling techniques piloted with *OrganicPad* and extend them to other areas of chemistry (and science).

There is a growing recognition that a working understanding of science requires not only a grasp of the core disciplinary ideas, but also the ability to combine disciplinary knowledge with a range of science practices. The recent National Research Council Framework for STEM education (22) defines eight “science practices” including modeling, explanation and argumentation, while the Next Generation Science Standards (NGSS) (49) and the recently redesigned high school AP courses (50) link disciplinary knowledge and science practices into performance expectations that are assessed through tasks that involve the ability to accurately apply working knowledge to new systems (transfer). Both require students to construct drawings (by which we mean models, including graphs, and representations) and to use data, concepts, and reasoning to construct scientific explanations and arguments about specific phenomena. However, a major problem with this evolving approach to teaching science is that the assessments have not kept pace with the ideas and practices that we would like students to develop. If students are to learn to construct models, defend arguments and develop explanations, they must be provided with a learning environment that allows them to develop these skills. Ideally, formative assessment activities, where students receive meaningful feedback, would be part of this learning environment. That is, we need to develop systems that will be able to recognize and respond to student-constructed models, explanations and arguments. Furthermore, if we as researchers want to learn about how students develop these skills, and how to help students develop them, we need systems that allow us to collect appropriate data for analysis. The rest of this chapter will focus on how and why we developed *beSocratic* – a formative assessment system – and research activities that have resulted.

***beSocratic*: A Formative Assessment System for Free-Form Diagrams, Models, and Structures**

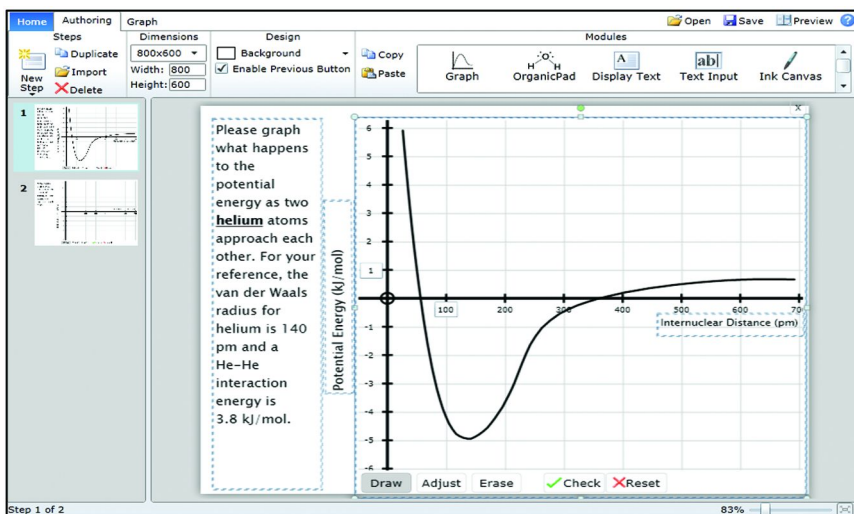
beSocratic builds upon our work with *OrganicPad*; indeed, *OrganicPad* is now subsumed within the new system. *beSocratic* is designed to allow students to construct drawings, graphs and diagrams. However, systems that can recognize

– a priori – any drawing that students might construct have yet to be developed. Even recognizing relatively simple drawings is extremely difficult if there is no point of reference for comparison. It is relatively simple to develop a system that can recognize and respond to chemical structures, since there is an underlying architecture and set of rules that can be used by the programmer. Recognizing drawings requires a much more complex system, and while there are systems that can recognize simple drawings (for example *Cogsketch* (51)), they are based on highly sophisticated artificial intelligence systems and can be quite difficult to use, both for the instructor and the researcher. It was our aim to develop a system that would be easy to use, but would be powerful enough to recognize many types of diagrams, graphs and some drawings. Our goal was to hit the balance among flexibility, free-form input and ease of use. Currently over 100 activities have been authored in the system and have been administered as assessments, in-class activities, or homework. Access to *beSocratic*, along with pre-made activities, can be obtained by contacting the primary author of this chapter. A user guide for how to author *beSocratic* activities can be found on the website (52).

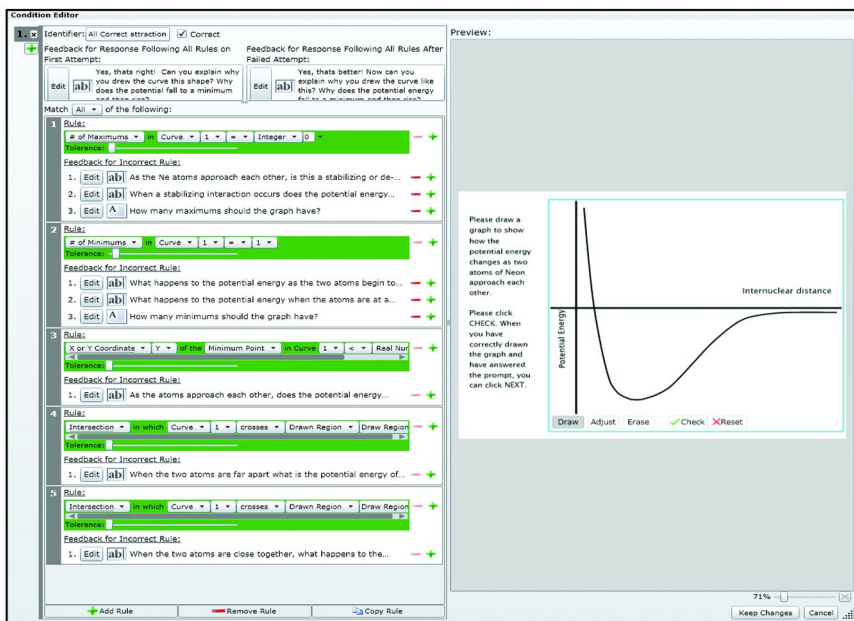
Description: *beSocratic* is an online, cross-platform, intelligent tutoring system (21) designed for the recognition, evaluation and analysis of free-form student drawings (53). It consists of two main interfaces: 1. an instructor interface that allows for the development of activities and analysis of student data and 2. a student interface where activities are presented and completed. This system was specifically built as both a tool for instructors and researchers and has been used for both purposes.

beSocratic activities are relatively easy to author (faculty have successfully developed activities after a two hour workshop). The authoring interface is purposefully designed to be reminiscent of *PowerPoint* or *Keynote*. That is, activities are developed as a series of slides, on which one or more *modules* are placed (Figure 2a). Most of the interactivity is gained through the *SocraticGraphs* module discussed below. Other modules allow positioning of text, images, text input boxes, drawing canvases, 3D molecular model viewers, *GraphPad* (54), and chemical structure drawing (*OrganicPad* module). All student input data, either drawing or text, is recorded for later analysis.

The *SocraticGraphs* module enables students to respond by drawing not only graphs, but also diagrams and pictures. Especially when used in conjunction with an underlying image, the range of responses that can be detected and responded to is quite broad (Figure 3). Student drawings are analyzed based on rules that have been pre-specified by the activity designer (i.e. researcher or instructor), such as the number of maxima/minima, area under the curve, slope, and intersections with coordinates or areas. The researcher/instructor can specify not only the shape of a curve, but also the number of curves and (if there is an underlying image) where student drawn responses should appear relative to that image. By using and combining these rules it is relatively simple to develop activities for drawing graphs and simple diagrams (Figure 2b).



(a)



(b)

Figure 2. Screenshot of beSocratic: (a) authoring interface and (b) designing contextual feedback with SocraticGraphs module.

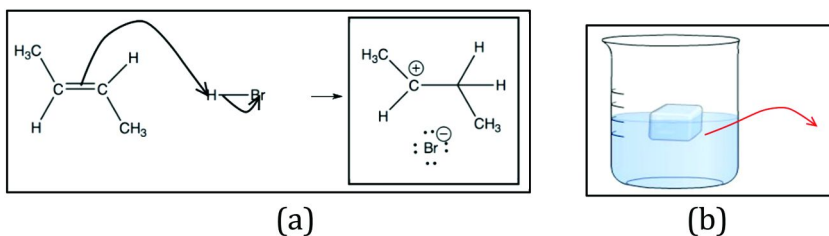


Figure 3. Examples of using *SocraticGraphs* with an underlying image: (a) arrow pushing in constructing mechanisms and (b) thermal energy transfer from the system to surroundings.

As with *OrganicPad*, students are presented with contextual feedback of increasing specificity when their submission does not meet one or more of the rules for a correct answer. Typically the feedback is designed to elicit reflection on the part of the student, rather than providing a correct/incorrect response. The feedback from the system usually requires a response from the student, either written or drawn, before the student can proceed. Even when a response is correct (or adequate), the student is also asked to explain their thinking in a pop-up text box before moving to the next page of the activity. This student response is also captured. An example of incorrect feedback is shown in Figure 4a, while Figure 4b displays a correct feedback prompt. This type of activity can provide rich data for both researcher and instructor. As we will discuss later, the data produced can be mined and modeled to investigate how students respond to such activities.

beSocratic also has a unique feature that allows students to edit a previously constructed drawing or text by making modifications according to their new understanding. More specifically, students can be presented with their initial model or explanation and asked to revise it by explaining or pointing out features that align with their new knowledge and those that do not. *beSocratic* can track not only the students' original submission but also their edits for later analysis. In fact this general procedure is applicable to a wide range of activities, including constructing models, explanations and arguments (see specific examples below).

Please draw a graph to show how the potential energy changes as two atoms of Neon approach each other.

Please click CHECK. When you have correctly drawn the graph and have answered the prompt, you can click NEXT.

As the Ne atoms approach each other, is this a stabilizing or destabilizing interaction?

it is stabilizing and then destabilizing

Close

Draw Adjust Erase Check Reset

(a)

Please draw a graph to show how the potential energy changes as two atoms of Neon approach each other.

Please click CHECK. When you have correctly drawn the graph and have answered the prompt, you can click NEXT.

Yes, that's better! Now can you explain why you drew the curve like this? Why does the potential energy fall to a minimum and then rise?

because as the He atoms approach the interaction is attractive, which lowers the PE, but when the atoms get too close the repulsions are stronger and the PE rises again

Close

Draw Adjust Erase Check Reset

(b)

Figure 4. Screenshots of feedback for (a) an incorrect student submission, and (b) a correct student submission.

beSocratic Data Analysis

There are a number of ways to visualize and analyze student submissions, both individually and for large data sets. For example, a specific student's response can be replayed so that sequences of their actions can be observed, coded or tagged for later analysis. This feature works with all modules in which students' submitted input, specifically including text, graphs and drawings. Alternatively, the grid view (Figure 5) presents a thumbnail of each student's final submission. Selecting a submission enlarges the thumbnail and provides the controls needed to replay the submission.

The grid view allows instructors and researchers to quickly scan the images for interesting submissions that may require further investigation or which might serve as useful (anonymous) exemplars for in-class discussion. *beSocratic* provides an excellent way to incorporate just-in-time teaching techniques (55). For example, in a large enrollment classroom setting we might have students vote (for example, by clicker) on the best answers and possible ways to improve the response.

beSocratic Post-Analysis Research Tools

beSocratic is capable of recording hundreds of student submissions for an activity. Since analyzing this volume of data can be very time consuming, we have integrated a set of post-analysis tools that helps facilitate the process in order to discover insights about student learning. Post-analysis in *beSocratic* is broken down into two stages: coding and clustering. During the coding phase, researchers are able to use *beSocratic* to attach codes to submissions either manually or, in some cases, automatically. For manual codes, researchers replay student submissions, pause the replays, and assign one or more custom codes at the paused position in the replay. In addition to these hand coded submissions, *beSocratic* can automatically assign codes for questions that used the *SocraticGraphs* module. In this case, the question's rules and feedback act as the codes themselves. It is important for us to code the replay instead of simply analysing the final submission. With the codes created in this way, *beSocratic* uses various clustering techniques (such as Hidden Markov Modeling (30)) to discover and visualize groups of students who have similar final answers and used similar actions to arrive at their final answer (Figure 6). By analyzing submissions in this way, *beSocratic* can quickly identify distinct strategies that students are using. Furthermore, *beSocratic* can use the results of the clustering (i.e. the strategies that students used) as input into future activities so that when a student is following a previously identified problematic strategy, the system can intervene with targeted feedback as an attempt to guide the student to a more correct strategy.

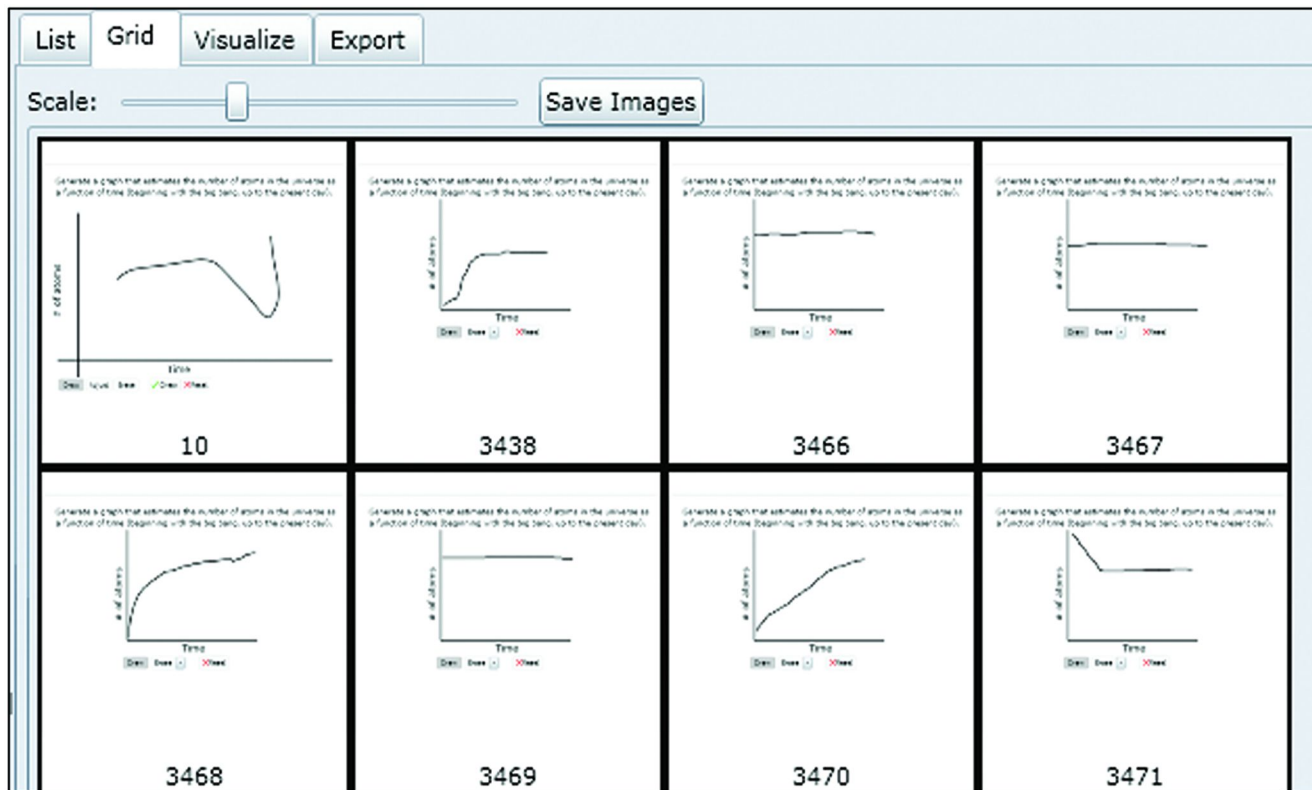


Figure 5. Grid view of a group of students' submissions for the question "Draw a graph of the number of atoms in the Universe vs time."

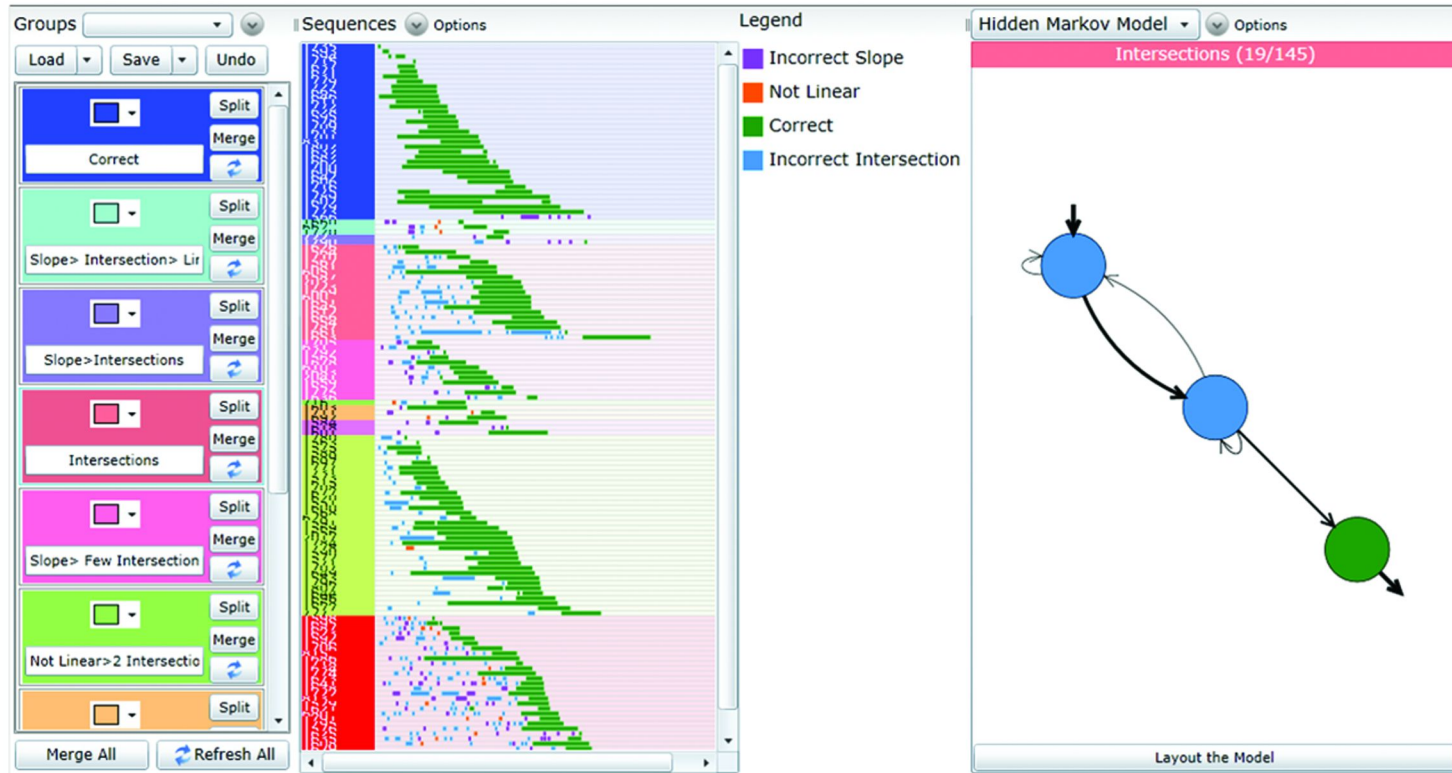


Figure 6. An example of hidden Markov modeling to determine students' strategies.

Examples of beSocratic Activities

As previously noted, there is an increasing move towards assessments that require students to construct rather than recognize. There is also emerging evidence that student understanding cannot be captured by forced choice instruments that probe only one aspect of a complex concept. For example, Talanquer (56) has shown that many students use recognition heuristics to answer the kinds of ranking tasks that are often addressed in multiple choice questions. Furthermore, we have found that students who are able to correctly identify (for example) relative boiling points of compounds often use inappropriate reasoning (39). Instead of possessing a coherent model of a concept, many students utilize a rather loosely woven tapestry of facts, heuristics, and skills that may allow them to choose a correct answer without constructing a model or explanation. If we want to promote robust learning, we must provide students with appropriate learning materials that allow them to develop these skills, rather than accepting the results of shallow learning.

We present here two possible approaches to using *beSocratic* to support the development of conceptual understanding while, at the same time, emphasizing important science practices.

1. The Development of a Model To Describe the Energy Changes as Molecules or Atoms Interact

It is well known that many students believe bonds contain energy that is released when they are broken. This “misconception” is persistent, pervasive, and resistant to instruction (57, 58). While there are many reasons for this (59), it is clear that current approaches to teaching bond energy ideas are not effective. We are using *beSocratic* to develop approaches, using the construction of models and diagrams, to help students develop a more coherent concept of chemical energy involving the role of energy in atomic and molecular interactions. An early activity involves students constructing graphical representations of forces and energy changes (potential, kinetic and total) as two isolated atoms approach each other. As students construct these graphs, feedback is provided based on the underlying logic that has been supplied by the instructional designer. Figures 4a and 4b show a student’s initial and final attempt to draw the potential energy (PE) curve as two neon atoms approach each other. After each attempt, the student is provided with a prompt (of increasing specificity if necessary), and finally asked to explain the shape of the curve they have drawn. Ultimately, they must construct not only the representation of the energy change, but also explain what that representation means.

Recall that models are important because they can be used to predict how a system will behave under different conditions. Typically in *beSocratic*, once the student has mastered the first activity they are asked to use that understanding in a new situation. So for example, in the interactions activity students are presented with their final PE curve of neon (*beSocratic* has a “copy previous” function that can copy a student’s input from one screen to another) and asked to draw a new

potential energy curve for the interaction of two argon atoms. That is, students are asked to show (and then explain) how the position of the minimum for argon is related to that of neon (Figure 7).

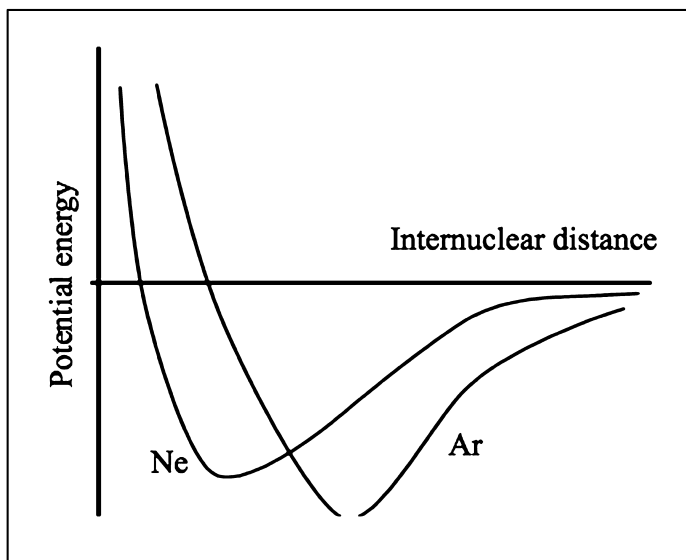


Figure 7. Development of a model for potential energy changes for interactions and bonding. A student's response indicating the potential energy change for the interaction of two argon atoms versus two neon atoms.

The students' responses for these activities can then be analyzed using a variety of techniques. For example, the students' graphing attempts can be clustered to determine the types of strategies present in that group (Figure 6). We can look at how student success on the initial activities follows through to the transfer activity by clustering the data from each activity. All of the student text responses have also been captured, providing a wealth of data that can be analyzed. While automated analysis of the text responses is not currently available, we are pursuing collaborations with other researchers to investigate this possibility (60).

2. Using *beSocratic* To Help Students Learn To Develop Arguments and Explanations

While *beSocratic* is not able to respond automatically to students' text submissions, there are a number of approaches we have used that involve student writing alone (that is, text without an associated drawing or model to describe). For example, we are using *beSocratic* to help students learn to construct arguments and explanations. Students might be asked to predict and explain their choice as to which of a given set of atoms is larger, has the highest ionization energy, or is the most acidic. Often when students are asked to do this kind of task, they will make

a prediction (a claim), but are unable to explain why their answer is correct. Even if an explanation is given, it is often in the form of a heuristic (56), rather than one in which students use data or scientific knowledge to provide their reasoning and support their prediction. Therefore, when students are initially assigned such a task, we tend not to see a rich explanation of the phenomenon; in fact, little use of data or scientific understanding to support the argument is observed.

We have developed a series of activities in which students are asked the initial question in *beSocratic*, and then introduced to the idea of providing an explanation that has three components: a claim, the supporting data or evidence on which they are making this claim, and the reasoning that links these two. The student is then asked the initial question in three separate ways.

1. What is the claim you are making?
2. What data, evidence or scientific principle(s) are you using to support this claim?
3. How does this data/evidence/principle support this claim (i.e. what is the reasoning behind your answer)?

The student is then presented with their initial response, using the “copy previous” feature, and asked to edit their answer in light of the new reasoning. Students’ initial and final responses can then be compared to evaluate the effectiveness of the activity. In this way, even though we cannot automatically analyze students’ text input with *beSocratic*, we ask student to reflect on their own writing and improve it.

For example, in an activity where students were asked to explain the trend in atomic radius across a row in the periodic table, one student wrote: “*As you go across a row, the atomic radius decreases.*” After the activity she edited her response to read (changes from initial submission underlined for emphasis): “*As you go across a row, the atomic radius decreases. This is because the number of protons increases as you go across a row. The more protons that are present, the stronger pull the nucleus has on the electrons. Therefore, the radius is smaller because the electrons are pulled in closer to the nucleus.*” In this way we have encouraged the students to provide a much more full explanation of the phenomenon. This use of the affordances of the technology to prompt students to reflect and retrieve relevant information can make student thinking more accessible to the instructors and researchers.

Conclusion

In this chapter we have attempted to present a number of alternate approaches to the use of technology for research on teaching and learning. It is our firm belief that appropriate use of technology can provide information that will result in real improvements in our approaches to the development of research-based pedagogies. However, if we limit ourselves to approaches in which students are asked to complete forced choice assessments, the result will be that students will

find it increasingly difficult to synthesize their ideas into coherent conceptual models.

The use of technology can help us learn how students develop not only knowledge, but also the science practices that allow them to use this knowledge in new situations.

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