Adaptive Support for Representation Skills in a Chemistry ITS Is More Effective Than Static Support

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Abstract. Multiple visual representations can enhance learning in STEM, provided that students have prerequisite representation skills to make sense of how the visuals show information and to fluently perceive meaning in the visuals. Prior research shows that instructional support for sense-making skills and perceptual fluency enhances STEM learning. This research also shows that students need different types of support, depending on their prior representation skills. Hence, instruction may be most effective if it adaptively assigns students to support for sense-making skills and perceptual fluency. We tested this hypothesis in an experiment with 45 undergraduates in an introductory chemistry course. Students were randomly assigned to a 6-week instructional module of an intelligent tutoring system (ITS) that (1) provided a static sequence of activities that supported sense-making skills and perceptual fluency or (2) adaptively assigned the activities. Results show that the adaptive version yielded significantly higher gains of chemistry knowledge. Our findings expand theories of representation skills and yield recommendations for ITSs with multiple visual representations.

Keywords: Multiple representations · Sense-making skills · Perceptual fluency

1 Introduction

Instruction in most science, technology, engineering, and math (STEM) domains uses multiple visual representations [1–3]. Compared to a single visual, multiple visuals can enhance learning of domain knowledge because they allow students to form more accurate mental models [4–6]. For example, instruction on chemical bonding typically uses the visuals in Fig. 1 that show complementary concepts of atomic structure [7].

But research also shows that multiple visuals can impede learning if students lack representation skills to make sense of how multiple visuals show information and to fluently perceive the information they show [3, 8]. Further, research shows that students need different types of instructional support for representation skills at different times during their learning trajectory [9, 10]. This research suggests that adaptive representation-skills supports may enhance students' learning more so than static supports.

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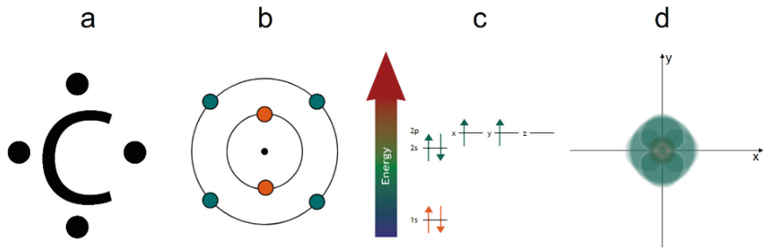

Fig. 1. (a) Lewis structure, (b) shell model, (c) energy diagram, and (d) orbital diagram of carbon.

While it is well known that adaptive support for problem solving enhances learning [11], this hypothesis has not been tested for representation skills. We address this gap in an experiment on chemistry learning. Our results show how different representation skills build on each other and yield guidance for the design of educational technologies.

2 Theoretical Background

Prior research distinguishes two types of representation skills (sense making and perceptual fluency) that are learned via different processes and need different support [6].

2.1 Sense-Making Skills

Students' learning of domain knowledge from multiple visuals depends on their ability to make sense of how the different visuals show complementary concepts [6, 12]. To this end, students map visual features of different representations to the concepts they show [4, 12]. That means students need to distinguish features that show meaningful information (e.g., the number of valence electrons shown in a Lewis structure, Fig. 1a) from incidental features (e.g., the color of electrons in the shell model, Fig. 1b) [13]. Then, students need to compare visuals [4, 14]. That is, they need to understand similarities between visuals (e.g., both Lewis structure and shell model show that carbon has four valence electrons, Fig. 1a–b) and differences (e.g., the shell model in Fig. 1b shows the core electrons, but the Lewis structure in Fig. 1a does not).

According to cognitive theories, students acquire sense-making skills through *learning processes* that are verbally mediated because students explain how visuals show concepts [15, 16]. These processes are explicit because students have to willfully engage in the explanations [17, 18]. Accordingly, *instructional activities* that support sense-making skills engage students in active reasoning about visuals, for example by asking them to self-explain similarities and differences between visuals [19, 20].

2.2 Perceptual Fluency

A largely separate line of research on expertise has focused on a second type of representation skills. Experts "see at a glance" what visuals show without perceived mental effort [21, 22]. They are very efficient at extracting meaning from visuals because they can effortlessly combine information from multiple visuals and quickly translate among them [23, 24]. This high efficiency results from perceptual chunking: visual cues retrieve corresponding schemas from long-term memory that describe concepts [25, 26].

According to cognitive theories, students acquire perceptual fluency via *inductive processes* involved in pattern learning [16, 27] that involve both bottom-up (cuing) and top-down (selection) mechanisms. Inductive processes are non-verbal [16, 25] because verbal reasoning is not necessary [24, 28] and may even interfere with pattern learning [29, 30]. Thus, perceptual induction does not require direct instruction but rather results from experience [24, 27]. Hence, *instructional activities* that support perceptual fluency expose students to many examples, for example in classification tasks [31], interleaved practice [32, 33], or games that require quick translations among visuals [34].

2.3 Combining Support for Sense-Making Skills and Perceptual Fluency

If students need sense-making skills and perceptual fluency, then combining activities that support sense-making skills and perceptual fluency should enhance learning of domain knowledge. Prior studies tested effects of (1) a combination of sense-making and perceptual-fluency activities, (2) only sense-making activities, (3) only perceptual-fluency activities, and (4) a control that received multiple visuals without representation-skills support. Experiments on elementary fractions [35] and undergraduate chemistry [36, 37] show that only the combination is more effective than the control.

Cross-sectional studies [9, 37] show that the effectiveness of specific sequences of sense-making and perceptual-fluency activities depends on students' knowledge about how the visuals show concepts. Specifically, novice students need to become familiar with each visual before they benefit from sense-making and perceptual-fluency activities. Intermediate students benefit from receiving sense-making activities followed by perceptual-fluency activities because sense-making skills enhance perceptual pattern learning by helping students attend to relevant visual features. Finally, advanced students benefit from receiving perceptual-fluency activities followed by sense-making activities because this helps them fluently use information from multiple visuals to make sense of concepts. Thus, the effectiveness of sense-making and perceptual-fluency activities varies depending on students' current skill level, which changes as they learn. Hence, prior research suggests a progression of representation skills [38].

3 Experiment

Based on this prior research, we hypothesize that instruction is most effective if it adaptively assigns sense-making and perceptual-fluency activities depending on a student's current skill level. We tested this hypothesis in an experiment with Chem Tutor, an in ITS for undergraduate chemistry. We first developed an adaptive version of Chem Tutor using data from a prior experiment and then compared it to a static version.

3.1 Chem Tutor: An ITS for Undergraduate Chemistry

Chem Tutor provides complex problems and individualized step-by-step guidance throughout the problem-solving process [11, 39]. It uses a cognitive model of the students' knowledge about how the visuals show chemistry concepts [40]. The model can detect multiple strategies and provides detailed feedback and hints on how to use the visuals [41]. Here, we use Chem Tutor's atomic structure module. It has six units, each with two of the visuals in Fig. 1 (see Table 1 below). Each unit has three problem types.

Regular Activities correspond to chemistry instruction that typically uses one visual at a time [42]. For example, students may be asked to construct an energy diagram of oxygen (see Fig. 4 below). They are first prompted to identify properties of the atom to plan the energy diagram. Next, they use an interactive tool to construct the visual. Students must construct a correct visual before they move on. Finally, they use the visual to make inferences about the atom. Thus, regular activities provide one visual at a time but provide no support for representation skills that involve comparing or translating among multiple visuals. Based on findings that students first have to become familiar with each visual [4], each unit starts with two regular activities, one for each visual.

Sense-Making Activities are designed to help students understand connections among multiple visuals, in line with instructional design principles based on the prior research on sense-making skills reviewed above [19, 20]. Sense-making activities ask students to *actively compare* pairs of visual representations. To this end, students are given two visuals and receive prompts to *self-explain* similarities and differences between the visuals. For example, the activity in Fig. 2 asks students to reflect on similarities between an energy diagram and a Lewis structure for magnesium. Given the energy diagram, students construct the Lewis structure of magnesium. Then, they receive self-explanation prompts to compare the visual representations. This example focuses on similar conceptual aspects shown by both visuals. Other sense-making activities focus on differences between visuals. Alternating activities focus on similarities and differences.

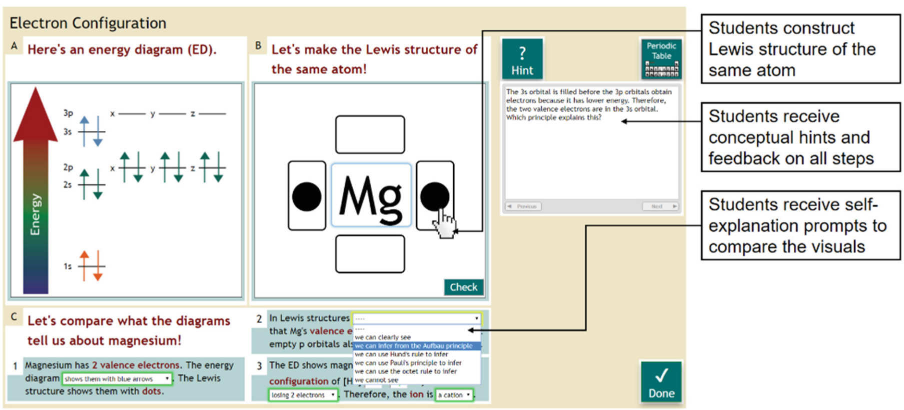

Fig. 2. Example sense-making activity in Chem Tutor.

Perceptual-Fluency Activities embody the principles reviewed in Sect. 2.2 [24, 27]. For example, students may have to select one of four energy diagrams that shows the same atom as a given Lewis structure (Fig. 4). The choices contrast relevant features, such as the number of valence electrons versus the total number of electrons. Each activity has one step, and students solve many of them in a row for a variety of atoms. Students receive immediate correctness feedback. To engage perceptual processing, students are asked to solve the activities fast and intuitively, without fear of mistakes (Fig. 3).

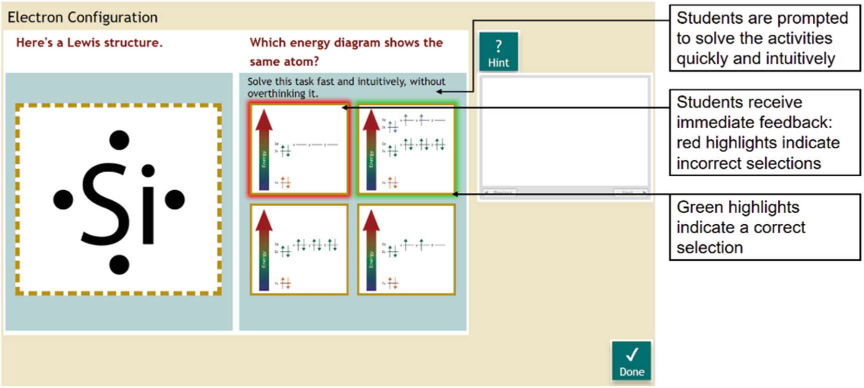

Fig. 3. Example perceptual-fluency activity in Chem Tutor.

3.2 Development of the Adaptive Assignment Algorithm

Data. To develop an algorithm that adaptively assigns these activities, we used data from 129 undergraduate students in an introductory chemistry course at a large university in the US Midwest. They completed one Chem Tutor unit per week, for six weeks.

Students were randomly assigned to one of five versions of Chem Tutor that varied whether they included sense-making activities and/or perceptual-fluency activities or not, and the order in which these activities were provided. That is, students received (1) regular activities only, (2) regular then sense-making, (3) regular then perceptual-fluency, (4) regular, sense-making then perceptual-fluency, or (5) regular, perceptual-fluency then sense-making activities. We controlled instructional time by equating the number of steps across conditions. For example, for unit 1, students in the regular-only condition received four regular activities with 67 steps in total. Students in the regular-sense condition received two regular activities and two sense-making activities with 67 steps in total. Pilot testing verified that instructional time did not differ between conditions. All conditions received the same two regular activities at the start of each unit. The content covered in the remaining activities was identical across conditions.

We assessed learning of the chemistry content with a pretest at the start of each unit and a posttest at the end of each unit. Each test had multiple-choice and short-answer items. Tests and grading scheme were developed by a chemist. Agreement between independent graders on 10% of the responses to the short-answer items was 88.55%.

Further, our goal was to predict benefit from sense-making and perceptual-fluency activities, so we mined the Chem Tutor logs for predictors. We focused on the first two regular activities that all conditions received for each unit. For each step, we computed performance based on whether a student's first attempt at the step was correct or incorrect. In sum, we computed performance measures for 134 steps across six units.

Analyses. To identify problem-solving steps that were predictive of students' benefit from sense-making and perceptual-fluency activities, we conducted linear regression analyses with 10-fold cross-validation. The regression models identified steps for which performance interacted with the experimental factors to predict pre-post gains. Such effects indicate aptitude-treatment interactions (ATIs) [43], such that low-performing students benefit from a different intervention than high-performing students.

We constructed a linear regression model for each unit. In each model, the dependent variable was pre-post gain. Predictors were the experimental factors (i.e., with/without sense-making activities; with/without perceptual-fluency activities, and the order of the activities), performance on each step in the first two regular activities in the unit, and the interaction of performance on each step with the experimental factors. The regression models outputted significance tests and regression coefficients for each predictor.

Adaptive Algorithm. We selected steps for which the regression analysis revealed significant ATIs because this means that the step predicts if a student will benefit from sense-making activities and/or perceptual-fluency activities. For example, a positive regression coefficient for an ATI between performance on a step and the sense-making factor indicates that students who get this step right benefit from sense-making activities. The activity in Fig. 4 shows two example steps for which we found significant positive interactions with the sense-making factor. This suggests that getting these steps

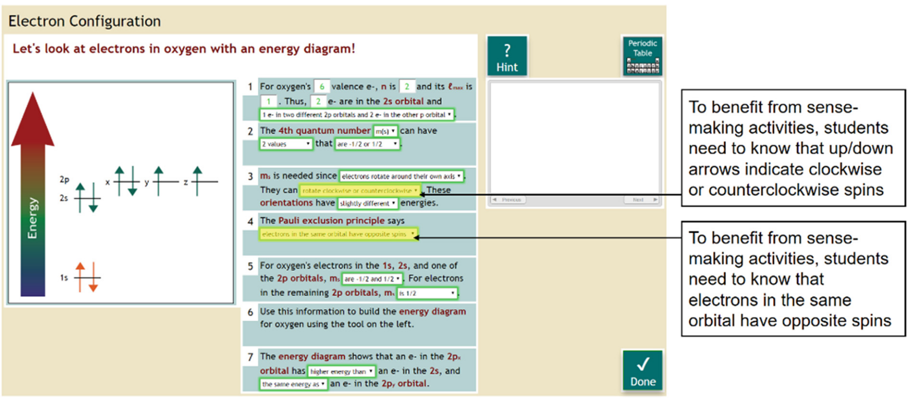

Fig. 4. Regular activity with two steps for which performance interacts positively with sense-making activity. Hence, these steps test prerequisites for sense-making activities.

right indicates prerequisite understanding of how the visual shows the concepts (e.g., how the energy diagram shows electron spins), which predicts benefit from sense-making activities. Hence, *if* a student gets any of these steps right, *then* he/she should receive sense-making activities. By contrast, a negative coefficient suggests that a student who gets this step wrong benefits from sense-making activities, possibly sense-making activities could rectify a misconception (e.g., comparing the energy diagram to another visual may help students interpret the energy diagram). Hence, *if* the student gets the step wrong, *then* he/she should receive sense-making activities. There were no cases that recommended sense-making and perceptual-fluency activities for the same unit.

We then formulated if-then rules so that *if* students exhibited some prerequisite or misconception that indicated sense-making or perceptual-fluency activities would be beneficial, *then* they would be assigned to them. The if-then rules were ordered so that rules corresponding to higher regression coefficients were prioritized. Table 1 summarizes how many steps tested prerequisites or misconceptions that indicated sense-making activities and perceptual-fluency activities. For each unit, a Python algorithm used performance on the first two regular problems to test whether students met conditions for the prerequisites or misconceptions for sense-making or perceptual-fluency activities. If they did, they received either sense-making or perceptual-fluency activities next. If not, they received regular activities on the same content.

Table 1. Topics and visuals in the six Chem Tutor units, and rules (in order of priority).

Unit	Topics	Visuals	Rules: *If* student exhibits at least 1 of…
1	Bohr model, quantum numbers 1 & 2	Shell models, orbital diagrams	4 misconceptions *then* sense-making
2	Quantum numbers 3 & 4, atomic orbitals	Orbital diagrams, energy diagrams	1 prerequisite *then* perceptual-fluency 2 prerequisites *then* sense-making
3	Configurations of atoms and ions	Energy diagrams, Lewis structures	2 misconceptions *then* perceptual-fluency 1 prerequisite *then* sense-making 4 misconceptions *then* sense-making
4	Atomic radii of atoms and ions	Lewis structures, shell models	1 misconception *then* sense-making 1 prerequisite *then* sense-making 2 misconceptions *then* perceptual-fluency
5	Ionization energies, electron affinities	Lewis structures, orbital diagrams	1 prerequisite *then* perceptual-fluency 1 misconception *then* perceptual-fluency
6	Energy, ions, and ionic compounds	Energy diagrams, shell models	2 prerequisites *then* sense-making 1 misconception *then* perceptual-fluency

3.3 Methods

Participants. We conducted the experiment as part of an introductory chemistry course for undergraduate students. The course had no prerequisites, but it was advertised to students in 100- and 300-level courses in chemistry and related programs. Fifty students enrolled, five dropped the course within the first three weeks, yielding $N = 45$ students.

Experimental Design. Students were randomly assigned to the static or the adaptive version of Chem Tutor. For each unit, the static version provided two regular activities, then two sense-making activities, then 16 perceptual-fluency activities. This corresponds to the most effective version in prior studies [9, 44]. The adaptive version provided two regular activities for each unit and then selected sense-making activities and perceptual-fluency activities based on the rules in Table 1. To control instructional time, we equated the number of problem-solving steps across conditions. For example, the static version of unit 1 had 67 steps in total. If—after a student completed the two regular activities—the algorithm indicated they needed more regular activities, the student received two more regular activities, yielding 67 total steps. If the algorithm indicated they needed more sense-making activities, the student received four sense-making activities, yielding 67 total steps. Hence, regardless of what the algorithm assigned, number of steps and content was identical to the static version. What differed was whether students received support for sense-making skills and perceptual fluency for all units (i.e., static version) or only the support that was indicated (i.e., adaptive version).

Measures. We assessed learning of chemistry content with a pretest and posttest as in the prior experiment. Students took a pretest at the start of each unit, an immediate posttest at the end of each unit, and a delayed posttest in the following week before they completed the pretest for the next unit. Agreement among independent graders of short-answer items based on 10% of the responses was 85.91%.

Procedure. At the start of each class, the instructor gave a 3-min overview of the topics. For the next hour, students worked at their own pace on the activities. The instructor and a teaching assistant circulated the class but gave only minimal help and directed students to read the Chem Tutor hints. Then, the instructor led a discussion on the topics. Students who were unable to attend could complete the activities in a lab.

3.4 Results

Prior Checks. First, we checked for learning gains using repeated measures ANOVAs with pretest, immediate, and delayed posttest as dependent measures. Results showed significant learning gains across units, $F(1, 43) = 50.36$, $p < .01$, p. $\eta^2 = .54$. Separate ANOVAs showed significant learning gains for each unit (for units 1, 3–6, *p*s < .01 with effect sizes ranging from p. $\eta^2 = .15$ to p. $\eta^2 = .54$; for unit 2, $p = .05$, p. $\eta^2 = .07$).

Second, a multivariate ANOVA showed no significant differences between conditions on the pretests for units 1–3, 5 (*p*s > .10). However, students in the static condition had marginally higher pretest scores for unit 4, $F(1, 43) = 3.07$, $p = .09$, p. $\eta^2 = .08$, and significantly higher pretest scores for unit 6 $F(1, 43) = 4.37$, $p = .04$, p. $\eta^2 = .09$.

Effects of Adaptive Assignment. To test if the adaptive version of Chem Tutor was overall more effective than the static version, we used a repeated measures ANCOVA model. The model included condition as independent factor, pretest scores across units as covariate, and immediate and delayed posttest scores across units as dependent measures. Results showed a significant effect of condition, $F(1, 42) = 7.52$, $p < .01$, p. $\eta^2 = .15$, such that the adaptive version yielded higher gains than the static version. We also tested if the effects of the adaptive version depended on prior knowledge. Results showed no significant interaction of condition with pretest, $F(1, 41) = 1.74$, $p = .19$.

Next, we tested effects for each unit (Fig. 5). Separate ANCOVAs showed significant advantages of the adaptive version for unit 1, $F(1, 42) = 5.72$, $p = .02$, p. $\eta^2 = .12$, unit 3, $F(1, 42) = 6.27$, $p = .02$, p. $\eta^2 = .13$, unit 4, $F(1, 42) = 7.38$, $p = .01$, p. $\eta^2 = .15$, and unit 6, $F(1, 42) = 7.37$, $p = .01$, p. $\eta^2 = .15$. For units 2 and 5, there was no significant effect of condition (*p*s > .10). For unit 5, we found a significant interaction of condition with pretest, $F(1, 41) = 5.55$, $p = .02$, p. $\eta^2 = .12$, such that the adaptive version was more effective for low-performing students, but the static version was more effective for high-performing students. No other interactions were significant (*p*s > .10).

Finally, we qualitatively explored how the adaptive algorithm assigned sense-making and perceptual-fluency activities. The algorithm assigned regular activities to 65% of the students at unit 1. Among them, 27% of the students received sense-making activities next, starting at unit 2; 73% received perceptual-fluency activities next, starting at unit 2 or 3. The algorithm assigned sense-making activities to 35% at unit 1. Among them, 75% of the students received perceptual-fluency activities next, starting at unit 2 or 3; 25% received more regular or sense-making activities. Finally, 87% of students received more sense-making activities after they completed perceptual-fluency activities for at least one unit, and 13% received more regular or perceptual-fluency activities.

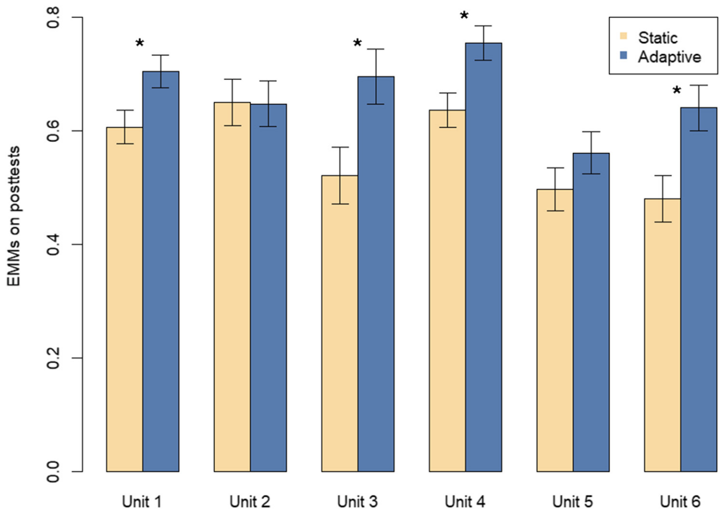

Fig. 5. Estimated marginal means (EMMs) averaged across immediate and delayed posttests, controlling for pretest. Error bars show standard errors of the man * show significant differences.

4 Discussion and Conclusion

Our results show that adaptive support for sense-making skills and perceptual fluency with visual representations is more effective than static supports for these representation skills. This finding expands prior research in several ways. First, prior studies show that students' benefit from different types of representation-skill supports depends on their current skill level, and that adapting support to students' problem-solving skills enhances learning (e.g., by adapting the choice of problems that practice domain knowledge to students' current domain knowledge). Yet, our study is the first to show that adapting support to students' representation skills enhances the effectiveness of problem-solving activities that practice domain knowledge.

Second, our results provide further evidence for a progression of representation skills that had been based on cross-sectional studies. The inspection of ATI effects in the prior study and the adaptive assignments in the current study suggest that students should start with regular activities or sense-making activities before they benefit from perceptual-fluency activities. Further, our findings confirm earlier cross-sectional results that students benefit from sense-making activities again after becoming perceptually fluent.

Third, our results may guide the design of educational technologies with multiple visuals. We used linear regression to identify steps that were predictive of benefit from sense-making and perceptual-fluency activities because they indicates prerequisite knowledge about visuals or misconceptions about visuals. We translated results into if-then rules that assign type of representation-skills support a student needs. This approach can be applied to any set of technology-based activities where students use visual representations to solve domain-relevant problems.

Our findings should be interpreted in light of several limitations. First, we found no advantage of the adaptive over the static version of Chem Tutor for units 2 and 5. For unit 2, this may be due to the lack of learning gains. For unit 5, the adaptive version was more effective only for low-performing students. It is possible that students in the prior experiment that was the basis for the algorithm were low-performers on this unit. For both units, we will use the current data to improve the algorithm. A second set of limitations relates to the sample. Our study was part of a course that involved other activities such as class discussions. While these activities may have affected learning, we do not see why they should have affected differences between conditions. Also, although students matched the target population of Chem Tutor, they were likely highly motivated and may have seen the visuals before. Further, our sample was small due to the small class size of 45 students. Hence, future research should replicate our results in other contexts, with other populations and larger samples. Third, our study did not compare adaptive representation-skills support to a control without representation-skills support. While the effectiveness of static representation-skills support has been established, future research should verify that adaptive representation-skill support is indeed more effective than regular activities alone. Finally, because the use of visuals in chemistry is similar to the use of visuals in other STEM domains, we expect that our findings will generalize broadly. Yet, future research should test if adaptive representation-skill support indeed enhances learning in other domains and with other visuals.

In conclusion, our study is the first to show that adaptive support for representation skills can significantly enhance learning of domain knowledge. Given that multiple visuals are widely used and that lack of representation skills is an obstacle in many STEM domains, such support may significantly enhance STEM learning.

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