Adaptive support for representational competencies during technology-based problem solving in chemistry

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Abstract

Background. A key aspect of STEM learning is the use of visual representations for problem solving. To successfully use visuals, students need to make sense of how they show concepts and to fluently perceive domain-relevant information in them. Adding support for sense making and perceptual fluency to problem-solving activities enhances students' learning of content knowledge. However, students need different types of representational-competency supports, depending on their prior knowledge. This suggests that adaptively assigning students to sense-making and perceptual-fluency support might be more effective than assigning all students to the same sequence of these supports.

Method. We tested this hypothesis in an experiment with 44 undergraduate students in a chemistry course. Students were randomly assigned to a ten-week sequence of problem-solving activities that either provided a fixed sequence of sense-making support and perceptual-fluency support or adaptively assigned these supports based on students' problem-solving interactions.

Findings. Results show that adaptive representational-competency supports reduced students' confusion and mistakes during problem solving while increasing their learning of content knowledge.

Contribution. Our study is the first to show that adaptive support for representational competencies can significantly enhance learning of content knowledge. Given the pervasiveness of visuals, our results may inform general STEM instruction.

Keywords

Multiple representations, representational competencies, sense-making competencies, perceptual fluency, chemistry

Visual representations play a key role in problem-solving practices in science, technology, engineering, and math (STEM) domains (Kozma, Chin, Russell, & Marx, 2000; Wertsch & Kazak, 2011). When scientists study a phenomenon of interest, they typically visually represent the phenomenon, so that they can use the visual representation to reflect on the nature of the phenomenon. During this reflection process, they may gather new data and revise their visual representation to reflect new discoveries. Indeed, observational studies of expert scientists in chemistry and other STEM domains shows that their problem-solving practices critically rely on such representation-reflection iterations (Fan, 2015; Kozma & Russell, 2005a; Latour, 1986). Therefore, an important part of STEM instruction is for students to learn to use visual representations to solve disciplinary problems (Gilbert, 2005; NRC, 2006; Rau, 2017). The goal of this article is to investigate ways to support students in this learning process.

Most STEM disciplines use established visual representations that have evolved as part of problem-solving practices that required reasoning about visuo-spatial concepts (Gilbert, 2005; NRC, 2006). Because different visual representations can illustrate different aspects of these phenomena, STEM instruction typically involves multiple visual representations (Ainsworth, 2006; Kozma et al., 2000; Rau, 2017). For example, chemists typically use a variety of visual representations (see Figure 1) to illustrate concepts related to atomic structure and bonding.

--- Insert Figure 1 about here ---

While multiple visual representations can help students learn, they also pose an educational dilemma (Ainsworth, 2006; NRC, 2006; Rau, Aleven, & Rummel, 2015). Instructional activities often present problems that engage students in reflection about domain-relevant concepts. Students are to explore these concepts by manipulating visual representations, which mimics common representation-reflection iterations that are part of disciplinary practices. However, because both the concepts and the representations are novel to students, students have to learn *about* how the visual representations show information about the concepts while also learning about the concepts *from* the visual representations. This conundrum is known as the representation dilemma (Dreher & Kuntze, 2015; Rau, 2017).

To overcome the representation dilemma, students need representational competencies, which allow them to understand how various visual representations show information about different aspects of complex concepts in the given domain (Gilbert, 2005, 2008; NRC, 2006). Indeed, representational competencies have been shown to enhance students' learning of domain knowledge in math (Cheng, 1999; Noss, Healy, & Hoyles, 1997), physics (Klein, Viiri, Mozaffari, Dengel, & Kuhn, 2018; Larkin & Simon, 1987), biology (Treagust & Tsui, 2013), and chemistry (Kozma et al., 2000; Stieff, Hegarty, & Deslongchamps, 2011).

However, supporting representational competencies during problem solving is not straightforward. Prior research, reviewed in detail below, shows that there are multiple types of representational competencies that require different types of instructional support

(Ainsworth, 2006; Kellman & Massey, 2013; Rau, 2017). Further, students need different types of instructional support at different times during their learning trajectory (Rau, 2018a, b). This suggests that adapting representational-competency supports in real time to individual students' needs may enhance their learning of domain knowledge. This article investigates this hypothesis in the context of chemistry problem solving.

In the following, we review prior research on representational competencies and ways to support them during problem solving. Then, we present our own prior work that has led to the development of a technology-based learning environment for undergraduate chemistry, which served as a platform for this study. We describe how we used prior data from this learning environment to develop adaptive support for representational competencies. We then report on a randomized experiment that was carried out as part of an undergraduate chemistry course. The experiment tested whether adaptive support for representational competencies is more effective than fixed support for representational competencies at enhancing chemistry learning outcomes as well as perceived and observed problem-solving difficulty. We conclude with a discussion of implications for learning with visual representations.

Literature Review

Representational Competencies

Two mostly separate lines of prior research have investigated which types of representational competencies enhance STEM learning (for an overview, see Rau, 2017). One line of research originates in theories of conceptual learning and focuses on deliberate, explanation-based processes involved in the acquisition of sense-making competencies (Chi, 2009; Schnotz, 2014). Another line of research originates in theories of perception and focuses on inductive pattern-recognition processes that yield perceptual intuitions (Gibson, 2000; Kellman & Massey, 2013). Both types of competencies play a crucial role in scientific practices (Dreyfus & Dreyfus, 1986; Latour, 1986). In the following, we review each line of prior research in turn.

Sense-Making Competencies

Sense-making competencies describe a student's ability to map visual features to meaningful concepts (Ainsworth, 2006; Bodemer & Faust, 2006). For example, a student may map the dots in a Lewis structure (see Figure 1a) to valence electrons within an atom. Further, when students work with multiple visual representations, sense-making competencies involve the ability to make connections among corresponding visual features of different representations by reasoning about the concepts they show (Ainsworth, 2006; Rau, 2017). For example, a student may connect the dots in a shell model (see Figure 1b) to the arrows in an energy diagram (see Figure 1c) because both features show the total electrons of an atom. The ability to make such connections also enables students to reason about differences and similarities between the representations (Ainsworth, 2006; Rau, 2017). For example, students may reason that both energy diagrams (see Figure 1c) and orbital diagrams (see Figure 1d) show the orbitals that electrons occupy, but that orbital diagrams do not show how many electrons reside in these orbitals, whereas energy diagrams do. Understanding such types of differences and similarities between representations is the basis for students' ability to flexibly choose appropriate representations for problem solving (Acevedo Nistal, Van Dooren, & Verschaffel, 2013; diSessa, 2004).

According to cognitive theories of learning, students acquire these competencies through sense-making processes (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Koedinger, Corbett, & Perfetti, 2012). These processes involve verbal explanations of how visual features map to concepts (Chi et al., 1989; Gentner, 1983). They are explicit because students have to willfully engage in them and because they require conscious effort (Chi, de Leeuw, Chiu, & Lavancher, 1994; Koedinger et al., 2012). According to Schnotz and Bannert's Integrated Model of Picture Comprehension (Schnotz, 2014; Schnotz & Bannert, 2003), these verbal explanation processes are a mechanism through which students integrate information from multiple representations into their existing schemas of domain knowledge.

According to theories of disciplinary practices, students' acquisition of sense-making competencies is mediated by participation in scientific practices (Airey & Linder, 2009; Kozma & Russell, 2005b; Wertsch & Kazak, 2011). That is, when students participate in scientific practices, they learn conventions that have been shaped by the history of a given scientific community (Latour, 1986; Vygotsky, 1978). They also learn conventions about how representations are commonly used to solve problems (Cobb & McClain, 2006; Roschelle, 1992).

Prior research has established several principles for the design of supports for sense-making competencies that can be added to problem-solving activities. First, students should verbally explain the mappings of visual features to concepts (Berthold & Renkl, 2009; Rau, 2017; Seufert & Brünken, 2006). For example, self-explanation prompts have been proven effective in engaging students in such explanations (Berthold, Eysink, & Renkl, 2008; Rau, Aleven, et al., 2015). Second, students should become active in making these mappings themselves (Bodemer & Faust, 2006; Chi, 2009). For example, interventions where students themselves had to actively construct connections among visuals and concepts have been proven more effective than interventions that presented students with pre-made mappings (Bodemer & Faust, 2006; Gutwill, Frederiksen, & White, 1999). Finally, students need assistance in making mappings between visual features and concepts (Ainsworth, Bibby, & Wood, 2002; Rau, Aleven, Rummel, & Pardos, 2014). For example, prior research shows that particularly students with low prior knowledge need help to focus on conceptually relevant visual features, rather than on surface features that bear no meaningful information (Bodemer & Faust, 2006; Stern, Aprea, & Ebner, 2003).

Perceptual Fluency

Perceptual fluency describes a student's ability to quickly and effortlessly see meaning in visual representations based on perceptual cues (Kellman & Massey, 2013; Massey, Kellman, Roth, & Burke, 2011; Rau, 2017). For example, chemists simply "see" that the visual representations in Figure 1 show carbon without having to think about it. Perceptual fluency also allows experts to fluently translate among different visual representations (Kellman & Massey, 2013; Massey et al., 2011; Rau, 2017). High levels of acuity, automaticity, and efficiency in processing visual representations frees cognitive resources for higher-order thinking about complex problems (Goldstone & Barsalou, 1998; Richman, Gobet, Staszewski, & Simon, 1996). Therefore, perceptual fluency enhances learning of STEM domain knowledge (Gilbert, 2005; Taber, 2014). For example, chemistry education research shows that a lack of perceptual fluency can impede students' learning: the cognitive effort involved in making sense of the representations without the ability to process them fluently can slow students' thinking and impede their ability to follow complex explanations about chemical bonding (Anderson & Bodner, 2008). Further, perceptual fluency allows experts to think creatively and react adaptively to novel situations (Dreyfus & Dreyfus, 1986; Gibson, 1969, 2000; Richman et al., 1996).

The processes through which students acquire perceptual fluency differ fundamentally from those through which students learn sense-making competencies. According to cognitive theories of learning, students learn perceptual fluency through implicit, nonverbal, inductive processes (Gibson, 2000; Goldstone, 1997; Kellman & Massey, 2013; Koedinger et al., 2012). That is, these processes occur unintentionally and often unconsciously (Frensch & Rünger, 2003; Shanks, 2005). Verbal reasoning and explicit instruction about the visual representations are not necessary but may even impede students' engagement in perceptual learning processes (Kellman, Massey, & Son, 2009; Schooler, Fiore, & Brandimonte, 1997). Rather, students inductively learn to recognize visual patterns through exposure to many examples (Kellman & Massey, 2013; Rau, 2017).

According to theories of disciplinary practices, students acquire perceptual fluency by engaging in nonverbal communication practices (Singer, 2017; Wertsch & Kazak, 2011). This may involve person-to-person communication about visuals, for example when students use gestures to direct each other's attention to visual cues (Singer, 2017), or it may involve visuals that mediate communication, for example when students learn to express themselves in terms of representations (Braden & Hortin, 1982). To this end, students need to become fluent in a "multimodal language" that they learn by repeatedly participating in disciplinary discourse (Airey & Linder, 2009; Schönborn & Anderson, 2006). For example, Airey and Linder (2009) describe how students who work together on problems with representations gradually learn to translate flexibly among the representations to the extent that doing so becomes "almost second nature" (p. 10). Further, as students see other members of the scientific community use representations to communicate, they start imitating these practices (Wertsch & Kazak, 2011). Through these processes, students gradually induce how visual representations provide information about disciplinary problems (Rau, 2017).

To help students acquire perceptual fluency during problem solving, prior research has established several design principles for instructional supports. These principles serve to ensure that students engage in implicit, nonverbal, inductive forms of learning. First, students should be exposed to a large variety of example representations (Kellman et al., 2008; Kellman et al., 2009). Second, these examples should present contrasting cases (Chase, Shemwell, & Schwartz, 2010) so that they vary irrelevant visual features that students should learn to ignore and repeat conceptually relevant visual features that students should attend to.

Third, students should be prompted to rely on their perceptual intuitions, so as to encourage implicit rather than explanation-based processing. Finally, immediate feedback on the accuracy of students' use of visual information is helpful, but this feedback should not provide detailed explanations so that students continue to engage in nonverbal processes as opposed to verbal reasoning processes.

Integrating Support for Sense-Making Competencies and Perceptual Fluency in Chemistry Instruction

In our own prior work, we developed Chem Tutor, an educational technology for undergraduate chemistry problem solving that provides support for sense-making competencies and perceptual fluency. Chem Tutor served as a platform for a series of prior studies that tested whether these supports enhance chemistry learning and how the supports should be sequenced.

Chem Tutor: Technology-Based Problem Solving with Support for Representational Competencies

The development of Chem Tutor was based on learner-centered studies of how students and instructors use visual representations in their teaching and learning (Rau, Michaelis, & Fay, 2015; Rau, Aleven, & Rummel, 2017). To this end, students were observed and interviewed while they solved chemistry problems that were posed in undergraduate chemistry courses and interviewed about difficulties in interpreting and manipulating the representations. Instructors' teaching practices were observed in lectures, discussion sessions, and laboratory sessions. Further, they were interviewed about their teaching strategies and about the difficulties they found prevalent among their students. These studies revealed a number of chemistry-specific competencies that relate to visual representations that instructors deem important but that their students struggle with. While these competencies are specific to particular chemistry concepts, they fall into the two broader categories of representational competencies outlined above; that is, they either involved making sense of how visual representations depict concepts or they involved fluent perception of information based on visual cues.

For each of the identified representational competencies, we then developed instructional activities. In doing so, we followed the instructional design principles reviewed above. For example, we found that understanding the probabilistic nature of the location of electrons within an atom is an important concept. To help students understand this concept, instructors typically use energy diagrams (see Figure 1c) and orbital diagrams (see Figure 1d). Several representational competencies relate to this concept. First, students have to make sense of similarities between the two representations, for example that the horizontal lines in the energy diagram correspond to the median of the probability distribution that is shown by the colored shapes in the orbital diagram. Second, students have to make sense of differences between the two representations, for example that the energy diagram shows how many electrons occupy each orbital, whereas the orbital diagram does not. Third, students have to become so fluent in translating between these representations so that when they see an energy diagram, they automatically mentally visualize the shape of the orbitals the electrons occupy.

To support sense-making competencies as in the first and second example, we developed activities that asked students to compare pairs of visual representations by mapping them to the concepts they illustrate. For example, Figure 2 shows an example sense-making activity that supports the sense-making competencies just described. Students first use an interactive tool to create an orbital diagram of the atom shown by an energy diagram. Then, they receive prompts to explain similarities and differences between the visual representations.

--- Insert Figure 2 about here ---

This example illustrates that these sense-making activities implement the design principles reviewed above to support sense-making competencies. First, to support conceptual reflection and explanation, students respond to the prompts via menu-based selection, which has been shown to support sense-making processes in prior studies with educational technologies (Aleven & Koedinger, 2002; Atkinson, Renkl, & Merrill, 2003) more effectively than open-ended responses to prompts (Gadgil, Nokes-Malach, & Chi, 2012; Johnson & Mayer, 2010). The options of the menu-based prompts were populated with students' statements in the interview studies mentioned above (Rau et al., 2015, 2017). Second, because students have to create one of the visual representations based on another representation and because the prompts are phrased as fill-in-the-gap sentences that students have to complete, this design ensures that students themselves have to become active in establishing the mappings between the visual representations (Bodemer & Faust, 2006; Bodemer, Ploetzner, Bruchmüller, & Häcker, 2005; Bodemer, Ploetzner, Feuerlein, & Spada, 2004). Finally, students receive assistance from Chem Tutor. If they make a mistake, they receive feedback specific to their mistake that provides a rationale for why their answer is wrong and provides suggestions for how to improve their reasoning. Further, students can ask for hints on each step that provide explanations about the mappings between the two representations based on the concept they show. The content and wording of error-feedback messages and hints was also based on the student and instructor interviews obtained from the learner-centered studies mentioned above (Rau et al., 2015, 2017).

To support perceptual fluency competencies as illustrated in the third example above, we developed activities that expose students to many example visuals while encouraging non-verbal processing. For example, Figure 3 shows an example perceptual-fluency activity that supports the competency described above. Here, students are given an energy diagram and are asked to select one of four given orbital diagrams that shows the same atom.

--- Insert Figure 3 about here ---

This example illustrates the design principles for perceptual-fluency supports described above. First, each perceptual-fluency activity is short as it contains only one step, and students receive many of these activities in a row. Therefore, students are exposed to a large variety of example representations. Second, the four choice options implement the contrasting cases principle. Based on the learner-centered studies mentioned above (Rau et al., 2015, 2017), we identified visual cues that students often confuse, fail to attend to, or are distracted by. The choice options contain visuals that have these features, so that students get practice in processing them accurately and efficiently. Third, to encourage implicit processing, students are prompted to solve the task quickly, without overthinking it, and without fear of making mistakes, so as to train their perceptual intuitions. These prompts are implemented in two ways: students watch a short video that explains the nature of perceptual trainings prior to the perceptual-fluency activities, and then receive written prompts to rely on their perceptual intuitions as part of each activity. Finally, students receive immediate feedback on their responses in the form of a red highlight if they chose a wrong option or a green highlight if they chose the correct option. If they chose the wrong option, they receive no explanation for why it is wrong, so as not to engage students in explanation-based processes that could interfere with perceptual learning, but a prompt to try again without overthinking it, so as to encourage experience-based learning.

In sum, these examples illustrate that sense-making and perceptual-fluency activities embody qualitatively different instructional design principles that emerged from the different lines of prior research reviewed above.

Prior Research on Effectiveness of Representational-Competency Supports

If students need both sense-making competencies and perceptual fluency to learn with visual representations, then supporting both types of competencies should enhance students' learning of domain knowledge. In our prior research, we tested this hypothesis in experiments on elementary-school math learning (Rau et al., 2017) and undergraduate chemistry learning (Rau & Wu, 2018). In these experiments, all students received an introduction to the topic and the visual representations. Then, students were randomly assigned to receive (1) both sense-making activities and perceptual-fluency activities, (2) only sense-making activities, (3) only perceptual-fluency activities, or (4) a control condition that received the same visual representations but without support for either type of representational competency. The content covered was identical across conditions. Learning of domain knowledge was assessed with a pretest, an immediate posttest (given immediately after students worked on instructional activities), and a delayed posttest (given one week after the instructional activities) that contained multiple-choice and open-response items.

Results from both experiments showed that students' learning of domain knowledge was enhanced *only* by the combination of both types of support. That is, only students who received sense-making *and* perceptual-fluency activities showed higher learning gains than the control condition. Students who received only sense-making activities had learning gains about as high as students in the control condition. Students who received only perceptual-fluency activities had lower learning gains than students in the control condition. These findings suggest that sense-making competencies and perceptual fluency interact to enhance one another.

To better understand the nature of this interaction, we investigated the relationship between sense-making competencies and perceptual fluency. To this end, we tested two hypotheses. First, one might hypothesize that perceptual fluency builds on sense-making competencies. Prior research shows that students have difficulties in making connections among representations and tend not to do so spontaneously (Ainsworth et al., 2002; Rau et al., 2014). Therefore, it may be unrealistic to expect that students can induce correct connections from perceptual-fluency activities unless they have a prerequisite level of sense-making competencies. This argument aligns with a broader literature that suggests that inductive learning without prior explicit instruction is often not successful (Kirschner, Sweller, & Clark, 2006). In line with this argument, participants in prior studies on perceptual-fluency activities typically had considerable prior knowledge about the representations (Kellman et al., 2008; Kellman et al., 2009). Indeed, Kellman and colleagues suggest that the acquisition of perceptual fluency does not exclusively rely on bottom-up processes but that it also draws on top-down processes that enable students to selectively attend to meaningful visual features (Kellman & Massey, 2013). Although these top-down processes may not be explicit or conscious but instead implicit and nonverbal, they may be informed by previously acquired sense-making competencies (Goldstone, 1997; Rau, 2017). Based on this reasoning, this hypothesis predicts that students' learning is enhanced if they receive sense-making activities followed by perceptual-fluency activities.

Second, one might hypothesize that sense-making competencies build on perceptual fluency. This argument is based on the observation that novices have to invest significant mental effort into interpreting representations, which can lead to cognitive overload and hence interfere with their ability to learn with visual representations. Therefore, before students are able to make sense of visual representations, they may need some preliminary level of perceptual fluency. In line with this argument, Kellman and colleagues (e.g., Kellman & Massey, 2013; Kellman et al., 2009) propose that perceptual fluency decreases cognitive load, which frees up the capacity necessary to engage in higher-order reasoning about domain-relevant knowledge. Based on this reasoning, this hypothesis predicts that students' learning is enhanced if they receive perceptual-fluency activities followed by sense-making activities.

We tested these hypotheses in experiments on elementary-school math learning (Rau et al., 2017) and undergraduate chemistry learning (Rau, 2018; Rau & Wu, 2018). In these experiments, students were randomly assigned to receive either sense-making activities followed by perceptual-fluency activities or vice versa. Learning outcomes were assessed with pretests, immediate and delayed posttests, as in the previous studies. Further, we used structural equation modeling to test how students' sense-making competencies enhanced their subsequent learning of perceptual fluency and vice versa. Results showed that students' prior knowledge about how the visual representations show domain-relevant concepts determined the direction of the relationship between sense-making competencies and perceptual fluency as well as which sequence was most effective. For students with low prior knowledge, sense-making competencies enhanced subsequent learning of perceptual fluency, and receiving sense-making activities followed by perceptual-fluency activities was most effective. For students with high prior knowledge, the effect was reversed: for them, perceptual fluency enhanced subsequent learning of sense-making competencies, and receiving perceptual-fluency activities before sense-making activities was most effective.

These findings suggest that students need different types of representational-competency supports as their learning progresses. As students' knowledge level changes during the course of a longer learning intervention and because not all students learn at the same rate, it seems reasonable to hypothesize that adapting representational-competency supports to the individual student's needs enhances their learning of domain knowledge. However, because these prior studies were cross-sectional, they did not test this hypothesis. Further, while prior research has investigated whether adaptive support for problem-solving skills enhances learning (e.g., Koedinger & Corbett, 2006; VanLehn, 2011), we are not aware of any prior studies that have tested whether adaptive support for representational competencies can enhance learning.

Research Questions and Hypotheses

The goal of this article is to investigate whether support for sense-making competencies and perceptual fluency that adapts to the individual student's needs during problem solving enhances learning of chemistry knowledge. Specifically, we investigated:

Research question 1: Does adaptive support for representational competencies reduce students' confusion about how visual representations show chemistry concepts, compared to fixed support?

Research question 2: Does adaptive support reduce errors students make during problem solving?

Research question 3: Does adaptive support increase students' pretest-to-posttest learning gains of chemistry content knowledge?

Based on our own prior research, we hypothesize that adaptive support (1) reduces confusion, (2) reduces errors during problem solving, and (3) increases learning gains more so than fixed support. To test these hypotheses, we developed an adaptive algorithm that predicts whether a student would benefit from sense-making activities or perceptual-fluency activities based on the student's problem-solving behaviors and then assigns subsequent activities appropriately. An experiment conducted as part of weekly assignments in an undergraduate chemistry course compared adaptive assignment of activities to a fixed sequence of activities within Chem Tutor.

Methods

Development of Adaptive Algorithm

To develop an algorithm that adaptively assigns representational-competency supports, we collected data that served as the basis for a model that predicts, based on a student's problem-solving behaviors, whether he/she would benefit from sense-making or perceptual-fluency activities.

Dataset

We used data from a pilot study with 129 undergraduate students who were enrolled in an introductory chemistry course at a large university in the United States Midwest. Students worked on one Chem Tutor unit per week, for ten weeks. Table 1 lists the topics covered in each unit as well as the visual representations used.

--- Insert Table 1 about here ---

Students were randomly assigned to one of five sequences of activities for the duration of the ten weeks. Students in a control condition received regular Chem Tutor activities that provided no support for sense-making competencies or perceptual fluency. Figure 4 shows an example regular activity. Here, students were given one visual representation at a time and were asked to solve chemistry problems using the information shown in the visual. Consecutive regular activities provided different visuals. Students in this condition received four regular activities per Chem Tutor unit.

--- Insert Figure 4 about here ---

Students in a sense-only condition received two regular activities followed by four sense-making activities per unit. Students in a perceptual-only condition received four regular activities followed by 32 perceptual-fluency activities. Students in a sense-perceptual condition received two regular activities followed by two sense-making activities followed by 16 perceptual-fluency activities. Students in a perceptual-sense condition received two regular activities followed by 16 perceptual-fluency activities followed by two sense-making activities. As shown in Table 2, the number of activities per condition was chosen so that the number of problem-solving steps was equal across the five conditions. For example, because each perceptual-fluency activity contains only one problem-solving step, 16 perceptual-fluency activities involve about as many steps as two sense-making activities. Because sense-making activities contain on average half the number of steps of a regular activity, two sense-making activities equate one regular activity. A pilot study had established that equating the number of problem-solving steps across conditions ensures that the average time on task was equal across conditions. Further, the content covered in each condition was identical. Finally, we used problem-solving behaviors on steps that were identical across conditions (i.e., in the first two regular activities per unit) to predict whether students' learning benefits from sense-making and perceptual-fluency activities.

--- Insert Table 2 about here ---

We assessed students' learning outcomes with pretests and posttests for each unit. The tests contained multiple-choice items as well as open-response items. The items tested students' conceptual understanding of the chemistry content covered in the given unit. As illustrated in Figure 5, students received a pretest at the beginning of each unit. Then, they worked on the Chem Tutor activities assigned to them based on their condition. Next, they received an immediate posttest. At the beginning of the following week, they first completed a delayed posttest of the content covered in the previous week's unit, then continued with the pretest for the current week's unit, and so forth. In the last week, they only completed the delayed posttest of the previous week. We used three different test versions for the pretest, immediate and delayed posttests. The test versions were equivalent in that the items asked the same questions but used different examples (e.g., different elements). The order of the test versions was counterbalanced.

--- Insert Figure 5 about here ---

To predict whether students' learning benefited from sense-making and/or perceptual-fluency activities, we focused on the first two regular activities in each unit that were the same across conditions. For each problem-solving step in these activities, we computed step performance based on whether a student's first attempt at solving the step was correct or incorrect. Across the ten units, this yielded step-performance measures for 171 steps per student.

Analyses

We searched for step-performance measures that were predictive of students' benefit from sense-making and perceptual-fluency activities. To this end, we constructed a linear regression model for each unit. The dependent variable for each model was the pretest-to-posttest learning gain (averaging the immediate and the delayed posttest) for the given unit. Predictors were the experimental factors (i.e., whether or not students received sense-making activities and whether or not they received perceptual-fluency activities), the step-performance measures on the first two regular activities in the given unit, and the interaction between each step-performance measure with each of the experimental factors. As there were no differences between the conditions that received sense-making and perceptual-activities (i.e., sense-perceptual and perceptual-sense), we did not distinguish between these conditions in the following analyses. The interaction effects between step-performance and the experimental factors were the key point of interest of the analysis: If performance on a given step interacts with one of the experimental factors, that indicates an aptitude-treatment interaction (Park & Lee, 2003) in the sense that low-performing students benefit from a different type of activity than high-performing students. The regression model yielded significance tests and regression coefficients for each predictor.

Results

The regression analyses identified steps for which performance interacted significantly with at least one of the experimental factors. We identified 20 significant interaction effects between step-performance measures and sense-making activities. Ten of them had a negative regression coefficient, which suggests that low-performing students are more likely to benefit from sense-making activities than high-performing students. Hence, these steps were indicative of a misconception that sense-making activities could remedy (i.e., the student made a mistake indicating lack of knowledge that the sense-making activities could provide). Figure 6 (Example 1) shows two steps for which we found significant negative interactions with sense-making activities. Both steps involve knowledge about the order in which orbitals are filled. Hence, this example suggests that sense-making activities that help students compare energy diagrams to another visual can help them understand orbital filling orders.

Ten of the interaction effects involving sense-making activities had a positive regression coefficient, which indicates that students with high performance on these steps were more likely to benefit from sense-making activities. Hence, these steps were indicative of prerequisite understanding that prepares students to learn from sense-making activities (i.e., the student correctly answered a question, thereby indicating that they possessed knowledge that the sense-making activities presumed). Figure 6 (Example 2) shows a step for which we found a significant positive interaction with sense-making activities. This example suggests that understanding Hund's rule is a prerequisite for students' benefit from sense-making activities.

--- Insert Figure 6 about here ---

--- Insert Figure 7 about here ---

--- Insert Figure 8 about here ---

Further, we identified 16 significant interaction effects between step-performance measures and perceptual-fluency activities. Fifteen of them had a negative regression coefficient, which indicates misconceptions that perceptual-fluency activities can remedy (i.e., the student made a mistake indicating lack of knowledge that the perceptual-fluency activities could provide). Figure 7 shows an example that suggests that students who construct an incorrect Lewis structure benefit from perceptual-fluency activities that ask them to quickly map Lewis structures to other visuals

One of the interaction effects involving perceptual-fluency activities had a positive regression coefficient, which indicates prerequisite knowledge for perceptual-fluency activities (i.e., the student correctly answered a question, thereby indicating that they possessed knowledge that the perceptual-fluency activities presumed). Figure 8 shows the corresponding step, which suggests that students need to understand how an atom's quantum numbers predict orbital shapes before they can benefit from perceptual-fluency activities that involve translations between orbital diagrams and other visuals. Table 3 provides a summary of the prerequisites and misconceptions identified per unit.

--- Insert Table 3 about here ---

Finally, we found no steps for which performance interacted significantly with both sense-making and perceptual-fluency activities. That is, there was no case in which receiving both sense-making activities and perceptual-fluency activities was predicted to be beneficial for the same Chem Tutor unit.

Adaptive Algorithm

We translated these results into if-then rules so that *if* a student's step-performance indicated some prerequisite or misconception suggesting that sense-making activities or perceptual-fluency activities would benefit the student, *then* they would be assigned next. For instance, the if-then rule corresponding to the misconception shown in Figure 6, Example 1 specified that *if* a student incorrectly stated that 3d orbitals are filled before the 4s orbital, *then* the student would receive sense-making activities for the given unit. A second if-then rule from the example in Figure 6 specifies that *if* a student incorrectly stated that 3d orbitals are filled after the 4p orbitals, *then* the student would receive sense-making activities next. Similarly, a third if-then rule corresponding to the prerequisite knowledge shown in Figure 6 (see Example 2) specified that *if* students correctly stated that Hund's rule says that orbitals have two electrons only if all same-energy orbitals have at least one electron, *then* they received sense-making activities next. The if-then rules were ordered so that those corresponding to higher regression coefficients were prioritized. For example, the regression coefficient for the third rule from the examples just mentioned (see Figure 6) had the highest regression coefficient among the rules for this unit. Therefore, if a student exhibited the prerequisite knowledge specified in this rule, the student would receive the sense-making activities as specified. These rules were executed by a Python algorithm. The algorithm used the rules to determine, based on a student's performance on the first two regular activities of a given unit, whether they met conditions for sense-making activities or perceptual-fluency activities. If they did, they would receive those activities next. If they did not meet conditions for either sense-making or perceptual-fluency activities, they received regular activities on the same content.

Methods

To investigate whether adaptively assigning sense-making and perceptual-fluency activities enhances students' learning more so than a fixed assignment of these activities, we conducted an experiment as part of an undergraduate chemistry course.

Participants

Participants were students enrolled in an introductory chemistry course for undergraduate students at a large university in the United States Midwest, taught by the first author. The course had no prerequisites but was advertised to students enrolled in 100- and 300-level courses in chemistry and related programs (e.g., biochemistry). Fifty students enrolled at the beginning of the semester, but five dropped within the first three weeks of the semester. One student who did not consent to his/her data being used for research was excluded from the analysis. Hence, a total of 44 undergraduate students participated in the experiment (n = 23 in the adaptive condition, n = 21 in the static condition). On average, their age was 19.64 years (sd = 1.16). Twenty-six students reported they were female, twelve were male, and six preferred not to say.

Experimental Design

The experiment was conducted across ten weeks, with students working on one Chem Tutor unit per week. Students were randomly assigned either to a fixed assignment of sense-making and perceptual-fluency activities or to an adaptive assignment of these activities for the duration of the experiment. Students in the fixed condition received the sequence of sense-making and perceptual-fluency activities that had been shown to be the most effective version of students with low prior knowledge in our prior studies (Rau, 2018). That is, for each unit, students first received two regular activities, then two sense-making activities, and then 16 perceptual-fluency activities. Students in the adaptive condition received the same two regular activities at the start of each unit. Then, the adaptive algorithm assigned them to sense-making and perceptual-fluency activities as per the rules described above for the remainder of the unit.

To equate average time on task across the conditions, we used the same procedure as described above; that is, we ensured each condition had the same number of problem-solving steps in each unit. For example, for the fixed condition, unit 1 contained 67 steps across all activities in this unit. For the adaptive condition, all possible options also totaled 67 steps. For example, if the algorithm decided a student needed more regular activities after the first two regular activities, these would add up to 67 steps in total including the first two regular activities. If the algorithm decided a student should receive sense-making activities, these would add up to 67 steps in total as well. Further, as described above, the content covered, and the visuals used by these activities was the same. Therefore, students in the fixed condition practiced the same content with the same visuals as students in the adaptive condition, regardless of which activities the adaptive algorithm assigned. Hence, the sole difference between the conditions was whether students received support for sense-making competencies as well as perceptual fluency in all units or whether they received support only for the representational competency for which they were predicted to need support.

Measures

We assessed the effects of adaptive vs. fixed representational-competency supports on students' learning of chemistry content in multiple ways. First, we were interested in whether adaptive support reduces students' confusion about how the visual representations show chemistry concepts during learning (research question 1). To this end, students were asked to write weekly reflection papers. They were told that they could reflect on anything they had learned in the given week's Chem Tutor assignment, with a particular focus on what they did or did not understand well. We then used a grounded analysis approach (Glaser & Strauss, 1967) to examine how students expressed confusion about the chemistry concepts. In their reflection papers. We identified points of confusion when students stated questions (e.g., "What can be accepted to increase charge asides from a proton?"), mentioned they did not understand something (e.g., "I also didn't get a grasp on Planck's constant."), or expressed uncertainty or difficulty understanding a concept or visual representation after completing instructional activities that covered these concepts or visuals (e.g., "I struggled with understanding the quantum numbering."). We did not include general expressions of confusion on concepts or representations not covered in the given week. We then coded the reflection papers for the number of times the student expressed confusion in the ways just described. In doing so, we counted the number of distinct concepts the student expressed confusion about. That is, if a student made two statements referring to confusion but they were referring to the same concept, they only counted as one expression of confusion. However, if the student made two statements about different concepts, they counted as two expressions of confusion. To establish inter-rater reliability, two graduate student researchers independently coded a random sample of twenty percent of the reflection papers with a resulting kappa of .78. One of the graduate students continued coding the remainder of the papers.

Second, we investigated whether adaptive support reduces students' errors during problem solving (research question 2). To this end, we computed error rates based on the log data obtained from Chem Tutor. Specifically, error rates were computed as the average number of times a student solved a step incorrectly on the first attempt.

Third, we tested whether adaptive support increases students' pretest-to-posttest learning gains (research question 3). To this end, we used pretests and posttests as in the pilot study. That is, students received a pretest immediately before they started working on the given week's Chem Tutor unit. Then, they received an immediate posttest right after they had finished working on the given week's Chem Tutor unit. Then, at the beginning of the following week, they received a delayed posttest on the previous week's Chem Tutor unit, which they completed before the pretest for the given week's Chem Tutor unit, and so forth. The delayed posttest for the tenth Chem Tutor unit was given at the beginning of the eleventh week's course meeting and concluded the study (see Figure 5). Each test contained multiple-choice items as well as open-response items. The items tested students' conceptual understanding of the chemistry content covered in the given unit. The open-response items asked students to make predictions about specific cases and explain their reasoning in relation to relevant concepts. For example, students were asked to compare whether the electrons of silicon or carbon are more likely to be farther from the nucleus and explain their reasoning in terms of valence electron's energy levels. The agreement among independent graders of 10% of the open-response items was 85.91%.

Procedure

The study took place in the Fall 2018 semester as part of the chemistry course described above. Consent to use students' data for research was obtained at the beginning of the course. The instructor of the course was blind to students' consent and received all data in anonymized fashion. The study began in week 2 of the course. At the beginning of each course meeting, the instructor gave a 3-minute overview of the content covered in the given week. Then, for about one hour, students worked independently and at their own pace on the assigned materials for the given week (i.e., pretest for unit 1, Chem Tutor unit 1, posttest for unit 1; delayed posttest for unit 1, pretest for unit 2, Chem Tutor unit 2, posttest for unit 2, etc.). Then, the instructor led a discussion of the content covered in class. As part of the discussion, students were given prompts to discuss as a whole class or in small groups. If students were unable to attend a course meeting, they were given a chance to complete the assigned materials in a research lab.

Results

We report partial η^2 for effect sizes. According to Cohen (1988), an effect size partial η^2 of .01 corresponds to a small effect, .06 to a medium effect, and .14 to a large effect. Table 4 shows the means and standard deviations by condition and assessment.

--- Insert Table 4 about here ---

Prior Checks

First, we checked if students showed significant pretest-to-posttest learning gains. To this end, we used a repeated measures ANOVA with pretest, immediate posttest, and delayed posttest as dependent measures. To prevent alpha-error accumulation, we use average scores on the pretests, immediate and delayed posttests across the ten units. We found large significant learning gains, $F(2, 86) = 63.879$, $p < .001$, p. $\eta^2 = .598$.

Second, we checked if there were differences between conditions on the pretests. To this end, we used an ANOVA with condition as independent factor and average scores on the pretests as the dependent variable. There were no significant differences between conditions on the pretests ($F < 1$). Because pretest scores correlated significantly with immediate posttest scores ($r = .657$, $p < .001$) and with delayed posttest scores ($r = .608$, $p < .001$), we include pretest as a covariate on all subsequent analyses.

Finally, we checked whether assumptions for ANOVA analyses were met. Kolmogorov-Smirnov tests showed that the distribution of none of the continuous variables used in our analyses significantly differed from the assumption of a normal distribution (ps > .200). Therefore, we can assume that the variables are normally distributed. Further, Levene's test for equality of variances showed that the error variance of the dependent variables did not significantly differ between groups (*p*s > .238). Therefore, we can assume homogeneity of variances.

Effects on Weekly Reflections

To address research question 1 (whether adaptive support reduces students' confusion about how visual representations show chemistry concepts), we used an ANCOVA with number of confusions mentioned across all reflection papers as the dependent measure, condition as the independent factor, and pretest scores averaged across the units as a covariate. In line with our hypothesis, results showed a significant medium-sized effect of condition, $F(1, 42) = 5.661$, $p = .022$, p. η^2 =.12, such that students in the static condition mentioned significantly more often that they were confused than students in the adaptive condition. Table 5 summarizes the number of times students mentioned confusion.

--- Insert Table 5 about here ---

A qualitative inspection of what students were confused about revealed three major themes, each regarding one particular type of representation. First, we found eight instances where students expressed confusion about energy diagrams. Their confusion ranged from expressing general uncertainty about how to interpret the diagram to uncertainty about how specific information about atoms is represented by the energy diagram and questions about how the energy diagram relates to other visuals. For instance, one student mentioned being confused about the relationships between the electron density distribution shown by the orbital diagram and the energy levels that are shown by the energy diagram. Another student found it difficult to create an energy diagram with the information from a Lewis structure. As shown in Table 5, students in both conditions mentioned being confused about this representation equally often.

Second, we found ten instances of students being confused by orbital diagrams. The majority of these instances were related to how the orbital diagram depicts information about specific orbitals (e.g., about the $2p_x$, $2p_y$, and $2p_z$ orbitals) or how to interpret visual features of the orbital diagram (e.g., shapes, size, and colors). One student mentioned difficulties in creating Lewis structures based on the orbital diagram. As shown in Table 5, students in the static condition expressed being confused by orbital diagrams more often than students in the adaptive condition.

Third, we found seven instances where students expressed being confused by Lewis structures. In part, confusion resulted from uncertainty about how Lewis structures relate to other visuals. In addition, students were confused about how to interpret specific features of the Lewis structure (e.g., dots) and about how to infer information about other atomic properties from Lewis structures (e.g., atomic radius or bonding valency). For example, one student mentioned that Lewis structures were especially confusing because they pair electrons rather than spacing them out. Another student mentioned difficulties remembering the steps involved in constructing Lewis structures. As shown in Table 5, students in the static condition expressed confusion about Lewis structures more often than students in the adaptive condition.

Finally, there were 25 instances of confusion related to other visuals and concepts addressed within the class. Five of those instances were specifically related to visuals that were used only once during the curriculum, such as density distributions. For example, two students mentioned that they had difficulties understanding density distributions. The remaining 20 instances where students expressed uncertainty about specific chemistry concepts. These instances referred to specific concepts without reference to a visual representation. Because of low occurrences for each concept (< 3), we assigned these instances to an "other" category. The concepts included quantum numbers, electron affinity, isomers, charges, paramagnetic and diamagnetic compounds, and acids and bases. For instance, two students mentioned confusion about the difference between cis and trans isomers and two students mentioned uncertainty about calculating formal charges. As shown in Table 5, students in the static condition expressed confusion about other visuals and concepts more often than students in the adaptive condition.

Effects on Errors during Problem Solving

To address research question 2 (whether adaptive support reduces errors students make during problem solving), we used an ANCOVA with error rates across all ten units as the dependent measure, condition as the independent factor, and pretest scores as a covariate. Results showed a large significant effect of condition, $F(1, 43) = 8.922$, $p = .005$, p. $\eta^2 = .18$. As illustrated in Figure 9, students in the static condition had significantly higher error rates than students in the adaptive condition, which is in line with our hypothesis.

--- Insert Figure 9 about here ---

Next, we sought to get insights into the nature of errors that were reduced in the adaptive condition compared to the static condition. In particular, we wondered whether adaptive support for representational competencies prevented particular types of mistakes. To this end, we qualitatively examined the steps during which error rates were particularly disparate between conditions (i.e., the error occurred at least twice as often in one condition compared to the other). Five themes emerged from this analysis. First, errors made on the perceptual-fluency activities were highly disparate across all units, so that students in the static condition made more errors on these activities.

The second-most prevalent difference between conditions regarded errors students made when using visual representations to reason about chemistry concepts that required them to extrapolate from information shown in the representation. Specifically, we found that students in the static condition made more errors when working with: energy diagrams to reason about magnetism (unit 3); Lewis structures and shell models to reason about periodic table trends such as nuclear charge and shielding (unit 4); Lewis structures and orbital diagrams to reason about periodic table trends such as ionization energy (unit 5); shell models to reason about lattice energy, electrostatic forces, and the Born-Haber cycle (unit 6); orbital diagrams to reason about electron sharing among bonded atoms (unit 7); space-filling models to reason about bond energy (unit 7); electrostatic potential maps to reason about bond stability and ionic compounds (unit 8); shell models to explain concepts related to atomic size, electron shielding, and electronegativity (unit 9); and when using ball-and-stick models to reason about bond stability (unit 10).

The third most prevalent difference was that students in the static condition made more errors when interpreting representations. Specifically, we found that students in the static condition made more errors when interpreting: how shell models show the first and second quantum numbers (unit 1); how orbital diagrams show the first quantum number (unit 2), how energy diagrams show valence electrons (unit 3); how Lewis structures and shell models each show atomic radii (unit 4); how many orbitals an orbital diagram shows (unit 5); how orbital diagrams and space-filling models each show electron clouds (unit 6); and how electrostatic potential maps show electronegativity differences between bonded atoms (unit 9).

The fourth most prevalent difference regarded errors made when constructing visual representations. Specifically, we found that students in the static condition made more errors when constructing: shell models (unit 1, unit 6); energy diagrams and orbital diagrams (unit 2); and Lewis structures (unit 3, unit 5).

Finally, the least prevalent difference was that students in the static condition made more errors when comparing different visual representations. Specifically, we found that students in the static condition made more errors when comparing: how energy diagrams and orbital diagrams show electrons and energy levels (unit 2); how Lewis structures and energy diagrams show valence electrons (unit 3); how Lewis structures and electrostatic potential maps show real versus formal charges (unit 9); and how ball-and-stick models and electrostatic potential maps show bonds and bond dipoles (unit 10).

In sum, the adaptive condition showed reduced errors specifically during steps that involved visual representations, especially when perceiving information and using that information to reason in ways that extended what was explicitly shown by the visuals.

Condition Effects on Learning Gains

To address research question 3 (whether adaptive support increases students' pretest-to-posttest learning gains of chemistry content knowledge), we used a repeated measures ANCOVA with immediate and delayed posttest scores as repeated dependent measures, condition as the independent factor, and pretest scores as the covariate. Results showed a large significant effect of condition, $F(1, 41) = 7.656$, $p = .008$, p. $\eta^2 = .16$. As illustrated in Figure 10, students in the adaptive condition had significantly higher learning gains than students in the static condition, which is in line with our hypothesis.

--- Insert Figure 10 about here ---

Inspection of Adaptive Assignments

Next, to gain additional insights into how the adaptive version of Chem Tutor might supported student learning, we qualitatively examined how the 23 students in the adaptive condition moved through the sense-making and perceptual-fluency activities across the units. Figure 11 shows that there were 22 unique sequences for $n = 23$ students, such that only two students received the exact same sequence. However, we discovered common themes of how students moved through the units across these sequences. To illustrate our findings, we selected one case of one student, Alex (pseudonym) who is representative of these themes (see red highlight in Figure 11).

--- Insert Figure 11 about here ---

As illustrated in Figure 11, many students (*n* = 10) received regular activities before they received either sense-making or perceptual-fluency activities, for at least the first unit. Otherwise (*n* = 13), they received sense-making activities in unit 1. Our examination of the log data showed that most of these students (*n* = 12) received sense-making activities because they made a mistake constructing a shell model. For example, Alex (pseudonym) constructed an incorrect shell model in unit 1. Therefore, he was assigned to sense-making activities, which asked him to reflect on how shell models show electrons in relation to orbital diagrams.

Further, the majority of the students (*n* = 19) received sense-making activities for at least one unit before receiving perceptual-fluency activities, whereas the remaining students (*n* = 4) received regular activities before perceptual-fluency activities. That is, no students received perceptual-fluency activities in unit 1. Most students first received perceptual-fluency activities in unit 3 (*n* = 12) or unit 2 (*n* = 9). Our inspection of the log data showed that all students who received perceptual-fluency activities in in unit 2 were assigned to them because they had demonstrated an understanding of orbital shapes in orbital diagrams. For example, Alex correctly explained that carbon has two orbitals with two electrons, and two orbitals with one electron. Therefore, he received perceptual-fluency activities in unit 2, which asked him to quickly translate between orbital diagrams and energy diagrams. Orbital diagrams use shapes to show which orbitals are occupied without differentiating between orbitals that contain one or two electrons. By contrast, energy diagrams explicitly indicate how many electrons occupy each orbital. Without understanding this concept, it may have been too difficult for Alex to translate between these representations.

All students who received perceptual-fluency activities in unit 3 were assigned to them because they made a mistake in constructing a Lewis structure or because they misinterpreted the atomic symbol in Lewis structures. For example, Alex thought the atomic symbol stands for the nucleus alone, rather than the nucleus and the core electrons. Therefore, he received perceptual-fluency activities, which asked him to quickly translate between energy diagrams and Lewis structures. To do so, he had to distinguish Lewis structures with the same number of valence electrons based on knowledge about their different number of core electrons. Hence, these activities likely offered Alex experience-based opportunities to learn that the atomic symbol of Lewis structures implies the core electrons.

Also, most students (n = 22) received at least one unit with sense-making activities and at least one unit with perceptual-fluency activities. Our inspection of the log data showed that in most units (all except unit 2, as mentioned in the example above), perceptual-fluency activities were assigned because students made an error indicative of a misconception. For example, Alex made a mistake in unit 8 indicating that he did not understand the concept of electronegativity, which describes the tendency of an atom to attract electrons. Electronegativity affects the distribution of electrons among bonded atoms. Therefore, he was assigned to perceptual-fluency activities, which asked him to quickly translate between shell models and electrostatic potential maps. Shell models contain information that can be used to retrieve knowledge about electronegativity trends in the periodic table. Electrostatic potential maps show electron distributions among bonded atoms. Hence, the perceptual-fluency activities offered opportunities for Alex to practice how electronegativity affects bonding.

Additionally, all students who received at least one unit of perceptual-fluency activities (n = 22) received additional sense-making activities after the perceptual-fluency activities (except for the only student who never received perceptual-fluency activities). Our inspection of the log data showed that the algorithm assigned sense-making activities for a variety of reasons; both to address misconceptions and because students had exhibited prerequisite knowledge for the sense-making activities. For example, in unit 4, Alex drew an incorrect number of valence electrons when constructing a Lewis structure. Therefore, he received sense-making activities, which asked him to use what he learned about shell models to reflect on how Lewis structures show valence electrons. In unit 7, Alex demonstrated prerequisite knowledge for sense-making activities by correctly explaining that electrons do not occupy fixed positions but rather have some likelihood of being in a certain region. The sense-making activities asked him to relate orbital diagrams to space-filling models, which presumes an understanding of electron distributions.

Finally, what stands out is that perceptual-fluency activities were almost never assigned for units 4-7 (with three exceptions). Our inspection of the log data showed that students rarely exhibited misconceptions that triggered the adaptive algorithm to assign perceptual-fluency activities. For example, Alex did not exhibit misconceptions about electron shielding (unit 4) and electron distributions (unit 7) and constructed correct Lewis structures (unit 5) and energy diagrams (unit 6). One possible reason is that most of the visual representations in these units had been used in previous units, so that students were less likely to have misconceptions about them.

Discussion

With respect to research question 1, the results show that adaptive support for representational competencies reduced students' confusion about the visual representations. In particular, students in the adaptive condition expressed being confused less often, particularly with respect to orbital diagrams, Lewis structures, and shell models. What stands out in our qualitative analysis of the reflection papers is that recurring themes referred to visual representations and how they related to specific concepts. Cases in which students referred to concepts irrespective of visual representations seemed to be unique cases that did not recur across multiple students. This suggests that students' learning of the concepts is indeed driven by their ability to interpret visual representations that illustrate the concepts.

With respect to research question 2, the results show that adaptive support reduced error rates during problem solving, compared to static support. Recall that the adaptive algorithm assigned students to sense-making and perceptual-fluency activities depending on a diagnosis of their misconceptions or prerequisites that was based on their performance on the first two regular activities in the given unit. It seems reasonable to assume that if students had the prerequisite knowledge to benefit from sense-making activities or perceptual-fluency activities, they would make fewer mistakes on those activities. Further, if students had misconceptions that could be addressed by sense-making or perceptual-fluency activities, they should make fewer errors that exhibit that misconception later on. The finding that students in the adaptive condition had lower error rates is altogether in line with the interpretation that students received the support they needed to successfully learn with the visual representations.

The qualitative inspection of which specific errors differed between conditions concurs with this interpretation. We found that students in the adaptive condition tended to make fewer errors on steps that involved interacting with visual representations, specifically, perceptually translating among the representations, using the information from the representations to reason about concepts, interpreting the representations, constructing them, and comparing them. Given that all these steps involved interactions with visual representations, it appears that adaptive support for representational competencies indeed helped students perform well on steps that relied on representational competencies, as it was designed to do. Further, our qualitative analysis showed that the impact of adaptive support was largest in reducing errors on perceptual-fluency activities and on steps that required students to use information from the representations to reason about chemistry concepts while extending beyond what was explicitly shown by the representations. Thus, it seems that the benefit of adaptive support for representational competencies particularly benefited students in preparing them for perceptual learning and for applying their knowledge about the visual representations to concepts that were abstract in the sense that they were not directly depicted.

With respect to research question 3, we found that adaptive support increased students' gains in chemistry knowledge more so than static support. Recall that students in both conditions received instruction on the same chemistry content. What differed between the conditions was merely how the sense-making and perceptual-fluency activities were assigned. Students in the static condition may have received support for representational competencies they did not need support for, either because they had already acquired those competencies or because they did not have the prerequisite knowledge to benefit from support for them. In the first case, students would have received redundant support. Prior research on the expertise-reversal effect shows that redundant support can distract from content (Chen, Kalyuga, & Sweller, 2016; Kalyuga, Ayres, Chandler, & Sweller, 2003). Further, prior research on scaffolding shows that support should be carefully calibrated to the students' needs in order to be effective and that overscaffolding can be counterproductive (Puntambekar & Kolodner, 2005; Reiser & Tabak, 2014). In the second case, students may have received sense-making activities or perceptual-fluency activities for which they were not ready. Sense-making activities may have been too difficult because they asked students to compare multiple visual representations, which requires students to consider how each visual representation depicts chemistry concepts. This requires more cognitive effort than using only one visual representation at a time. The qualitative inspection of errors lends credibility to this interpretation, given that students in the static condition made more errors on steps that asked them to compare visual representations. Perceptual-fluency activities may have been more difficult for students who lacked prerequisites because understanding how each of the visuals shows chemistry concepts can enhance top-down processes involved in perceptual learning that allow students to quickly attend to conceptually visual features. Our inspection of how the adaptive algorithm assigned students to activities as well as Alex's case provide several examples of how adaptive assignment to sense-making and perceptual-fluency activities may have supported students' learning.

Taken together, these findings expand prior research in several ways. First, our own prior research showed that students' benefit from sense-making and perceptual-fluency activities depends on their prior knowledge level (Rau, 2018). Further, prior research showed that adapting the assignment of particular problem types to students' given problem-solving skill level enhances their learning (e.g., Koedinger & Corbett, 2006; VanLehn, 2011). Yet, our study is the first to show that adaptively assigning activities that support specific representational competencies can enhance students' learning of domain knowledge, even when the content covered is the same across conditions. Hence, adaptive support for representational competencies can enhance the effectiveness of activities in which students use visual representations to learn about domain knowledge.

Second, our results provide further evidence for how support for sense-making and perceptual-fluency competencies should be sequenced as students' learning progresses, beyond the cross-sectional findings from prior research (Rau et al., 2017; Rau, 2018; Rau & Wu, 2018). The results of the pilot study that were the basis for the adaptive assignment algorithm had suggested that students should start with regular activities or sense-making activities before they can benefit from perceptual-fluency activities. Our examination of how the algorithm actually assigned students showed that the majority of students started with this sequence. Further, the adaptive assignment algorithm provided students with sense-making activities after they had received perceptual-fluency activities. This assignment was based on the algorithm's decision that each individual student had acquired prerequisites or exhibited misconceptions that would allow them to benefit from sense-making activities. This finding aligns with earlier cross-sectional results that students benefit from sense-making activities again after becoming perceptually fluent (Rau, 2018). Also, in spite of these commonalities, most students received unique sequences, which supports the idea that students move through a learning progression of representational competencies at their own speed.

Third, the current results also provide further evidence for earlier findings that students should receive both sense-making and perceptual-fluency activities (Rau et al., 2017; Rau & Wu, 2018) because the adaptive assignment algorithm assigned most students to both types of representational-competency supports. However, simply combining these activities is not maximally effective, as evidenced by the significant difference between the static and adaptive conditions. If any combination of sense-making and perceptual-fluency activities was equally effective, there should not have been a significant differences between these conditions. Rather, adapting the combination and sequence to students' learning progress seems to be important to ensure that students benefit from them.

Finally, our results may guide the design of representational-competency supports for problem-solving activities that ask students to interact with multiple visuals. We used linear regression to identify steps that were predictive of benefit from sense-making and perceptual-fluency activities because they indicate prerequisite knowledge about visuals or misconceptions about visuals. We translated these results into simple if-then rules that assign the type of representational-competency support a student needs. This methodological approach can be applied to any set of technology-based activities where students use visual representations to solve domain-relevant problems.

Limitations

Our findings should be interpreted in light of several limitations. First, several limitations relate to the choice of sample. Our study was part of a course that involved other activities such as class discussions, which likely affected pretest-to-posttest learning gains. However, we do not see why they should have affected differences between conditions. Also, because participating students were enrolled in a chemistry class, they were likely highly motivated to learn chemistry. They may also have seen the visuals in other chemistry classes before. Again, because this was true for all students in the sample, we do not believe this confounded the experimental design, although it may have affected the overall learning gains.

Second, our sample was relatively small due to the small class size of 45 students. This sample size is sufficient for testing differences between two conditions, but it is not sufficient for testing for aptitude-treatment interactions. For example, it is possible that the adaptive assignment algorithm better predicted benefit from sense-making and perceptual-fluency activities if they started out with low prior knowledge. To analyze such effects, future research should repeat the experiment with a larger sample.

Third, we did not compare the adaptive condition to control conditions that received only sense-making activities, only perceptual-fluency activities, or only regular activities. In part, this was due to the small sample size, in part, this was due to prior studies showing that the combination of sense-making and perceptual-fluency activities that we used in the static condition was more effective than any of these control conditions. Nevertheless, future research should verify that adaptive representation-skill support is indeed more effective than these control conditions within one experiment.

Finally, because our study investigated learning with visuals in chemistry, we cannot assume that our findings necessarily generalize to other STEM domains. The use of visuals in chemistry is similar to other STEM domains because they are used to show concepts that are invisible or not observable with the regular eye and because a variety of visuals are used to illustrate different concepts. Nevertheless, each domain relies on its own set of visuals that were developed to address the communication needs of the given scientific community. Therefore, future research should test whether adaptive representational-competency support also enhances learning in other domains and with other visuals.

Conclusions

In conclusion, our study is the first to show that adaptive support for representational competencies can significantly enhance learning of content knowledge by reducing students' confusion as well as errors during problem solving. We found medium to large effect sizes that are due to the individualized order in which students received support for representational competencies while the content covered was identical in both conditions. Given that multiple visuals are widely used and that lack of representational competencies is an obstacle in many STEM domains, our findings suggest that adaptive support for representational competencies may significantly enhance STEM learning.

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