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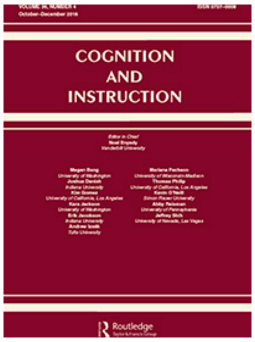

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Combining Instructional Activities for Sense-Making Processes and Perceptual-Induction Processes Involved in Connection-Making Among Multiple Visual Representations

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ABSTRACT

Connection-making among multiple representations is a crucial but difficult competence in STEM learning. Prior research has focused on one type of learning process involved in connection-making: sense-making processes leading to conceptual understanding of connections. Yet, other research suggests that a second type of learning process is important: inductive learning processes leading to perceptual intuitions about connections. We investigate whether combining instructional activities designed to support sense-making processes for understanding of connections (understanding activities) and instructional activities that support inductive processes for perceptual intuitions about connections (perception activities) enhances students' learning of chemistry knowledge. A laboratory-based experiment with 117 undergraduate students compared students in (a) a control condition that received only conventional activities that did not require connection-making; (b) a condition that received conventional and understanding-activities; (c) a condition that received conventional and perception-activities; and (d) a combined condition that received conventional, understanding-activities, and perception-activities. Results show that only the combined condition outperformed the control condition on a test of chemistry knowledge. Eye-gaze data and verbal reports show that understanding-activities and perception-activities have complementary effects on how students integrate information from multiple representations during the learning phase. Finally, we found that students' spatial skills moderate their benefit from understanding-activities and perception-activities.

Introduction

Instruction in most science, technology, engineering, and mathematics (STEM) domains uses multiple visual representations to help students learn content (Ainsworth, 2008; Gilbert, 2008; NRC, 2006). Visual representations depict information about concepts using visual features (e.g., color, shape) that have similarity-based mappings to the concepts (Schnotz, 2005). Typically, a single visual representation focuses on only few concepts involved in a complex phenomenon. Consequently, STEM instruction often uses multiple visual representations to illustrate complex phenomena. Therefore, students need to make connections among concepts shown across multiple visual representations. As illustrated in Figure 1, *making connections* between visual features

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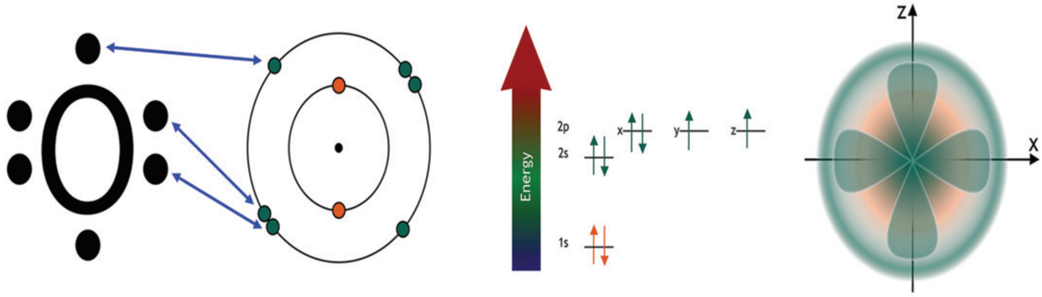


Figure 1. Visual representations of oxygen (from left to right): Lewis structures show valence electrons, Bohr models show all electrons on atomic shells, energy diagrams show electrons in orbitals by energy levels, orbital diagrams show the spatial arrangement of nonempty orbitals. Connecting visual features such as the dots in the Lewis structure and the Bohr model allows students to connect concepts shown across visuals, such as that an atom not only has valence electrons (shown in both Lewis structure and Bohr model) but also core electrons (shown in the Bohr model, but not in the Lewis structure).

of different visual representations is a key mechanism through which students connect concepts, which is crucial to gaining new content knowledge.

Imagine, for example, students learning about atomic structure with the visual representations shown in Figure 1A and 1B. A key connection is indicated by the arrows: Students have to learn that the Lewis structure (1A) uses dots to show only valence electrons, whereas the Bohr model (1B) uses dots to show valence electrons on the outer shell of an atom and core electrons on the inner shell. By making connections between the visual features (i.e., dots), students connect concepts that are shown across visuals to learn new content; for example, that atoms are composed of multiple shells, each of which hold electrons. Such connections help them learn new content knowledge. For example, the connections between the dots in the Lewis structure and Bohr model help students understand that both the valence and core electrons are paired or unpaired in the shell, which has an effect on how many bonds an atom forms. Using multiple visuals that illustrate complementary concepts of complex phenomena is common practice in chemistry instruction and many other STEM domains. Hence, connection-making among visuals plays an important role in students' learning (e.g., Ainsworth, 2006).

Yet, making such connections is not straightforward: How are students to know that the black dots in the Lewis structure (1A) do not show the electrons as the dots in the inner shell of the Bohr model (1B)? Indeed, it is well documented that connection-making is difficult for students (de Jong et al., 1998; McElhaney, Chang, Chiu, & Linn, 2015), and that these difficulties can jeopardize students' learning (Ainsworth, 2008; Cheng & Gilbert, 2009). This conundrum is known as the *representation dilemma* (Dreher & Kuntze, 2015; Rau, 2017a): Students often have to learn new content from new representations they may not yet understand. That means that while students acquire content knowledge, they also have to acquire *visual skills*: knowledge about how multiple visual representations show information (Gilbert, 2008; NRC, 2006; Rau, 2017a). We consider visual skills to be a specific type of representational competency. According to diSessa (2004), representational competencies involve the ability to invent new representations, to critique representations, to learn new representations, to understand the use and purpose of representations in the given discipline, and the ability to explain representations. By contrast, visual skills describe a more narrow set of competencies that enable students to explain and use specific visuals that are commonly used in instruction in a given domain. In this article, we focus on a particular set of visual skills that enable students to make connections among multiple visual representations while they learn new content knowledge.

Research on visual skills draws on multimedia learning research, which documents that prior visual skills are crucial prerequisites for students' ability to learn from visual representations (Ainsworth, 2008; NRC, 2006). This research has also investigated how to compensate for students' lack of visual skills through the design of instructional activities, so as to enhance students' learning of content knowledge (Bodemer & Faust, 2006; Seufert, 2003). However, a limitation of multimedia learning research is that it has focused on the acquisition of content knowledge, rather than on the acquisition of visual skills (Rau, 2017a). Hence, multimedia learning research has not examined which visual skills students need to acquire, and how to support learning of these visual skills while students learn content knowledge.

According to multimedia learning theories (Mayer, 2009; Schnotz, 2005), learning with visuals involves both conceptual and perceptual processes. Yet, research that investigates how to support students' learning with multiple visual representations has mostly focused on *conceptual understanding of connections* (henceforth *connection-understanding*). Connection-understanding is a type of visual skill that describes students' ability to explain mappings between visual features of different representations based on the concepts they show. For example, a chemist can explain connections between the Lewis structure and the Bohr model by reasoning about shells: Although valence electrons on the outer shell determine how many bonds an atom forms, electrons on inner shells are also important because they shield negatively charged valence electrons from the positively charged nucleus. Therefore, atoms with more inner shells hold on to valence electrons less tightly and—consequently—valence electrons are more likely to shift away from the atom when bonding (i.e., more ionic bonds). Thus, the chemist can make connections among concepts related to chemical bonding because he/she has conceptual understanding of the connections between the visuals.

Recent research suggests that an additional type of visual skills plays an important role in students' learning: *perceptual expertise in making connections* (henceforth *connection-perception*), which is the ability to automatically perceive meaning in visual representations and to quickly translate among them (Kellman & Massey, 2013; Massey, Kellman, Roth, & Burke, 2011). For example, a chemist may use the pairing of dots in the Bohr model in Figure 1 as a visual cue to automatically induce its Lewis structure, and vice versa. This translation may be so automatic that the chemist can mentally visualize the Bohr model when looking only at the Lewis structure. The chemist perceives these connections not through reasoning about concepts but through low-level inductive processes that are triggered by visual cues.

The fact that separate lines of research have focused on connection-understanding and on connection-perception is all the more striking because much evidence suggests that these visual skills are strongly intertwined. Indeed, connection-understanding draws on students' perceptual induction of relevant visual features, and connection-perception can reduce the cognitive demands when students explain their understanding of why visual features map to one another (Goldstone, Schyns, & Medin, 1997). A possible reason for the separate nature of literatures on connection-understanding and connection-perception may be that these visual skills are acquired via qualitatively different types of learning processes. Students acquire connection-understanding by verbally and explicitly explaining how visual features of the representations map to one another and by providing them with feedback and guidance on how to make these mappings (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Gentner, 1983; Schnotz, 2005). By contrast, connection-perception results from experience with a large variety of visual representations that yields visual shortcuts (Massey et al., 2011; Rau, 2017a). Students acquire connection-perception by inducing mappings between visual representations based on experience. The acquisition of connection-perception does not rely on explicit, verbal explanations of mappings but instead involves implicit, nonverbal learning processes. Consequently, connection-perception can be acquired without connection-understanding. For example, students may acquire an intuitive idea of whether or not two visuals show the same atom, without being able to explicitly explain why. Such perceptual intuitions result from inductive learning based on experience with multiple visual representations. Thus, from a theoretical perspective, even though connection-understanding and connection-perception are intertwined, they are acquired via qualitatively different processes (i.e., explicit, verbal explaining versus implicit, non-verbal induction).

These theory-based distinctions have yielded different practical interventions for connection-understanding and connection-perception that reflect the different nature of the learning processes through which these visual skills are acquired. Instructional activities that support conceptual understanding of connections among visual representations (henceforth *understanding-activities*) provide explicit instruction to explain connections. By contrast, instructional activities that support perceptual induction of connections among visual representations (henceforth *perception-activities*) provide implicit learning experiences by exposing students to numerous examples in activities that ask students to categorize or sort a variety of visuals. Perception-activities purposefully discourage explanations, for example by prompting students to solve the activities quickly, intuitively, without thinking, and without being afraid of making mistakes. One rationale underlying this choice is that explaining does not enhance connection-perception, but would unnecessarily take up instructional time at the expense of exposing students to a large variety of visual representations (Kellman & Massey, 2013; Rau, 2017a). From this perspective, even though students could, in principle, acquire connection-perception from understanding-activities, this would take too much time to be practical. Another rationale underlying the choice to discourage verbal explanations is that some research suggests that verbalization can interfere with students' learning of perceptual knowledge (Schooler, Ohlsson, & Brooks, 1993). Thus, from this perspective, students may not be able to learn connection-perception from understanding-activities.

Because research on understanding-activities and perception-activities has been mostly separate, we do not know (a) whether instruction needs to include both understanding-activities and perceptual-activities, and if so, (b) how these activities interact in enhancing students' learning of content knowledge. We address these open questions in an experiment in which students learned about chemistry with or without understanding-activities and perception-activities.

Theoretical background

In the following, we first review the separate lines of research on understanding-activities and perception-activities. Then, we consider potential interactions among these visual skills. This leads to our hypothesis that combining these two types of activities in instruction should yield higher learning gains of content knowledge than either type of activity alone. Figure 2 provides an overview of the mechanisms that underlie this hypothesis.

Understanding-activities

Design principles for understanding-activities

Much research has investigated how instruction can support students in explaining how different visual representations map to one another based on the concepts they show. Such understanding-activities prompt students to explain comparisons between visual representations in reference to key concepts. For example, a student may be prompted to use atomic structure concepts to explain why the six electrons shown in the Lewis structure in Figure 1A reside on the outer shell shown in the Bohr model in Figure 1B. The student may also be asked to explain differences between the representations, for instance that the Lewis structure does not show inner-shell electrons. The student may receive assistance in the form of increasingly detailed prompts or feedback on incorrect explanations.

This example illustrates some of the major instructional design principles that have proven effective in research on understanding-activities. First, students should verbally explain which visual features of representations show corresponding or complementary information. For example,

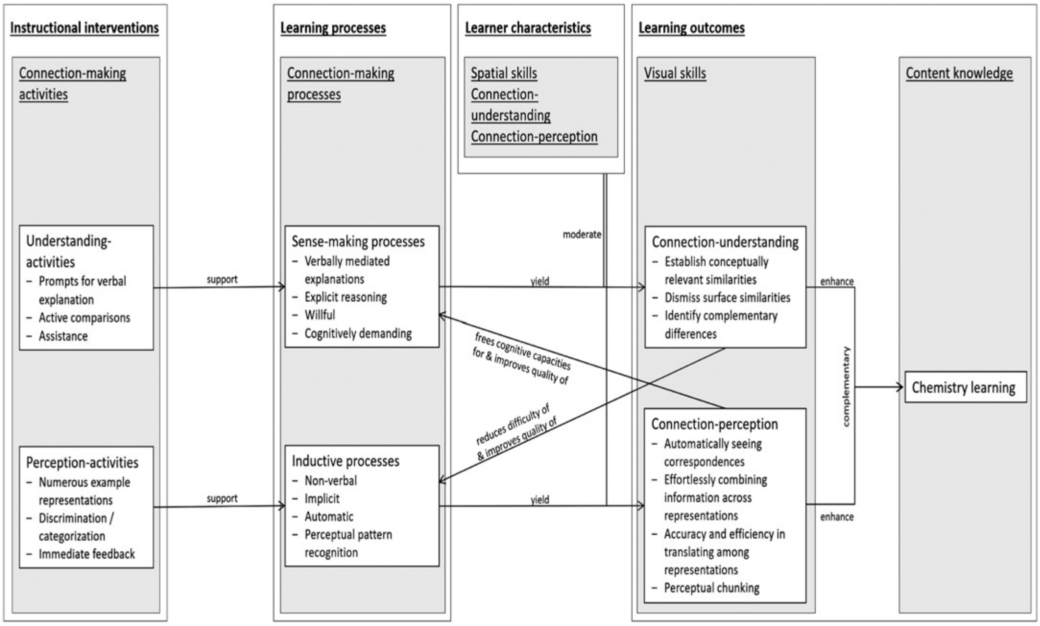


Figure 2. Model of hypothesized mechanisms by which working on understanding activities and perception activities fosters learning processes (sense-making processes, inductive processes) and visual skills (connection-understanding and connection-perception) that enhance students' learning of content knowledge in chemistry.

prompting students to self-explain mappings between visual representations was shown to enhance learning of content knowledge in physics (Berthold, Eysink, & Renkl, 2008; van der Meij & de Jong, 2011), biology (Seufert, 2003), and math (Berthold & Renkl, 2009). Second, understanding-activities are most effective if they require students to actively compare how different visual representations show similar or complementary concepts. Several experiments on math and science learning demonstrated that students who are asked to actively map visual features that show corresponding information show higher learning outcomes than students who are presented with premade mappings of visual features (Bodemer & Faust, 2006; Stern, Aprea, & Ebner, 2003). Finally, because students have a tendency to focus on surface features instead of conceptually relevant features (Ainsworth, Bibby, & Wood, 2002; Rau, Aleven, Rummel, & Pardos, 2014), they need assistance in identifying relevant visual features across the representations. Such assistance can be provided in the form of conceptually focused feedback on student-generated connections (Bodemer & Faust, 2006; Rau, Aleven, & Rummel, 2017b). Assistance is particularly important for students with low prior content knowledge (Bodemer & Faust, 2006; Stern et al., 2003) and for students with low spatial skills (Barrett & Hegarty, 2016).

The literature abounds with examples of understanding-activities used in STEM education. Many educational technologies for STEM learning are specifically designed to help students explain connections among visual representations in a way that aligns with the instructional design principles just described (Cobb & McClain, 2006; Wu, Krajcik, & Soloway, 2001). Other interventions that range from classroom-based discussions to on-the-job training also incorporate these principles. For example, teachers may directly prompt students to explain why they need multiple visual representations to illustrate a given concept (Talanquer, 2013). Teachers may direct students' visual attention to corresponding visual features through gestures (Nathan, Walkington, Srisurichan, & Alibali, 2011). Such explanations of mappings that are also prevalent in apprenticeship situations where trainees learn skills that require the integration of information across multiple representations (Cope, Bezemer, Kneebone, & Lingard, 2015).

Understanding-activities support sense-making processes

From a cognitive psychology perspective, understanding-activities target verbally mediated sense-making processes (Koedinger, Corbett, & Perfetti, 2012; Rau, 2017a). Sense-making processes are verbally mediated because they involve explanations of principles by which visual representations depict information (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Gentner, 1983). They are explicit in that students have to willfully engage in them (Chi, de Leeuw, Chiu, & Lavancher, 1994; diSessa & Sherin, 2000). Sense-making processes require considerable cognitive effort (Schnotz, 2005) and typically do not happen automatically (Ainsworth et al., 2002; Rau et al., 2014). Therefore, understanding-activities are designed so that students have to actively compare the representations while providing conceptually focused assistance for students to do so.

The multiple representations literature describes sense-making processes in terms of structure mapping (Ainsworth, 2006; Gentner & Markman, 1997; Schnotz, 2005) because students map visual features of the representations to abstract concepts. Via structure mapping, students learn to determine similarities between representations (i.e., which information is shown in different representations) and differences (i.e., which information is shown in one but not the other representation; Gentner, Loewenstein, & Thompson, 2003). Sense-making processes are also involved when students learn to make conceptual inferences by distinguishing relevant from irrelevant visual features (Rau, 2017a) and to explain why a visual representation is most appropriate for solving a given problem (Acevedo Nistal, Van Dooren, & Verschaffel, 2015; diSessa, 2004).

Sense-making processes yield connection-understanding

According to cognitive learning theories (Koedinger et al., 2012), engaging in sense-making processes allows students to acquire principled understanding of complex concepts. With respect to connection-making, sense-making processes yield connection-understanding: knowledge and skills that allow students to map features of visual representations to one another based on principled reasoning that the representations depict information about the same concept (Eilam & Ben-Peretz, 2012; Schnotz, 2005). To this end, students need to dismiss mappings that are based on surface similarities among visual representations; that is, shared visual features that do not depict corresponding concepts (Gentner & Markman, 1997). Instead of relying on surface similarities, students have to reason about at least two types of mappings. First, students need to establish mappings based on *conceptually relevant similarities* between visual representations; that is, shared visual features that are relevant to the to-be-learned concept (Ainsworth, 2006; Seufert, 2003). For example, the Lewis structure and the Bohr model in Figure 1 indicate that oxygen has six valence electrons. Second, students need to identify *complementary differences* between visual representations; that is, information that is shown in one but not the other visual representation (Acevedo Nistal et al., 2015; diSessa, 2004). For example, the Bohr model shows oxygen's inner-shell electrons, but the Lewis structure does not.

Connection-understanding enhances learning of content knowledge

Connection-understanding plays an important role in students' learning of content knowledge. Cognitive learning theories posit that connection-understanding enables students to integrate information from visual representations with their prior knowledge about the content (Mayer, 2009; Schnotz, 2005). Furthermore, connection-understanding allows students to integrate information about domain-relevant concepts across multiple visual representations (Ainsworth, 2006, 2014). Further, connection-understanding allows students to choose appropriate representations for specific tasks because they know which representation makes different concepts particularly salient (Acevedo Nistal et al., 2015; diSessa, 2004).

The STEM education literature also acknowledges the importance of this type of visual skill. Specifically, several studies on STEM learning show that students' lack of connection-understanding interferes with their learning of content knowledge (e.g., Patel & Dexter, 2014; Savec, Sajovic, & Grm, 2009). Consequently, STEM education practice guides consider connection-understanding as an important educational goal (NCTM, 2006; NGSS, 2013; NMAP, 2008; NRC, 2012).

Perception-activities

Design principles for perception-activities

A second, mostly separate line of research has focused on activities that engage students in non-verbal inductive processes. Such *perception-activities* have emerged from research on perceptual learning and are intended to build perceptual intuition that experts have through experience with multiple representations throughout their career (Kellman & Massey, 2013; Rau, 2017a). To avoid explicit, verbal explanations, perception-activities provide students with numerous example representations, ask them to categorize the examples, and provide immediate correctness feedback. For example, a student may be given one Bohr model and be asked to select one of several Lewis structures that shows the same atom. The student may be prompted not to overthink the problem and to solve it fast while relying on his/her intuitive knowledge. If the student chooses the wrong Lewis structure, he/she will be told that the choice was incorrect, without an explanation. Through these activities, students can gain perceptual intuitions that expert chemists have likely gained through experience with multiple visual representations throughout their career. As a consequence of such extensive experiences, chemists can eye-ball whether two visuals show the same atom.

This example illustrates some of the core principles that have been shown to be particularly effective in supporting connection-perception. First, activities that ask students to discriminate and categorize numerous examples have been shown to be effective in research on fractions, algebra, and chemistry learning (Kellman et al., 2008; Wise, Kubose, Chang, Russell, & Kellman, 2000). Second, students should receive immediate correctness feedback on these discrimination and categorization problems (Massey et al., 2011). Explanations are not provided so as to engage implicit and nonverbal learning processes instead of verbal, explanation-based processes (Rau, 2017a). Third, students should practice with many varied examples sequenced such that consecutive examples emphasize relevant visual features (Kellman, Massey, & Son, 2009; Massey et al., 2011). Experiments in a variety of domains, including math and chemistry, showed that such perception-activities enhanced learning of content knowledge (Kellman et al., 2009; Massey et al., 2011; Wise et al., 2000).

The STEM education literature suggests that perception-activities are becoming increasingly prevalent in STEM education. This literature describes a variety of activities that explicitly support connection-perception, for instance, through technology-based interventions (Kellman et al., 2008; Wise et al., 2000) or through card games (Moreira, 2013; Welsh, 2003). Furthermore, several qualitative studies detail how implicit aspects of instruction support students in acquiring perceptual intuitions of using visual representations through exposure to multiple examples without explicit instruction (Airey & Linder, 2009), corrective feedback (Cope et al., 2015), or discourse that is mediated through visual representations (Airey & Linder, 2009; Wertsch & Kazak, 2011).

Perception-activities support inductive processes

From a cognitive psychology perspective, perception-activities engage students in nonverbal inductive processes (Koedinger et al., 2012; Rau, 2017a). When students are exposed to many varied examples that they have to discriminate or categorize, they engage inductive processes that result in automatic pattern recognition (Gibson, 2000; Richman, Gobet, Staszewski, & Simon, 1996). Combining such inductive learning experiences with immediate feedback yields increased accuracy and efficiency in extracting information from perceptual patterns (Koedinger et al., 2012; Richman et al., 1996).

According to the perceptual learning literature, such inductive learning processes are not necessarily willful or planned (Gibson, 2000; Richman et al., 1996). Rather, they are implicit because they happen unintentionally and sometimes unconsciously (Shanks, 2005). They are considered non-verbal because they do not require explicit reasoning (Koedinger et al., 2012). Indeed, explicit reasoning may unnecessarily take up instructional time that would be better spent on experience with additional examples (Kellman & Garrigan, 2009; Kellman & Massey, 2013) and it may even interfere with students' ability to engage in inductive learning processes (Schooler, Ohlsson, & Brooks, 1993; Shanks, 2005). For this reason, perception-activities typically provide only *correctness feedback*, instead of explanation-based feedback.

Inductive processes yield connection-perception

According to cognitive learning theories, engaging in inductive processes allows students to develop acuity in discriminating and categorizing stimuli (Koedinger et al., 2012). With respect to connection-making, inductive processes yield connection-perception: the ability to just see whether two visual representations show the same information, to combine information from different visual representations without any perceived mental effort, and to quickly translate among them (Chase & Simon, 1973; Kellman & Massey, 2013). The ability to make connections efficiently automatically results from perceptual chunking (Goldstone et al., 1997; Kellman & Massey, 2013). Rather than mapping particular visual features to one another, the expert treats the entire visual representation as one perceptual chunk. Literature on perceptual expertise suggests that connection-perception involves accuracy and efficiency in discriminating, classifying, and categorizing visual representations (Goldstone, 1997). Thus, connection-perception describes automaticity and efficiency in translating between perceptual chunks.

Connection-perception enhances learning of content knowledge

Research suggests that connection-perception enhances students' learning of content knowledge. According to cognitive learning theories, connection-perception frees cognitive resources that students can invest in higher-order thinking about the content (Gibson, 2000; Richman et al., 1996). Specifically, connection-perception eliminates costly visual search processes because students can draw on perceptual cues to extract meaningful information from visual representations, allowing them to engage in effortful learning processes (Kellman & Massey, 2013). The STEM education literature parallels this claim. For example, students' ability to automatically infer connections among visual representations provides the cognitive capacity they need to reason about complex concepts in chemistry (Gilbert, 2005; Taber, 2014) and physics (Airey & Linder, 2009). Consequently, connection-perception is considered to be an important learning goal in STEM disciplines and educational practice guides (Gilbert, 2008; NRC, 2006).

Potential interactions among connection-understanding and connection-perception

The research reviewed thus far illustrates that connection-understanding and connection-perception are acquired via different types of learning processes that are supported by different types of instructional activities. Understanding-activities support students' engagement in sense-making processes that yield connection-understanding (top half of Figure 2). By contrast, perception-activities support inductive learning processes that lead to connection-perception (bottom half of Figure 2). In our prior research (Rau, 2017b; Rau, Michaelis, & Fay, 2015), we tested whether connection-understanding and connection-perception are indeed separate types of visual skills. For two different chemistry topics, we developed and validated tests for connection-understanding, connection-perception, and content knowledge. Confirmatory factor analyses showed that connection-understanding and connection-perception are independent visual skills, and both are predictive but independent of content knowledge. Further, expert interviews and think-alouds, as well as eye tracking with students, showed that the learning processes that students engage in when working on understanding-activities and perception-activities are indeed qualitatively different.

Given that connection-understanding and connection-perception both play an important role in domain expertise, it seems logical to hypothesize that instruction that combines both types of activities should yield higher learning gains of domain knowledge, compared to instruction that provides only one or neither of these activities. To the best of our knowledge, our own prior experiment (Rau et al., 2017b) is, to date, the only one to experimentally test this hypothesis. This prior experiment was conducted with elementary-school students learning about fractions with multiple visual representations. All students worked on conventional activities that they typically encounter in fractions textbooks. In these conventional activities, students typically do not have to make connections among visual representations but receive only one visual representation at a time. Students in a control condition received only conventional activities. Students in an understanding-condition received conventional activities plus understanding-activities. Students in a perception-condition received conventional activities plus perception-activities. Students in an understanding-perception condition received all three types of activities. The number of activities per condition was controlled so that time on task was the same across conditions. Students' learning gains were assessed with content knowledge pre- and post-tests. Results showed that only the understanding-perception condition outperformed the control condition. By contrast, the understanding-condition and the perception-condition did not outperform the control condition.

The finding that the understanding-perception condition outperformed the control condition was expected because the conventional activities did not support students in making connections among different visual representations. As argued previously, making connections between visual representations allows students to connect concepts shown across the different representations, which is crucial to gaining new knowledge.

However, the finding that the understanding-condition and the perception-condition did not outperform the control condition was puzzling. If only the combination of understanding-activities and perception-activities enhances students' learning of content knowledge, then these activities must interact with one another in some way that we had not anticipated. We see two possible mechanisms. First, connection-understanding (that results from understanding-activities) may enhance students' learning from perception-activities. Recall that understanding-activities provide explicit instruction on relevant visual features. When students work on perception-activities, such understanding may help them to more quickly attend to the relevant features, allowing them to more easily induce correct connections across a larger variety of visual representations. By contrast, students without connection-understanding (i.e., students in the perception-condition who did not receive understanding-activities) may have to induce mappings without knowledge about relevant features. Yet, research documents that students have difficulties discovering connections without explicit instruction (Ainsworth et al., 2002; Rau et al., 2014), especially if they have low prior knowledge (Stern et al., 2003) and low spatial skills (Barrett & Hegarty, 2016; Stieff, 2007). Thus, students without connection-understanding may fail to induce correct mappings from perception-activities, whereas students with connection-understanding may induce higher-quality mappings and experience less difficulty while working on perception-activities.

A second possible mechanism may be that connection-perception (that results from working with perception-activities) enhances students' benefit from understanding-activities. Perception-activities reduce the cognitive load that students experience when they make connections among visual representations because it eliminates the need for trial-and-error strategies when students visually search for relevant features in the representations. Consequently, when students work on understanding-activities, connection-perception may enhance students' ability to establish complex mappings between multiple visual features and domain-relevant concepts. By contrast, students without connection-perception (i.e., students in the understanding-condition who did not receive perception-activities) have no (or suboptimal) perceptual intuitions about which visuals correspond to one another. This may increase the demands related to visual search and may, hence, increase the risk of cognitive overload when students are asked to make sense of connections. Thus, students without connection-perception may fail to learn from sense-making activities due to cognitive overload, whereas students with connection-perception may have sufficient cognitive capacity for sense-making processes, allowing them to engage in higher-quality explanations.

A second experiment on fractions learning investigated these two mechanisms by examining errors students made while working on these instructional activities (Rau, Aleven, & Rummel, 2017a). The results showed that working on understanding-activities reduced the number of errors students made while working on subsequent perception-activities. This finding supports the notion that connection-understanding reduces the difficulty of inductive processes students engage in when working on perception-activities. However, the experiment did not find evidence that working on perception-activities enhances students' learning from subsequent understanding-activities.

These two prior experiments have several limitations that we address in this article, regarding our assessment of student characteristics and of learning processes.

Student characteristics that may moderate learning with visual representations

Prior visual skills

One limitation of our prior experiments is that they did not assess students' prior connection-understanding or prior connection-perception. The finding that understanding-activities and perception-activities interact with one another suggests that connection-understanding may enhance students' learning from perception-activities, and that connection-perception may enhance students' learning from understanding-activities. Therefore, students' prior visual skills may moderate their learning from these activities.

Spatial skills

In contrast to visual skills that are specific to a given visual representation and the domain-relevant concepts it shows, spatial skills are general abilities that allow students to mentally or physically transform objects in space (Uttal et al., 2013). A further limitation of our prior studies on connection-understanding and connection-perception is that they did not consider spatial skills. It is well established that students with low spatial skills tend to show lower learning outcomes in STEM disciplines that heavily rely on the use of visual representations in instruction (Langlois, Bellemare, Toulouse, & Wells, 2015; Stieff, 2007). Spatial skills are important for learning with visual representations because it requires that students integrate visuo-spatial relationships into a mental model of the content knowledge (Hegarty & Waller, 2005). Consider again the visual representations in Figure 1. The Lewis structure (1A) shows paired and unpaired valence electrons, the Bohr model (1B) shows all electrons in atomic shells, the energy diagram (1C) depicts electrons in orbitals with their energy level, and the orbital diagram (1D) shows the spatial arrangement of nonempty orbitals. To understand atomic structure, students have to integrate this information into a visuospatial mental model of how electrons are arranged relative to the atom's nucleus and how they move according to probabilistic laws. This integration requires students to hold the relative location of visual features in working memory, mentally rotate the features, and map them to one another (Hegarty & Waller, 2005). Because spatial skills describe this very ability, the cognitive load imposed by connection-making is arguably higher for students with low, rather than with high, spatial skills (Stieff, 2007; Uttal et al., 2013). Therefore, students with low spatial skills are at higher risk of cognitive overload during connection-making and may, therefore, fail at this task, which might jeopardize their learning success (Hegarty & Waller, 2005; Stieff, 2007).

Consequently, spatial skills may moderate students' benefit from connection-making activities. First, it is possible that low-spatial-skills students benefit more from understanding-activities and perception-activities than high-spatial-skills students. High-spatial-skills students may succeed in making connections among multiple visual representations spontaneously, while they work on conventional activities that do not explicitly ask them to make connections. By contrast, low-spatial-skills students may only succeed in making connections if they receive the support provided by understanding-activities and perception-activities. Second, it is possible that high-spatial-skills students benefit more from understanding-activities and perception-activities than low-spatial-skills students. High-spatial-skills students may not spontaneously make connections when working with conventional activities unless explicitly asked to do so (i.e., in understanding-activities and perception-activities). These students may benefit from connection-making because they have the cognitive resources to successfully make correct connections. By contrast, low-spatial-skills students may not have the cognitive resources to engage in successful connection-making. If they fail to make correct connections even when supported in doing so, instructional time may be better spent on conventional activities in which students learn about one visual representation at a time.

Thus, it is conceivable that spatial skills moderate students' benefit from understanding-activities and perception-activities, but the direction of a moderation effect is unclear.

Assessments of learning processes

A further limitation of our prior experiments is that they only considered errors during problem solving as a measure of the difficulty of students' sense-making and inductive processes. Counting the number of errors likely does not capture the quality of these processes. Prior research suggests that measures of visual attention and verbal reasoning may yield additional insights into the processes of how students learn to make connections.

Eye-tracking to assess visual attention processes during connection-making

Eye-tracking research draws on the eye-mind assumption, which posits that the duration of eye-gaze fixations reflects the duration of cognitive processes that a student executes on the information he/she is looking at (Underwood & Everatt, 1992). Therefore, eye-tracking research assumes that eye-gaze fixations indicate whether students process the information they are looking at. Of particular interest for connection-making is switching between representations. In their seminal study, Hegarty and Just (1993) found that students who switched more frequently between representations during a learning phase showed higher learning gains on a posttest. Drawing on information processing theory (Kintsch & Van Dijk, 1978), Hegarty and Just argued that information from both representations needs to be activated in working memory for connection-making to occur. When students switch between representations, they load information from both representations into working memory, allowing them to make connections. Switching between representations has been used as an indicator of students' engagement in connection-making processes as they learn with multiple representations (Johnson & Mayer, 2012; Rau et al., 2015; Stalbovs, Scheiter, & Gerjets, 2015).

Cued retrospective reports to assess verbal reasoning about connections

Prior research has used verbal protocols to assess connection-making processes. Asking students to verbally report how they make connections can provide insights into particular aspects of the mappings students learn about. For example, students who are successful in making connections have been shown to use representations to reflect on conceptual aspects of the to-be-learned content (Plötzner, Bodemer, & Neudert, 2008) and to discuss conceptually relevant visual features of the representations (Jarodzaka, Scheiter, Gerjets, & van Gog, 2010). Research also shows that verbal protocols are a useful method to investigate whether instructional activities designed to support connection-making increases students' ability to focus on conceptually relevant similarities and differences between representations, rather than on surface connections (Ainsworth & Loizou, 2003; Rau et al., 2017a).

Few studies have used eye-tracking methods in conjunction with verbal protocols. Stieff, Hegarty, and Deslongchamps (2011) collected verbal protocols from students while tracking their eye-gaze behaviors as they worked on multirepresentational instructional materials. They found that eye-tracking provided insights into whether, and with what intensity, students engaged in connection-making processes, whereas verbal protocols provided insights into why students made these connections. Switching between representations correlated with the quality of students' conceptual reasoning about representations.

There is, however, a concern that collecting verbal protocols concurrently with eye-tracking may interfere with eye-tracking (Van Gog, Paas, Van Merriënboer, & Witte, 2005). First, verbal protocols can slow down the problem-solving process (Ericsson & Simon, 1987), which may interfere with the eye-mind assumption that the duration of eye-gaze fixations reflects the duration of cognitive processes. Second, head movements that result from talking during verbal protocols can impede the accuracy of the eye-tracking data for some eye trackers (Holmqvist et al., 2011). Van Gog et al. (2005) described an alternative methodology of *cued retrospective reports*. In a series of studies, they recorded students' eye-gaze and then replayed the eye-gaze recordings to students, asking them to verbally report on their problem-solving strategies, thus using eye-gaze recordings as cues for retrospective verbal reports. In the same study, the authors validated this method by formally comparing cued retrospective reports and concurrent eye-tracking and verbal reports. In our prior research, we have used cued retrospective reports to assess whether students rely on surface features to make connections, or on conceptually relevant visual features, and whether they can use these connections to draw inferences about the to-be-learned content (Rau et al., 2015).

Goals of the present experiment

The goal of this article is to investigate how best to support students' acquisition of visual skills related to connection-making while they learn content knowledge from visual representations. In doing so, we address several limitations of our prior research by investigating whether prior visual skills and spatial skills moderate students' learning and by using more sophisticated measures to assess the quality of learning processes. Further, we test whether findings from our prior research on fractions learning generalize to a different domain in which visual representations serve a similar instructional role (namely, to show complementary conceptual aspects of the content): chemistry (Gilbert, 2005; Kozma & Russell, 2005).

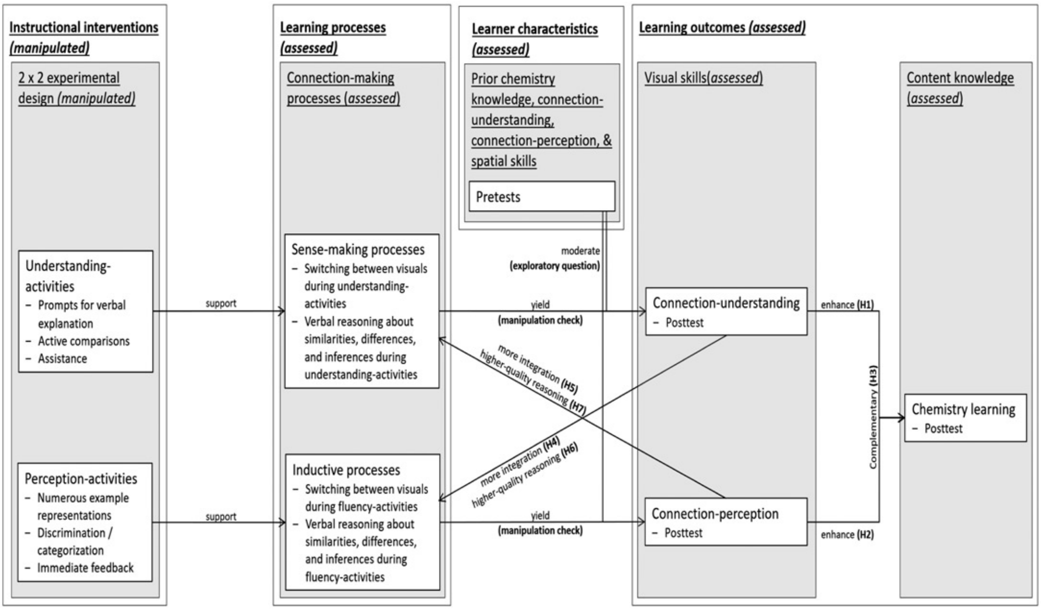
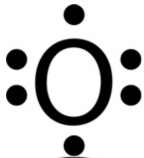
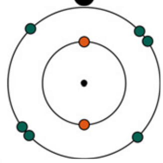
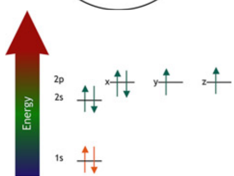
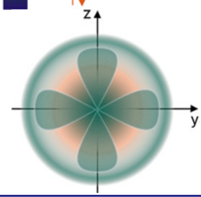


Figure 3. Methodological model of manipulation checks, hypothesis tests (H1-H7), and exploratory questions.

Figure 3 shows how our methodological approach aligns with the hypothesized mechanisms we described here. Students in all conditions worked on conventional activities that did not explicitly require students to make connections among multiple visual representations. The experimental manipulation determined whether—in addition to conventional activities—students also received instructional activities that involved explicit connection-making; specifically, we used a 2 (understanding-activities: yes/no) × 2 (perception-activities: yes/no) design. To mimic the constraints of regular educational settings, we held time on task constant across conditions. To this end, the intervention conditions received fewer conventional activities than a control condition without connection-making activities. We used pretests and post-tests to assess learning of chemistry knowledge, connection-understanding, and connection-perception, as well as students' prior spatial skills. Further, we used eye-tracking measures of how frequently students switch between visual representations to assess their integration of information across representations and cued retrospective reports to assess the quality of their verbal reasoning about connections.

We hypothesized that understanding-activities enhance students' learning of content knowledge (hypothesis 1), that perception-activities enhance students' learning of content knowledge (hypothesis 2), and that students who receive both show the highest learning gains on a content knowledge test (hypothesis 3). With respect to eye-tracking measures, we hypothesized that connection-understanding (i.e., resulting from understanding-activities) yields more integration across representations while students work on perception-activities (hypothesis 4), and that connection-perception (i.e., resulting from perception-activities) yields more integration across representations while students work on understanding-activities (hypothesis 5). With respect to verbal reasoning measures, we hypothesized that connection-understanding yields higher-quality reasoning about connections while students work on perception-activities (hypothesis 6), and that connection-perception yields higher-quality reasoning about connections while students work on understanding-activities (hypothesis 7). Finally, we explored whether the effects of understanding-activities and perception-activities are moderated by prior connection-understanding, prior connection-perception, and spatial skills.

Table 1. Overview of visual representations used in Chem Tutor.

Representation name	Example: Oxygen atom	Conceptual foci
Lewis structure		Explicitly shows atom identity; shows lone and paired valence electrons
Bohr model		Shows atom shells; shows inner electrons; shows lone and paired valence electrons
Energy diagram		Shows atom shells; shows orbitals; shows energy level of electrons; shows spin state of electrons; shows inner electrons; shows lone and paired valence electrons
Orbital diagram		Shows electron density distribution of orbitals; shows spatial arrangement of orbitals

Methods

Participants

One-hundred and seventeen undergraduate students (23 men, 94 women) from a large public university in the mid-western United States participated in the experiment. The experiment was announced in introductory courses and via posters in the chemistry department. Seventy-nine percent of the participants were enrolled in an introductory general chemistry course for non-science majors, 13.4% were enrolled in an introductory general chemistry course for science majors, 2.5% were enrolled in an advanced general chemistry course, and 5% were not currently enrolled in a chemistry course. Participants had to be over 18 years old to participate. Information about age and other personal statistics were not collected due to restrictions by our institution's internal review board.

Instructional materials

We conducted our experiment in the context of an educational technology: Chem Tutor, an intelligent tutoring system for chemistry (Rau, 2017b; Rau et al., 2015). Intelligent tutoring systems are grounded in cognitive theories of learning and artificial intelligence. They pose complex problem-solving activities and provide individualized step-by-step guidance at any point during the problem-solving process (VanLehn, 2011). At the heart of intelligent tutoring systems lies a cognitive model of the students' problem-solving steps. This model can detect multiple strategies a student might use to solve a problem and provide detailed feedback and hints on how to solve the next step (Corbett, Koedinger, & Hadley, 2001). Chem Tutor has several units that cover different chemistry topics. For this experiment, students worked with the unit covering atomic structure. This unit uses the visual representations shown in Figure 1, which are commonly used in instructional materials on this topic. Table 1 shows examples for each visual representation

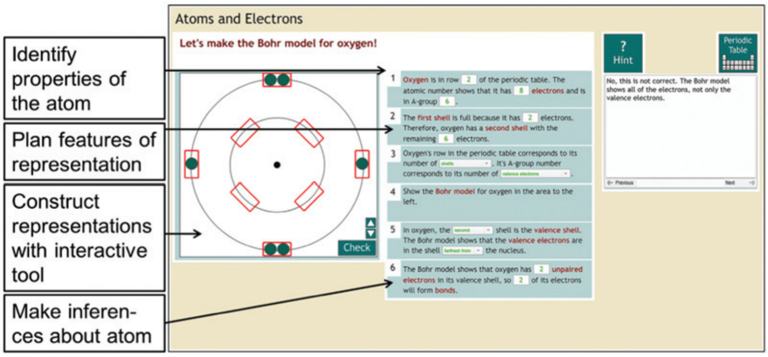


Figure 4. Sample conventional activity.

and describes the conceptual aspects of atomic structure that each of them emphasizes. Chem Tutor features three types of activities, described in the following. All activities include functionalities that are common to intelligent tutoring systems: hints for the current problem-solving step and error-specific feedback. The design of these activities followed a learner-centered approach. Specifically, this design approach involved surveys of undergraduate chemistry students, interviews and eye-tracking studies with undergraduate and graduate students, and extensive pilot testing to ensure the activities align with student thinking and instructional practices in undergraduate chemistry (Rau, 2017b; Rau et al., 2015).

Conventional activities without connection-making support

The learner-centered design approach for Chem Tutor involved a review of textbooks commonly used in undergraduate chemistry courses (Rau, 2017b). This review revealed that students typically use one visual representation at a time to solve chemistry problems. Hence, Chem Tutor's conventional activities introduce students to one visual representation at a time and provide no opportunities for connection-making among different visual representations. They sequence different visual representations across consecutive activities as detailed in the following. This sequence was shown to be effective in our prior research on intelligent tutoring systems with multiple visual representations (Rau, Aleven, & Rummel, 2013). Figure 4 shows an example conventional activity in which students construct a Bohr model of oxygen. Students are guided through this activity by first being prompted to identify properties of the atom. Second, they are asked to plan how to construct the visual representation. Third, they use an interactive tool to construct the visual representation. Students must construct a correct representation before they can move on. Finally, students are prompted to draw inferences about the atom based on the representation. Thus, conventional activities allow students to interact with one visual representation at a time, but provide no support for connection-understanding or connection-perception.

Understanding-activities that support sense-making processes involved in connection-making among visual representations

Understanding-activities were designed to enhance learning of chemistry knowledge while supporting students' engagement in sense-making processes involved in connection-making. We designed the understanding-activities based on the instructional design principles previouslyh reviewed. Students are asked to actively compare visual representations. To support students in verbally explaining these comparisons, Chem Tutor provides self-explanation prompts that ask students to reflect on similarities and differences between the representations. Chem Tutor

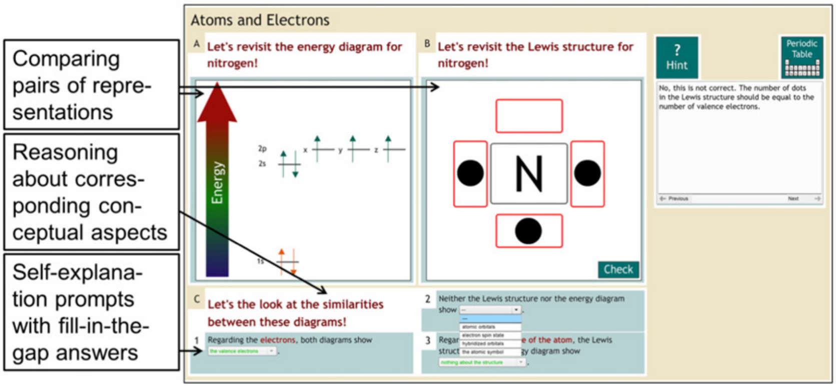


Figure 5. Sample understanding-activity.

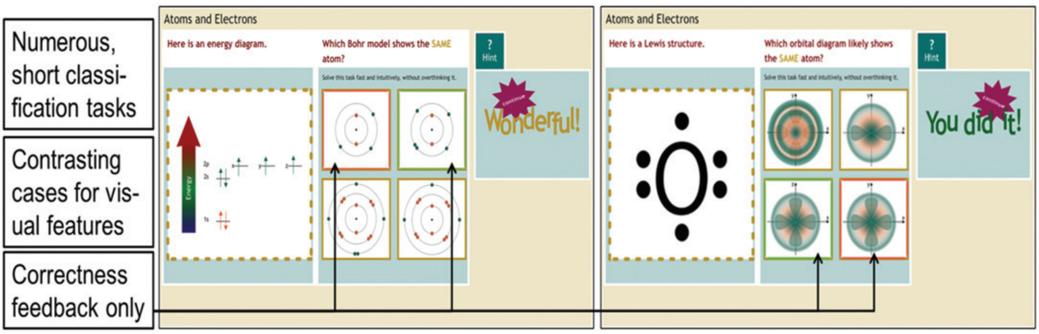


Figure 6. Sample perception-activities.

implements self-explanation prompts through menu-based selection. Menu-based prompts have been shown to support self-explanation in several empirical studies with intelligent tutoring systems and have been shown to be more effective than open-ended prompts in educational technologies (Rittle-Johnson, Loehr, & Durkin, 2017). Students receive assistance for their self-explanations through hints on demand and through error-specific feedback if they make mistakes. The hints explain how the visual representations show the concepts targeted in the self-explanation prompts. Feedback messages provide conceptual explanations that are specific to a misconception that may have led the student to make the given mistake.

Figure 5 shows an example understanding-activity in which students reflect on similarities between an energy diagram and Lewis structure for nitrogen. Given the energy diagram, students construct the Lewis structure of the same atom. Then, students receive self-explanation prompts to compare representations. This example focuses on similarities (conceptual aspects depicted in both representations). Other understanding-activities focus on differences between representations. Chem Tutor alternates between understanding-activities that focus on similarities and differences.

Perception-activities that support inductive processes involved in connection-making among visual representations

Perception-activities were designed based on the design principles reviewed previously: Students encounter many varied example representations in short classification problems and receive immediate correctness feedback on these problems. The visual representations in perception-activities expose students to varying irrelevant visual features and to recurring conceptually relevant features.

Figure 6 shows an example perception-activity in which students identify one of four Bohr models that shows the same atom as a given energy diagram. To encourage students to rely on nonverbal, inductive strategies while solving these problems, Chem Tutor shows a prompt before each activity asking students to "solve this problem fast, without overthinking it." Students have to click "okay" in response to this prompt before they see the perception-activity. Hints provide no information about how to make the connections but encourage students to rely on their intuition.

Experimental design

We used a 2 (understanding-activities: yes vs. no) $\times$ 2 (perception-activities: yes vs. no) design that yields four conditions that correspond to different versions of Chem Tutor: (a) the *control condition* worked on conventional activities only, (b) the *understanding condition* received conventional activities and understanding-activities, (c) the *perception condition* received conventional activities and perception-activities, and (d) the *combined condition* received conventional activities, understanding-activities, and perception-activities. Students were randomly assigned to conditions.

The instructional activities were sequenced as follows. The curriculum was broken up into six topics that corresponded to representation pairs (Bohr-Lewis; Lewis-energy; Bohr-orbital; Lewis-orbital; energy-orbital; Bohr-energy). For each topic, instructional activities were provided in the following order: first, students worked on conventional activities. Next (if they were in the understanding or combined condition), they worked on understanding-activities. Then (if they were in the perception or the combined condition), they worked on perception-activities. The rationale for this sequence is the following. First, conventional activities were provided first because they introduce students to each visual representation, one at a time, without supporting connection-making. Having at least a preliminary familiarity with each visual representation is considered a prerequisite for the ability to make connections (Ainsworth, 2006, 2014). Second, understanding-activities were presented before perception-activities because this sequence was found to be more effective than the reverse sequence in our prior research on fractions learning (Rau et al., 2017a). Third, repeating the sequence of conventional, understanding, and perception-activities across topics that correspond to representation pairs allows us to examine effects of perception-activities on students' learning of connections-understanding in the understanding-activities even though perception-activities were provided after understanding-activities for each topic. In particular, this is possible because we chose the sequence of representation pairs so that each consecutive topic contained at least one visual representation students had encountered before. Finally, the sequence of activities ensured that students in all conditions received the same amount of practice with each visual representation.

The number of activities per condition was chosen such that each condition spent the same amount of time on instructional activities. To this end, we equated the number problem-solving steps across all activities because the activity types differ in terms of how many problem-solving steps they involve. For example, each perception-activity had only one problem-solving step, whereas conventional activities had between seven and 13 problem-solving steps. Table 2 provides an overview of the number of activities per activity type by condition. The table illustrates that students in the control condition received more conventional activities than the experimental conditions, and that students in the combined condition received fewer understanding-activities than students in the understanding condition. Table 2 also illustrates that all connection-making conditions (understanding condition, perception condition, combined condition) received the same number of conventional activities. Pilot testing verified that the instructional activities took about the same amount of time for all conditions.

Table 2. Sequence and number of activities per condition and topic. B = Bohr model, L = Lewis structure, E = energy diagram, O = orbital diagram, → indicates direction of translation. Blue-italicized activities were compared in the analyses of how connection-fluency affects students' connection-making processes while they work on understanding-activities. Red-underlined activities were compared in the analyses of how connection-understanding affects students' connection-making processes while they work on perception-activities.

Condition	Topic	Conventional	Understanding	Perception
Control	Bohr-Lewis	4: B, L, B, L		
	Lewis-energy	4: L, E, L, E		
	Bohr-orbital	4: B, O, B, O		
	Lewis-orbital	4: L, O, L, O		
	Energy-orbital	4: E, O, E, O		
	Bohr-energy	4: B, E, B, E		
Understanding	Bohr-Lewis	2: B, L	4: B→L, L→B, B→L, L→B	
	Lewis-energy	2: L, E	4: *L→E, E→L*, L→E, E→L	
	Bohr-orbital	2: B, O	4: *B→O, O→B*, B→O, L→B	
	Lewis-orbital	2: L, O	4: *L→O, O→L*, L→O, O→L	
	Energy-orbital	2: E, O	4: *E→O, O→E*, E→O, O→E	
	Bohr-energy	2: B, E	4: *B→E, E→B*, B→E, E→B	
Perception	Bohr-Lewis	2: B, L		24: **B→L, L→B …**, B→L, L→B …
	Lewis-energy	2: L, E		24: **L→E, E→L …**, L→E, E→L …
	Bohr-orbital	2: B, O		24: **B→O, O→B …**, B→O, L→B …
	Lewis-orbital	2: L, O		24: **L→O, O→L …**, L→O, O→L …
	Energy-orbital	2: E, O		24: **E→O, O→E …**, E→O, O→E …
	Bohr-energy	2: B, E		24: **B→E, E→B …**, B→E, E→B …
Combined	Bohr-Lewis	2: B, L	2: B→L, L→B	12: **B→L, L→B …**
	Lewis-energy	2: L, E	2: ***L→E, E→L***	12: **L→E, E→L …**
	Bohr-orbital	2: B, O	2: ***B→O, O→B***	12: **B→O, O→B …**
	Lewis-orbital	2: L, O	2: ***L→O, O→L***	12: **L→O, O→L …**
	Energy-orbital	2: E, O	2: ***E→O, O→E***	12: **E→O, O→E …**
	Bohr-energy	2: B, E	2: ***B→E, E→B***	12: **B→E, E→B …**

Specifically, the sequence of activities per condition was as follows, as illustrated in Table 2. Students in the *control condition* received four conventional activities for each of the six topics. For example, for the Bohr-Lewis topic, the first activity was a conventional activity with a Bohr model, the second activity was a conventional activity with a Lewis structure, the third activity with a Bohr model, the fourth activity with a Lewis structure. Then, students moved on to the Lewis-energy topic and worked on one conventional activity with a Lewis structure, one with an energy diagram, one with a Lewis structure, one with an energy diagram, and so forth.

Students in the understanding-condition received two conventional activities followed by four understanding-activities for each topic. For example, for the Bohr-Lewis topic, the first activity was a conventional activity with a Bohr model, the second a conventional activity with a Lewis structure. The third activity was an understanding-activity in which students were given a Bohr model and had to construct a Lewis structure and were prompted to self-explain connections between the two visual representations. The fourth activity was an understanding-activity where, given a Lewis structure, students had to construct a Bohr model, and then received self-explanation prompts. The fifth activity was an understanding-activity with a given Bohr model, and the sixth activity was an understanding-activity with a given Lewis structure. Then, students moved on to the Lewis-energy topic and worked on one conventional activity with a Lewis structure, one with an energy diagram, then one understanding-activity with a given Lewis structure, one understanding-activity with a given energy diagram, one understanding-activity with a given Lewis structure, one understanding-activity with a given energy diagram, and so forth.

Students in the *perception-condition* received two conventional activities followed by 24 perception-activities for each topic. For example, for the Bohr-Lewis topic, the first activity was a conventional activity with a Bohr model, the second a conventional activity with a Lewis structure. Then, they received a sequence of 24 perception-activities that randomly varied whether they were given a Bohr model and had to select the corresponding Lewis structure or were given a

Lewis structure and had to select the corresponding Bohr model. Then, students repeated the same sequence of activities in the Lewis-energy topic.

Students in the combined condition received two conventional activities followed by two understanding-activities for each topic. For example, for the Bohr-Lewis topic, the first activity was a conventional activity with a Bohr model, the second a conventional activity with a Lewis structure. The third activity was an understanding-activity in which students were given a Bohr model and had to construct a Lewis structure and were prompted to self-explain connections between the two visual representations. The fourth activity was an understanding-activity where, given a Lewis structure, students had to construct a Bohr model, and then received self-explanation prompts. Then, students received a sequence of 12 perception-activities that randomly varied whether they were given a Bohr model and had to select the corresponding Lewis structure or were given a Lewis structure and had to select the corresponding Bohr model. Then, students repeated the same sequence of activities in the Lewis-energy topic.

Procedure

The experiment was conducted in a research laboratory. Because the instructional activities and tests took about 3 hr altogether, which was deemed too long for a single session, the experiment was conducted in two 1.5-hr sessions. The two sessions were scheduled on separate days no more than 3 days apart. The 3-day time window was chosen so as to accommodate undergraduate student participants' class schedules.

In session 1, students first received a chemistry knowledge pretest, a spatial skills test, and a visual skills pretest that assessed prior connection-understanding and connection-perception. Then, they worked on instructional activities corresponding to their condition, using Chem Tutor on an eye-tracking computer. Students worked through the instructional activities at their own pace. After completing half of the instructional activities, students took intermediate post-tests of chemistry knowledge and visual skills. In session 2, students finished the instructional activities and took final post-tests of chemistry knowledge and visual skills. Finally, we collected cued retrospective reports, detailed in the following.

Measures

Learning outcome measures

Visual skills tests

An understanding-test and a perception-test assessed students' connection-understanding and connection-perception, respectively. Each included four multiple-choice items. The tests were developed and evaluated as part of the learner-centered development approach for Chem Tutor, mentioned previously (Rau, 2017b). Specifically, a confirmatory factor analysis established that the two tests assess different types of connection-making competencies. Both tests have good reliability with Cronbach's $\alpha = .82$ for the understanding-test and $\alpha = .75$ for the perception-test. The visual skills tests were administered three times (pretest, intermediate, posttest). Example items are provided in Figures A.1 and A.2 of the appendix.

Content knowledge tests

A chemistry knowledge test assessed students' content knowledge about atomic structure. This test included nine multiple-choice items that assessed students' reproduction and transfer. Reproduction items used a format similar to the Chem Tutor activities. Transfer items asked students to apply the knowledge covered in Chem Tutor in ways that differed from the Chem Tutor activities (e.g., using novel visual representations not covered in Chem Tutor or without representations). This test was also developed and evaluated using the previous learner-centered development approach (Rau, 2017b). The test has good reliability with Cronbach's $\alpha = .79$. The chemistry knowledge test was administered three times (pretest, intermediate, posttest). Example items are provided in Figure A.3 of the appendix.

Spatial skills tests

We used the Vandenberg and Kuse test for *mental rotation ability* (Peters et al., 1995) to assess spatial skills. This test was evaluated in prior research (Peters et al., 1995). We chose this test because it has been used in prior research on the role of spatial skills for chemistry learning (e.g., Stieff, 2007; Stull, Hegarty, Dixon, & Stieff, 2012). Mental rotation skills are particularly important for connection-making in chemistry, which often involves mentally rotating two-dimensional depictions of three-dimensional objects. Example items are provided in Figure A.4 of the appendix.

Scoring and administration

All tests were delivered on a computer. We computed test scores as a proportion of the maximally achievable score. The visual skills and chemistry knowledge tests were provided three times, using three test forms that were isomorphic: They asked structurally identical questions but used different content (e.g., different atoms). The order in which students received these test forms was counterbalanced. As part of the previously mentioned learner-centered approach, an evaluation ensured that the different test forms were indeed of equivalent difficulty (Rau, 2017b).

Learning process measures

Eye-tracking measures of visual attention

To collect *visual attention measures*, we recorded eye-gaze behaviors with a SensoMotoric Instruments remote eye tracker (SMI RED250). The eye tracker used a 250 Hz sampling rate and a high-speed event detection algorithm with a velocity threshold of 40°/s and minimum fixation duration of 100ms. To generate visual attention measures that assess how students process the visual representations, we created areas of interest that correspond to the visual representations. We computed *switching between representations* as the number of times two consecutive fixations involved different representations per tutor problem. For example, a fixation on a Lewis structure followed by a fixation on a Bohr model counts as one switch between representations.

Cued retrospective reports to assess verbal reasoning

We used the cued retrospective report method as described by Van Gog et al. (2005). Students were told that they would view their own eye-tracking data while being asked to "relive" how they solved the tutor problems and to "think aloud" while doing so. Students first watched a video of someone else's cued retrospective report. Then, they were asked to try the method on a practice problem. Once students were comfortable with the method, they were presented with a random selection of problems from that day's session. Building on prior research (Rau et al., 2015), we coded these reports for explaining differences or similarities between representations and for making conceptual inferences. Table A.1 of the appendix provides definitions and examples for each code. Inter-rater reliability was substantial (Kappa = .867 for differences, Kappa = .915 for similarities, Kappa =.890 for concepts).

Table 3. Means and standard deviations (in parentheses) of time spent on tutor activities (excluding tests) and test scores by condition and test time.

	Control Condition	Understanding Condition	Perception Condition	Combined Condition
Time spent on tutor activities	1 h 38 m 32 s (5 m 24 s)	1 h 38 m 59 s (5 m 21 s)	1 h 51 m 59 s (5 m 23 s)	1 h 50 m 06 s (4 m 55 s)
Spatial skills				
Pretest	.58 (.24)	.53 (.23)	.63 (.18)	.55 (.20)
Chemistry knowledge test				
Pretest	.49 (.20)	.38 (.22)	.47 (.21)	.42 (.20)
Intermediate test	.60 (.23)	.52 (.19)	.55 (.23)	.58 (.19)
Final posttest	.62 (.19)	.55 (.17)	.60 (0.18)	.61 (.20)
Understanding-test				
Pretest	.52 (.23)	.36 (.24)	.38 (.22)	.46 (.26)
Intermediate test	.58 (.25)	.58 (.23)	.56 (.18)	.57 (.22)
Final posttest	.63 (.23)	.60 (.24)	.65 (.20)	.71 (.21)
Perception-test				
Pretest	.36 (.23)	.29 (.18)	.35 (.20)	.35 (.18)
Intermediate test	.43 (.19)	.40 (.25)	.48 (.20)	.47 (.24)
Final posttest	.47 (.22)	.47 (.26)	.52 (.21)	.57 (.17)

Results

Table 3 shows students' scores on the tests by condition and test-time. To report effect sizes, we use partial η^2. According to Cohen (Cohen, 1988), an effect size partial η^2 of .01 corresponds to a small, .06 to a medium, and .14 to a large effect.

Manipulation checks

First, we tested for differences between conditions on prior content knowledge and spatial skills. A MANOVA showed no significant differences between conditions on the chemistry knowledge pretest, $F(3,112) = 1.415$, $p = .242$, or on the spatial skills test, $F(3,112) = 1.289$, $p = .250$. The chemistry knowledge pretest and the spatial skills test correlated significantly with students' scores on the chemistry knowledge intermediate and final posttests ($r = .569$, $p < .001$ for pretest with intermediate posttest, $r = .403$, $p < .001$ for pretest with final posttest, $r = .421$, $p < .001$ for spatial skills with intermediate posttest, $r = .306$, $p < .001$ for spatial skills with final posttest). Therefore, both the chemistry knowledge pretest and spatial skills were included as covariates in the analyses reported in the following.

Second, we tested for differences between conditions on time spent on instructional activities. An ANCOVA controlling for prior content knowledge and spatial skills showed no significant differences between conditions on time-spent ($F < 1$). Time-spent correlated significantly with students' scores on the intermediate chemistry knowledge posttest ($r = -.340$, $p < .001$) and on the final posttest ($r = -.271$, $p < .001$). However, these correlations were not as reliable after controlling for chemistry knowledge pretest scores ($r = -.160$, $p = .087$ for time-spent with intermediate posttest, $r = -.138$, $p = .141$ with final posttest). Therefore, in the analyses reported here, we tested whether time-spent was a significant predictor of students' learning outcomes or not and included time-spent as a covariate only if it was a significant predictor.

Third, we verified that students' chemistry knowledge improved as a result of working with Chem Tutor. A repeated measures ANOVA with chemistry knowledge test scores as the dependent measure and test-time (pretest, intermediate and final posttest) as the repeated, within-subjects factor showed significant learning gains, $F(2,232) = 37.310$, $p < .001$, p. $\eta^2 = .24$.

Fourth, we verified that understanding-activities enhanced connection-understanding. To this end, we used a repeated measures ANCOVA with scores on the understanding post-tests as dependent measures, understanding-condition as between-subjects factor, test-time (intermediate and final posttest) as within-subjects factor, prior chemistry knowledge and scores on the understanding pretest as covariates. One student was excluded from this analysis because she did not finish the final understanding post-test. Time-spent was a significant predictor and was therefore added as a covariate in this ANCOVA model. Results showed a marginal positive main effect of the understanding-condition on the understanding-posttests, $F(2,111) = 3.524$, $p = .063$, p. $\eta^2 = .03$. We also tested whether prior connection-understanding affected students' benefit from understanding-activities. Adding students' scores on the understanding-pretest and an interaction with the understanding-condition to the ANCOVA model showed a marginal interaction, $F(2,109) = 3.292$, $p = .072$, p. $\eta^2 = .03$, such that students with low prior connection-understanding benefited more from understanding-activities than students with high prior connection-understanding.

Finally, we tested whether perception-activities enhanced connection-perception. The same student as in the previous analysis was excluded from this analysis because she did not finish the perception post-test. We used a repeated measures ANCOVA with scores on the perception posttests as dependent measures, perception-condition as between-subjects factor, test-time (intermediate and final posttest) as within-subjects factor, prior chemistry knowledge and scores on the perception pretest as covariates. Time-spent on instructional activities was a significant predictor and was therefore added as a covariate in this ANCOVA model. Results showed a significant positive effect of the perception-condition on the perception post-tests, $F(2,111) = 3.865$, $p = .050$, p. $\eta^2 = .03$. We also tested whether prior connection-perception affected students' benefit from perception-activities. There was no significant interaction between the perception pretest and perception-condition ($F < 1$).

Effects on learning outcome measures

No students were excluded from the analyses of condition effects on learning outcome measures.

To test for effects of condition on students' learning of content knowledge, we used repeated measure ANCOVAs with scores on the chemistry knowledge test as dependent measure, test-time (intermediate and final post-test) as the repeated, within-subjects factor, understanding-condition and perception-condition as between-subjects factors, pretest scores on the chemistry knowledge test and scores on the spatial skills test as covariates. To test whether spatial skills moderate the effects of understanding-condition and perception-condition, we included interactions of understanding-condition and perception-condition with spatial skills in the ANCOVA model. To test whether prior connection-understanding and prior connection-perception affect students' benefit from understanding-activities and perception-activities, we tested for interactions of scores on the understanding-pretest and the perception-pretest with understanding-condition and perception-condition. None of these interactions were significant ($F < 1$), and were, therefore, excluded from the ANCOVA model. Time-spent on instructional activities was not a significant predictor and was, therefore, excluded from the ANCOVA model. Finally, we also tested for additional aptitude treatment interactions of understanding-condition and perception-condition with scores on the chemistry knowledge pretest, but these were not significant ($F < 1$) and were therefore excluded from the ANCOVA model.

With respect to hypothesis 1 (understanding-activities enhance students' learning of content knowledge), we found no significant main effects of the understanding-condition on learning of chemistry knowledge, $F(1,109) = 1.393$, $p = .241$. Results did not show a significant moderating role of spatial skills ($F < 1$).

With respect to hypothesis 2 (perception-activities enhance students' learning of content knowledge), we found a significant positive effect of the perception-condition on learning of chemistry knowledge, $F(1,109) = 6.284$, $p = .014$, p. $\eta^2 = .06$. There was a significant interaction between perception-condition and spatial skills, $F(1,109) = 7.149$, $p = .009$, p. $\eta^2 = .06$, such that students with high spatial skills showed a larger benefit from the perception-condition than students with low spatial skills. Figure 7 illustrates this interaction effect with a post-hoc median split into groups with low versus high spatial skills.

The main-effect of the perception-condition was qualified by a significant interaction between understanding-condition and perception-condition on learning of chemistry knowledge, $F(1,109) = 4.048$, $p = .047$, p. $\eta^2 = .04$. To examine this interaction, we used post-hoc comparisons that tested hypothesis 3 (providing both understanding-activities and perception-activities will yield the highest learning gains). The post-hoc comparisons showed that students in the perception-condition showed significantly lower learning outcomes than students in the control condition, $F(1,109) = 9.344$, $p = .003$, p. $\eta^2 = .08$, indicating that perception-activities reduced students learning if students did not also receive understanding-activities. However, students in the combined condition showed significantly higher learning outcomes on the chemistry knowledge test

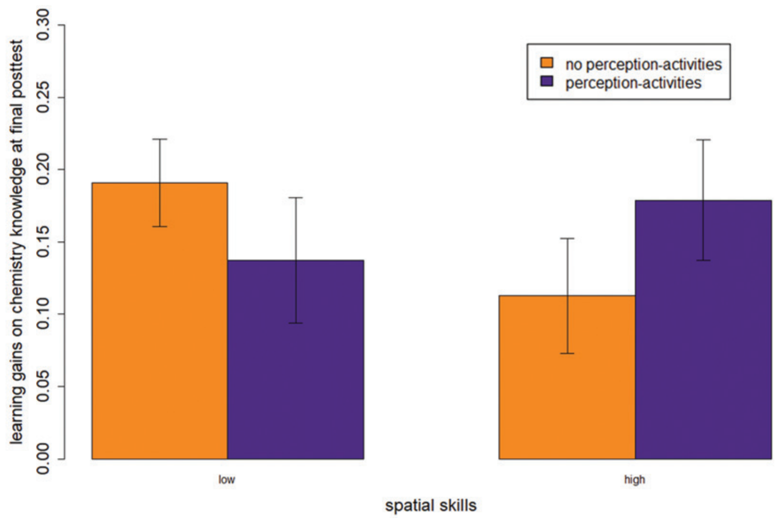


Figure 7. Effects of perception-activities on learning of chemistry knowledge at the final post-test by spatial skills (median split). Bars show estimated marginal means, brackets show standard errors of the mean.

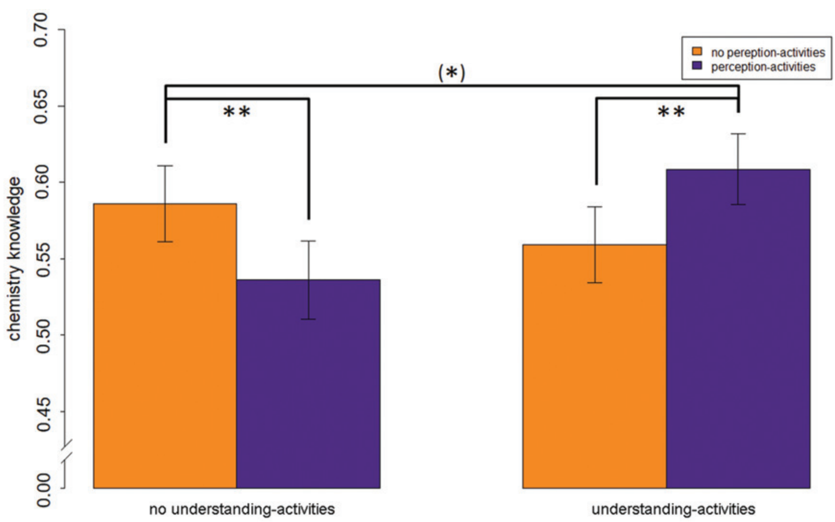


Figure 8. Effects of understanding-condition and perceptual-condition on learning of chemistry knowledge. Bars show estimated marginal means, brackets show standard errors of the mean. (*) indicates marginal difference, * indicates significant difference at $p < .05$, ** indicates significant difference at $p < .01$.

Table 4. Means and standard deviations (in parentheses) of eye-gaze switches between representations per problem-solving activity by condition and activity type.

	Switches per problem-solving sctivity	
Condition	Understanding-activities	Perception-activities
Individual	n/a	n/a
Understanding	0.70 (0.88)	
Perception		4.30 (1.81)
Combined	2.55 (1.89)	5.78 (2.70)

than students in the understanding condition, $F(1,109) = 7.099$, $p = .009$, p. $\eta^2 = .061$, indicating that perception-activities enhanced students' learning if students also received understanding-activities. Finally, a comparison of the combined condition and the control condition showed a marginal advantage for the combined condition, $F(1,56) = 2.689$, $p = .10$, p. $\eta^2 = .05$, which was qualified by a significant interaction with spatial skills, $F(1,56) = 5.338$, $p = .025$, p. $\eta^2 = .087$, such that the combined condition yielded higher learning outcomes for students with high spatial skills, whereas the control condition yielded higher learning outcomes for students with low spatial skills. Figure 8 illustrates these findings.

Effects on learning process measures

Eye-tracking measures of visual attention

Sixteen students were excluded from the analysis of the eye-tracking data due to poor calibration results or low tracking ratio, yielding a total of $N = 101$. The number of excluded students did not differ by condition ($\chi^2 < 1$). Table 4 provides a summary of the visual attention measures.

One goal of the analysis of the eye-tracking data was to test whether connection-understanding (resulting from working on understanding-activities) yields more integration across representations while students work on perception-activities (hypothesis 4). To this end, we compared the perception-condition (which did not receive understanding-activities) to the combined condition (which received understanding-activities) on visual attention measures obtained while students worked on perception-activities (i.e., the red-underlined activities in Table 2). We used an ANOVA with condition as the independent factor and switching between representations on perception-activities as dependent measure. An interaction effect between scores on the understanding-pretest and condition was not significant ($F < 1$) and was, therefore, excluded from the ANOVA model. Results showed that students who received understanding-activities switched more frequently between representations while working on perception-activities, $F(1, 51) = 5.342$, $p = .025$, p. $\eta^2 = .10$. This result suggests that connection-understanding enhances students' ability to integrate information across the visual representations while they work on perception-activities and hence supports hypothesis 4.

A second goal was to test whether connection-perception (resulting from perception-activities) yields more integration across representations while students work on understanding-activities (hypothesis 5). To this end, we compared the understanding-condition (which did not receive perception-activities) to the combined condition (which received perception-activities) on visual attention measures obtained while students worked on understanding activities they received after perception-activities (starting in the second topic on Lewis-energy; i.e., the blue-italicized activities in Table 2). We used an ANOVA with condition as independent factor and switching between representations while working on understanding-activities as dependent measure. An interaction effect between scores on the perception-pretest and condition was not significant, $F(1, 51) = 1.083$, $p = .303$, and was therefore excluded from the ANOVA model. Results showed that students who received perception-activities switched more frequently between representations while working on understanding-activities, $F(1, 53) = 20.182$, $p < .001$, p. $\eta^2 = .28$. This result

Table 5. Means and standard deviations (in parentheses) of verbal report codes per problem-solving activity by condition and activity type.

Condition	Understanding activities	Perception activities
Control condition	n/a	n/a
Understanding-condition		
Similarities	1.15 (0.83)	
Differences	2.44 (1.27)	
Conceptual inferences	3.78 (1.27)	
Perception-condition		
Similarities		0.75 (0.61)
Differences		0.74 (0.51)
Conceptual inferences		1.51 (0.75)
Combined condition		
Similarities	1.74 (1.21)	0.43 (0.68)
Differences	2.67 (0.98)	1.17 (0.74)
Conceptual Inferences	4.49 (1.01)	1.77 (0.80)

suggests that connection-perception enhances students' ability to integrate information across the visual representations while they work on understanding-activities and hence supports hypothesis 5.

Cued retrospective reports to assess verbal reasoning

Cued retrospective reports could not be collected for the students that had been excluded from the analysis of eye-tracking data due to poor eye-tracking data quality. For two additional students, we failed to complete collection of cued retrospective reports due to time constraints in session 2. Altogether, we have complete cued retrospective reports from $N = 99$ students. Table 5 summarizes the verbal reasoning measures.

To test whether connection-understanding (resulting from working on understanding-activities) yields higher-quality reasoning about connections while students work on perception-activities (hypothesis 6), we compared the perception-condition to the combined condition on verbal reasoning measures obtained while students worked on perception-activities (i.e., the red-underlined activities in Table 2). We used a MANOVA with condition as independent factor and student utterance codes described previously (similarities, differences, and conceptual inferences; also see Table A.1 in the appendix) as dependent measures. Interaction effects between scores on the understanding-pretest and the perception-condition were not significant for any of the dependent measures (Fs < 1) and were, therefore, excluded from the MANOVA model. Results showed no significant effect of condition on conceptual inferences, $F(1,\ 48) = 1.514$, $p = .225$. Counter to hypothesis 6, students who received understanding-activities mentioned marginally fewer similarities, $F(1,\ 48) = 3.105$, $p = .084$, p. $\eta^2 = .06$. In support of hypothesis 6, students who received understanding-activities mentioned significantly more differences than students who did not receive understanding-activities, $F(1,\ 48) = 5.692$, $p = .021$, p. $\eta^2 = .11$.

To test whether connection-perception (resulting from perception-activities) yields higher-quality reasoning about connections while students work on understanding-activities (hypothesis 7), we compared the understanding-condition to the combined condition on the verbal reasoning measures we obtained while students worked on understanding activities (i.e., the blue-italicized activities in Table 2). We used a MANOVA with condition as independent factor and student utterances codes as dependent measures. Interaction effect between scores on the perception-pretest and the understanding-condition were not significant for any of the dependent measures (Fs < 1) and were, therefore, excluded from the MANOVA model. Counter to hypothesis 7, results showed no significant effects on differences ($F < 1$). However, in support of hypothesis 7, students who received perception-activities mentioned marginally more similarities, $F(1,42) = 3.612$, $p = .064$, p. $\eta^2 = .08$, and made significantly more conceptual inferences while working on understanding-activities compared to students who did not receive perception-activities, $F(1,42) = 4.155$, $p = .048$, p. $\eta^2 = .09$.

Discussion

This experiment used the perspective of the representation dilemma to investigate how best to support students' acquisition of visual skills related to connection-making while they learn content knowledge from visual representations. We tested two types of instructional activities designed to help students learn to make connections while they learn content knowledge: (a) understanding-activities to help students engage in explicit, verbally mediated sense-making processes that lead to the acquisition of connection-understanding (i.e., the ability to make sense of connections by mapping corresponding visual features to one another; top half of Figure 2), and (b) perception-activities to help students engage in implicit, nonverbal inductive processes that lead to the acquisition of connection-perception (i.e., the ability to quickly and effortlessly translate between visual representations; bottom half of Figure 2). Both types of connection-making activities were designed based on principles offered by prior research on connection-understanding and connection-perception. By investigating the effects of combining these different types of connection-making activities, our research takes a first step toward integrating two, thus far, separate lines of research on connection-understanding and connection-perception.

One goal of our experiment was to investigate whether instruction should support students' acquisition of both connection-understanding and connection-perception to enhance their learning of content knowledge. Results on the chemistry knowledge posttests revealed a significant interaction effect among understanding-activities and perception-activities, such that perception-activities were only effective if students also received understanding-activities, and understanding-activities were only effective if students also received perception-activities. Counter to hypothesis 1, when not combined with perception-activities, understanding-activities were ineffective (medium effect size). Counter to hypothesis 2, when not combined with understanding-activities, perception-activities were detrimental to students' learning (medium effect size). In support of hypothesis 3, students who received both understanding-activities and perception-activities showed higher learning outcomes than students in the control condition (medium effect size). Hence, the results suggest that only a combination of understanding-activities and perception-activities was effective.

To gain insights into the mechanisms underlying this interaction effect, we analyzed eye-tracking measures of visual attention and cued retrospective reports on verbal reasoning. One hypothesized mechanism was that understanding-activities interact with perception-activities because connection-understanding helps students integrate information across representations (hypothesis 4) and increases the quality of connections that students make based on inductive processes (hypothesis 6). In support of hypothesis 4, the eye-tracking data revealed that students who received understanding-activities switched more frequently between representations while working on perception-activities, compared to students who did not receive understanding-activities. In line with prior research, we view switching between representations as an indication of students' attempts to integrate information across representations (Johnson & Mayer, 2012; Stalbovs et al., 2015). Further, in support of hypothesis 6, results from the cued retrospective reports suggest that students who received understanding-activities noticed more differences between representations when working on perception-activities.

We also investigated a second hypothesized mechanism, namely that perception-activities interact with understanding-activities because connection-perception frees cognitive capacity for sense-making processes, allowing students to better integrate information across representations (hypothesis 5) and engage in higher-quality explanations of connections (hypothesis 7). In support of hypothesis 5, the eye-tracking data revealed that students who received perception-activities switched more frequently between representations when working on understanding-activities, compared to students who did not receive perception-activities. In support of hypothesis 7, results from the verbal reports suggest that students who received perception-activities noticed more similarities between visual representations and related them more frequently to conceptual inferences while working on understanding-activities, compared to students who did not receive perception-activities.

In sum, these analyses provide support for both hypothesized mechanisms. The eye-tracking data suggest that understanding-activities and perception-activities enhance one another by fostering students' ability to visually integrate information across the visual representations. The cued retrospective reports reveal that these visual integration processes yield higher-quality reasoning about connections. Furthermore, the cued retrospective reports suggest qualitative differences between these two mechanisms. First, connection-understanding enhances students' ability to notice differences between visual representations while they work on perception-activities. Noticing differences is particularly important for perception-activities because they require students to discriminate between visual representations. Apparently, students who received understanding-activities before perception-activities are better able to dismiss visual representations that do not show the same atom. For example, consider the cued retrospective report from a student in the combined condition when working on perception-activities in which he had to identify which one of four energy diagrams showed the same atom as a given Bohr model: "Looking at the Bohr Model right off the bat, all of them [electrons] are paired and it [the atom] has 3 shells so looking to the energy diagrams we want to find one with 3 shells and completely filled with arrows that are paired so that would be the upper right one." This student seemed to distinguish which visual features would have to be present in the energy diagram before even finding it among the four answer choices. It is possible that improved ability to discriminate between visual representations allows students to more quickly attend to the visual representations that show the same atom and hence to better integrate complementary conceptual information from these representations. This, in turn, may account for their increased learning of content knowledge from the perception-activities.

Second, connection-perception seems to enhance students' ability to reason about similarities and to make conceptual inferences while they work on understanding-activities. Noticing similarities is particularly important for understanding-activities because they require students to explain how visual features map to one another because they show corresponding concepts. For example, consider the cued retrospective report of a student in the combined condition when working on an understanding-activity that compares the Bohr model and the energy diagram:

> Um, next we're asked to compare these again and so regarding the number of electrons, um, … both of them show the total number of electrons, um, the Bohr model shows them in terms of dots on shells, the energy shows them in terms of arrows, um, trying to determine the identity of the atom; it can be inferred from the number of electrons both from the shell and the total number of arrows.

In this case, explaining mappings between visual features across the two representations that show the total number of electrons allows the student to integrate corresponding information from the visual representations and to infer the atom's identity from the total number of electrons. Hence, this example illustrates that noticing similarities can enhance students' ability to learn content knowledge from understanding-activities.

In sum, the cued retrospective reports suggest that the combination of understanding-activities and perception-activities is effective because they enhance visual integration processes that may behaviorally look identical (i.e., switching between representations) but that are qualitatively different (noticing differences versus noticing similarities and making conceptual inferences). In line with research on expertise that suggests that experts flexibly iterate between implicit perceptual and explicit conceptual processes (Goldstone et al., 1997), we propose that the complementary effects of understanding-activities and perception-activities results from students needing to flexibly move between both processes to most effectively learn new content.

A further goal was to explore whether prior visual skills moderate students' learning from understanding-activities and perception-activities. We did not find interactions of understanding-activities with prior connection-perception or of perception-activities with prior connection-understanding on students' learning of content knowledge. Hence, our results do not provide evidence that students' benefit (in terms of learning of content knowledge) from perception-activities depends on their prior connection-understanding, or that their benefit from understanding-activities is affected by prior connection-perception. This might result from the fact that the students in the present experiment had little exposure to the visual representations prior to the experiment, so that they had very limited prior visual skills. Therefore, future research should investigate whether the results generalize to more experienced student populations.

Finally, a goal of our experiment was to explore whether spatial skills moderate the effects of understanding-activities and perception-activities on students' learning of content knowledge. Our results suggest that spatial skills moderate the effectiveness of perception-activities, but not of understanding-activities. Students with high spatial skills benefited from perception-activities, but students with low spatial skills did not. Recall that we argued that, for students with low spatial skills, the task of spatially aligning visual features during connection-making activities takes up more cognitive resources than for students with high spatial skills. Therefore, the task of connection-making is more likely to result in cognitive overload, which may jeopardize their benefit from connection-making activities. Perception-activities ask students to map visual representations to one another that are not always spatially aligned (see Figure 7). Therefore, connection-making in the perception-activities relies on the student's ability to mentally rotate the visual representations. Apparently, the cognitive load associated with this mental rotation task interfered with low-spatial-skills students' benefit from perception-activities—to the extent that they were better off with conventional activities offered in the control condition, which did not explicitly require them to make connections.

Taken together, our findings expand prior research on connection-making among multiple visual representations. Prior research has thus far only tested whether understanding-activities alone are effective (e.g., Berthold et al., 2008; Bodemer & Faust, 2006; Seufert, 2003; Stern et al., 2003; van der Meij & de Jong, 2011) or whether perception-activities alone are effective (e.g., Kellman et al., 2008; Wise et al., 2000). At first glance, our findings seem to contradict this prior research, but that is not necessarily the case. It is possible that understanding-activities in prior research were effective because students had sufficient prior connection-perception. Further, it is possible that perception-activities in prior research were effective because students had sufficient prior connection-understanding. The fact that our experiment did not reveal significant interactions of understanding-activities and perception-activities with prior connection-perception and connection-understanding does not necessarily contradict this interpretation; our results may be due to students having relatively low prior levels of connection-perception and connection-understanding or being unfamiliar with the visual representations. Given that prior research did not assess students' prior levels of connection-understanding and connection-perception, this interpretation is post-hoc and impossible to verify. Our findings illustrate that there is much to be learned considering not only prior visual skills, but also students' acquisition of visual skills while they learn content knowledge from the visual representations—as advocated by the representation dilemma perspective. Hence, more research is needed to investigate whether the effectiveness of understanding-activities depends on students' connection-perception and whether the effectiveness of perception-activities depends on students' connection-understanding, both as a result of experiences before *and* during the learning phase.

In addition, these findings extend our prior experiments on fractions learning (Rau et al., 2017a, 2017b). First, our findings are in line with the findings from the prior experiment showing that a combination of understanding-activities and perception-activities, but not either type of connection-making activity alone, yielded higher learning outcomes on a fractions knowledge test than a control condition that did not receive connection-making activities (Rau et al., 2017b). Our experiment was conducted in a different STEM domain (chemistry, not math), student population (undergraduate students, not elementary students), and learning context (university, not elementary school) and yielded similar findings. Hence, our findings suggest that there may be a general principle, namely that a combination of instructional activities designed to support connection-understanding and connection-perception enhances students' learning of content knowledge. Further, by combining eye-tracking data and cued retrospective reports, our experiment yields novel insights into the nature of the interaction among understanding-activities and perception-activities. We found that understanding-activities and perception-activities interact by enhancing qualitatively different types of visual integration processes that have complementary benefits for students' learning of content knowledge. Therefore, this experiment expands our understanding of the mechanism underlying the effects of connection-understanding on students' nonverbal inductive processes and the effects of connection-perception on students' verbal sense-making processes. Finally, our results on spatial skills extends prior research on perception-activities (e.g., Kellman et al., 2009; Wise et al., 2000), as well as our prior experiments on fractions learning (Rau et al., 2017a, 2017b) which have not investigated the moderating role of spatial skills on students' benefit from perception-activities.

Limitations and open questions

One methodological limitation of the experiment is that it was conducted in a laboratory setting. This methodological choice allowed us to maximize the internal validity of the experiment, for instance by controlling for time on task, ensuring that participants completed all activities, and allowing us to collect eye-tracking data and cued retrospective reports. Yet, these advantages come at the expense of external validity. In particular, Chem Tutor was designed as a homework system for undergraduate chemistry courses. In future research, we will investigate whether the effects generalize to homework settings.

Another limitation of this experiment is that understanding-activities were provided before perception-activities for each of the six topics. Even though this sequence was found to be more effective than the reverse sequence in our prior research on fractions learning (Rau et al., 2017a), different sequences of understanding-activities and perception-activities have not been compared in chemistry learning. Because the results from this experiment suggest that connection-understanding is a prerequisite for students' benefit from perception-activities, we consider it likely that providing understanding-activities before perception-activities is more effective than the reverse sequence also for chemistry learning. Yet, this assertion remains to be tested empirically.

A further limitation of this experiment results from the fact that it was carried out in the context of a particular educational technology: an intelligent tutoring system that provides interactive representations and step-by-step guidance. Hence, we need to investigate whether other types of understanding-activities and perception-activities yield similar results. Such activities may be provided through different types of educational technologies, as well as nontechnology-based activities. For instance, many educational games foster inductive learning processes. Specifically, in chemistry education, there are several games that ask students to rapidly translate among visual representations—that is, they are designed to enhance connection-perception (e.g., Eastwood, 2013; Moreira, 2013). Based on this experiment, one might hypothesize that these games will be effective only if students also receive instructional activities that target connection-understanding or if students have sufficient prior connection-understanding. Future research should test this hypothesis.

A further, related limitation regards this experiments' focus on cognitive processes. This perspective cannot account for the social and cultural factors that play a role in students' learning with visual representations. Visual representations play an important social role in learning because experts use them to communicate ideas with others in a way that is shaped by the cultural role that the visuals play in the given discipline (Vygotsky, 1978; Wertsch, 1997). Students have to learn how to use visual representations in a way that allows them to participate in the discourse prevalent in the expert community (e.g., Lave & Wenger, 1991; Vygotsky, 1978; Wertsch & Kazak, 2011). Hence, both sense-making processes and inductive processes can be viewed as socially mediated learning processes. Research provides numerous examples of sense-making processes in connection-making being socially mediated; for example, when students collaboratively co-construct meaning of visual representations by explicitly negotiating how they show concepts and how to use them to communicate ideas (e.g., Cobb & McClain, 2006; Greeno & Hall, 1997). Research also provides examples of social mediation of implicit processes in connection-making, for example when students use nonverbal cues such as gaze direction and gesturing to mimic how experts use visual information to solve problems (Cope et al., 2015) and when students imitate experts' use of visual representations, sometimes before they know what the visual representations mean (Airey & Linder, 2009). It would be interesting to investigate how socially mediated sense-making processes and inductive processes interact when students learn content knowledge in contexts that put an emphasis on socially embedded learning. For example, future research could observe students in cognitive apprenticeships or in inquiry-based learning interventions, using discourse data to assess verbal sense-making processes (e.g., negotiating the meaning of visual representations) and gesture data to assess nonverbal inductive processes (e.g., pointing to visual representations). It is possible that instructional activities that put an emphasis on socially embedded learning with visual representations are only effective if they indeed engage students in both sense-making processes and inductive processes.

A related open question regards the role of visual representations in different domains. Although visual representations are prevalent in all STEM domains, they play a different cultural role in discipline discourse that is determined by how the visual representations are used to solve problems in the given discipline (Greeno & Hall, 1997; Reed, 2012). Consider, for example, the two domains in which we have conducted our research. In chemistry, visual representations are a "visual language" in which experts think and communicate (Schönborn & Anderson, 2006, p. 95). In early math learning, visual representations play a prevalent training wheel role to make abstract concepts accessible to students; but math experts tend to rely on symbolic notations more so than on visuals to think and communicate (Rau, 2017a) . Given that the goal of education is to prepare students to participate in discipline discourse, it is very likely that the role that visual representations play in discipline discourse affects the role of visual skills for students' learning of content knowledge. For example, in domains in which multiple visual representations are not as prevalent in discipline discourse, connection-perception may be important at early stages of learning, but not at later stages of learning where students may be expected to move beyond the "training wheels phase" of relying on visual representations. Hence, future research should investigate whether our findings about connection-understanding and connection-perception generalize to other domains in which visual representations play a different cultural role for learning than in elementary-school fractions and undergraduate chemistry.

Further open questions regard the role of spatial skills. First, we note that we focused on a particular type of spatial skills, namely mental rotation ability. Although mental rotation abilities are particularly important for connection-making in chemistry and our choice of test aligns with prior research in this field (e.g., Stieff, 2007; Stull et al., 2012), it is possible that other spatial skills also play an important role. Future research in other domains than chemistry should consider other types of spatial skills that students need to make connections. Second, our findings regarding spatial skills yield pressing open questions. Low-spatial-skills students in our experiment benefited most from the control condition that did not involve any instructional activities that require explicit connection-making. Yet, given the well-documented importance of connection-making for success in chemistry and other STEM domains, it is hardly desirable for low-spatial-skills students to not receive any connection-making activities. Our results merely suggest that the current form of perception-activities—which were developed based on current instructional design principles—are less effective for low-spatial-skills students than conventional activities. Therefore, an important goal for future research is to develop new forms of perception-activities that provide additional support that low-spatial-skills students may need to benefit from connection-making activities. For example, they may benefit from activities in which visual representations are spatially aligned, so that they do not have to mentally rotate the representations to establish connections. Another possibility is to prepare students for perception-activities with a spatial skills training (NRC, 2006; Uttal et al., 2013). Given the results from this experiment, we might expect that redesigned perception-activities that accommodate the needs of low-spatial-skills students would then also allow them to benefit from understanding-activities in their current form, but this assertion remains to be tested empirically. It may be that understanding-activities also need to be redesigned to accommodate the needs of low-spatial-skills students, so as to maximize their effectiveness in enhancing their learning of content knowledge.

A final open question regards the specificity of our findings to visual skills. Many other types of skills beyond visual representations can be distinguished depending on whether they are acquired via explicit sense-making processes or by implicit inductive processes (Koedinger et al., 2012). It is possible that our findings reflect general principles of how explicit and implicit learning processes interact, beyond visual skills. In general, different types of interventions are needed to support students' engagement in sense-making processes versus inductive processes (Koedinger et al., 2012). To date, little research has investigated how these different types of learning processes relate to one another, whether they enhance one another, and how best to combine instructional activities designed to support them.

Conclusions

To conclude, our experiment contributes to research on the representation dilemma by investigating how best to support students' acquisition of visual skills involved in connection-making while they learn content knowledge from the visual representations. To this end, we combined two thus far separate lines of research on connection-making: research that has focused on understanding-activities that support students' engagement in sense-making processes that yield connection-understanding (top half of Figure 2) and research that has focused on perception-activities that support students' engagement in inductive processes that yield connection-perception (bottom half of Figure 2). Both types of activities are designed to support students' learning of visual skills while they learn content knowledge from the visual representations. This experiment makes an important theoretical contribution by establishing that the connection-understanding and connection-perception serve complementary roles for students' learning of content knowledge. Furthermore, the experiment provides novel insights into how these visual skills complement one another: Connection-understanding enhances students' ability to engage in productive inductive learning processes that yield connection-perception, and connection-perception enhances students' ability to engage in productive sense-making processes that yield connection-understanding. The experiment also makes an important practical contribution by suggesting that instructional interventions should indeed combine understanding-activities and perception-activities so as to enhance students' learning of content knowledge. Our results replicate and expand previous experiments that found similar effects in a different domain, with a different population, and in a different learning context. Given that the ability to make connections among representations is critical to students' learning success in many STEM domains, this research has the potential to impact a broad range of educational practices.

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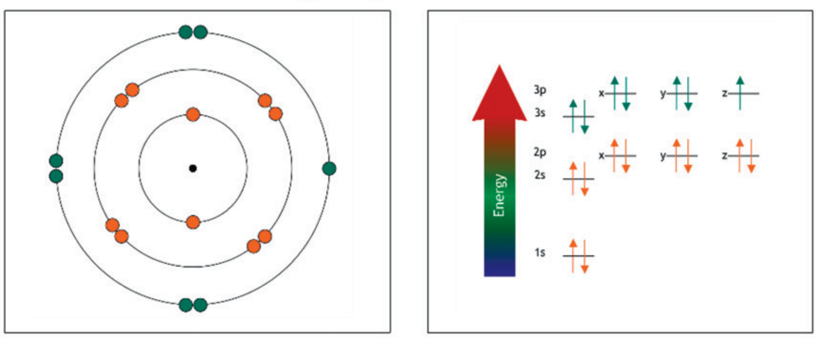
Appendix

Table A.1. Coding scheme for verbal reports.

Code	Definition	Example
Differences	The student correctly refers to structural features of two different representations that depict different concepts or information	"um, it [Bohr model] only shows the shells. It doesn't show the orbitals […]. But in contrast, in the energy diagram, it shows orbitals and shells […]."
Similarities	The student correctly explains a mapping between structural features of two different representations that depict the same concept or information	"both of them [Bohr model, energy diagram] show the total number of electrons. Um, the Bohr model shows them in terms of dots, the energy [diagram] shows them in terms of arrows"
Conceptual inferences	The student correctly describes a concept relating to atomic structure	"they [the electrons] have to be really far away from each other because they repel"

Test

Which of the following statements accurately describe the differences between the Bohr model and the energy diagram of chlorine?

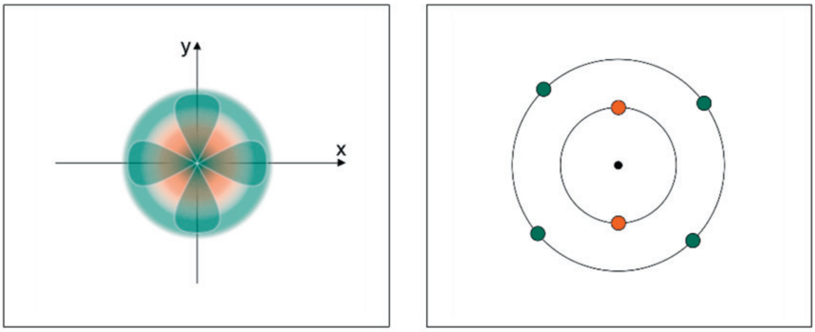


- ☐ The Bohr model shows all of the electrons, but the energy diagram does not
- ☐ The Bohr model shows which orbital the electrons occupy, but the energy diagram shows the shells they occupy
- ☐ The Bohr model shows which shell the electrons occupy, but the energy diagram shows which orbital they occupy
- ☐ The energy diagram shows paired and unpaired electrons, but the Bohr model does not
- ☐ The energy diagram shows the electron spin state, but the Bohr model does not
- ☐ The energy diagram shows that chlorine has one unpaired electron, but the Bohr model does not
- ☐ None of the above

Figure A.1 Example problems of the understanding test.

Test

Which of the following statements accurately describe the similarities between the orbital diagram and the Bohr model of carbon?



- ☐ Both representations show how many electrons carbon has
- ☐ Both representations accurately show where carbon's electrons are located
- ☐ In both representations, the nucleus is located at the center
- ☐ Both representations provide enough information to infer which atom they show
- ☐ Both representations show how the electrons orbit around the nucleus
- ☐ Both representations show that electrons are never located exactly at the nucleus
- ☐ None of the above

Figure A.1. Continued.

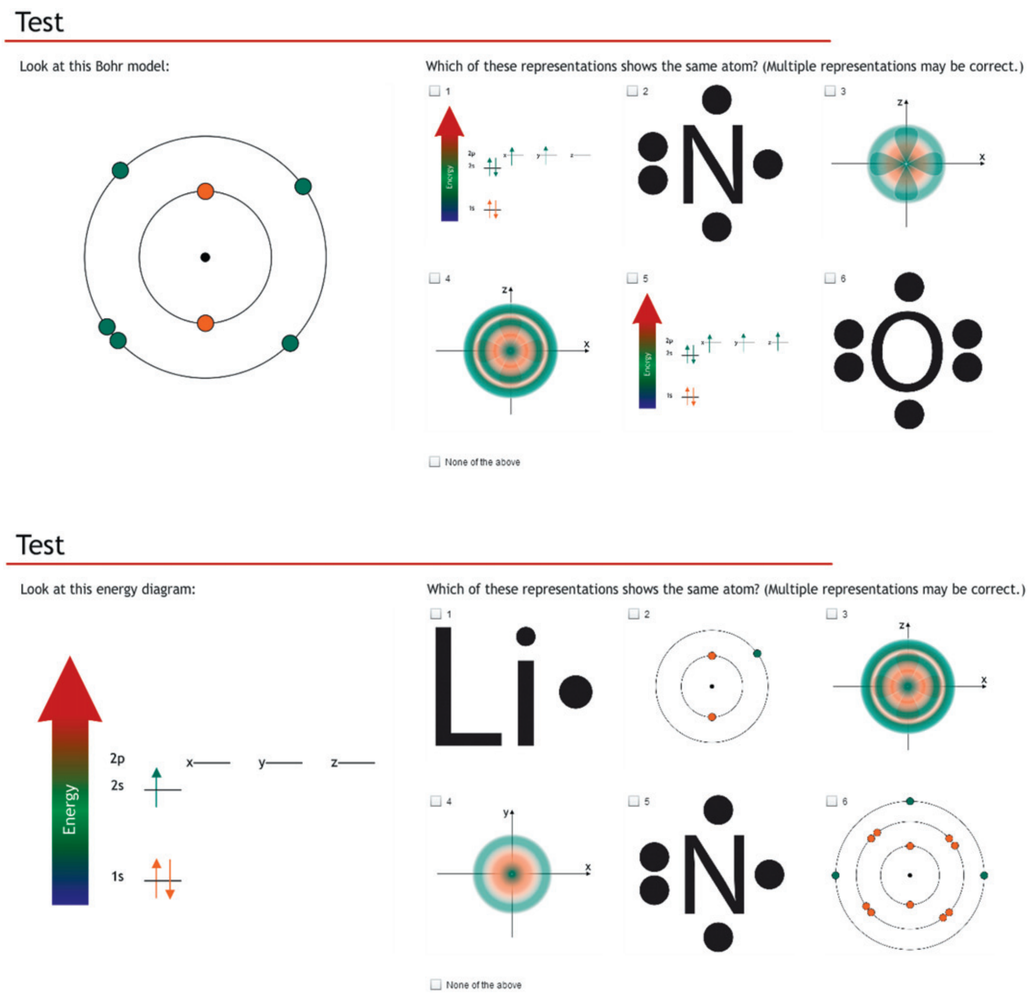


Figure A.2. Example problems of the perception test.

Test

In which pair of elements are the chemical properties of the elements most similar?

- A. Sodium and chlorine
- B. Hydrogen and carbon
- C. Sulfur and oxygen
- D. Nitrogen and carbon
- E. Hydrogen and oxygen

Test

Which of the following is NOT a valid electron arrangement for a neutral atom in its ground state?

	1s	*2s*	*2p*	*3s*
A.	(↑ ↓)	(↑ ↓)	(↑ ↓) (↑ ↓) (↑ ↓)	( )
B.	(↑ ↓)	(↑ ↓)	(↑ ↓) (↑ ↓) (↑ ↓)	(↓)
C.	(↑ ↓)	(↑ ↓)	( ) (↑) (↑)	
D.	(↑ ↓)	(↑ ↓)	(↑ ↓) (↑ ↓) ( )	

- E. More than one are not valid.

Test

Which of the following statements is NOT true?

- A. Electrons only move within certain energy levels, or orbitals.
- B. The exact location of an electron can be determined by orbitals.
- C. The wave functions of electrons form atomic orbitals.
- D. Atomic orbitals form specific shapes around the nucleus.
- E. All of the above are true.

Figure A.3. Example problems of the chemistry knowledge test.

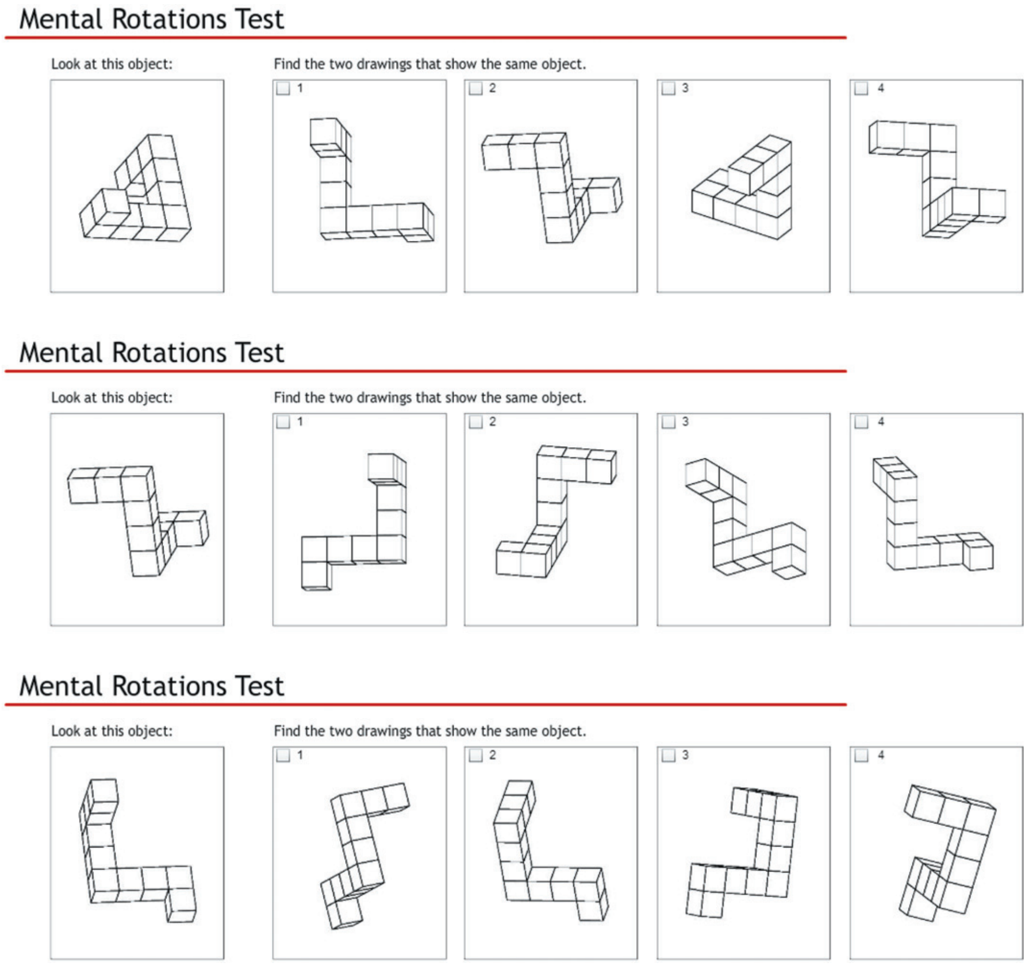


Figure A.4. Example problems of the Vandenberg & Kuse mental rotation test.