A Framework for Educational Technologies that Support Representational Competencies

Martina Angela Rau

Abstract—Visual representations are ubiquitous in STEM disciplines. Yet, students' difficulties in learning with visual representations are well documented. Therefore, to succeed in STEM, students need representational competencies—the ability to use visual representations for problem solving and learning. Educational technologies that support students' acquisition of representational competencies can significantly enhance their success in STEM disciplines. Current design frameworks for educational technologies do not offer sufficient guidance to develop supports for representational competencies. This paper presents a new design framework that describes an iterative, step-by-step approach for the design of educational technologies that support representational competencies (SUREC) in a way that aligns with the demands specific to the target discipline. The paper illustrates how this framework was used to inform the design of an intelligent tutoring system for undergraduate chemistry. An evaluation study suggests that the SUREC framework yielded an effective educational technology that enhances students' learning of content knowledge.

Index Terms—Educational technologies, multiple representations, representational competencies, discipline-based research

✦

1 INTRODUCTION

LEARNING of content knowledge in science, technology, engineering, and mathematics (STEM) disciplines depends on students' ability to think in terms of visual representations [1], [2]. For example, astronomers visualize the solar system, engineers visualize machines, and chemists visualize atoms and electrons. Content knowledge in the STEM disciplines is often inherently visuo-spatial [1], [3], [4]. To make new content accessible to students, instructional materials in STEM tend to rely on visual representations, such as the ones shown in Fig. 1 for atoms in chemistry. Usually, a single visual representation does not suffice to depict the complexity of the content [5], [6], [7], [8]. Hence, instruction typically uses *multiple* visual representations, where different representations emphasize complementary aspects of the to-be-learned content. Indeed, the educational psychology literature provides evidence that multiple representations can lead to higher learning outcomes of content knowledge than a single representation [7], [9].

Yet, prior research documents that learning with multiple visual representations is challenging because students may fail to understand the visual representations or may fail to integrate information from multiple visual representations [10], [11], [12]. This phenomenon is known as the *representation dilemma* [13]: On the one hand, students learn new content *from* visual representations they may not yet understand. On the other hand, students have to learn *about* visual representations that show content they do not yet understand. To resolve the representation dilemma, research within the Learning Sciences field has focused on *representational*

competencies: capabilities that enable students to learn *with* multiple visual representations, including the ability to select and produce appropriate visual representations to solve tasks, to reason about concepts, and to use visual representations to discuss ideas with others [1], [2], [14], [33].

Failure to acquire critical *representational competencies* can severely impede students' learning of content knowledge [8], [15], [16]. Unfortunately, many instructors have an *educational blind spot* about representational competencies [14]: students' lack of representational competencies often goes unnoticed because instructors tend to assume that students can interpret and navigate the multiplicity of visual representations [6], [8], [14], [16].

To address these issues, prior research has investigated how best to help students acquire representational competencies. The main conjecture of this research is that enhancing students' representational competencies enhances their learning of content knowledge [2], [7]. Indeed, a considerable number of empirical studies in the STEM disciplines show that instructional support for representational competencies can improve students' learning of content knowledge e.g., [9], [17], [18].

Educational technologies can be particularly effective in supporting representational competencies. First, they offer effective ways to augment visual representations through means such as color highlighting [19], dynamic linking [20], [21], and animations [22]. Second, educational technologies can provide opportunities for problem solving with interactive visual representations, which has been shown to be effective in STEM disciplines [23], [24]. Third, they can provide adaptive feedback on these interactions, which can be effective in enhancing representational competencies and content knowledge [25], [26]. Finally, educational technologies can model and trace students' representational competencies and adapt instruction accordingly, for instance by selecting problems or visual representations of appropriate difficulty [27], [28].

● *The author is with the Department of Educational Psychology, University of Wisconsin-Madison, Madison, WI 53706. E-mail: marau@wisc.edu.*
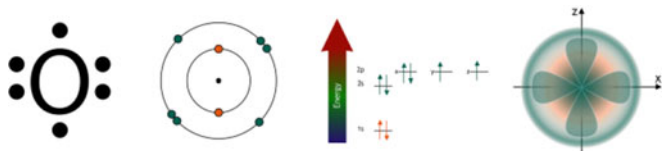
Fig. 1. Multiple visual representations of atoms: Lewis structure, Bohr model, energy diagram, and orbital diagram for oxygen.

Despite these advantages, current design frameworks provide little guidance for the development of educational technologies that support representational competencies. On the one hand, a number of design frameworks focus on the development of educational technologies e.g., [29], [30], [31], [32]. However, they do not take representational competencies into account. As detailed in the following section, the design of support for representational competencies requires a different design methodology than described in existing design frameworks. On the other hand, a few design frameworks focus on support for representational competencies e.g., [7], [33]. However, they tend to describe broad principles for learning with visual representations but fail to provide concrete guidance for iterative design processes that align educational technologies with the specific demands of the target discipline.

Consequently, instructional designers may fail to incorporate support for representational competencies altogether. Even if they do incorporate support for representational competencies, they have to rely on ad-hoc approaches to design such support. Yet, research on the educational blind spot e.g., [15], [16] suggests that instructional designers may overestimate students' representational competencies. Therefore, ad-hoc approaches may yield inadequate or even missing support for students' representational competencies, which may jeopardize students' learning of content knowledge [10], [11].

To address this issue, I describe a new framework that provides principled guidance for the design of educational technologies that provide **su**pport for **re**presentational **c**ompetencies (SUREC). The following section describes existing frameworks that the SUREC framework builds on. Next, I describe how the SUREC framework expands prior frameworks. To this end, I detail design approaches that are specific to representational competencies and illustrate SUREC framework with an educational technology for chemistry, Chem Tutor. I conclude with a discussion of implications for the design of educational technologies with multiple visual representations.

2 EXISTING DESIGN FRAMEWORKS

2.1 Educational Technologies

In general, the goal of educational technology design frameworks is twofold. One goal is to align educational technologies with the educational goals of the target discipline (e.g., learning of content knowledge, achievement on standardized tests). A second goal is to align educational technologies with the given educational context (e.g., classroom, homework). To achieve this alignment, design frameworks typically use iterative, step-by-step approaches. A careful analysis of the educational goals and the context is typically followed by a development phase, which is followed by another analysis phase to test the technology (or a prototype) in the field, which is again followed by a development phase, and so forth. In essence, educational technology design frameworks provide detailed guidance for instructional designers to engage in the steps involved in this iterative design process.

Many frameworks focus on aligning educational technologies with discipline-specific educational goals [19], [29], [30], [31], [32], [34], [35], [36], [37]. These frameworks tend to use a learner-centered approach: they provide guidance for analyzing cognitive requirements of the learning tasks while building on students' prior knowledge. For example, the Analysis Design Development Implementation Evaluation (ADDIE) model [29], [30] describes five iterative steps in which instructional designers analyze an educational issue, design and develop an intervention, which is then implemented and evaluated with formative and summative methods. Another example is the Four-Component Instructional Design (4C/ID) model [35], which describes which instructional methods are best suited for knowledge of different levels of complexity, and how such instructional methods should be sequenced.

Several design frameworks put an additional emphasis on the educational context. These user-centered design approaches focus on enhancing the usability of the technology [31], [32], [38], [39], [40], [41], [42]. They provide guidance for the design of educational technologies that align with the given classroom practices. For example, the ASSURE model [31] includes students and teachers into the design process that involves *analyzing* educational standards and classroom culture, creating lesson plan *state* these goals, *selecting* software that meets these goals, *using* the software while *requiring* student participation, and *evaluating* attainment of goals. Another example is described by [32], who present an approach that helps developers navigate design conflicts that result from the fact that educational technologies have multiple stakeholders with sometimes conflicting needs, such as teachers' needs to organize a classroom and students' needs for entertainment.

An advantage of these frameworks is that they are widely applicable: they are often agnostic to the discipline (e.g., math, chemistry) and to the knowledge type (e.g., procedural, conceptual knowledge). This broad applicability is made possible by learner-centered and user-centered methods that discover potential obstacles to students' learning in a bottom-up (i.e., data-driven) fashion.

However, these bottom-up approaches are suboptimal for discovering challenges that result from lack of representational competencies. As mentioned, the literature on the educational blind spot documents that most people (including instructors, instructional designers, and students) are not aware that representational competencies pose a major obstacle to students' learning [13], [14]. Therefore, bottom-up approaches may fail to reveal that representational competencies pose an issue for students' learning, and may fail to detect students' difficulties in acquiring representational competencies. Hence, a limitation of current educational technology design frameworks is that their methods are suboptimal for educational technologies that support representational competencies.

2.2 Support for Representational Competencies

The goal of design frameworks for the support of representational competencies is to create instructional interventions

that help students acquire representational competencies. Ainsworth's Design, Functions, and Tasks (DeFT) framework [7] describes a number of competencies that students need to acquire to learn with visual representations. DeFT describes principles for the design of instructional support that helps students acquire these competencies. For example, students need to make connections among multiple visual representations. To this end, instruction should help students explain connections between visual features that show corresponding concepts (e.g., the dots in the Lewis structure and the green dots in the Bohr model both show valence electrons).

diSessa's metarepresentation competence (MRC) framework [33] describes discipline-specific considerations for instruction that supports representational competencies. It emphasizes the importance of meta-cognitive knowledge about representations (e.g., which visual representation is appropriate for which type of concept or task). For example, the MRC framework suggests that in addition to helping students understand the strengths and limitations of conventional representations by asking students to critique representations, students should also modify existing representations and invent their own.

A major advantage of these frameworks is that they are applicable to a broad range of disciplines; both the DeFT and the MRC framework describe general representational competencies that play a role in any STEM discipline. However, the broad applicability of these frameworks also yields a major limitation. Even though many representational competencies are important across disciplines [43], they are used in discipline-specific ways because different disciplines use different types of visual representations for different purposes [9], [44]. For example, an important cross-cutting representational competency involves understanding that visual representations are used in science to model real-world phenomena [43], but that they are limited in their capability to capture the complexity of these phenomena. Yet, the visual representations and the real-world phenomena are specific to the given discipline. Hence, instructional support for representational competencies needs to be tailored to the demands of the target discipline. Existing frameworks for representational competencies do not provide guidance for iterative, step-by-step design processes that guide development of supports for representational competencies that tailor to the target discipline.

3   DESIGN FRAMEWORK FOR SUPPORT OF REPRESENTATIONAL COMPETENCIES (SUREC)

This brief review of existing design frameworks shows that there is a gap between (1) frameworks that provide step-by-step guidance for iterative design processes to align educational technologies with discipline-specific demands *without* focusing on representational competencies, and (2) frameworks that focus on representational competencies *without* providing guidance for step-by-step design processes to tailor to discipline-specific demands. The goal of this paper is to close this gap by providing a new design framework for educational technologies that provide **su**pport for **r**epresentational **c**ompetencies. The SUREC framework provides step-by-step guidance for an iterative design process that tailors

support for representational competencies to discipline-specific demands. It builds on the existing design frameworks just reviewed, but differs from them in taking putting a stronger emphasis on top-down (i.e., theory-driven) approaches to identify obstacles related to representational competencies.

To illustrate the SUREC framework, I use the development of Chem Tutor as an example. I chose this example from chemistry for two reasons. First, chemistry is a suitable discipline to illustrate the framework because representational competencies play a major role in chemistry learning. Chemistry instruction uses visual representation to illustrate phenomena that cannot be observed with the regular eye [45], [46]. Because different visual representations provide complementary insights [4], [47], chemistry instruction typically uses multiple visual representations. For example, when learning about atomic structure, students typically encounter the representations in Fig. 1. To integrate the information presented by these representations to learn about atomic structure, students need to understand how each of them depicts concepts and to make connections among them [4], [48]. There is much evidence that students' difficulties in learning chemistry concepts are related to their difficulties in acquiring these representational competencies [24], [49], [50].

A second reason why chemistry is a suitable discipline to illustrate the SUREC framework is that the role of representational competencies for learning of content knowledge in chemistry is similar to other STEM disciplines. As in most STEM disciplines, representational competencies are important because multiple visual representations provide complementary views on important concepts [51], [52]. If students rely on only one visual representation, they may miss important conceptual aspects, which can severely interfere with their learning [47]. Thus, the need for support for representational competencies in chemistry stems from the fact that different representations provide complementary information [4], [53]—just like it does in other STEM disciplines [54], [55], [56]. Therefore, the illustration of the SUREC framework described is likely applicable to other STEM disciplines.

In the following, I describe the SUREC framework in "steps". However, I note that these steps are iterative and non-linear. For example, the insights gained through research in one step may yield new questions about the previous step. As a result, it may be necessary to engage in several iterations across these steps. I will discuss:

Step 1: Identify which visual representations are typically used in the target discipline to depict relevant concepts, using top-down approaches that involve the review of discipline-based research and common educational materials, and/or (semi-) structured interviews or surveys with educators and students.

Step 2: Identify candidate representational competencies, using top-down approaches that involve the review of literatures on theories of learning and discipline-based research.

Step 3: Test whether these representational competencies are indeed distinguishable competencies, and whether they relate to the target content knowledge, combining top-down and bottom-up approaches.

Step 4: Investigate which problem-solving behaviors are associated with these representational competencies (e.g., students' explanations of commonly used visual representations, student-generated representations), combining top-down and bottom-up approaches.

Step 5: Use iterative design and pilot-testing methods to develop the educational technology, combining top-down and bottom-up approaches.

Step 6: Evaluate the effectiveness of components of the educational technology for target learning outcomes, using controlled experiments.

Step 7: Evaluate the effectiveness of the educational technology in the context for which it was designed, using field experiments.

In the following, I detail each step while illustrating how they were carried out in the design of Chem Tutor.

3.1 Step 1: Identify Visual Representations and Relevant Concepts

A first step in developing an educational technology for representational competencies is to investigate which visual representations are used in educational and professional contexts within the target discipline. Because these representations are generally used to illustrate abstract concepts, this investigation will document relevant concepts that the educational technology should target.

Given the educational blind spot on representational competencies [13], [14], I recommend to rely on top-down approaches that are guided by educational practice guides that describe cross-cutting representational competencies [14], [43] and discipline-specific education literature on representational competencies. For many STEM disciplines, research documents which visual representations best communicate which concepts and which representations may help students overcome common misconceptions. The literature review will yield a list of representations that are used for particular concepts. It will describe which representations are used throughout the curriculum, which representations are used for particular concepts, and which representations are most important.

Following the literature review, I suggest reviewing educational materials commonly used in the target context (e.g., textbooks). This review can verify and augment the list of visual representations and concepts. For example, it is possible that some materials use additional visual representations to illustrate particular concepts or that some visual representations are not used at all.

Further, I recommend conducting interviews or surveys with educators and students. Structured or semi-structured interviews can be used to identify educator preferences for particular visual representations. Educators may skip particular visual representations used in textbooks, and they may provide additional visual representations not covered in the textbook. Similarly, students may prefer particular visual representations, or they may search other resources for additional visual representations. Information from interviews and surveys should be used to alter the list of visual representations and concepts. The outcome of Step 1 is an overview of which visual representations are used for which concepts.

3.1.1 Representations and Concepts in Chemistry

To design Chem Tutor, I reviewed chemistry education research as well as high school and undergraduate curricula. Although Chem Tutor targets undergraduates, I included high school curricula because they offer insights into students' prior instructional experiences. Knowing about representations students have encountered in prior instruction is important because these representations can sometimes introduce misconceptions. I then used semi-structured interviews with college educators to address questions that emerged from these reviews.

My review suggests that the visual representations depicted in Fig. 1 are commonly used in instruction on atomic structure. The *Lewis structure* (Fig. 1, left) is the most commonly used visual representation [57], [58]. Lewis structures are ubiquitous in high school and undergraduate curricula [59], [60], [61], [62], [63], [64], [65], [66]. Although Lewis structures are highly abstract, they contain visuo-spatial information that can be used to make predictions about reactive behaviors and substance properties [57]. *Bohr models* (Fig. 1, center-left) are used extensively at the high school level, but not at the undergraduate level [47], [58], [67]. Although they are intuitive, they have been criticized for being simplistic and misleading [47], [67] because they do not accurately reflect the probabilistic nature of electron arrangement.

Two visual representations are commonly used to address misconceptions about the probabilistic nature of electrons being located in orbitals. First, *energy diagrams* (Fig. 1, center-right) are commonly used at both the high school and undergraduate levels. They depict electrons with an up-spin or down-spin as arrows, and they use lines to show orbitals [67]. Energy diagrams are often used to illustrate hybridization [67]. Second, *orbital diagrams* (Fig. 1, right) are used at the undergraduate level, but only infrequently at the high school level. They show electron density functions rather than the electrons themselves [68], [69]. Such statistical models yield a density function that essentially describes the shape of an electron cloud that corresponds to the orbital of an atom.

This review yielded specific questions about the use of Bohr models in undergraduate instruction. To address these questions, I interviewed college educators about their views on Bohr models. All college educators viewed Bohr models as historic rather than scientific models. Some of them were not aware that Bohr models are prevalent in high school curricula. The interviews suggested that college educators seem to expect that high school instruction addresses the shortcomings of Bohr models, although they acknowledged that misconceptions consistent with the Bohr model are prevalent among undergraduate students, which is consistent with the chemistry education literature [47], [67].

3.1.2 Implications for Chem Tutor

Based on the review of chemistry education research and of chemistry curricula, the four visual representations depicted in Fig. 1 were included in the Chem Tutor curriculum. Apart from the Bohr model, none of the visual representations are controversial with respect to their educational merit. The decision to include the Bohr model may be controversial because it has been blamed for misconceptions [47], [67]. Yet, given that students encounter Bohr models in high

school chemistry instruction, it seems important to help them understand the limitations of Bohr models so that they can incorporate more advanced concepts of atomic structure into their mental models [24], [70]. Hence, Chem Tutor includes Bohr models and features activities that highlight the limitations of this particular visual representation through comparisons to other representations (as detailed below).

3.2 Step 2: Identify Representational Competencies

Now that visual representations have been identified based on the fact that they depict domain-relevant concepts, we need to ask what representational competencies students need in order to learn these concepts. Given the educational blind spot on representational competencies, I again recommend to use top-down approaches to address this question.

First, I recommend conducting a thorough literature review on representational competencies in general and of representational competencies in the target discipline. Literatures on domain expertise can further provide useful insights into the function of visual representations in the target discipline. For example, some disciplines view visual representations as "training wheels" that make abstract concepts accessible to learners, but that are no longer used by experts [9]. In other disciplines, visual representations are considered a "visual language" that is essential for expert problem solving and in communication in scientific and professional communities [9].

The literature review will yield a list of representational competencies that are considered (often implicitly) to be important learning goals. For example, in "training wheel" disciplines, the ability to map a visual representation to abstract concepts may be a particularly important representational competency. In a "visual language" discipline, the ability to fluently use a given visual representation to solve a large variety of problems may be an important representational competency.

Second, guided by the review, I recommend conducting a theoretical cognitive task analyses on educational materials [71], [72]. Cognitive task analysis is a method that uses interviews and observations to describe the knowledge and skills experts use to solve tasks. Cognitive task analysis can be used to describe which representational competencies are relevant for particular topics, concepts, and problem-solving tasks. It can also reveal additional competencies that students need to understand a specific concept given a particular visual representation.

The outcome of Step 2 is an overview of representational competencies that students need in order to learn the target concepts.

3.2.1 Representational Competencies in Chemistry

My review of cognitive theories of learning (e.g., [7], [73], [74], [75]), socio-cultural theories of learning (e.g., [76], [77]), research on expertise [78], [79], and the chemistry education literature (e.g., [4], [48]) suggests that two representational competencies play a particularly important role for chemistry learning: conceptual sense making of connections and perceptual fluency in connection making [9], [80].

Conceptual Sense-Making of Connections. Domain experts have the ability to *conceptually make sense* of connections [4],

[7], [9], [53], [55]: they can relate visual features of different representations that show corresponding concepts. Sense-making processes are verbally mediated explanation-based processes by which students reason about principles [73], [81]. When students conceptually make sense of connections, they seek to understand which features of different representations show the same information and how representations differ in what information they show. For example, in Fig. 1, both Lewis structure and Bohr model show the valence electrons as dots, but the Bohr model shows all electrons, whereas the Lewis structure shows only the valence electrons. Conceptual sense making is important because it allows students to integrate information shown by different representations into one mental model about the target concepts (e.g., the concept that valence electrons reside on the atom's outer shell). The importance of conceptual connection-making processes is widely recognized in STEM education [54], [55], [56] and chemistry education [48], [49], [82].

Perceptual Fluency in Connection Making. A second important representational competency is *perceptual fluency* in making connections among visual representations [78], [79], [83]. Experts can quickly and effortlessly map visual features of one representation to another. Perceptual fluency allows students to "just see" whether two visual representations show the same information and to combine information from representations without any perceived mental effort. For example, consider again the Lewis structure and Bohr model of oxygen shown in Fig. 1. A student who is perceptually fluent will quickly see that the number of electrons on the outer shell of the Bohr model equals the number of valence electrons in the Lewis structure. Because the student makes these connections quickly and automatically, without much perceived mental effort, he/she has the cognitive capacity to think about higher-order concepts. For instance, perceptual fluency might free cognitive capacity to think about the fact that oxygen, indicated by the "O" in the Lewis structure, is in the second row of the periodic table, and therefore has two shells, as shown in the Bohr model. The importance of perceptual connection-making processes is widely recognized in STEM education [4], [9], [48], [84] and chemistry education [9], [48], [85], [86].

3.2.2 Implications for Chem Tutor

The literatures just reviewed suggest that both conceptual sense making of connections and perceptual fluency in connection making are particularly important representational competencies in chemistry. Thus, it seems reasonable to propose that Chem Tutor should provide instructional support for students (1) to conceptually make sense of connections among representations that are typically used in chemistry education and in chemistry professional practices, and (2) to become perceptually fluent in making connections. Yet, the goal to develop separate types of instructional support for these two representational competencies relies on the assumption that conceptual sense making and perceptual fluency in connection making are indeed different, distinguishable competencies. I investigated the accuracy of this assumption in Step 3.

3.3 Step 3: Test If Competencies Are Distinct Competencies that Relate to Content Knowledge

After having identified candidate representational competencies, we need to empirically test whether these competencies are distinct from one another, and whether they relate to the target content knowledge. To do so, I recommend developing and evaluating tests that assess the target representational competencies, to evaluate that the tests assess distinguishable competencies, and to test whether they indeed correlate with content knowledge.

To develop the tests, I recommend a combination of top-down and bottom-up approaches. Top-down approaches can draw on the literature on representational competencies in the given discipline and / or cognitive task analyses conducted as part of Step 2. The literature can be used to develop the test items themselves. Bottom-up approaches use empirical data obtained from interviews or think-aloud studies with advanced students and experts [87], [88], [89] to gain detailed insights into the nature of representational competencies and content knowledge. Top-down and bottom-up approaches can be combined by using the literature review to develop interview questions or coding schemes for empirical data.

If the goal of the educational technology is to target multiple representational competencies (e.g., conceptual and perceptual connection making), the next step is to evaluate whether tests can differentiate between these representational competencies. To this end, I recommend conducting a factor analysis on data from students of the target population. Specifically, different factor models should be compared to test whether the different representational competencies load on different (as opposed to the same) factors (hypothesis 1). For example, if the hypothesis is that there are two distinguishable representational competencies, the factor analysis should compare a one-factor model that assumes that the competencies are not distinguishable and a two-factor model that assumes that the two competencies are distinguishable.

Next, the goal is to test whether the representational competencies are associated with content knowledge (hypothesis 2). To this end, I recommend conducting regression analyses that test whether students' performance on the representational competency tests predicts their performance on a content knowledge test. Significant, positive regression weights indicate that students with higher representational competencies have higher content knowledge. This correlation provides (correlational, not causal) evidence for the major assumption underlying the development of an educational technology for representational competencies: that supporting representational competencies can enhance students' learning of content knowledge.

3.3.1 Developing Tests for Chem Tutor

To investigate whether conceptual sense making of connections and perceptual fluency in connection making among multiple visual representations selected for Chem Tutor, I developed tests that assess these competencies. Further, to investigate whether these competencies relate to students' content knowledge, I developed a test to assess knowledge about atomic structure.

Development of the Conceptual Connections Test. The conceptual connections test was designed to assess students' ability to make sense of connections among visual representations of atomic structure. To develop this test, I combined top-down approaches with bottom-up approaches. I used the review of research on representational competencies from Step 2 (i.e., top-down) to develop materials for an interview study (i.e., bottom-up). The interview contained open-ended questions that presented participants with two visual representations at a time. For each representation pair, participants were asked two questions: (1) "What are similarities between [representation 1] and [representation 2] of [atom]?" and (2) "What are differences between [representation 1] and [representation 2] of [atom]?" Participants were five Ph.D. students who had experience as teaching assistants, and 21 undergraduate students with varying levels of exposure to chemistry courses. All responses were transcribed.

To develop a coding scheme for the interview data, I drew on the chemistry education literature and research on connection-making (i.e., top-down). These literatures provided descriptions of concepts related to atomic structure and common student misconceptions, and coding schemes for connection-making [11]. In addition, I reviewed the transcripts obtained from the interview study (i.e., bottom-up), so as to identify concepts they refer to when making connections among representations, as well as misconceptions about atomic structure. This approach yielded a matrix of surface-level connections, conceptual similarities, conceptual differences, inferences, and misconceptions for seven chemistry concepts.

Finally, building on this matrix, I developed a multiple-choice test that assessed students' ability to conceptually make sense of the similarities and differences between visual representations with respect to how they depict chemistry concepts. Specifically, correct choices used language adapted from correct explanations of conceptual similarities, conceptual differences, and inferences obtained from Ph.D. students and undergraduate students. Incorrect choice options were developed based on statements that corresponded to surface-level connections or misconceptions.

Development of the Perceptual Connections Test. The perceptual connections test was designed to assess students' ability to fluently translate among multiple visual representations of atomic structure. To this end, I combined a top-down approach with a bottom-up approach. The top-down approach entailed reviewing Kellman and colleagues' research on perceptual connection making [85]. They provide students with one representation and ask them to select another representation that shows the same information from a number of choice options. The bottom-up approach entailed reviewing chemistry curricula to identify commonly used visual representations and commonly used atoms. Next, I created test items in which students were given one visual representation (e.g., a Bohr model), and a selection of six other visual representations (e.g., Lewis structure, energy diagram, orbital diagram). Their task was to select all other visual representations that show the same atom. So as to not force students to select any visual representations, they had the option to select "none of the above."

Development of the Chemistry Knowledge Test. The chemistry knowledge test was designed to assess students'

conceptual understanding of atomic structure regardless of the representational competency involved. To this end, I combined a top-down and bottom-up approach. The top-down approach entailed reviewing the chemistry education literature on important concepts and common misconceptions related to atomic structure. Further, I reviewed test items in chemistry curricula, as well as assessments used in introductory undergraduate chemistry courses. The bottom-up approach involved incorporating the concepts identified as part of the interviews with Ph.D. students and undergraduates, just described. Based on these approaches, I developed multiple-choice test items and open-ended items designed to assess students' knowledge about atomic structure.

Test Evaluation. Next, the goal was to test whether the conceptual and perceptual connections tests assess distinguishable aspects of students' representational competencies (hypothesis 1), whether performance on the conceptual connections test is positively associated with chemistry knowledge (hypothesis 2a), and whether performance on the perceptual connections test is positively associated with chemistry knowledge (hypothesis 2b). To this end, the tests were administered to $N = 72$ undergraduate students enrolled in an introductory chemistry course.

To test hypothesis 1, I compared two factor models using SPSS AMOS. The two-factor model distinguished between conceptual sense making of connections and perceptual fluency in making connections, whereas the one-factor model did not. Following [90], [91], a model has a good fit if it has an RMSEA of $< .06$, a TLI and CFI of $> .90$, and a Cmin/df of < 2.5. Results show that the two-factor model (RMSEA $=$ .066, TLI $= .94$, CFI $= .96$, Cmin/df $= 1.95$) had a better model fit than the one-factor model (RMSEA $= .107$, TLI $= .84$, CFI $= .88$, Cmin/DF $= 3.46$). Thus, the results are in line with hypothesis 1 and support the notion that conceptual sense making of connections and perceptual fluency in connection making are distinguishable representational competencies.

To test hypotheses 2a and 2b, I conducted a regression analysis with students' performance on the chemistry knowledge test as a dependent measure, and students' performance on the conceptual and the perceptual connections tests as predictors. Results showed that both performance on the conceptual connections test ($\beta = .338$, $p < .01$) and performance on the perceptual connections test ($\beta = .454$, $p < .01$) were significant predictors of students' performance on the chemistry knowledge test, explaining altogether 52.6 percent of the variance of students' performance on the chemistry knowledge test. Thus, the results are in line with hypotheses 2a and 2b and support the assumption that conceptual sense making of connections and perceptual fluency in connection making with the chosen visual representations relate to students' knowledge about atomic structure.

3.3.2   Implications for Chem Tutor

Before we develop instructional support for different representational competencies, we have to verify the assumptions underlying this goal. For Chem Tutor, I first had to establish that conceptual sense making of connections between multiple visual representations of atomic structure and perceptual fluency in making connections are indeed distinguishable representational competencies. Furthermore, I had to verify

the assumption that these representational competencies are related to students' understanding of chemistry concepts related to atomic structure. The results from the test analysis support these assumptions and—consequently—the goal of developing separate learning activities that support students' acquisition of representational competencies related to (1) conceptual sense making of connections and (2) perceptual fluency in making connections.

3.4   Step 4: Investigate Problem-Solving Behaviors Associated with Representational Competencies

Building on the identification of distinguishable representational competencies, we can now design instructional supports that help students acquire these competencies. Effective instructional support should help students use visual representations adequately to solve problems. Ideally, students should learn to use and construct visual representations in the same way as experts in the target discipline. Instructional support will be most effective if it focuses on problem-solving behaviors that students of the target population do not spontaneously engage in; if they did, they would not require instructional support for these behaviors. Furthermore, instructional support should help students overcome particular difficulties they are likely to encounter when solving problems with visual representations. The goal of Step 4 is therefore to identify "desirable" problem-solving behaviors that (1) characterize the representational competencies experts use to solve problems with visual representations but (2) that are uncommon or particularly difficult for students.

To this end, I recommend combining top-down and bottom-up approaches to investigate how experts and students use visual representations to solve problems. Think-aloud studies and interviews with experts and students can serve to identify problem-solving behaviors common among experts and students while they use premade visual representations or create the own representations to solve problems (i.e., bottom-up). These problem-solving behaviors can be mapped to the representational competencies and concepts from Step 2 (i.e., top-down). Identifying problem-solving behaviors that are common among experts but not among students should be supported by the educational technology.

When gathering data, a particular focus should be on identifying how experts and students attend to visual features that are conceptually relevant. Eye-tracking data [92], [93], [94] or a combination of eye-tracking and think-aloud techniques [95], [96] can provide useful information about visual attention behaviors. Visual attention behaviors that are associated with high-quality reasoning behaviors may indicate which visual features the educational technology should draw students' attention to.

In sum, the goal of Step 4 is to identify the "knowledge gap" that the educational technology seeks to close with respect to how students should use visual representations to solve problems in the target discipline.

3.4.1   Problem-Solving Behaviors for Chem Tutor

The design of Chem Tutor drew on a combination of think-alouds, interviews, and eye-tracking methods. I describe

how these methods informed the conceptual sense-making and perceptual fluency-building problems.

Conceptual Sense-Making. One goal the Chem Tutor is to present students with problems that help them engage in conceptual reasoning about why two commonly used visual representations depict the same atom, how the representations differ in what they show about atoms, and how representations show corresponding information about atoms. To inform the design of these problems, I investigated which concepts about atomic structure are particularly difficult for chemistry undergraduate students (research question 1). In addition, I was interested in identifying which reasoning behaviors are common among experts (i.e., Ph.D. students in chemistry) but uncommon in the target population (i.e., among undergraduates; research question 2). Further, I investigated which visual attention behaviors indicate low and high quality reasoning about chemistry concepts (research question 3).

To address these questions, I made use of the interview study described above, in which Ph.D. students ($n = 5$) and undergraduate students ($n = 21$) were asked to describe similarities and differences between visual representations of atoms. As part of this study, students' visual attention behaviors were recorded with an eye-tracker. Students were asked to think about how to respond to the interview question, indicate that they are ready to respond (allowing the experimenter to annotate the eye-tracking data), and then verbally respond to the interview question. This procedure has been evaluated in usability research on educational technologies, and has been shown to maintain the quality of the eye-tracking data while yielding valid insights in cognitive mechanisms of problem solving [97]. To analyze the interview data, I used the matrix coding scheme described above.

To address research question 1 (which concepts about atomic structure are particularly difficult for the target population), and research question 2 (which reasoning behaviors are common among Ph.D. students but not among undergraduates), I compared undergraduates to the Ph.D. students in the following way. I assumed that concepts and reasoning patterns are important if they occur frequently among Ph.D. students. Further, I assumed that, if these concepts and reasoning patterns occur infrequently among undergraduate students, they are difficult. Hence, differences between undergraduate and Ph.D. students yield the "knowledge gap" that Chem Tutor would seek to close. I used chi-square tests to compare the frequency with which undergraduates versus Ph.D. students mentioned the concepts and reasoning behaviors identified above. The analysis identified several reasoning behaviors that were more frequent among Ph.D. students than among undergraduate students.

To explore which visual attention behaviors are associated with high quality reasoning about chemistry concepts (research question 3), I considered visual attention measures that are commonly used in research on learning with visual representations. Specifically, I considered the frequency of switching between visual representations, because switching between conceptually relevant parts of the instructional materials is often used to indicate that students attempt to conceptually integrate these parts [98],

[99]. I computed switches between visual representations as the number of times an eye-gaze fixation on one representation was followed by fixation on another representation. Further, I considered first-fixation durations and second-fixation durations on visual representations. First-fixation durations are often considered to indicate initial processing of material [100], [101], [102], whereas second-fixation durations (i.e., re-inspecting the material after the first fixation) are considered to reflect intentional processing to integrate the information with previously attended information [100], [101], [102]. I computed first-fixation durations as the sum of fixation durations when students first attended to a visual representation. I computed second-fixation durations as the sum of durations of all except the first fixations on the representations.

I then conducted regression analyses that tested whether the visual attention measures are predictive of students' conceptual sense-making and reasoning about chemistry concepts (assessed based on the coding scheme described in section 3.3.1). Results from the regression analyses show that second-inspection durations are predictive of both productive and unproductive verbal reasoning behaviors. On the one hand, students may spend their inspection time to think about surface-level connections that are conceptually irrelevant, which reduces their chances of noticing conceptually relevant differences between visual representations. On the other hand, students may spend their inspection time to think about conceptually relevant differences between visual representations. Making sense of differences between representations leads students to think about inferences they can make about atoms in a way that goes beyond what the representations explicitly show. Frequency of switching between representations was not predictive of students' verbal reasoning about visual representations. Taken together, these findings suggest that it is the content of students' processing rather than what they visually attend to that predicts the quality of their reasoning about visual representations. It seems that reasoning about how given visual representations differ with respect to which information they depict about chemistry concepts is most important for students' ability to make sense of connections.

Perceptual Fluency-Building. Another goal of Chem Tutor is to present students with problems that help them become more efficient in their perceptual processing of visual representations so that they can make connections without having to invest much mental effort. In developing these problems, I drew on the principles established by prior research on perceptual learning, described above. According to Kellman and colleagues' perceptual learning paradigm [75], [103], [104], fluency-building problems help students induce relevant visual features by exposing them to many examples of visual representations. Students are asked to select corresponding representations from choices that present contrasting cases. Contrasting cases vary irrelevant visual features that students are likely distracted by to draw their attention to features that are conceptually relevant for connection making.

To identify which features the perceptual fluency-building problems should include, I conducted an empirical study that investigated which visual features lead students to make incorrect connections. Visual features that mislead students to

make incorrect connections are the visual features that students must learn *not* to attend to. Hence, these visual features should be included in contrasting cases in perceptual fluency-building problems. For the study, prototypes of the perceptual fluency-building problems were created. Each problem presented a visual representation of an atom (e.g., a Lewis structure of oxygen) and four choice options that showed atoms in one other visual representation (e.g., a Bohr model of carbon, a Bohr model of oxygen, a Bohr model of hydrogen, a Bohr model of chlorine). Students had to select which choice shows the same atom. The problems were created for all possible pairings of the four visual representations shown in Fig. 1, for 18 atoms (i.e., atoms in the first three rows of the periodic table). Participants were 65 undergraduates enrolled in a chemistry course.

To test which visual features lead students to make incorrect connections, I defined which visual features each visual representation contains (e.g., the Bohr model of oxygen shows two shells, eight electrons, six valence electrons). Second, I created contingency tables for each pair of two visual representations that mapped those visual features onto one another that denote *incorrect* mappings. For example, an incorrect mapping might be between the valence electrons shown in the Lewis structure and the total electrons shown in the Bohr model.

The contingency tables for incorrect mappings allowed identifying which visual features students lead to incorrect connections. This analysis revealed a number of features that account for students' incorrect choices between pairs of representations. Overall, connections between representations that shared many features were easier than connections between representations that shared few features. Further, for some pairs of representations, the direction of the translation mattered (e.g., given a Bohr model, select a Lewis structure versus given a Lewis structure, select a Bohr model). The analysis revealed why these visual features might be distracting. First, students seem likely to misinterpret particular features. Second, students seem to rely too strongly on some features, failing to take additional features into account. Finally, the analysis revealed particular difficulties students have with particular mappings among visual features.

3.4.2 Implications for Chem Tutor

For Chem Tutor's conceptual sense-making problems, the findings imply that students should be prompted to think about the complementary functions of the different visual representations rather than about conceptually relevant similarities between them. Furthermore, it seems to be important to draw students' attention away from surface-level features that are not conceptually relevant. Instead, students should be prompted to make inferences about those aspects of chemistry concepts that are not directly shown in the visual representations.

For Chem Tutor's perceptual fluency-building problems, the findings yielded a number of visual features to be included in contrasting cases that help them correctly interpret the given visual features and use additional relevant features to disambiguate the meaning of the given visual features. In addition, the findings suggested that certain visual representations are difficult for students, and

therefore students may need to receive conceptual instruction about these visual representations before they work on perceptual fluency-building problems with these visual representations. Finally, the findings on the difficulty of mappings yield insights into how best to sequence the perceptual fluency-building problems.

3.5 Step 5: Iteratively Design and Pilot-Test the Educational Technology

Building on the findings from Step 4 about what constitutes desirable but difficult problem-solving behaviors, we can now develop the educational technology. In doing so, I recommend using a process that frequently iterates between design, pilot-testing, and re-design phases.

Iterative design processes for the development of educational technologies are detailed elsewhere (e.g., [32], [34], [106]), so I will review them only briefly. A first step is to sketch out problem-solving activities on paper. Paper-based problems should be pilot-tested with students of the target population and reviewed by instructors. After incorporating findings from pilot-testing into paper-based problems, they can be tested again. The second step is to build low-fidelity prototypes, which can be pilot-tested with the target population, reviewed by instructors, and redesigned accordingly. Third, high-fidelity prototypes can be developed, pilot-tested, reviewed, and redesigned, until a satisfactory result is reached. Finally, the prototypes should be turned into the final version by removing any remaining glitches and inconsistencies.

3.5.1 Iterative Design Process for Chem Tutor

The goal of the iterative design process for Chem Tutor was to develop an Intelligent Tutoring System (ITS) for undergraduate students that promotes learning of foundational chemistry concepts through problem solving, specifically by helping them acquire the representational competencies identified above. I used Cognitive Tutor Authoring Tools (CTAT; [106]), which facilitates iterating between design, pilot-testing, and redesign. CTAT supports the development of a different type of ITS than the traditional rule-based version, called example-tracing tutors [106]. Example-tracing tutors have the same functionalities as traditional ITSs: they use a cognitive model of students' problem-solving steps to provide individualized step-by-step guidance at any point during the problem-solving process [27], detect multiple strategies a student might use to solve a problem [106], and provide detailed feedback and (on the student's request) hints on how to solve the next step [107]. In contrast to traditional ITSs, example-tracing tutors use a cognitive model that is not based on production rules but instead rely on generalized examples of correct and incorrect problem solutions. Building on problem solutions to develop a cognitive model has several advantages. First, it allows to directly draw on the problem-solving behaviors (successful and unsuccessful ones) discovered in Step 4. Second, it allows for rapid iterations of prototyping and pilot-testing because changes to the cognitive model can be easily and quickly implemented and tested.

In developing Chem Tutor, I followed the iterative design processes for the development of educational technologies just described. I engaged in several rounds of
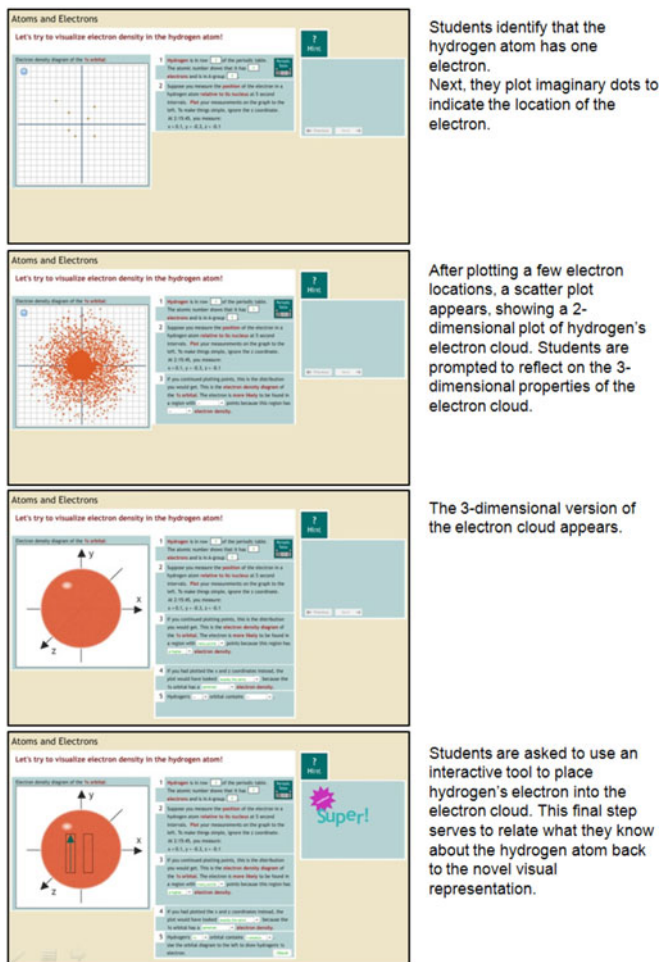
Fig. 2. Introductory problem in which students construct an orbital diagram for hydrogen. Students first plot locations of electrons in a coordinate system. They are prompted to reason about the properties of the electron cloud and about the number of electrons it contains.

sketching out problems on paper, trying them out with undergraduate students, and reviewing them with chemistry instructors. I incorporated changes based on their feedback. Second, I built low-fidelity prototypes using CTAT. The low-fidelity prototypes allowed the user to solve problems, but did not yet include hints or error feedback functionalities. Again, I tested these prototypes with undergraduate students and reviewed them with chemistry instructors and made changes according to their suggestions. Furthermore, I observed errors made by undergraduate students and engaged in in-promptu interviews about what led them to make certain mistakes. This information was used to inform the design of error feedback messages. Third, and building on Step 4, I developed high-fidelity prototypes, which featured all functionalities common to ITSs: detection of multiple solution paths, step-specific hints on demand, and error feedback based on detection of certain misconceptions. Again, the high-fidelity prototypes were tested with undergraduate students and reviewed by chemistry instructors. At this stage, pilot-testing focused on the way in which feedback and hints were provided to students, and on whether Chem Tutor detected common correct and incorrect problem-solving strategies. Based on findings from high-fidelity prototyping, I developed the final version of Chem Tutor.

3.5.2 Final Version of Chem Tutor

The final version of Chem Tutor is available online (https://chem.tutorshop.web.cmu.edu). It provides a number of problem types that use the visual representations identified in Step 1, that target the representational competencies identified in Step 2, and that foster the problem-solving behaviors identified in Step 4.

Introduction to Chem Tutor. Students first receive a brief introduction into the topic of atomic structure, and into the visual representations. Specifically, the introduction explains what information each of the visual representations (see Fig. 1) show about atomic structure. To this end, it emphasizes which visual features show relevant concepts and what inferences they allow about properties of the atom at the macroscopic level.

In light of the findings from Step 4, particular attention was given to explaining how one particular visual representation depicts atoms: orbital diagrams. To this end, the introduction section included an interactive exercise in which students plot imaginary location coordinates of electrons in a hydrogen atom, to illustrate how the orbital shape reflects the probabilistic nature of electron density (i.e., the likelihood of an electron occupying a certain space). The design of this problem was informed by a practice problem that one of the interviewed chemistry instructors uses to introduce orbital diagrams. Fig. 2 shows a sequence of screen shots from this introductory tutor problem, illustrating that students are asked to re late what they know about atoms and electrons to the way in which the orbital diagram depicts the hydrogen atom. Furthermore, this sequence of screen shots illustrates how the student-generated plot of electron locations morphs into the 2-dimensional and then into the 3-dimensional orbital diagram.

Conceptual Sense-Making Problems. Chem Tutor provides problems designed to help students conceptually make sense of how different representations provide corresponding and complementary information about chemistry concepts. Fig. 3 shows an example problem in which students make sense of connections between the Bohr model and the energy diagram for the chlorine atom. Based on principles established by the review of prior research on conceptual sense making of connections carried out as part of Step 2, the problems ask students to explicitly compare visual representations, and prompt students to self-explain connections between the visual representations. First, students are given the visual representation of an atom (here, the Bohr model for chlorine) and are asked to use an interactive tool to construct a different representation of the same atom (the energy diagram). Students receive error feedback while they are constructing the visual representations. The error feedback messages were designed based on the review of common student misconceptions about the given visual representations in Steps 1 and 2, on the observations of problem-solving behaviors in Step 4, as well as on observations from pilot testing in Step 5.

Second, students are prompted to self-explain which concepts are depicted in both representations (e.g., both show the total number of electrons) or on what information is shown in one representation but not in the other (e.g., the energy diagram shows the energy level of electrons

Fig. 3. Example of a conceptual sense-making problem. Students first construct a different visual representation of the same atom, then receive sense-making prompts to reflect on differences and limiations of the two visual representations.

Fig. 4. Example of a perceptual fluency-building probem. Students receive many rapid classification tasks. They are prompted to solve these tasks fast, based on perceptual strategies. The choice options use contrasting cases to emphasize relevant visual features. Students receive immediate feedback.

occupying each orbital, but the Bohr model does not). The self-explanation prompts in these problems use a fill-in-the-gap format with menu-based selection. Menu-based prompts have been shown to support self-explanation in several empirical studies with ITSs [108], [109], [110], and have been shown to be more effective in enhancing learning outcomes than open-ended prompts [17], [111], [112]. The self-explanation prompts were designed in alignment with prior research on learning with multiple representations, and on the observation of problem-solving behaviors in Step 4. Specifically, based on the findings on students' verbal reasoning strategies, the self-explanation prompts were designed so as to draw students' attention to the differences between visual representations. Further, in light of the observation that Bohr models are used in high school but not at the undergraduate level (see Step 1), the self-explanation prompts for this particular problem (i.e., making sense of connections between the Bohr model and the energy diagram) were designed to draw students' attention to

limitations of the Bohr model. Also, the sense-making problems focus on those concepts that Ph.D. students were shown to mention more frequently than undergraduates in (see Step 4). Finally, the wording of the prompts was based on actual student statements obtained in Step 4.

Perceptual Fluency-Building Problems. Chem Tutor provides problems that foster inductive learning processes to help students develop perceptual experience in making connections among multiple visual representations. Fig. 4 shows two example problems in which students are presented with one visual representation and have to select one out of four representations that shows the same atom. These two examples illustrate how Chem Tutor's perceptual fluency-building problems embody principles for perceptual learning, identified as part of the review of prior research in Step 2. First, the perceptual problems are designed to foster non-verbal, inductive learning processes. Each problem involves a one-step discrimination and classification task, and students receive numerous of these

problems in a row. To foster non-verbal rather than verbal strategies, Chem Tutor prompts students to solve these problems fast, without overthinking them. Second, students receive immediate correctness feedback. Third, the perceptual fluency-building problems embody the contrasting cases principle because the four alternative representations emphasize features that students should learn to pay attention to (e.g., an incorrect representation might show the same number of shells as the correct representation but a different number of valence electrons). In choosing the alternative representations, I drew on the results from the observations of problem-solving behaviors in Step 4: the different representations show variations of irrelevant features and contrast visual features that provide relevant information (e.g., geometry, location of the local charges). In summary, the perceptual fluency-building problems are designed to help students become faster and more efficient at extracting relevant information from visual representations based on repeated experience with a large variety of problems.

3.6 Step 6: Evaluate Effectiveness of Components that Support Representational Competencies

The key assumption in designing different types of instructional support for the target representational competencies is that each type of support will enhance students' learning of content knowledge. To empirically evaluate this assumption, I recommend conducting an experiment under controlled conditions to test whether different types of instructional support for the identified representational competencies enhance students' learning of the target domain knowledge. To this end, the experiment should test the hypothesis that adding support for each of the representational competencies enhances the effectiveness of the educational technology. Ideally, students should be randomly assigned to different versions of the educational technology that do or do not contain the components that support students' acquisition of representational competencies. Students' domain knowledge should be assessed before and after the intervention. The hypothesis is supported if students in the experimental condition with instructional support for the representational competencies show higher learning gains than students in the control condition without such support.

3.6.1 Controlled Evaluation of Chem Tutor

For Chem Tutor, the main underlying assumption is that conceptual sense-making problems designed to enhance students' ability to make sense of multiple visual representations of atoms, and perceptual fluency-building problems designed to enhance students' perceptual fluency in making connections will foster students' conceptual understanding of atomic structure. To test this assumption, I conducted a controlled experiment that tested the hypothesis that a version of Chem Tutor that provides conceptual and perceptual problems enhances students' learning of chemistry knowledge more than a version of Chem Tutor without these problems.

One-hundred and seventeen undergraduate students participated in the experiment (for a detailed description, refer to [113]). The experiment used a 2 (conceptual sense-making problems: yes/no) x 2 (perceptual fluency-building problems: yes/no) experimental design to investigate the hypotheses. Students were randomly assigned to one of four conditions, which differed in the components they contained. All students worked through Chem Tutor's introduction. Students in the no-conceptual / no-perceptual condition worked on problems designed to resemble regular textbook exercises. In these problems, they used only one visual representation at a time and did not receive support for connection making. Students in the conceptual / no-perceptual condition worked on regular problems and conceptual connection-making problems. Students in the no-conceptual / perceptual condition worked on regular problems and perceptual connection-making problems. Students in the conceptual / perceptual condition worked on regular problems, conceptual connection-making problems, and perceptual connection-making problems. Students' chemistry knowledge was assessed before and after their work with Chem Tutor.

Results revealed significant learning gains, $F(2, 232) = 37.31$, $p < .01$, p. $\eta^2 = .24$. Results show that the main effect of conceptual sense-making problems was not significant, $F(1, 109) = 1.39$, $p > .10$. There was a positive main effect of perceptual fluency-building problems, $F(1, 109) = 6.28$, $p < .05$, p. $\eta^2 = .06$. The interaction of conceptual and perceptual support was significant, $F(1, 109) = 4.05$, $p < .05$, p. $\eta^2 = .04$, such that perceptual support was effective only if provided in combination with conceptual support: Students who did not receive conceptual sense-making problems had significantly lower learning outcomes if they received perceptual support than without perceptual support, $F(1, 110) = 9.34$, $p < .01$, p. $\eta^2 = .08$. By contrast, students who received conceptual support had significantly higher learning outcomes if they received perceptual support than without perceptual support, $F(1, 110) = 9.34$, $p < .01$, p. $\eta^2 = .08$. Finally, there was a marginally significant advantage of the conceptual / perceptual condition over the no-conceptual/no-perceptual condition, $F(1, 110) = 2.69$, $p = .10$, p. $\eta^2 = .05$.

These results support the hypothesis that conceptual and perceptual problems enhance the effectiveness of Chem Tutor. (A detailed discussion of the interaction effect is provided in [113].)

3.6.2 Implications for Chem Tutor

The experiment tested the overall assumption that providing students with conceptual sense-making problems and with perceptual fluency-building problems would enhance their learning of chemistry. The results are in line with this assumption: combining support for sense-making of connections and for perceptual fluency enhances their learning of chemistry.

3.7 Step 7: Evaluate Effectiveness of Support for Representational Competencies in the Field

A limitation of any controlled experiment is that it likely does not represent the context for which the educational technology was designed. The experiment with Chem Tutor, for example, was conducted in a research lab, even though Chem Tutor was designed for the use in introductory undergraduate courses. Therefore, a final step is to evaluate the educational technology in the field. To this

end, the experiment should test the hypothesis that the educational technology enhances students' learning of the content knowledge in the target educational context. A field evaluation should assess students' domain knowledge before and after they work with the educational technology in the target educational context. If possible, a control condition that corresponds to "business as usual" should not receive the educational technology. Instead, the students in the control condition may work on regular instructional activities. The hypothesis is supported if students in the experimental condition show significant learning gains.

3.7.1   Field Evaluation of Chem Tutor

Even though the controlled experiment just described established the effectiveness of the different modules in Chem Tutor, it remains an open question whether Chem Tutor is effective in the target context. To address this question, I conducted a field study.

The tests were the same as the ones used in the controlled experiment, described in Step 6. Participants were 62 undergraduate students enrolled in a general chemistry for non-science majors. All students worked on introduction, regular problems, conceptual sense-making problems, and perceptual fluency-building problems, which corresponds to the most successful version of Chem Tutor from the experiment in Step 6. Students accessed all materials (i.e., Chem Tutor and the tests) online, with a personal user account that was created for the purpose of the study. Students were invited to participate in the study one month before semester end. Students were free to use the system at any time and to take breaks whenever they wanted to, but they had to finish their work by the end of the semester. Results showed significant learning gains, $F(2, 122) = 10.38$, $p < .01$, p. $\eta^2 = .15$.

3.7.2   Implications for Chem Tutor

The field study suggests that working with Chem Tutor yields significant and large learning gains. These results were obtained in a natural context, in which undergraduate students used Chem Tutor as they normally would use an online educational technology as part of a chemistry course. Thus, the findings suggest that Chem Tutor may add value to common undergraduate chemistry instruction: supporting students' representational competencies can enhance their learning of chemistry knowledge in the educational context the technology was designed for.

4   Conclusion

Visual representations are ubiquitous learning tools across all STEM disciplines [1], [2]. Yet, learning with visual representations is difficult because students often face the *representation dilemma:* they have to learn new content from new visual representations [13]. Their learning of content knowledge therefore depends on their representational competencies; that is, the ability to understand how visual representations depict the to-be-learned content and to use visual representations for problem solving [1], [2], [14]. Much research documents students' difficulties in acquiring representational competencies [6], [7], [8], [10], [11], which impedes their success in STEM disciplines [16], [18], [58],

[74], [84], [114], [115], [116], [117]. Instructors and content developers have an *educational blind spot* about representational competencies and are often not aware of students' difficulties in acquiring representational competencies and tend to assume that students "see" what a visual representation means [6], [7], [8], [15]. Given the critical role of representational competencies, it is important that to design educational technologies that support representational competencies.

Existing design frameworks do not provide adequate guidance for the development of educational technologies that support representational competencies. One the one hand, design frameworks for educational technologies lack a focus on representational competencies. Due to the educational blind spot about representational competencies, the emphasis on bottom-up (i.e., learner-centered, user-centered) methods in educational technology frameworks may be inadequate for the design of support for representational competencies. On the other hand, frameworks for representational competencies do not describe detailed step-by-step processes to align instructional support with specific demands of the target discipline and educational context.

To close this gap, the goal of this paper was to describe a new design framework for educational technologies that provide instructional **su**pport for **re**presentational **c**ompetencies (SUREC). Compared to prior frameworks for educational technologies, the SUREC framework puts a stronger emphasis on top-down approaches, so as to ensure that learning obstacles related to representational competencies receive attention in the design process. Compared to prior frameworks for representational competencies, the SUREC framework provides an iterative step-by-step process that can be used to align the educational technology with specific difficulties students have with representational competencies in the target discipline and with educational goals and educational practices of the target discipline. Therefore, the SUREC framework closes the gap between prior frameworks for educational technologies and prior frameworks for representational competencies. I illustrated the SUREC framework at the example of an ITS for undergraduate chemistry: Chem Tutor. Data from a controlled lab-based evaluation and a field evaluation suggests that the SUREC framework yielded a successful educational technology.

The SUREC framework can be used for other STEM disciplines than chemistry and for additional representational competencies than the ones the present Chem Tutor problems focus on. Because representational competencies are a critical aspect of students' learning of content knowledge across all STEM discipline, the goal of developing educational technologies for representational competencies is relevant across STEM disciplines. The iterative step-by-step approach ensures that the educational technology aligns with the specific demands of the target discipline. This is important because the way in which visual representations are used varies by discipline [6], [8] because the design of the visual representations themselves as well as how they are used within the discipline is shaped by the cultural history of discipline discourse [4], [6], [53], [76]. Even though I illustrated the SUREC framework in chemistry and further illustrations of the success of the SUREC framework in other disciplines are pending, the fact that chemistry is similar to

many other STEM disciplines suggests that the SUREC framework may be widely applicable. In particular, chemistry instruction heavily relies on multiple visual representations because different visual representations provide complementary information about key concepts. This role of visual representations is similar to instruction in other STEM disciplines [1], [2], [14], [15], [114].

In sum, the SUREC framework closes a gap in prior design frameworks by describing an iterative, step-by-step process to ensure that educational technologies help students acquire representational competencies that are specific to the target discipline. Visual representations are pervasive in all STEM disciplines, and students' documented difficulties in learning with visual representations impede their success in STEM. The SUREC framework may have a significant impact on STEM education because (1) educational technologies that enhance students' representational competencies have the potential to enhance students' learning of content knowledge in a variety of STEM domains, and (2) because such technologies can be easily disseminated to large student populations via course managements such as Moodle.

ACKNOWLEDGMENTS

REFERENCES

[1] J. K. Gilbert, "Visualization: An emergent field of practice and inquiry in science education," in *Visualization: Theory and Practice in Science Education*, J. K. Gilbert, M. Reiner, and M. B. Nakhleh, Eds. Berlin, Germany: Springer, 2008, pp. 3–24.

[2] J. K. Gilbert, "Visualization: A metacognitive skill in science and science education," in *Visualization: Theory and Practice in Science Education*, J. K. Gilbert, Ed. Berlin, Germany: Springer, 2005, pp. 9–27.

[3] M. Stieff, "Mental rotation and diagrammatic reasoning in science," *Learn. Instruction*, vol. 17, no. 2, pp. 219–234, 2007.

[4] R. Kozma and J. Russell, "Students becoming chemists: Developing representational competence," in *Visualization in Science Education*, J. Gilbert, Ed. Berlin, Germany: Springer, 2005, pp. 121–145.

[5] G. E. Höst, K. J. Schönborn, and K. E. L. Palmerius, "Students' use of three different visual representations to interpret whether molecules are polar or nonpolar," *J. Chemical Edu.*, vol. 89, no. 12, pp. 1499–1505, 2012.

[6] J. Airey and C. Linder, "A disciplinary discourse perspective on university science learning: Achieving fluency in a critical constellation of modes," *J. Res. Sci. Teaching*, vol. 46, no. 1, pp. 27–49, 2009.

[7] S. Ainsworth, "DeFT: A conceptual framework for considering learning with multiple representations," *Learn. Instruction*, vol. 16, no. 3, pp. 183–198, 2006.

[8] K. J. Schönborn and T. R. Anderson, "The importance of visual literacy in the education of biochemists," *Biochemistry Mol. Biol. Edu.*, vol. 34, no. 2, pp. 94–102, 2006.

[9] M. A. Rau, "Conditions for the effectiveness of multiple visual representations in enhancing STEM learning," *Educational Psychology Rev.*, pp. 1–45, 2016, doi: 10.1007/s10648-016-9365-3.

[10] S. Ainsworth, P. Bibby, and D. Wood, "Examining the effects of different multiple representational systems in learning primary mathematics," *J. Learn. Sci.*, vol. 11, no. 1, pp. 25–61, 2002.

[11] M. A. Rau, N. Rummel, V. Aleven, L. Pacilio, and Z. Tunc-Pekkan, "How to schedule multiple graphical representations? A classroom experiment with an intelligent tutoring system for fractions," in *Proc. 10th Int. Conf. Learn. Sci.*, 2012, pp. 64–71.

[12] D. Bodemer and U. Faust, "External and mental referencing of multiple representations," *Comput. Human Behavior*, vol. 22, no. 1, pp. 27–42, 2006.

[13] A. Dreher and S. Kuntze, "Teachers facing the dilemma of multiple representations being aid and obstacle for learning: Evaluations of tasks and theme-specific noticing," *J. für Mathematik-Didaktik*, vol. 36, no. 1, pp. 23–44, 2014.

[14] National Research Council, *Learning to Think Spatially*. Washington, DC, USA: National Academies Press, 2006.

[15] D. H. Uttal and K. O'Doherty, 'Comprehending and learning from 'visualizations': A developmental perspective," in *Visualization: Theory and Practice in Science Education*, J. Gilbert, Ed. Berlin, Germany: Springer, 2008, pp. 53–72.

[16] A. M. Strickland, A. Kraft, and G. Bhattacharyya, "What happens when representations fail to represent? Graduate students' mental models of organic chemistry diagrams," *Chemistry Edu. Res. Practice*, vol. 11, no. 4, pp. 293–301, 2010.

[17] J. van der Meij and T. de Jong, "The effects of directive self-explanation prompts to support active processing of multiple representations in a simulation-based learning environment," *J. Comput. Assisted Learn.*, vol. 27, no. 5, pp. 411–423, 2011.

[18] J. P. Gutwill, J. R. Frederiksen, and B. Y. White, "Making their own connections: Students' understanding of multiple models in basic electricity," *Cognition Instruction*, vol. 17, no. 3, pp. 249–282, 1999.

[19] R. E. Mayer, "The promise of multimedia learning: Using the same instructional design methods across different media," *Learn. Instruction*, vol. 13, no. 2, pp. 125–139, 2003.

[20] D. Bodemer, R. Ploetzner, I. Feuerlein, and H. Spada, "The active integration of information during learning with dynamic and interactive visualisations," *Learn. Instruction*, vol. 14, no. 3, pp. 325–341, 2004.

[21] T. de Jong and W. R. van Joolingen, "Scientific discovery learning with computer simulations of conceptual domains," *Rev. Educational Res.*, vol. 68, no. 2, pp. 179–201, 1998.

[22] S. Ainsworth, "How do animations influence learning?" in *Current Perspectives on Cognition, Learning, and Instruction: Recent Innovations in Educational Technology that Facilitate Student Learning*, D. H. Robinson and G. Schraw, Eds. Charlotte, NC: Information Age Publishing Inc., 2008, pp. 37–67.

[23] G. M. Bodner and D. S. Domin, "Mental models: The role of representations in problem solving in chemistry," *Univ. Chemistry Edu.*, vol. 4, no. 1, pp. 24–30, 2000.

[24] H. K. Wu and P. Shah, "Exploring visuospatial thinking in chemistry learning," *Sci. Edu.*, vol. 88, no. 3, pp. 465–492, 2004.

[25] K. Reimer and P. S. Moyer, "Third-graders learn about fractions using virtual manipulatives: A classroom study," *J. Comput. Math. Sci. Teaching*, vol. 24, no. 1, pp. 5–25, 2005.

[26] J. Suh and P. S. Moyer, "Developing students' representational fluency using virtual and physical algebra balances," *J. Comput. Math. Sci. Teach.*, vol. 26, no. 2, pp. 155–173, 2007.

[27] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems and other tutoring systems," *Educational Psychologist*, vol. 46, no. 4, pp. 197–221, 2011.

[28] B. Grawemeyer, "Evaluation of ERST–an external representation selection tutor," in *Diagrammatic Representation and Inference*, D. Barker-Plummer, R. Cox, and N. Swoboda, Eds., Berlin, Germany: Springer, 2006, pp. 154–167.

[29] K. L. Gustafson and R. M. Branch, "What is instructional design?" in *Trends and Issues in Instructional Design and Technology*, R. A. Reiser and J. V. Dempsey, Eds. Englewood Cliffs, NJ, USA: Merrill/Prentice Hall, 2002, pp. 16–25.

[30] M. Molenda, J. R. Pershing, and C. M. Reigeluth, "Designing instructional systems," in *The ASTD Training and Development Handbook*, R. L. Craig, Ed., 4th ed. New York, NY, USA: McGraw-Hill, 1996, pp. 266–293.

[31] J. Russel, D. Sorge, and D. Brickner, "Improving technology implementation in grades 5-12 with the ASSURE Model," *THE J.*, vol. 21, no. 9, pp. 66–71, 1994.

[32] M. A. Rau, V. Aleven, N. Rummel, and S. Rohrbach, "Why interactive learning environments can have it all: Resolving design conflicts between conflicting goals," in *Proc. SIGCHI ACM Conf. Human Factors Comput. Syst.*, 2013, pp. 109–118.

[33] A. A. diSessa, "Metarepresentation: Native competence and targets for instruction," *Cognition Instruction*, vol. 22, no. 3, pp. 293–331, 2004.

[34] K. R. Koedinger, "Toward evidence for instructional design principles: Examples from Cognitive Tutor Math 6," in *Proc. Annu. Meet. North Amer. Chapter Int. Group Psychology Math. Edu.*, 2002, http://eric.ed.gov/?id=ED471749

[35] J. J. G. van Merrienboër, R. E. Clark, and M. B. M. de Croock, "Blueprints for complex learning: The 4C/ID-model," *Educational Technol. Res. Develop.*, vol. 50, no. 2, pp. 39–64, 2002.

[36] D. H. Andrews and L. A. Goodson, "A comparative analysis of models of instructional design," *J. Instructional Develop.*, vol. 3, no. 4, pp. 2–16, 1980.

[37] R. A. Reiser, "A history of instructional design and technology," in *Trends and Issues in Instructional Design and Technology*, R. A. Reiser and J. V. Dempsey, Eds. Upper Saddle River, NJ, USA: Prentice Hall College Division, 2001, pp. 53–64.

[38] E. Soloway, et al., "Learning theory in practice: Case studies of learner-centered design," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, 1996, pp. 189–196.

[39] DBRC, "An emerging paradigm for educational inquiry," *Educational Researcher*, vol. 32, no. 1, pp. 5–8, 2003.

[40] S. Jackson, J. S. Krajcik, and E. Soloway, "The design of guided learner-adaptable scaffolding in interactive learning environments," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, 1998, pp. 187–194.

[41] C. Bereiter and M. Scardamalia, "Learning to work creatively with knowledge," in *Powerful Learning Environment*, E. de Corte, Ed. Oxford, U.K.: Elsevier, 2003.

[42] S. Barab and K. Squire, "Design-based research: Putting a stake in the ground," *J. Learn. Sci.*, vol. 13, no. 1, pp. 1–14, 2004.

[43] National Research Council, *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas*. Washington, DC, USA: The National Academies Press, 2012.

[44] B. Eilam and M. Ben-Peretz, *Teaching, Learning, and Visual Literacy: The Dual Role of Visual Representation*. Cambridge, U.K.: Cambridge Univ. Press, 2012.

[45] R. Justi and J. K. Gilbert, "Models and modelling in chemical education," in *Chemical Education: Towards Research-Based Practice*, O. de Jong, R. Justi, D. F. Treagust, and J. H. van Driel, Eds. Norwell, MA, USA: Kluwer Academic Publishers, 2002, pp. 47–68.

[46] B. Davidowitz and G. Chittleborough, "Linking the macroscopic and sub-microscopic levels: Diagrams," in *Multiple Representations in Chemical Education*, J. K. Gilbert and D. F. Treagust, Eds. Berlin, Germany: Springer, 2009, pp. 169–191.

[47] D. L. Gabel and D. M. Bunce, "Research on problem solving: Chemistry," in *Handbook of Research on Science Teaching and Learning*, D. L. Gabel, Ed. New York, NY, USA: MacMillan, 1994, pp. 301–326.

[48] H. K. Wu, J. S. Krajcik, and E. Soloway, "Promoting understanding of chemical representations: Students' use of a visualization tool in the classroom," *J. Res. Sci. Teaching*, vol. 38, no. 7, pp. 821–842, 2001.

[49] Y. J. Dori and M. Barak, "Virtual and physical molecular modeling: Fostering model perception and spatial understanding," *Educational Technol. Soc.*, vol. 4, no. 1, pp. 61–74, 2001.

[50] V. Talanquer, "Chemistry education: Ten facets to shape us," *J. Chemical Edu.*, vol. 90, pp. 832–838, 2013.

[51] R. K. Coll and D. F. Treagust, "Learners' mental models of metallic bonding: A cross-age study," *Sci. Edu.*, vol. 87, no. 5, pp. 685–707, 2003.

[52] L. L. Jones, K. D. Jordan, and N. A. Stillings, "Molecular visualization in chemistry education: The role of multidisciplinary collaboration," *Chemistry Edu. Res. Practice*, vol. 6, no. 3, pp. 136–149, 2005.

[53] R. Kozma, E. Chin, J. Russell, and N. Marx, "The roles of representations and tools in the chemistry laboratory and their implications for chemistry learning," *J. Learn. Sci.*, vol. 9, no. 2, pp. 105–143, 2000.

[54] I. T. Miura and J. M. Yamagishi, "The development of rational number sense," in *Making Sense of Fractions, Ratios, and Proportions*, B. Litwiller and G. Bright Eds. Reston, VA, USA: National Council of Teachers of Mathematics, 2002.

[55] Y. Patel and S. Dexter, "Using multiple representations to build conceptual understanding in science and mathematics," in *Proc. Soc. Inf. Technol. Teacher Edu. Int. Conf*, 2014, pp. 1304–1309.

[56] E. C. Rathmell and L. P. Leutzinger, "Number representations and relationships," *Arithmetic Teacher*, vol. 38, no. 7, pp. 20–23, 1991.

[57] M. M. Cooper, S. M. Underwood, and C. Z. Hilley, "Development and validation of the implicit information from Lewis structures instrument (IILSI): Do students connect structures with properties?" *Chemistry Edu. Res. Practice*, vol. 13, no. 3, pp. 195–200, 2012.

[58] C. J. Luxford, "Use of multiple representations to explore students' understandings of covalent and ionic bonding as measured by the bonding representations inventory," Dept. Chemistry Biochemistry, Miami Univ., Oxford, OH, USA, 2013.

[59] T. L. Brown, H. E. LeMay, B. E. Bursten, C. J. Murphy, and P. M. Woodward, *Chemistry - The Central Science*, 12th ed. Englewood Cliffs, NJ, USA: Prentice Hall, 2011.

[60] S. Ege, *Organic Chemistry: Structure and Reactivity*, 4th ed. Boston, MA, USA: Houghton Mifflin Company, 1999.

[61] J. M. Hornback, *Organic Chemistry*. Pacific Grove, CA, USA: Brooks/Cole Publishing Company, 1998.

[62] M. Loudon, *Organic Chemistry*. Greenwood Village, CO, USA: Roberts and Company Publishers, 2009.

[63] J. W. Moore, C. L. Stanitski, and P. C. Jurs, *Chemistry: The Molecular Science*, 4th ed. Boston, MA, USA: Cengage Learning, 2010.

[64] A. C. Wibraham, *Chemistry*. Englewood Cliffs, NJ, USA: Prentice Hall, 2005.

[65] [Online]. Available: http://www.aleks.com/about_aleks

[66] [Online]. Available: http://www.cbc.arizona.edu/tpp/chemthink/Main/

[67] C. Nakiboglu, "Instructional misconceptions of Turkish prospective chemistry teachers about atomic orbitals and hybridization," *Chemistry Edu. Res. Practice*, vol. 4, no. 2, pp. 171–188, 2003.

[68] C. F. Matta and R. J. Gillespie, "Understanding and interpreting molecular electron density distributions," *J. Chemical Edu.*, vol. 79, no. 9, pp. 1141–1152, 2002.

[69] G. P. Shusterman and A. J. Shusterman, "Teaching chemistry with electron density models," *J. Chemical Edu.*, vol. 74, no. 7, pp. 771–776, 1997.

[70] A. Bergqvist, M. Drechsler, O. de Jong, and S. N. Chang Rundgren, "Representations of chemical bonding models in school textbooks-help or hindrance for understanding?" *Chemistry Edu. Res. Practice*, vol. 14, no. 4, pp. 589–606, 2013.

[71] R. E. Clark, D. F. Feldon, J. J. G. Van Merrienboër, K. A. Yates, and S. Early, "Cognitive task analysis," in *Handbook of Research on Educational Communications and Technology*, J. M. Spector, M. D. Merrill, J. J. G. Van Merrienboer, and M. P. Driscoll, Eds. Mahwah, NJ, USA: Lawrence Erlbaum Associates, 2007, pp. 577–593.

[72] J. M. Schraagen, S. F. Chipman, and V. L. Shalin, *Cognitive Task Analysis*. Mahwah, NJ, USA: Erlbaum Associates, 2000.

[73] K. R. Koedinger, A. T. Corbett, and C. Perfetti, "The knowledge-learning-instruction framework: Bridging the science-practice chasm to enhance robust student learning," *Cognitive Sci.*, vol. 36, no. 5, pp. 757–798, 2012.

[74] W. Schnotz, "An integrated model of text and picture comprehension," in *The Cambridge Handbook of Multimedia Learning*. Cambridge, U.K.: Cambridge Univ. Press, 2005, pp. 49–69.

[75] P. J. Kellman and C. M. Massey, "Perceptual learning, cognition, and expertise," in *The Psychology of Learning and Motivation*, B. H. Ross Ed. Cambridge, MA, USA: Elsevier Academic Press, 2013, pp. 117–165.

[76] J. V. Wertsch and S. Kazak, "Saying more than you know in instructional settings," in *Theories of Learning and Studies of Instructional Practice*, T. Koschmann Ed. Berlin, Germany: Springer, 2011, pp. 153–166.

[77] L. S. Vygotsky, "Internalization of higher psychological functions," in *Mind in Society*, M. W. Cole, V. John-Steiner, S. Scribner, and E. Souberman Eds. Cambridge, MA, USA: Harvard University Press, 1978, pp. 52–57.

[78] M. T. H. Chi, P. J. Feltovitch, and R. Glaser, "Categorization and representation of physics problems by experts and novices," *Cognitive Sci.*, vol. 5, pp. 121–152, 1981.

[79] E. J. Gibson, "Perceptual learning in development: Some basic concepts," *Ecological Psychology*, vol. 12, no. 4, pp. 295–302, 2000.

[80] M. A. Rau, "Enhancing undergraduate chemistry learning by helping students make connections among multiple graphical representations," *Chemistry Edu. Res. Practice*, vol. 16, pp. 654–669, 2015.

[81] M. T. Chi, M. Bassok, M. W. Lewis, P. Reimann, and R. Glaser, "Self-explanations: How students study and use examples in learning to solve problems," *Cognitive Sci.*, vol. 13, no. 2, pp. 145–182, 1989.

[82] V. Talanquer, "Commonsense chemistry: A model for understanding students' alternative conceptions," *J. Chemical Edu.*, vol. 83, no. 5, pp. 811–817, 2006.

[83] R. Goldstone, *Perceptual Learning*, New York, NY, USA: Academic Press, 1997.

[84] R. Even, "Factors involved in linking representations of functions," *J. Mathematical Behavior*, vol. 17, no. 1, pp. 105–121, 1998.

[85] J. A. Wise, T. Kubose, N. Chang, A. Russell, and P. J. Kellman, "Perceptual learning modules in mathematics and science instruction," in *Teaching and Learning in a Network World*, P. Hoffman and D. Lemke, Eds. Amsterdam, The Netherlands: IOS Press, 2000, pp. 169–176.

[86] K. S. Taber, "Revisiting the chemistry triplet: Drawing upon the nature of chemical knowledge and the psychology of learning to inform chemistry education," *Chemistry Edu. Res. Practice*, vol. 14, no. 2, pp. 156–168, 2013.

[87] K. A. Ericsson and H. A. Simon, "How to study thinking in everyday life: Contrasting think-aloud protocols with descriptions and explanations of thinking," *Mind Culture Activity*, vol. 5, no. 3, pp. 178–186, 1998.

[88] K. A. Ericsson and H. A. Simon, *Protocol Analysis: Verbal Reports as Data*. Cambridge, MA, USA: MIT Press, 1984.

[89] K. A. Ericsson and H. A. Simon, "Verbal protocols on thinking," in *Introspection in Second Language Research*, C. Faerch and G. Kasper, Eds. Bristol, U.K., Multilingual Matters, 1987, pp. 24–53.

[90] L. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equation Model. Multidisciplinary J.*, vol. 6, no. 1, pp. 1–55, 1999.

[91] J. L. Arbuckle and W. Wothke, *Amos User's Guide: Version 4.0*, chicago, IL, USA: Small Waters Corporation, 1999.

[92] M. L. Lai, et al., "A review of using eye-tracking technology in exploring learning from 2000 to 2012," *Educational Psychology Rev.*, vol. 10, pp. 90–115, 2013.

[93] O. R. Anderson, B. C. Love, and M. J. Tsai, "Neuroscience perspectives for science and mathematics learning in technology-enhanced learning environments," *Int. J. Sci. Math. Edu.*, vol. 12, no. 3, pp. 467–474, 2014.

[94] J. S. Gomes, M. Yassine, M. Worsley, and P. Blikstein, "Analysing engineering expertise of high school students using eye tracking and multimodal learning analytics," in *Proc. 6th Int. Conf. Educational Data Min.*, 2013, pp. 375–377.

[95] C. Conati, C. Merten, K. Muldner, and D. Ternes, "Exploring eye tracking to increase bandwidth in user modeling," in *Proc. 10th Int. Conf. User Model.*, 2005, pp. 357–366.

[96] T. Van Gog, F. Paas, J. J. G. Van Merriënboer, and P. Witte, "Uncovering the problem-solving process: Cued retrospective reporting versus concurrent and retrospective reporting," *J. Experimental Psychology*, vol. 11, pp. 237–244, 2005.

[97] K. Holmqvist, M. Nystrom, R. Andersson, R. Dewhurst, H. Jarodzka, and J. van de Weijer, *Eye Tracking: A Comprehensive Guide to Methods and Measures*. London, U.K.: Oxford University Press, 2011.

[98] C. I. Johnson and R. E. Mayer, "An eye movement analysis of the spatial contiguity effect in multimedia learning," *J. Experimental Psychology: Appl.*, vol. 18, no. 2, pp. 178–191, 2012.

[99] L. Mason, P. Pluchino, M. C. Tornatora, and N. Ariasi, "An eye-tracking study of learning from science text with concrete and abstract illustrations," *J. Experimental Edu.*, vol. 81, no. 3, pp. 356–384, 2013.

[100] J. Hyönä, R. F. Lorch, and M. Rinck, "Eye movement measures to study global text processing," in *The Mind's Eye: Cognitive and Applied Aspects of Eye Movement Research*. Amsterdam, The Netherlands: Elsevier, 2003, pp. 313–334.

[101] J. Hyönä and A. M. Nurminen, "Do adult readers know how they read? Evidence from eye movement patterns and verbal reports," *Brit. J. Psychology*, vol. 97, no. 1, pp. 31–50, 2006.

[102] L. Mason, P. Pluchino, and M. C. Tornatora, "Effects of picture labeling on science text processing and learning: Evidence from eye movements," *Reading Res. Quart.*, vol. 48, no. 2, pp. 199–214, 2013.

[103] P. J. Kellman and P. B. Garrigan, "Perceptual learning and human expertise," *Physics Life Rev.*, vol. 6, no. 2, pp. 53–84, 2009.

[104] C. M. Massey, P. J. Kellman, Z. Roth, and T. Burke, "Perceptual learning and adaptive learning technology-developing new approaches to mathematics learning in the classroom," in *Developmental Cognitive Science Goes to School*, N. L. Stein and S. W. Raudenbush, Eds. Evanston, IL, USA: Routledge, 2011, pp. 235–249.

[105] K. R. Koedinger and A. Corbett, "Cognitive tutors: Technology bringing learning sciences to the classroom," in *The Cambridge Handbook of the Learning Sciences*. R. K. Sawyer, Ed., 1st ed. Cambridge, U.K.: Cambridge Univ. Press, 2006, pp. 61–77.

[106] V. Aleven, B. M. McLaren, J. Sewall, and K. R. Koedinger, "A new paradigm for intelligent tutoring systems: Example-tracing tutors," *Int. J. Artif. Intell. Edu.*, vol. 19, no. 2, pp. 105–154, 2009.

[107] A. T. Corbett, K. Koedinger, and W. S. Hadley, "Cognitive tutors: From the research classroom to all classrooms," in *Technology Enhanced Learning: Opportunities for Change*, P. S. Goodman, Ed. Mahwah, NJ, USA: Lawrence Erlbaum Associates Publishers, 2001, pp. 235–263.

[108] V. A. W. M. M. Aleven and K. R. Koedinger, "An effective metacognitive strategy: Learning by doing and explaining with a computer-based Cognitive Tutor," *Cognitive Sci.*, vol. 26, no. 2, pp. 147–179, 2002.

[109] R. K. Atkinson, A. Renkl, and M. M. Merrill, "Transitioning from studying examples to solving problems: Effects of self-explanation prompts and fading worked-out steps," *J. Educational Psychology*, vol. 95, no. 4, pp. 774–783, 2003.

[110] M. A. Rau, V. Aleven, and N. Rummel, "Successful learning with multiple graphical representations and self-explanation prompts," *J. Educational Psychology*, vol. 107, no. 1, pp. 30–46, 2015.

[111] S. Gadgil, T. J. Nokes-Malach, and M. T. Chi, "Effectiveness of holistic mental model confrontation in driving conceptual change," *Learn. Instruction*, vol. 22, no. 1, pp. 47–61, 2012.

[112] C. I. Johnson and R. E. Mayer, "Applying the self-explanation principle to multimedia learning in a computer-based game-like environment," *Comput. Human Behavior*, vol. 26, no. 6, pp. 1246–1252, 2010.

[113] M. A. Rau and S. P. W. Wu, "Support for sense-making processes and inductive processes in connection-making among multiple visual representations," *Instructional Science*, submitted for publication.

[114] S. Ainsworth, "The educational value of multiple-representations when learning complex scientific concepts," in *Visualization: Theory and Practice in Science Education*, J. K. Gilbert, M. Reiner, and A. Nakama, Eds. Berlin, Germany: Springer, 2008, pp. 191–208.

[115] M. Cook, E. N. Wiebe, and G. Carter, "The influence of prior knowledge on viewing and interpreting graphics with macroscopic and molecular representations," *Sci. Edu.*, vol. 92, no. 5, pp. 848–867, 2007.

[116] S. A. Özgün-Koca, "Ninth grade students studying the movement of fish to learn about linear relationships: The use of video-based analysis software in mathematics classrooms," *Math. Educator*, vol. 18, no. 1, pp. 15–25, 2008.

[117] R. Plötzner, D. Bodemer, and I. Feuerlein, "Facilitating the mental integration of multiple sources of information in multimedia learning environments," presented at World Conf. Educational Multimedia, Hypermedia Telecommun., Tampere, Finland, 2001.

Martina Angela Rau received the BA and MA degrees in psychology from the University of Freiburg, Germany, and the PhD degree in human-computer interactions from Carnegie Mellon University, in 2009 and 2013, respectively. She is an assistant professor in the Department of Educational Psychology, University of Wisconsin-Madison, with an affiliate appointment in the Department of Computer Sciences. She won the best paper award at the 6th International Conference on Educational Data Mining in 2013, and the best student paper award at the International 14th International Conference on Artificial Intelligence in Education in 2009. In 2013, she was awarded the Siebel Scholarship, which is awarded annually for academic excellence and demonstrated leadership to 85 top students from the world's leading graduate schools.