Representational Mode, Instructional Format, and Cognitive Load:

Optimizing the Instructional Design of Science Simulations

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Abstract

Simulations represent a special kind of instructional animation, allowing for highly interactive, learner-controlled manipulation of parameters. We propose that the effectiveness of simulations for science education depends on design aspects such as the representational format chosen to depict key concepts in the simulation and the instructional format employed to facilitate learning. Design decisions that are not based on models of human cognition can lead to high levels of working memory load, which may contribute to the instructional failure of educational simulations. We hypothesize that the addition of iconic representations can help novice learners interpret the visual representations in a simulation and thereby improve learning. This hypothesis was tested in two experiments, which were conducted with high school chemistry students to examine the effects of representational format of visual information (symbolic versus symbolic plus iconic) in chemistry simulations. Additionally, Study 1 examined how instructional format of the learning materials (exploratory simulation versus worked-out example) interacts with the individual factors of prior knowledge and executive functions to affect learning. Study 2 examined the effects of the learner characteristics factors (prior knowledge and spatial ability) as well as representational format (symbolic versus symbolic plus iconic).

Overall, the data support our hypotheses that design features, such as the addition of iconic representations, can help scaffold students’ visual processing and improve learning, and that learners benefit more from simulation exploration than from worked-out examples. The effectiveness of these simulations features was moderated by interactions with individual learner characteristics. The results are discussed in light of recent research on cognitive load and on the effectiveness of different instructional approaches.
Representational Mode, Instructional Format, and Cognitive Load: Optimizing the Instructional Design of Science Simulations

What makes computer animations and simulations effective instructional formats for learning science? Commonly held beliefs suggest that adding visual materials enhances learning compared to learning from verbal materials only, that dynamic visualizations (animations) are more effective than static visualizations (pictures), and that interactive dynamic visualizations (simulations) result in better learning than visualizations without significant interactivity (animations). However, recent research suggests that each of these beliefs can be challenged for specific learners, topics, and settings. In addition, there is mounting evidence suggesting that the effectiveness of visualizations also depends on a number of other factors, including the design of the materials and the level of cognitive load they impose.

The present paper reports findings from a 3-year, USDOE/IES funded project *Molecules and Minds: Optimizing Simulations for Chemistry Education*, which investigated the impact of design factors on the effectiveness of simulations for learning high school chemistry. This paper will focus on two of these design factors: the representational format chosen to depict key concepts in the simulation, and the instructional method chosen to facilitate learning.

Review of the Literature

Research on learning from visual information in the past four decades has focused on the cognitive processing of visual displays and has described the benefit of using visual representations for learning scientific concepts. Researchers have studied the comprehension of graphics and pictures (Schnotz & Kulhavy, 1994; Willows & Houghton, 1987) and how learning scientific information from diagrams, maps, and charts can be more effective than learning from text (Guthry, Weber, & Kimmerly, 1993; Hegarty & Just, 1993; Kosslyn, 1989; Levie & Lentz, 1982; Mandl & Levin, 1989; Shah, 1989; Shah & Carpenter, 1995; Winn, 1991). Others investigated the benefit of learning from combinations of visual and verbal information, as described by Dual Coding Theory (Clark & Paivio, 1991; Mayer, 1989, 1994; Mayer & Gallini, 1990; Paivio & Csapo, 1973; Paivio, 1990; Rieber, 1990; 1991) and by the Cognitive
Theory of Multimedia Learning (Mayer, 2001; Mayer & Moreno, 1998, 1999; Plass, Chun, Mayer, & Leutner, 1998; Plass, Chun, Mayer, & Leutner, 2003). Investigators studied how combinations of visual and verbal information can be presented most effectively, focusing, for example, on temporal and spatial arrangement of the two types of information (Kulhavy, Stock, & Kealy, 1993; Kulhavy et. al., 1992; Mayer, 2001; Rieber, 1991), and on effects of the modality (narration versus on-screen text) of verbal information that accompanies visual displays (Brünken, Steinbacher, Plass, & Leutner, 2002; Brünken, Plass, & Leutner, 2003; Moreno & Mayer, 1999; Tabbers, Martens, & van Merrienboer, 2004). Cognitive Load Theory uses the concept of extraneous cognitive load to describe the added cognitive load that is attributable to the presentation of the information, whereas intrinsic cognitive load describes the inherent complexity of the materials (Sweller, 1999).

There has been significant interest in the comparison of the educational effectiveness of animations, i.e., visualizations that change over time, to that of static visualizations. Reviews of this research have not been able to identify overall benefits of animations over static pictures. Instead, they suggest that a more appropriate approach is to ask under what conditions and for whom one type of visualizations might be more effective than the other (Betrancourt, 2005). Other reviews have found that learner variables such as prior knowledge moderate the effectiveness of these representations, with low prior knowledge learners benefiting more from static images, and high prior knowledge learners benefiting more from dynamic visualizations (Kalyuga, in press). In some cases, research has even shown that dynamic visualizations can interfere with learners’ performance of relevant cognitive processes, resulting in worse learning outcomes compared to non-animated, static visualizations (Schnottz, Böckler, & Grzondziel, 1999). There are also indications that the effectiveness of a particular animation depends on the design of the visualization, especially the appropriateness of the design for the specific learning goal and related tasks (Schnottz & Bannert, 2003).

In comparison to animations, i.e., dynamic representations that do not allow for significant user interactions, simulations can represent complex dynamic system in which learners can manipulate parameters to explore and observe the behavior of a system (Gogg & Mott, 1993; Towne, 1995). This
exploratory nature of simulations allows learners to engage in processes of scientific reasoning, i.e.,
problem definition, hypothesis generation, experimentation, observation and data interpretation, and
predictions based on results (De Jong & van Joolingen, 1998; Towne, 1995). Therefore, simulations have
the potential to allow learners to better understand scientific phenomenon and transfer knowledge in novel
situation than do other visual representations. In addition, while learners often experience difficulties
interpreting information from multiple representations such as text, pictures, and animation, the dynamic
visualizations of system behavior in simulations assist learners in interpreting concurrent changes in
variables (Van der Meij & de Jong, 2006) by revealing the underlying computational model (de Jong,
1991). Finally, simulations can effectively present the underlying conceptual or operational model, which
cannot easily be accomplished through other modes of representation. Simulations containing conceptual
models hold “principles, concepts, and facts related to the (class of) system(s) being simulated” while
those containing operational models include “sequences of cognitive and noncognitive operations
(procedures) that can be applied to the (class of) simulated system(s).” (De Jong & van Joolingen, 1998,
p. 180).

However, learning from interactive simulations can pose a challenge because some learners may
not possess the required cognitive ability (Chambers et al, 1994; De Jong, & van Joolingen, 1998) or
metacognitive skills (De Jong, & van Joolingen, 1998) necessary to pursue scientific reasoning through
simulations. In addition, compared to static visualizations, the dynamic presentation of information in
simulations can impose additional cognitive load on learners. Although the dynamic integration of
information in a simulation can assist learners in understanding the dynamic relationship between
variables and representations, it can also cause problems because “learners need to attend to and relate
changes that occur simultaneously in different regions of various representation” (Van der Meij & de
Jong, 2006, p. 201), possibly resulting in cognitive overload (Lowe, 1999; Van der Meij & de Jong,
2006). Lowe (2003) attributes this added cognitive load to the changes in the form of representation,
position of visual entities, and inclusion (appearance and disappearance) of visual components, which add
to the visual complexity of simulations and may result in a split-attention effect. Such a high degree of
visual complexity may interfere with extraction and integration of relevant information from dynamic representation and incorporation of the information into learner’s prior knowledge (Lowe, 2003).

Research on science simulations has mainly focused on the question of how learners can be supported to overcome the challenges imposed by scientific reasoning processes (De Jong & van Joolingen, 1998). In particular, research focused on providing direct and timely access to domain knowledge (Elshout & Veenman, 1992; Leutner, 1993), activation of learner’s prior knowledge to assist the integration of experimental outcomes from simulation (Lewis, Stern & Linn, 1993), and supporting clear learning goals by providing different assignments (de Jong et al, 1994; Swaak, van Joolingen & de Jong, 1998). Research related to metacognition in learning from simulations investigated the metacognitive scaffolds to support hypothesis generation (Quinn & Alessi, 1994; Shute & Glaser, 1990; van Joolingen & de Jong, 1991), support for regulative learning processes through gradual increase in complexity of the simulated model (Swaak, van Joolingen & de Jong, 1998), and metacognitive support to monitor learning and discovery processes (Gruber, Graf, Mandl, Renkl & Stark, 1995; Njoo & de Jong, 1993). Research also investigated the effect of the number of variables in the simulation model (Quinn & Alessi, 1994) and control over variables (Rieber & Parmley, 1995) on learning. The problem of added cognitive load imposed by visual complexity of interactive simulations has received little attention.

The present studies

Much of the existing research on visualizations has focused on the question of whether static images, animation, or simulation are more effective, and what scaffolds need to be provided for the integration of simulation into the curriculum. As part of the Molecules and Mind project, a three-year, federally funded study to investigate how the design of science simulations can be optimized, our work adds a different perspective to the research on science simulations by asking the question, What are principles of simulation design that make them effective for science learning?

The approach taken by our research is to improve simulations by focusing on their visual design. Specifically, we focus on the representation type used for key concepts in the simulation, as well as on their interaction design, with particular attention to the instructional format used. There is a wealth of
research suggesting that the design of learning materials, including instructional simulations, must take into account the characteristics of specific learners (e.g., prior knowledge) and be consistent with the nature of human cognitive architecture (Mayer, 2001, 2005; Sweller, 1999). We are therefore also interested in the question of how individual learner characteristics may moderate the effects of representation type and instructional format.

**Representation type.** In science education, important information is often presented visually (e.g., in charts, graphs, diagrams, etc.), both amongst experts and for relative novices in a classroom setting. There are many advantages to representing information visually, however, the interpretation of visual representations requires a certain amount of domain specific knowledge and “visual literacy.” Representations that are the clearest and most efficient for experts may be confusing for novice learners. This suggests that the particular format of visual representations should be considered when designing materials for novice learners.

Schnozt distinguishes two types of representations for his *Integrative Theory of Text and Picture Comprehension*, namely descriptive and depictive representations (Schnozt & Bannert, 2003). Descriptive and depictive representations are similar to the symbols and icons identified in Peirce’s (1955) classification of signs that increase in complexity and abstraction: *icons* (depictive representations), which are the most basic, rely on physical resemblance to convey meaning; *indices* obtain meaning from temporal or spatial proximity; and *symbols* (descriptive representations) are abstract, arbitrary and rely on social conventions for meaning. Deacon (1997) argues that the different types of representations (i.e., icon, index, and symbol) correspond to a developmental trajectory through which learners progress whenever acquiring symbolic representation in a new domain, and that a learner’s developmental state may affect how a sign is actually interpreted, and not necessarily on the way in which the sign was intended to be interpreted (Homer & Nelson, 2005).

This research suggests that for novices in any domain, iconic visual representations may be more easily understood and therefore, icons should be incorporated into the design of visual materials for novice learners with low prior knowledge in the domain. From a computational perspective of visual
complexity, adding any visual elements to a visual display would lead to a more complex display. From an information design perspective informed by a cognitive load approach, we submit that adding icons that represent key concepts in the simulation display (for example, depicting temperature as burners and pressure as weights, see Figure 2) leads to a more complex visualization (i.e., with more visual elements) that induces less extraneous load because the added information externally represents information that the learner would otherwise have to hold internally in working memory. In other words, we argue that a display with a higher visual complexity can be less difficult to understand than one with lower complexity. This would be the case when the higher complexity is due to the addition of iconic representations that depict key concepts that previously were only represented using symbols. The increased comprehension is due to the fact that learners can better relate the added iconic information to their prior knowledge than the symbolic ones.

Our prior research provides preliminary support for this claim. We have found that adding iconic representations of key information in a computer-based simulation affects the cognitive load imposed by interacting with the simulation and can influence learning outcomes (Lee, Homer, & Plass, 2006). This is consistent with previous research that shows the different effectiveness of written and pictorial instructions (Carlson, Chandler, & Sweller, 2003). In the current set of studies, we investigated whether adding iconic information to chemistry simulations will improve learning outcomes of low-prior knowledge learners. We were also interested in examining the effects of the individual learner characteristics of executive functions (Study 1) and spatial ability (Study 2).

**Instructional Format.** There is an ongoing debate about the efficacy of different types of instructional formats in which a direct learning approach is compared to an unguided discovery learning approach (Kirschner, Sweller, & Clark, 2006).

Discovery learning and exploration-based learning are terms that cover a number of different approaches. These approaches have in common that the learning goals, as well as the path through the learning materials to meet them, are determined by the learner. Proponents argue that the active engagement of learners in discovery learning environments leads to better long-term retention and
transfer (Mayer, 1987); develops learning strategies (CTGV, 1993); situates learning (Lave & Wenger, 1990); allows individuals the opportunity of self-directed experimenting and discovery, leading to increased motivation (De Hoog, De Jong, & De Vries, 1991); and builds on learner's prior knowledge and understanding (Brown, Collins, & Duguid, 1989). Supporters point to research demonstrating that discovery learning is most successful when students have sufficient reference knowledge and undergo structured discovery experiences (Roblyer, Edwards & Havriluk, 1997).

Proponents of the direct instruction approach point out that much of what teachers know about science was learned through explicit teaching and that teacher-centered methods such as direct instruction and scaffolding are more effective than pure discovery environments (Brophy & Good, 1986). Furthermore they argue that the planning, verification, and monitoring processes involved in pure discovery methods are difficult for learners to perform (de Jong & van Joolingen, 1998) and are more likely to generate inconsistent or misleading feedback, encoding errors and causal misattributions (Mayer, 2004). The problem, Mayer (2004) asserts, is our tendency to equate active learning with active teaching whereby effective cognitive engagement as a result of behavioral activity such as exploration. Evidence continues to mount, proponents argue, that guided methods are more effective, particularly when knowledge transfer is the objective and when human cognitive architecture is considered (Kirschner, Sweller, & Clark, 2006). The worked-out example approach is a direct-instruction method which has been shown to reduce cognitive load by relieving demands on working memory for novice learners with limited schema, making the limitations of unguided instruction most apparent (Renkl & Atkinson, 2000).

Our simulations exemplify a discovery-based learning environment, albeit not an unguided one: Learners are given broad goals and are then permitted to freely explore the situation. Such exploration requires that individuals self-regulate their learning, which involves metacognitive processes of monitoring, evaluating, and controlling learning processes. Self-regulation has been identified as a significant predictor of learning outcomes (Graesser, McNamara, & VanLehn, 2005; Pintrich & de Groot, 1990; Plass & Kalyuga, in press; White & Fredriksen, 2005; Zimmerman & Schunk, 2001). Since the assessment of self-regulation relies on self-reports by learners, we measured executive functions, the
cognitive ability underlying self-regulation. Executive functions, measured by the Stroop task (Stroop, 1935), are associated with frontal lobe development and allow individuals to monitor, evaluate and control their thoughts and behaviors (Stuss & Benson, 1986).

STUDY 1

Study 1 was designed to answer the question of how to optimize the design of computer-based science simulations by reducing extraneous cognitive load for a variety of learners. The approaches to reducing cognitive load involved (1) modifying the instructional format used in the simulations and (2) manipulating the representation format of visual information. According to Cognitive Load Theory, problem-solving and exploratory learning environments can be cognitively demanding, especially for novice learners, and may result in poor learning outcomes (Handelsman et al., 2004; Kirschner et al., 2006; Klahr & Niegam, 2004). In Study 1, therefore, instructional format was investigated by comparing highly interactive exploratory simulations that required learners to generate and test hypotheses, to less interactive, direct instruction versions based on a worked-out example.

We examined prior knowledge as an individual differences factor, hypothesizing that the addition of icons would be most beneficial for low prior-knowledge learners. We also examined the ways in which executive functions interacted with instructional design. We hypothesized that learners with low executive functions would have the worst learning outcomes in the exploration conditions because they would have the greatest difficulty self-directing their learning, while learners with higher executive functions would have better learning outcomes in the exploratory learning condition because of the advantages, such as increased interest and motivation, that have been associated with exploratory learning (Steffe & Gale, 1995).

Method

Participants

The participants for this study came from four science classes in a New York City public high school with racially and ethnically diverse populations. Participants’ age ranged from 16-18 year ($M = 17$) and they had not studied any materials related to the simulation content (i.e., ideal gas laws). The
original sample included 70 students, but due to technical problems, data was lost for several students resulting in a complete set of data for a total of 64 students (37 female).

Materials

*Instructional materials* included four versions of a simulation of the Ideal Gas Law designed using Flash MX 2004 software and delivered on a web page and viewed on desktop PCs. The four versions of the simulation varied across two factors: instructional format (*exploratory* versus *worked-out*) and representational format (*symbolic* versus *iconic*). The *exploratory* versions of the simulation were highly interactive guided explorations that required learners to generate and test hypotheses, while the *worked-out* versions were less interactive, and took a worked-out example approach in which learners are taken through the simulation step-by-step. In the *symbolic* versions of the simulation, essential information was presented in a symbolic format (e.g., numbers were given to indicate temperature), while in the *iconic* versions, iconic representations were added to represent the same essential information. Although the addition of iconic representation will increase the visual complexity of the interface, our hypothesis is that it will decrease cognitive load and enhance learning by supporting participants’ low domain knowledge. Figures 1 and 2 are screenshots from simulations that used an exploratory instructional format, and Figure 3 is a screenshot from a simulation that used a worked-out example instructional format.

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Insert Figures 1, 2 & 3 about here

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*Pre-test* of prior knowledge consisted of 9 items. Three short-answer questions tested general knowledge of situations that involve different properties of gas, and 6 multiple-choice questions tested for knowledge of relations between the properties of gas. *Executive Functions* were assessed using a computer-based version of the color-word Stroop task (Stroop, 1935), an interference task where students’ reaction time (RT) is recorded. *Knowledge Post-test* included 16 items that assessed learning at two levels. A 10-item multiple-choice questionnaire assessed *recall* and basic comprehension. A 6-item, short-answer questionnaire assessed higher-level *transfer*, which required explaining different phenomena
and real life applications of the gas laws. Multiple-choice and short answer scores were examined separately as indicators of recall and transfer.

Procedure

Participants were tested in groups of approximately 15-20 students. The study took place in a science classroom with each participant working on an individual computer. The procedure consisted of four parts: test of prior knowledge, Stroop task, instructional phase, and post-test. Participants were randomly assigned to one of the four treatment conditions (i.e., symbolic worked-out; iconic worked-out; symbolic exploratory; or iconic exploratory). Prior to the experiment, all participants completed a demographic questionnaire. All students completed the procedure within a 50-minute class period.

Results

Four ANOVAs were conducted to examine how each of the learner characteristic variables interacted with the design variables to affect learning outcomes. Separate analyses were conducted for each learner characteristic variables (prior knowledge and executive functions) and for both learning outcomes (recall and transfer). Each analysis was conducted as a 2 x 2 x 2 between-subjects ANOVA, with either total score on recall or total score on transfer as the dependent variable. The independent variables consisted of representational format (icon and symbolic), instructional format (exploratory and worked-out), and either prior knowledge or executive functions (low and high–median split).

Learner Characteristics

Prior knowledge. Table 1 reports the means and standard deviations of recall and transfer scores for low and high prior knowledge groups by condition. Our hypothesis was that prior knowledge would interact with representational format to affect learning outcomes, with low prior knowledge learners benefiting more from the addition of iconic representations.

For recall, there were significant main effects of prior knowledge, $F (1, 56) = 21.87, MSE =$
48.07, $p < .01$, partial eta squared $\eta^2_p = .28$; and instructional format, $F (1, 56) = 4.37$, $MSE = 9.60$, $p = .04$, $\eta^2_p = .07$. Overall, the participants did significantly better in the exploratory conditions ($M = 3.8$, $SD = 1.9$) than in the worked example conditions ($M = 3.0$, $SD = 1.4$, $d = .47$), and, not surprisingly, the high prior knowledge participants did significantly better on the recall questions ($M = 4.3$, $SD = 1.5$) than did the low prior knowledge participants ($M = 2.5$, $SD = 1.5$, $d = 1.2$). For the short answer questions, which assessed knowledge transfer, there was a significant main effect of prior knowledge, $F (1, 56) = 4.73$, $MSE = 24.73$, $p = .04$, $\eta^2_p = .08$. Contrary to our hypotheses, there were no significant interactions between prior knowledge and design factors for either of the outcome measures.

**Executive Functions.** Table 2 reports the means and standard deviations of performance scores for recall and transfer tests for both executive functions groups by condition. We had hypothesized that low executive function learners would benefit from the addition of iconic representations, and that they would show the greatest learning outcome scores in the conditions with the worked-out example, while high executive function learners would have the best learning outcomes in the conditions with guided exploration.

For recall, there were no significant main effects or interactions. For transfer, there was a significant interaction between instructional format and executive functions, $F (1, 56) = 5.44$, $MSE = 29.16$, $p = .02$, $\eta^2_p = .09$. As hypothesized, participants with higher executive functions did significantly better in the exploratory conditions ($M = 3.44$, $SD = .60$) than in the worked example conditions ($M = 1.84$, $SD = .58$, $d = 2.71$). Although participants with lower executive functions did better in the worked example conditions ($M = 2.77$, $SD = .56$) than in the exploratory conditions ($M = 1.63$, $SD = .61$), this difference failed to reach significance, $p = .087$. However, the difference in the means was in the hypothesized direction. The interaction between executive functions and instructional format for transfer
questions is illustrated in Figure 4.

Representational Type and Instructional Format

The lack of a significant effect for the addition of icons is somewhat surprising given previous work where the addition of icons seemed to contribute to better learning outcomes (Lee et al., 2006). Additional analyses were conducted to further explore the possible effects of icons on learning outcomes. The independent variables were representational type of visual information (symbolic vs. iconic) and instructional format (worked-out vs. exploratory). The dependent variables under analysis were differences between the pre-test and post-test z-scores (calculated separately for multiple-choice and short-answer), which served as indicators of the relative gains in learners’ knowledge from the instructional session.

Since we had a specific a priori directional hypothesis about the expected pattern of means, a one-tailed planned-comparisons test of the hypothesis was used for data analysis. The hypothesis was that simulations using added iconic representations would be more beneficial for learners than symbolic-only representations. The relevant contrasts for testing this hypothesis were: both icon conditions vs. both symbolic conditions; icons vs. symbolic for worked-out example; and icons vs. symbolic for exploratory. For recall, none of the contrasts indicated significant differences. For transfer, the overall comparison of iconic vs. symbolic representational format conditions just failed to reach significance \( t = 1.51, p = 0.070 \), but the contrast was significant in the worked example \( t = 2.02, p = .026 \). Thus, the results of these analyses suggest that adding iconic representations to simulations can improve overall transfer performance in worked-out examples.

Discussion

Study 1 tested hypotheses on how computer simulations can be designed to optimize cognitive load and increase learning outcomes. Of particular interest was how the representational type of visual
information and the instructional format of the simulation interact with learners’ levels of prior knowledge and executive functions. Empirical evidence was obtained by allowing high school students with different levels of knowledge of chemistry and different levels of executive functions to interact with different versions of a simulation of the ideal gas law.

The hypothesis that instructional format would interact with executive functions to affect learning outcomes was supported. Prior research has tended to argue that the decreased cognitive load resulting from a more direct instructional approach, such as worked-out examples, results in improved learning compared to a more open, exploratory learning approach. In the current study, as hypothesized, we found that the effectiveness of instructional format was dependent upon learners’ levels of executive functions, with worked-example being more beneficial to learners with lower levels of executive functions and exploratory version being more beneficial to learners with higher levels of executive functions. This is an intriguing finding that warrants further research to determine if executive functions interact with instructional design in other learning environments.

It was also hypothesized that the addition of icons to the simulation would not increase cognitive load, even though they add to the visual complexity of the simulation, and would actually help students with low prior knowledge. Although there was some indication in the planned-comparisons tests that icons were beneficial to learning, overall the data did not support our hypothesis that adding icons would improve learning for low prior knowledge students. However, the added icons did not hinder learning, suggesting that they did not add to cognitive load. These findings point to the need for further research on the potential of using added iconic representations to visual learning environments. It is possible that the effects of icons may be moderated by individual characteristics, such as spatial ability.

STUDY 2

A second study was conducted to further examine the effects of adding icons to a visual learning environment. For this study, a different but related simulation was developed to illustrate the kinetic theory of heat. The design for Study 2 was similar to the first study except that all students were given the simulations in a guided-exploration instructional format. To further examine the effects of individual
learner characteristics, spatial ability was also assessed using the water-level task (Piaget & Inhelder, 1956). It was hypothesized that icons would assist learners with the lowest prior knowledge and learners with the lowest spatial ability.

Method

Participants

The participants for this study (N = 93; approximately 40% female) came from a large public high school in rural Texas. A majority of the students were of Hispanic decent (88%) with the remaining students being White (non-Hispanic) (10%), African-American (1%) or “other” (1%). The students ranged from 16-18 years of age (M = 17) and had not studied any materials related to the simulation content (i.e., kinetic theory of heat).

Materials

Instructional materials included two versions of a simulation of the Kinetic Theory of Heat designed using Flash MX 2004 software and delivered on a web page and viewed on desktop PCs. The versions varied in their representational format (symbolic versus iconic). Similar to Study 1, in the symbolic version of the simulation, essential information was presented in symbolic format (e.g., numbers were given to indicate temperature), while in the icon version, iconic representations were added to represent the same essential information. Figures 5 and 6 are screenshots from the Kinetic Theory of Heat simulations with and without icons.

Pre-test of prior knowledge consisted of 8 items. Three short-answer questions tested general knowledge of situations that involve properties of gas, and 6 multiple-choice questions tested for knowledge of kinetic theory of heat. Spatial ability was assessed using a paper-and-pencil version of the water-level task in which participants were shown 6 pictures of empty bottles in different orientations and were asked to draw what the water level would look like if the bottles were half-full of water. The degree
to which the drawn line deviated from the horizontal line was recorded and an average “deviation” score was calculated for each participant.

*Knowledge Post-test* included 16 items that assessed learning at two levels. A 10 item multiple-choice questionnaire assessed *recall* and basic *comprehension*. A 6-item, short-answer questionnaire assessed higher-level *transfer*, which required explaining different phenomena and real life applications of the kinetic theory. Multiple-choice and short answer scores were examined separately as indicators of *recall* and *transfer*.

**Procedure**

Participants were tested in groups of approximately 15-20 students in grades 11 and 12. The study took place in a science classroom with each participant working on an individual computer. The procedure consisted of four parts: test of prior knowledge, water-level task, instructional phase, and post-test. Before beginning, participants were randomly assigned to one of the two treatment conditions (i.e., *iconic* vs. *symbolic*). Prior to the experiment, all participants completed a demographic questionnaire. All students completed the procedure within a 50-minute class period.

**Results**

Separate ANCOVAs were conducted for recall and transfer as dependent variable with representational format as an independent variable and prior knowledge and spatial ability as covariates. The model tested included interactions between the two individual difference measures (i.e., prior knowledge and spatial ability) and the representational format.

For recall, there were significant main effects of representational format, $F(1, 87) = 6.81, MSE = 58.11, p = .007$, partial eta squared $\eta^2_p = .08$; of prior knowledge, $F(1, 87) = 5.39, MSE = 41.12, p = .02$, $\eta^2_p = .06$; and of spatial ability, $F(1, 87) = 5.52, MSE = 42.09, p = .02, \eta^2_p = .06$. A significant interaction was found between representational format and prior knowledge, $F(1, 87) = 7.00, MSE = 53.49, p = .01$, $\eta^2_p = .08$. This interaction is displayed in Figure 7, which illustrates the relation between pretest scores and scores on the recall test for both the icon and symbolic representational conditions. In both conditions, posttest scores increased with higher pretest scores, however, this difference between high and
low scores was less in the icon condition.

For transfer, the only significant finding was a main effect of prior knowledge, $F(1, 87) = 12.33$, $MSE = 31.77$, $p = .001$, partial eta squared $\eta_p^2 = .12$. One possible problem, however, is the relatively low scores the students received on the transfer posttest: The average score was 2.3 out of a maximum possible of 8, suggesting that there may be a floor effect for transfer.

Discussion

Study 2 tested hypotheses on how computer simulations can be designed to optimize cognitive load and increase learning outcomes. Of particular interest was how the representational type of visual information in the simulation interacts with learners’ levels of prior knowledge and spatial ability. Empirical evidence was obtained by allowing high school students with different levels of knowledge of chemistry and different levels of spatial ability to interact with different versions of a simulation of the kinetic theory of heat.

The analysis of recall test data showed that adding icons increased learning for all learners, that learners with high prior knowledge recalled more information than learners with low prior knowledge, and that learners with high spatial ability recalled more information than learners with low spatial ability. An interaction of representation type and prior knowledge further indicates that low-prior knowledge learners benefited more from the simulation variant with added icons, whereas high-prior knowledge learners benefited more from the simulations without added icons. This pattern was not replicated for the transfer test, but the low mean scores on this test suggest a floor effect.

Overall, the results of Study 2 provide further support for the claim that icons can facilitate learning in visual learning environments, particularly for low prior knowledge learners. This finding suggests that factors such as the representational format of the information in visual displays need to be considered in the design of simulations for novice learners. These findings also provide further support
for the hypothesis that addition of icons to the simulation would not increase cognitive load, even though they add to the visual complexity of the simulation, and would actually help students with low prior knowledge.

GENERAL DISCUSSION

What makes computer animations and simulations effective instructional formats for learning science? Our research suggests that design factors, namely the representation type of key concepts in the simulation, as well as the instructional format (simulation exploration vs. direct instruction) affect the effectiveness of computer simulations, and that individual difference variables such as prior knowledge and executive functions moderate these effects.

This research has important educational and theoretical implications. On the educational side, this research provides suggestions of how the design of simulations for science education can be improved. Our results show that learners’ prior knowledge needs to be considered in selecting the representation type of key information in the simulation. For learners with low prior knowledge, adding iconic representations can result in improved learning, especially recall. In addition, the determination of the instructional format of the visualization requires the consideration of learner variables such as executive functions, i.e., individuals’ ability to monitor, evaluate, and control their learning. Learners with high executive functions learned more with exploratory simulations than with worked-out examples, whereas the trend for learners with low executive functions was the opposite, i.e., they learned better with worked-out examples than with simulation exploration.

On the theoretical side, our research shows that recall was improved when iconic representations of key information are added to the simulation display, even though this meant that the visual complexity of the display increased. Iconic representations are more closely related to the referent they represent, allowing learners to more easily to perceive the structural relations of the content (Schnotz & Bannert, 2003). In comparison, symbols, such as verbal codes, are arbitrary representations of content, in which structural relations must be represented through propositions. Such propositions require additional mental effort by the learner to be processed. The sign used to represent key information in a simulation, then,
appears to affect the cognitive load experienced by students learning with the simulations.

In addition, our research suggests that a simple comparison of instructional approaches may be too simplistic, and that learner characteristics such as prior knowledge and executive functions need to be considered in order to determine which instructional approach is appropriate for a given learner and topic.

Further studies are required to replicate these results with other materials, including subject areas that are either more or less intrinsically difficult, and with learners with different levels of prior knowledge. These findings need to be tested both in the more controlled setting of a laboratory and in authentic educational settings. Future research should also investigate how representational format of visual materials and instructional format interact with a broader range of learners’ individual differences, for example, verbal and spatial abilities.

Further work should also look at how icons influence learning with simulations in longer learning situations (e.g., over time in an actual chemistry class). It is possible that the treatment in the current set of studies was too brief for the effects of icons to be fully seen, especially given the low levels of prior knowledge of the participants. Research should also examine the effects of added icons for learners with higher levels of prior knowledge and the effects of exposure to a series of related simulations, and should include measures of cognitive load.

In summary, the findings from the two studies presented here provide an example where exploratory simulations are more effective for science learning than direct instruction. The findings also provide support for the claim that the effective design of instructional simulations must take into account the representation type used to represent key concepts of the content. Finally, our findings provide support for the importance of considering individual learner differences when designing educational materials: For simulation-based learning environments to be cognitively efficient and educationally effective, they should be based on the specific needs and characteristics of learners, including their prior knowledge and executive functions.
References


Marie Njoo, Ton De Jong. Exploratory learning with a computer simulation for control theory: Learning processes and instructional support., 821-844.


Table 1

Mean (SD) Post-test Scores for Recall and Transfer by Simulation Design Condition for High and Low Prior Knowledge.

<table>
<thead>
<tr>
<th></th>
<th>Symbolic Worked-out</th>
<th>Iconic Worked-out</th>
<th>Symbolic Exploratory</th>
<th>Iconic Exploratory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Prior Knowledge</td>
<td>2.38 (1.30)</td>
<td>1.75 (1.04)</td>
<td>2.71 (1.38)</td>
<td>3.22 (1.79)</td>
</tr>
<tr>
<td>High Prior Knowledge</td>
<td>3.75 (1.04)</td>
<td>4.11 (.93)</td>
<td>4.88 (1.36)</td>
<td>4.29 (2.56)</td>
</tr>
</tbody>
</table>

**Recall:**

**Transfer:**
Table 2

Mean (SD) Post-test Scores for Recall and Transfer by Simulation Design Condition for Low and High Executive Functions.

<table>
<thead>
<tr>
<th></th>
<th>Symbolic</th>
<th>Iconic</th>
<th>Symbolic</th>
<th>Iconic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worked-out</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Executive Functions</td>
<td>3.22 (1.20)</td>
<td>3.50 (1.51)</td>
<td>3.89 (2.09)</td>
<td>3.50 (2.17)</td>
</tr>
<tr>
<td>High Executive Functions</td>
<td>2.86 (1.57)</td>
<td>2.56 (1.51)</td>
<td>3.83 (1.17)</td>
<td>3.80 (2.25)</td>
</tr>
</tbody>
</table>

|                             |          |        |          |        |
| Exploratory                 |          |        |          |        |
| Low Executive Functions     | 2.17 (1.60) | 3.38 (2.52) | 1.83 (1.62) | 3.83 (1.91) |
| High Executive Functions    | 1.57 (1.70) | 2.11 (2.78) | (3.14)   | 3.05 (3.13) |
Figure Captions

Figure 1. A screenshot of the Gas-Law simulation (exploratory instructional format) using symbolic representations for key semantic information about the pressure, volume and temperature of the gas.

Figure 2. A screenshot of the modified Gas-Law simulation with added iconic representations for key semantic information about pressure (represented by weights) and temperature (represented by flames).

Figure 3. A screenshot of the Gas-Law simulation using added iconic representations for worked-out example instructional format.

Figure 4. Interaction of instructional format (worked-out example vs. exploratory) and executive functions (high vs. low) for post-test of transfer (Study 1, Ideal Gas Law simulation).

Figure 5. A screenshot of the Kinetic Theory simulation using symbolic representations.

Figure 6. A screenshot of the Kinetic Theory simulation with added iconic representations.

Figure 7. Relation between prior knowledge and recall for icon and symbolic conditions (Study 2, Kinetic Theory of Heat simulation).
Figure 1
Figure 2
Suppose you wish to work out how the gas pressure changes when you change the temperature. In this case the volume of the gas remains constant. For each step in the simulation, click the numbered icon to watch the video. Enter the result in your chart for pressure and temperature. You can watch the video again by clicking the text again.

1. Select a value for the volume and lock it.
2. Set the volume to 5 L and lock it.
3. Select a value for the temperature.
4. Check the value for the pressure.
5. Increase the temperature.
6. What happens to the pressure?
7. Increase the temperature further.
8. What happens to the pressure?
9. Decrease the temperature.
10. What happens to the pressure?
Figure 4
Figure 5
Figure 6
Figure 7