Optimizing Cognitive Load in Simulations for Science Education

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Abstract

Simulations represent a special kind of instructional animation, with highly-interactive learner-controlled choice of parameters. We propose that high levels of working memory load may be responsible the instructional failure of educational simulations for certain learners. An experiment was conducted to examine how representational format of visual information (symbolic versus symbolic plus iconic) and instructional format (exploratory versus worked-out) interact with individual factors (prior knowledge and executive functions) to affect the instructional effectiveness of simulations. High school chemistry students interacted with different versions of a simulation of the ideal gas law. Overall, the data support our theoretical model of how design features interact with individual learner characteristics to affect the instructional effectiveness of simulations.
What makes computer animations and simulations effective instructional formats for learning science? There is a commonly held belief that interactive dynamic animations, or simulations, are beneficial because they facilitate an active engagement in the learning process. This potential benefit is believed to be particularly strong for science education, where simulations can present dynamical representations of complex processes that would otherwise be difficult to visualize, such as processes involving sub-microscopic particles. However, the increased availability of animations and simulations in educational settings has not resulted in the expected improvement in students’ academic performance. Recent research suggests that although animations can enhance learning under some conditions (Schnotz & Rasch, 2005; Tversky, Morrison, & Betrancourt, 2002), non-animated, static images often result in better learning outcomes (Schnotz, Böckler, & Grzondziel, 1999). This paper addresses the questions of why, under what conditions, and for whom are instructional simulations effective?

There is a wealth of research suggesting that the design of learning materials, including instructional simulations, must be consistent with the nature of human cognitive architecture and take into account limitations of the perceptual and cognitive systems (Mayer, 2001, 2005; Sweller, 1999). One such limitation is the capacity of working memory (Miller, 1956). Cognitive load theory (CLT) describes two different sources of cognitive load for learning materials: intrinsic and extraneous load (Sweller, 1999). Intrinsic load refers to the complexity of the material to be learned and is often described as the level of element interactivity in learning materials. Extraneous load refers to the design of the instruction and the presentation of the materials, which includes the instructional format as well as the representational format of information (Sweller, 1999).
Much of the research on cognitive load has been done on verbal materials or combinations of visual and verbal materials, showing that in order to be effective, temporal and spatial arrangements of the information, as well as the modality of the verbal information (e.g., narration versus on-screen text) must be taken into account (Brünken, Steinbacher, Plass, & Leutner, 2002; Brünken, Plass, & Leutner, 2003; Kalyuga, Chandler, & Sweller, 1999; Mayer, 2001; Rieber, 1991; Sweller, 1999).

However, verbal and visual materials differ in significant ways that affect the amount of cognitive effort required to process information in these two formats. Whereas verbal information consists of discreet symbolic representations that are processed sequentially, visual information is inherently relational and its elements can be encoded simultaneously (Clark & Paivio, 1991). The focus of the present paper is therefore on cognitive load induced by visual displays.

**Visual Cognitive Load**

Recent research in cognitive science and neuroscience has dramatically improved our understanding of how visual information is processed. Current working memory models include separate cognitive systems – the visuo-spatial sketchpad and the phonological loop – for processing visual and verbal information (Baddeley, 1986; Baddeley & Logie, 1999). There is a large body of research on the processes involved in the perception and comprehension of visual information (Arnheim, 1969; Levie, 1987; Winn, 1994), and for specific types materials, such as charts, graphs, and diagrams, effects of the design of visual displays on comprehension are well understood (Bertin, 1983; Shah & Hoeffner, 2002; Winn, 1991).

*Cognitive Load Theory* can be used as a theoretical framework for designing visual displays in order to optimize the cognitive load experienced by learners. Our previous work with
science simulations has shown that intrinsic load in these simulations can be manipulated, and
learning enhanced, when a complex simulation that may induce high load in learners, e.g., a
simulation of the Ideal Gas Law, is presented in two separate parts, e.g., one for Charles’ Law
and one for Boyle’s Law (Lee, Plass, & Homer, 2006). We have also found indications that the
issue of redundancy in visual materials has to be treated differently than in verbal materials. In
verbal information, added (redundant) material would always be represented in symbolic form
(language), but for visual information, it can be added in different modes of representation.

Peirce (1955) identified three modes of representation that increase in complexity and
abstraction: icons, which are the most basic, rely on physical resemblance to convey meaning,
indices obtain meaning from temporal or spatial proximity, and symbols are abstract, arbitrary
and rely on social conventions for meaning. Symbols are also unique in that their meaning comes
partially by being part of a network of related symbols. There is evidence that within any given
domain, novices begin with the more basic iconic or indexical modes of representation and only
gradually, with learning, develop representations that are fully symbolic (Deacon, 1997; Homer
& Nelson, 2005). Instructional simulations are often designed by domain experts and use
abstract, symbolic representations that assume domain-specific knowledge that may be lacking in
novice learners. Novices may actually benefit from more basic, iconic visual representations in
simulations.

Our research has found that the representation format of key visual material in a
simulation affects the amount of cognitive load it imposes. Unlike for verbal information, where
adding redundant information is very likely to result in increased cognitive load, we found that
adding iconic representations to the display may increase learning, even though this information
is redundant, supplementing existing symbolic representations of the same content (Lee et al.,
2006). Indeed, a comparison of the effectiveness of written and pictorial instructions for building molecular models in chemistry revealed similar findings (Carlson, Chandler, & Sweller, 2003). In this study, intrinsic load was associated with the complexity of the molecule being constructed. Carlson et al. found that written and pictorial instructions were equally effective for building simple molecular models. However, for building complex molecules the pictorial directions (i.e., iconic representations) were more effective for students than the written directions (i.e., symbolic representations). These results indicate that pictorial, iconic representations reduced cognitive load compared to the written, symbolic information, freeing cognitive resources and allowing students to solve complex tasks.

In the current study, we are interested in whether adding iconic information to chemistry simulations will increase comprehension of the simulation subject, especially for novice learners. Although adding redundant iconic information creates a visually more complex display from a computational perspective, it may actually reduce cognitive load for learners. This is because adding icons creates external representation of information that the learner would otherwise have to hold internally in working memory.

*Instructional format*

According to CLT, problem-solving and exploratory learning environments can be cognitively very demanding, especially for novice learners, and may result in poor learning outcomes. Indeed, approaches where learners receive only minimal instructional guidance have recently come under considerable criticism by science educators and educational psychologists (Handelsman et al., 2004; Kirschner, Sweller, & Clark, 2006; Klahr & Niegam, 2004). Several studies have demonstrated that using appropriately structured worked-out examples could be superior to purely problem-based instruction (Paas, 1992; Sweller & Cooper, 1985; Zhu &
Simon, 1987). Therefore, instructional format was also investigated in the current study 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. The worked-out simulations included a series of animations demonstrating step-by-step procedures of actual hypotheses testing. It was expected that the worked-out instructional format would enhance learning outcomes for less experienced or able learners and, therefore, adding iconic representations would have greater effects on learning when used with worked-out simulations for these learners.

**Learners’ prior knowledge**

The cognitive load generated by processing visual representations depends not only on characteristics of the visual displays, but also on characteristics of specific learners, and, in particularly, their prior knowledge (e.g., Kalyuga, 2006; Lee et al., 2006; Mayer & Sims, 1994; Plass, Chun, Mayer, & Leutner, 2003). Prior knowledge, i.e., organized knowledge structures from long-term memory, can reduce working memory limitations by chunking bits of information together into a single, higher-level element (Chi, Glaser, & Rees, 1982). Prior knowledge in the domain of the subject matter being taught is one of the strongest predictors of learning outcomes in most learning environments, a phenomenon recently described in terms of an *Expertise Reversal Effect* (Kalyuga, 2005; Kalyuga, Ayres, Chandler, & Sweller, 2003). In accordance with general cognitive studies of expert-novice differences (e.g., Chase & Simon, 1973; De Groot, 1965), studies on the expertise reversal effect have found that many instructional design techniques that are highly effective with less knowledgeable learners, lose their effectiveness and can even have negative consequences when used with more experienced learners, and vice versa.
A number of studies of individual differences in learning from text and visual displays have demonstrated that the instructional advantages of diagrams depend on student domain-specific knowledge and experience (e.g., Hegarty & Just, 1989; Lowe, 1993; Schnotz, 2002; Schnotz, Picard, & Hron, 1993). Less knowledgeable learners can have difficulty processing visual information because of the limited capacity of working memory and a lack of background knowledge required to easily interpret the visual information. Cognitive load increases when novice learners have to interpret the meaning of symbolic representations that implicitly assume prior domain-specific knowledge. Acquiring sufficient knowledge in a domain reduces working memory overload and allows for effective learning from more abstract, symbolic representations by tapping into relevant schematic representations already held in long-term memory.

Executive Functions

Executive functions describe a set of cognitive abilities that allow learners to monitor and control their mental activities and behavior. Executive functions are high-level abilities that influence more basic functions, such as attention and memory. Executive functions are highly relevant for CLT as they describe the performance of the cognitive architecture’s hypothesized central executive (Baddeley & Logie, 1999). Because executive functions enable the intentional allocation of mental resources, such as attention and memory, higher levels of executive functions should result in lower levels of cognitive load and increased learning. Although some recent research suggests that certain executive functions (e.g., shifting, updating, and inhibition) predict greater academic achievement (St Clair-Thompson & Gathercole, 2006), there has been surprisingly little work on the effects of executive functions in complex learning environments.

Current Study

The current study aims to answer the question of how to optimize the instructional design
of science simulations by reducing extraneous load for a variety of learners. The approaches to reducing extraneous cognitive load involved altering the representation format of visual information and modifying the instructional format used in the simulations. This study was based on two assumptions about the effective design of simulations. First, simulations should be designed to optimize visual cognitive load, for example, by adding iconic information to the display, which may have different effects for simulations with lower complexity (worked-out simulations) than for simulations with higher complexity (exploratory simulations). Second, the effectiveness of the simulation design will depend on learners’ individual differences, such as level of domain-specific knowledge and executive functions.

It is the interaction between design features and learner characteristics that is of particular interest in the current study. In accordance with the expertise reversal effect, adding iconic representations to simulations may be instructionally effective only for novice learners and become less effective as learners’ levels of expertise increase. Adding redundant, iconic representations can help novices learn by providing a context for interpreting the visual information. Therefore, we suggest that adding iconic representations to symbolic information will reduce cognitive load for low-prior knowledge learners, but will have little or no effect on high-prior knowledge learners.

Similarly to the predictions for the expertise reversal effect with prior knowledge, we expect design features of the simulations to interact with executive functions to affect instructional effectiveness. To date, no research has explicitly examined how executive functions interact with either instructional format or representational format of simulations. However, given that executive functions involve planning, monitoring and updating behavior, we predict that using a worked-out example would be a more effective approach for learners with lower
levels of executive functions. In contrast, learners with higher levels of executive functions may benefit more from guided exploration, which allows learners to have more control of the simulation. Furthermore, because executive functions involve control of attention, adding icons may benefit learners with lower levels of executive functions by highlighting key features of the simulation, thereby serving as an external means of focusing attention.

Method

Participants

The participants for this study came from four science classes from a New York City public high school with a racially and ethnically diverse population (approximately 7% White, 45% African-American, 42% Hispanic, and 5% Asian students, Pacific Islanders, Alaskan Natives, and Native Americans). The sample was diverse economically, with approximately 51% eligible for free lunch. The students ranged in age from 16-18 year ($M = 17$). At the time of the experiment, the students had not studied any materials related to the simulation content (i.e., ideal gas laws). The original sample included 70 students, but due to loss of data from several students during transmission, a complete set of data was obtained for a total of 64 students, 37 of which were female.

Materials

Instructional materials included four versions of a simulation of the Ideal Gas Law (describing the relationships among pressure, temperature, and volume of an idealized gas) designed using Flash MX 2004 software and delivered on a web page that was viewed using 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 work-out versions were less interactive, and took a worked-out example approach. In the worked-out version, participants were presented with a series of animations that demonstrated step-by-step procedures of actual hypothesis testing, with learner interactions limited to selecting sequential procedural steps to study and controlling animations using standard start, stop, continue, and rewind video control features. In the symbolic versions of the simulations, essential information was presented in symbolic format (e.g., numbers were given to indicate temperature), while in the icon versions, iconic representations were added to represent the same essential information (e.g., in addition to the temperature being presented in numerical format, flames were used, with more flames appearing at higher temperatures.) 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.

Pre-test of prior knowledge consisted of 9 items. Three short-answer questions tested general knowledge of situations that involve properties of gas. Prior knowledge of relations between gas characteristics was assessed using 6 multiple-choice questions. Three of these questions tested general knowledge of gas features and basics of kinetic theory. Another three questions tested qualitative relationships between gas characteristics.

Executive Functions were assessed using a computer-based version of the color-word Stroop task (Stroop, 1935). In the Stroop task, a word (RED, GREEN, or BLUE) appears on the screen written in red, green, or blue colored font. Participants must press a key, as quickly as possible, to identify the font color, regardless of the word name. In the first part of the test, the
font colors and word names are congruent (i.e., the word “red” appears in red color font), in the second part they are mismatched (e.g., the word “red” appears in a green color font). An interference score is calculated for each participant (interference = average response time with the incongruent stimuli – average response time with the congruent stimuli). Higher levels of executive functions are indicated by lower interference scores.

Post-test included 16 items that assessed learning at two levels. A 10 item multiple-choice questionnaire assessed recall and basic comprehension. It included two questions on knowledge of basics of kinetic theory; three questions on qualitative relations between pressure, volume, and temperature; three questions on quantitative relationships; and two questions that tested knowledge of graphical representations of relationships.

A 6-item, short-answer questionnaire was developed to assess higher-level transfer, which required explaining different phenomena and real life situations using the learned gas laws. Two of these were questions on applying knowledge to explain real-life phenomena; two questions required applying knowledge to predict phenomena; and two questions required applying knowledge to suggest solutions to some real-life problems.

Procedure

Participants were tested as in groups of approximately 15-20 students. Testing took place in a science classroom with each participant working on an individual laptop computer. Verbal directions were given to the entire group and then experimenters and research assistants were present to answer any questions. The testing consisted of four parts: test of prior knowledge, Stroop task, instructional phase, and post-test. Before beginning, 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, which was returned with consent letters.

_instructional phase._ Students who studied worked-out simulations were instructed to follow the suggested procedural steps for establishing relationships between gas characteristics and to read carefully the provided explanations. When students clicked on each step note, a brief animation displayed the corresponding changes in the simulation and diagram. In exploratory simulations, students were instructed to systematically manipulate the temperature, volume, and pressure of the gas, and to observe the resulting change in the other properties of the gas. Before they started to explore, students had been advised to practice changing different variables by moving the sliders. General exploration guidelines were also provided. For example, students were advised to lock one of the variables and systematically explore how changing one of the remaining variables would affect the other unlocked variable (In the simulations, one variable was always “locked.”). In both versions of the simulation, students were advised to take all the time they needed to study the material and not to proceed to the test until they had studied (or explored) the simulations thoroughly. All students completed the procedures within a 50-minute class period.

Results

For both pre- and post-tests multiple-choice questions, a score of 1 was allocated for each correct answer. Short-answer questions were scored independently by two graders according to the specified scales (for most questions, the scores were 0 for no answer or completely incorrect answer, 1 for some elements of a correct answer indicated, 2 for most elements of a correct answer indicated, and 3 for a complete correct answer). For the pre-test, the multiple-choice and short answer scores were combined for a total score of prior knowledge. For the post-test, the multiple-choice and short answer scores were examined separately as indicators of recall and
One-way ANOVAs were conducted to confirm that the treatment groups (representation format x instructional format) did not differ significantly on either of the two learner characteristics variables: prior knowledge or executive functions. In addition, analyses were conducted to confirm that prior knowledge and executive functions were independent factors and not significantly correlated with each other. Median splits were done on the learner characteristics variables to create “high” and “low” groups. ANOVAs were then 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 multiple choice (i.e., comprehension) or total score on short answer (i.e., transfer) as the dependent variable. For all analyses, 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).

*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, $F(1, 56) = 4.37, MSE =$
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 both outcome measures.

**Executive Functions.** Table 2 reports the means and standard deviations of recall and transfer 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.

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*Insert Table 2 about here*

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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.

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Insert Figure 4 about here

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**Representational 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 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 format 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-tests $z$-scores (calculated separately for multiple-choice and short-answer), which served as indicators of the relative gains in learners’ knowledge due to the instructional session. Standardized $z$-scores were used as indicators of students’ relative standing and changes in performance because the pre-test and post-tests were structurally different.

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

This paper tested hypotheses on how computer simulations can be designed to optimize the cognitive load and learning outcomes of a variety of learners. Of particular interest was how the representational format 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.

It was 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 treatment in the current study was too brief to find effects for icons, especially given the low-levels of prior knowledge of the participants. Further research should examine the effects of added icons for learners with higher levels of prior knowledge and also examine the effects of increased exposure to the simulations (or exposure to a series of related simulations) and should include measures of
cognitive load.

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 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.

Further studies are required to replicate these results with other materials, including subject areas that are both more and 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 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.

The results presented above suggest that in order for simulation-based learning environments to be cognitively efficient and pedagogically effective, they should be tailored to individual learners. These findings provide further support for the claim that the effective design of instructional simulations must take into account the nature of the human cognitive architecture and variations in individual learner characteristics.
References


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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>
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<tr>
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<td>( n = 16 )</td>
<td>( n = 17 )</td>
<td>( n = 15 )</td>
<td>( n = 16 )</td>
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<tr>
<td><strong>Recall:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<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>
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<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>
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<td><strong>Transfer:</strong></td>
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<td></td>
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<tr>
<td>Low Prior Knowledge</td>
<td>1.25 (.96)</td>
<td>1.88 (2.28)</td>
<td>2.79 (3.03)</td>
<td>1.39 (1.69)</td>
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<td>High Prior Knowledge</td>
<td>2.56 (1.90)</td>
<td>3.44 (2.39)</td>
<td>2.50 (2.04)</td>
<td>3.79 (3.44)</td>
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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 Worked-out $n = 16$</th>
<th>Iconic Worked-out $n = 17$</th>
<th>Symbolic Exploratory $n = 15$</th>
<th>Iconic Exploratory $n = 16$</th>
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<tr>
<td><strong>Recall:</strong></td>
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<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>
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<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>
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<tr>
<td><strong>Transfer:</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Executive Functions</td>
<td>2.17 (1.60)</td>
<td>3.38 (2.52)</td>
<td>1.83 (1.62)</td>
<td>1.42 (1.91)</td>
</tr>
<tr>
<td>High Executive Functions</td>
<td>1.57 (1.70)</td>
<td>2.11 (2.78)</td>
<td>3.83 (3.14)</td>
<td>3.05 (3.13)</td>
</tr>
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</table>
Figure Captions

Figure 1. A screenshot of the 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 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 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.
When exploring a system with many variables, a good strategy is to change only one variable to observe its effects on another variable. Try locking one of the variables and explore how changing one variable affects the other unlocked variable.

For example, work out how the gas pressure changes when you change the volume (with constant temperature).

- How will it change if you double the volume? Record the results in your chart.
- Explore other relationships between other variables and record the results in your chart.

Feel free to explore the simulation. You can set as many values for the gas characteristics as you wish, remember that several values are needed for each chart to obtain a good graph.

Do not proceed to the test before you have explored the gas characteristics thoroughly and completed all the charts.
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- How will it change if you double the volume? Record the results in your chart.
- Explore other relationships between other variables and record the results in your chart.

Feel free to explore the simulation. You can set as many values for the gas characteristics as you wish; remember that several values are needed for each chart to obtain a good graph.

Do not proceed to the test before you have explored the gas characteristics thoroughly and completed all the charts.
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 item 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?