Design Factors for Effective Science Simulations: Representation of Information

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ABSTRACT

We propose that the effectiveness of simulations for science education depends on design features such as the type of representation chosen to depict key concepts. We hypothesize that the addition of iconic representations to simulations can help novice learners interpret the visual simulation interface and improve cognitive learning outcomes as well as learners’ self-efficacy. This hypothesis was tested in two experiments with high school chemistry students. The studies examined the effects of representation type (symbolic versus iconic), prior knowledge, and spatial ability on comprehension, transfer, and self-efficacy under low cognitive load (Study 1, N=80) and high cognitive load conditions (Study 2, N=91). Results supported our hypotheses that design features such as the addition of iconic representations can help scaffold students’ comprehension of science simulations, and that this effect was strongest for learners with low prior knowledge. Adding icons also improved learners’ general self-efficacy.

Keywords: cognitive load; icons; interface design; learning; prior knowledge; representation; science; self-efficacy; simulation; spatial ability; symbols

INTRODUCTION

What makes computer animations and simulations effective instructional tools for learning science? We currently see a growing excitement about using simulations, microworlds, and games to learn and teach, yet there are also voices who are concerned about the potentially...
high cognitive load involved in learning from such exploratory environments (Kirschner, Sweller, & Clark, 2006). Evidence is mounting that the effectiveness of visual environments for learning depends on a variety of design factors, including the information design and interaction design of the materials, and the level of cognitive load they impose. This article will focus on one of these design factors, namely the type of representation chosen by the designer to depict key concepts in the simulation.

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 our perceptual and cognitive systems (Mayer, 2001, 2005; Plass, Homer, & Hayward, 2006; 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 that compete for the limited working memory resources of learners: intrinsic cognitive load and extraneous cognitive load (Sweller). Intrinsic load refers to the processing of essential information and is determined by the complexity of the material to be learned. Intrinsic load is often described as the level of element interactivity in learning materials, that is, as the number of items a learner has to hold in working memory in order to comprehend the material. Extraneous load refers to processing nonessential information and is determined by the design of the instruction and the presentation of the materials, which includes the instructional format as well as the format of the representation of information (Sweller). Instructional designers aim to reduce extraneous cognitive load, especially in situations when intrinsic cognitive load is high.

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, Plass, & Leutner, 2002; Brünken, Steinbacher, Plass, & Leutner, 2002; 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). Because we are interested in identifying design factors for effective simulations, we focus in the present article on cognitive load induced by visual (pictorial) materials.

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). There is a large body of research on the processes involved in the perception and comprehension of visual information (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 (Shah & Hoeffner, 2002; Winn, 1991). 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 (Guthrie, Weber, & Kimmerly, 1993; Hegarty & Just, 1993; Kosslyn, 1989; Leivie & Lentz, 1982; Mandl & Levin, 1989; Shah & Carpenter, 1995; Winn, 1991). Much less empirical research is available on the design of educational simulations.

Learning from Animations and Simulations

There has been significant interest in the use of simulations and animations in education. Initial research was concerned with the comparison
of the educational effectiveness of animations, that is, visualizations that change over time, to that of static visualizations (Höffler & Leutner, 2007). 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, 2008). 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 (Schnotz, 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 (Schnotz & Bannert, 2003).

In comparison to animations, which do not allow for significant user interactions, simulations can represent complex dynamic systems 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, that is, problem definition, hypothesis generation, experimentation, observation, and data interpretation (De Jong & Van Joolingen, 1998; Towne, 1995). Therefore, simulations have the potential to allow learners to understand scientific phenomena and transfer knowledge to novel situations better than other visual representations. In addition, while learners experience difficulties interpreting information from multiple representations such as text, pictures, and animation the dynamic visualizations of system behavior in simulations can assist learners in interpreting concurrent changes in variables by revealing the underlying computational model (De Jong, 1991; Van der Meij & De Jong, 2006).

Although there are advantages to using simulations, learning from interactive simulations can also impose high cognitive load because some learners may not possess the required knowledge, cognitive abilities, or metacognitive skills necessary to pursue scientific reasoning through simulations (De Jong & Van Joolingen, 1998). Even though the integration of information in a simulation can help learners understanding the dynamic relationship between variables and representations, cognitive resources are required to relate the multiple changes that occur simultaneously in the various representations within a simulation (Van der Meij & De Jong, 2006). The integration of multiple representations may therefore result in high cognitive load (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. 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).

In order to optimize the information design and interaction design of simulations, it is useful to identify design principles that are based on an understanding of how our cognitive architecture processes information. Several design factors for effective simulations for science learning have already been identified (Lee et al., 2006). For example, one line of research has investigated how learners can be supported to overcome the challenges imposed by the scientific reasoning processes (De Jong & Van Joolingen, 1998). In particular, this research focused on providing direct and timely access to domain knowledge (Elshout & Veenman, 1992; Leutner, 1993) and the activation of learner’s prior knowledge to assist the integration of experimental outcomes from simulation (Lewis,
Stern, & Linn, 1993). Research has also focused on methods of clearly communicating learning goals by providing different assignments (De Jong et al., 1994; Swaak, Van Joolingen, & De Jong, 1998). Research on metacognition in learning from simulations investigated the use of metacognitive scaffolds to support hypothesis generation (Quinn & Alessi, 1994; Shute & Glaser, 1990; Van Joolingen & De Jong, 1991), and how to provide metacognitive support to monitor learning and discovery processes (Gruber, Graf, Mandl, Renkl, & Stark, 1995; Njoo & De Jong, 1993).

Other research on design factors has examined questions related to the difficulty of the information presented, investigating, for example, the effect of the number of variables in the simulation model (Quinn & Alessi, 1994) and how learning is affected by the available level of control over variables (Rieber & Parmley, 1995). This line of research also showed that the interactivity afforded by simulations, especially the possibility to manipulate the content of the visualization by adjusting parameters, improved learning (Chandler, 2004; Hegarty, 2004; Plass, Homer, Milne, & Jordan, 2007; Rieber, 1990; Wouters, Tabbers, & Paas, 2007), and increased intrinsic motivation (Rieber, 1991).

In summary, research on learning from simulations has shown that the cognitive load imposed by the dynamic and often complex content and by the requirements of interacting with the simulation may pose significant challenges for learners. Several design factors have been identified to address this issue, especially related to the difficulty of the simulations and to the support of learners’ scientific inquiry and metacognition, and the impact of different levels of learner control and interactivity. Our research aims at identifying load-reducing design features that are related to the information design, or visual design, of simulations. In the present research, we focus on the question of how the type of representation of key concepts in a simulation affects cognitive and affective learning outcomes. We are also interested in the question of how learner characteristics may moderate the effects of representation type.

**Representation of Knowledge**

In science education, important information is often presented visually, for example, in charts, graphs, or diagrams, both among 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 most efficient for experts may be difficult to comprehend for novice learners. This suggests that the particular format of visual representations should be considered when designing materials for novice learners.

Schnotz distinguishes two types of representations for his *Integrative Theory of Text and Picture Comprehension*, namely descriptive and depictive representations (Schnotz & 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, and *symbols* (descriptive representations) are abstract, arbitrary and rely on social conventions for meaning.1 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. A learner’s developmental state affects how a sign is actually interpreted, with a true understanding of symbols not being possible until a certain level of knowledge has been acquired (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 more from the use of basic, iconic visual representations in simulations.
This research suggests that for novices in a particular domain, iconic visual representations may be more easily understood than symbolic representations, and therefore, icons should be incorporated into the design of visual materials for novice learners who possess low prior knowledge in the domain. Yet, what are the possible consequences of adding icons to a display that already represents the information in symbolic format, that is, as numbers and words? From a computational perspective of visual complexity, adding any visual elements to a visual display would lead to a more complex visual display. Because of this increased level of visual complexity, a higher amount of cognitive resources would be required to process this information. From an information design perspective, therefore, adding icons to the simulation would increase cognitive load and, in turn, reduce learning. Yet, from an information design perspective informed by a cognitive load approach, adding icons that represent key concepts in the simulation display (for example, depicting temperature as burners and pressure as weights, see Figure 2) should enhance learning, especially for students with low prior knowledge. From this perspective, adding icons provides learners with representations that they can better relate to their prior knowledge.

Our prior research provides preliminary findings on this issue. We have found that adding iconic representations of key information in a computer-based simulation was one of the design features that affected the cognitive load imposed by interacting with the simulation and improved learning outcomes (Lee, Plass, & Homer, 2006). This is consistent with previous research that showed a different effectiveness of written and pictorial instructions (Carlson, Chandler, & Sweller, 2003). 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. Research has also found that feedback in simulations is more effective when it is provided in graphical rather than textual form (Rieber, 1996; Rieber, Tzeng, & Tribble, 2004; Rieber et al., 1996).

**Learner Characteristics**

The cognitive load generated by processing visual representations depends not only on the design 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, that is, organized knowledge structures from long-term memory, can reduce working memory limitations by chunking several bits of related 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, 2006, 2007; 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; Schnitz, 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 load and allows for effective learning from more abstract, symbolic representations by tapping into relevant schematic representations already held in long-term memory.

The Present Studies

The studies presented here were conducted to investigate the impact of adding iconic representations of key information to a simulation of the kinetic theory of heat. These simulations were designed for high school chemistry with the goal of fostering students’ science learning as well as increase their science-related self-efficacy. Self-efficacy, that is, learners’ predictive judgment of their efficacy of performing a task (Bandura, 1986), relates to self-regulation (Zimmerman, 2000) and is a predictor of learning success (Pajares, 1996). We had found in our previous research that the RAPUNSEL game, which was developed to teach middle school students how to program, was able to improve students’ computer-related self-efficacy (Plass et al., 2007). We argue that RAPUNSEL was able to increase self-efficacy by allowing even low prior-knowledge learners to successfully program. In the current study, therefore, we proposed that the addition of icons would make the chemistry simulations more comprehensible for low prior-knowledge learners and therefore improve their self-efficacy.

For the current study, we were therefore interested in the effect of iconic representations on learning outcomes, both the comprehension of the principles of kinetic theory as well as the transfer of this knowledge to new situations. In addition, we were interested whether adding iconic representations would affect learners’ self-efficacy. Of particular interest was the interaction of design features and learner characteristics. The expertise reversal effect would predict that adding iconic representations to simulations would be effective only for novice learners and would become less effective as learners’ levels of expertise increased. Adding redundant, iconic representations can help novices learn by providing a context for interpreting the visual information. Therefore, we expected that adding iconic representations to symbolic information would improve learning for low-prior knowledge learners, but will have little or no effect on high-prior knowledge learners. We also included a measure of spatial ability into the design of the study in order to examine possible moderating effects of this learner variable. We hypothesized that icons would assist learners with low prior knowledge, as well as learners with low spatial ability.

STUDY 1

Participants and Design

The participants for this study (N = 80; 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). Participants were randomly assigned to one of two treatment conditions: One group received the simulation with symbolic representations only, that is, without icons (SYMB), the other group received the same simulations with added icons for key information (ICON), see Figures 1 and 2.

Materials

The computer-based instructional materials included two versions of a simulation of the kinetic theory of heat designed using Flash MX 2004 software (Macromedia, 2004), which was delivered on a Web page and viewed by learners on desktop PCs. The versions varied in their type of representation (symbolic versus iconic). In
Figure 1. Screen shot from the low-load kinetic theory simulation without chart, with symbolic representations

![Image](image1.png)

Figure 2. Screen shot from the low-load kinetic theory simulation without chart, with added iconic representations

![Image](image2.png)

the symbolic version of the simulation, essential information was presented in symbolic format (e.g., numbers were given to indicate pressure and temperature), while in the icon version, iconic representations were added to represent the same essential information. Figures 1 and 2 are screenshots from the kinetic theory of heat simulations with and without icons.

Independent variables included demographics and learners’ prior knowledge, spatial ability, and self-efficacy. The computer-based demographic questionnaire asked students
about their age, gender, ethnicity, and prior chemistry experience. The knowledge pre-test, also administered on the computer, consisted of eight items. Two short-answer questions tested general knowledge of situations that involve properties of gas, and six multiple-choice questions tested for knowledge of kinetic theory of heat. Learners received up to two points for each open-ended question and one point for each correct multiple-choice item. Two raters scored the short answers. When their scores differed, the raters resolved their disagreements through discussions of the merit of the response. Learners’ spatial ability was assessed using a paper-and-pencil version of the water-level task (Piaget & Inhelder, 1956), in which participants were shown six 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. Learners’ pre-treatment self-efficacy was assessed using a computer-based 11-item scale adapted from Jinks and Morgan (1999).

The dependent measures included a comprehension test, knowledge transfer test, and a test of learners’ self-efficacy. The comprehension post-test included 10-item, multiple-choice questions that tested learners’ understanding of the kinetic theory of heat. Learners received one point for each correct answer. The knowledge transfer post-test consisted of six open-ended items in which learners were asked to provide written explanations of different phenomena and real life applications of the kinetic theory. Learners received up to two points for their response to each question. Two scorers rated the written responses, using the method described previously for the knowledge pre-test. Learners’ post-treatment self-efficacy was assessed using the same measure as the pre-test.

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. Participants were first provided with an overview of the study, and all students consented to participate. They then completed the demographics questionnaire, knowledge pre-test, self-efficacy pre-test, and water level task. Participants were then randomly assigned to one of the two treatment conditions (i.e., iconic vs. symbolic) and spent approximately 20 minutes exploring the kinetic theory of heat using the computer simulation. Finally, participants completed the self-efficacy post-test, comprehension post-test, and transfer knowledge post-test. All students completed the procedure within a 50-minute class period.

Results

Table 1 shows the means and standard deviations for all three dependent measures by treatment group. Separate Analyses of Covariance (ANCOVA) were conducted for each of the two learning outcome measures (comprehension, transfer), with representation type as factor with two levels (SYMB, ICON) and prior knowledge and spatial ability as covariates. The analysis model included interactions between prior knowledge and representation type and spatial ability and representation type.

For comprehension, there was only a significant main effect of prior knowledge, $F(1, 74) = 20.48$, $MSE = 161.23$, $p < .001$, partial eta squared $\eta^2_p = .22$. Similarly, the only statistically significant finding for transfer was a main effect of prior knowledge, $F(1, 74) = 12.05$, $MSE = 31.72$, $p = .001$, $\eta^2_p = .14$. In other words, learners with higher prior knowledge comprehended the simulation better and were able to provide more answers to transfer questions than learners with low prior knowledge. Adding icons to the simulations did not have an impact on learning outcomes, and neither did learners’ spatial abilities.

Because neither prior knowledge nor spatial ability were expected to affect self-efficacy, an independent samples t-test was used to compare the changes of the self-efficacy scores for the two
treatment groups from the pre- to the post-test. Although the means were in the right direction (see Figure 3), no statistically significant difference in changes to self-efficacy as result of the use of the simulations was found between the two groups.

Discussion

The findings from this study did not support our hypotheses: The addition of iconic representations of key information in the simulation did not lead to an increase in either the comprehension of the principles of kinetic theory or the transfer of this knowledge to new situations. In addition, although the directions of the means of the changes to self-efficacy were as expected, with self-efficacy scores decreasing after use of the simulations without icons and self-efficacy scores increasing after use of the simulation with icons, these differences were not statistically significant.

What may have led to these findings? Previous research has shown that methods to reduce extraneous load were only necessary when the overall load of the learning task was high). Likewise, we only expect spatial ability to impact learning outcomes when the overall learning task is difficult (Plass et al., 2003). It is possible that the cognitive load experienced

<table>
<thead>
<tr>
<th></th>
<th>Knowledge Pre-Test</th>
<th>Comprehension Post Test</th>
<th>Transfer Post Test</th>
<th>Self-Efficacy Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Icon (N =38)</td>
<td>4.78 (1.60)</td>
<td>9.92 (3.42)</td>
<td>2.85 (1.71)</td>
<td>-.51 (4.02)</td>
</tr>
<tr>
<td>Icon (N = 42)</td>
<td>3.97 (1.50)</td>
<td>9.57 (3.01)</td>
<td>2.54 (1.82)</td>
<td>.42 (4.61)</td>
</tr>
</tbody>
</table>

Figure 3. Self-efficacy changes for low-load simulations by treatment group (iconic vs. symbolic)
by students during learning with this simulation was not very high. We therefore decided to increase the load induced by the learning activity by adding a second representation of the simulation content. This second representation was a chart, commonly found in simulations, which displayed the results of the learners’ explorations of the simulation on the right side concurrently with the changes to the simulation on the left. Prior research has shown that processing of multiple representations that were dynamically linked placed high demands on learners’ cognitive processing (Van der Meij & De Jong, 2006; Lee et al., 2006). Study 2 was a replication of Study 1 with these revised materials that induced higher cognitive load.

**STUDY 2**

**Participants and Design**

The participants for this study (N = 91; 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). Participants were randomly assigned to one of two treatment conditions: One group received the simulation with chart and with symbolic representations only, that is, without icons (SYMB), the other group received the same simulation with chart with added icons for key information (ICON), see Figures 4 and 5.

**Materials**

The computer-based instructional materials included the same two versions of a simulation of the kinetic theory of heat as in study 1, with the addition of a chart to the right of the simulation. The two versions varied in their type of representation (symbolic versus iconic).

Independent variables included the same demographic questionnaire and measures of learners’ prior knowledge, spatial ability, and self-efficacy as in study 1.

![Screen shot from the high-load kinetic theory simulation with chart, with symbolic representations](image)
The dependent measures included the same comprehension test, knowledge transfer test, and measure of learners’ self-efficacy as study 1.

Procedure

As in study 1, 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 used for this study was the same as in study 1, with the exception of the treatments, as described previously.

Results

Table 2 shows the means and standard deviations for all three dependent measures by group. Separate ANCOVA were conducted for each of the two learning outcome measures (comprehension, transfer), with representation type as factor with two levels (SYMB, ICON) and prior knowledge and spatial ability as covariates. The analysis model included interactions between prior knowledge and representation type and spatial ability and representation type.

For comprehension, there were significant main effects of representational type, $F(1, 85) = 5.91, MSE = 40.96, p < .05$, partial eta squared $\eta^2_p = .065$; of prior knowledge, $F(1, 85) = 5.17, MSE = 35.87, p < .05$, $\eta^2_p = .06$; and of spatial ability, $F(1, 85) = 7.52, MSE = 52.18, p < .01$, $\eta^2_p = .08$. A significant interaction was found for representational type and prior knowledge, $F(1, 85) = 5.03, MSE = 34.91, p < .05$, $\eta^2_p = .06$. The interaction of representational type and spatial ability failed to reach significance. Figure 6 illustrates the interaction of pre-test scores and treatment condition for the comprehension test. In both conditions, post-test comprehension scores increased with higher pre-test 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, $F(1, 85) = 10.82, MSE = 27.82, p = .001$, $\eta^2_p = .11$. The relatively low scores the students received on the transfer post-test, with an average score of...
Table 2. Mean (SD) scores for knowledge pre-test, comprehension and transfer post-tests, and change to self-efficacy (post-test minus pre-test) by simulation design condition, for high cognitive load simulation (with chart)

<table>
<thead>
<tr>
<th></th>
<th>Knowledge Pre-Test</th>
<th>Comprehension Post Test</th>
<th>Transfer Post Test</th>
<th>Self-Efficacy Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Icon (N = 45)</td>
<td>4.53 (1.52)</td>
<td>10.18 (2.87)</td>
<td>2.64 (1.51)</td>
<td>-.20 (2.17)</td>
</tr>
<tr>
<td>Icon (N = 46)</td>
<td>4.13 (1.42)</td>
<td>10.28 (2.97)</td>
<td>2.28 (1.87)</td>
<td>.93 (3.33)</td>
</tr>
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2.5 out of a maximum possible of 12, suggests that there may be a floor effect for transfer.

The comparison of the changes of the self-efficacy scores of the two treatment groups from pre- to post-test showed that self-efficacy increased for learners using the simulations with icons, and decreased for learners who received the simulation without icons, see Figure 7. These differences are statistically significant, t(87) = -1.90, p < .05 (one-tailed), d = .40, which is considered a medium to small effect.

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 representation 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 the comprehension test results showed that adding icons increased learning for all learners, independent of their prior knowledge or spatial ability. The interaction of prior knowledge and representation type indicates that learners with low prior knowledge
especially benefited from the simulation with added icons. Learners with high prior knowledge still benefited, but less so than those with low prior knowledge, which is in line with our predictions.

The analysis also revealed that learners with high spatial ability overall comprehended the simulation better than learners with low spatial ability, which is in line with prior research on the effect of spatial ability on multimedia learning (Plass & Kalyuga, in press). These patterns were not replicated for the transfer test, but the low mean scores on this test suggest a floor effect.

GENERAL DISCUSSION

What makes computer animations and simulations effective instructional formats for learning science? Our research suggests that design factors such as the type of representation of key concepts in the simulation affect the effectiveness of computer simulations when cognitive load is high, and that individual difference variables such as prior knowledge moderate these effects.

The results from the simulations with higher cognitive load, which included a chart with the data points obtained in the simulation, show that adding iconic representations resulted in an overall improvement of comprehension of the content of the simulation. In addition, we found that especially learners with low prior knowledge benefited from the added icons, whereas learners with high prior knowledge benefited less from icons or may even have found them distracting. This is in line with the expertise reversal effect, which has been observed under a variety of conditions, and which states that materials that are effective for novice learners are often not effective for learners with high prior knowledge, and vice versa. Translated to our study, learners with low prior knowledge comprehended the kinetic theory of heat better when learning from a simulation with icons.
added. This effect is much smaller for learners with higher prior knowledge. We should note that since none of the learners had studied the topic of kinetic theory of heat before, even high prior knowledge learners in this study were far from being experts on the topic. We therefore did not see a complete reversal of the effectiveness of the two simulations, which one might expect if this study were replicated, for example, with chemistry majors in a college setting.

Perhaps even more interesting than the results for learning outcomes are our findings for the changes learners’ perceived self-efficacy. Adding icons to the simulation not only increased learners’ comprehension of the chemistry concepts, but also improved their perception of their own ability to learn. In contrast, simulations without icons, representing information only symbolically, resulted in a reduced perception of learning ability. The type of information representation in this simulation affected learners’ self-assessment of their ability to learn chemistry, specifically, icons appear to have improved the learnability of the materials.

This research has important implications for simulation design as well as for theory development. For simulation design, this research provides suggestions on 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 comprehension. It is important to note that due to the nature of the materials, the exposure time to the simulations was with approximately 20 minutes relatively short. It is intriguing that despite this very short treatment time, and despite the relatively small change in the treatments, consisting only of the addition of icons, improvements of comprehension as well as learners’ self-efficacy were found for students who received simulations with icons compared to the students who learned from simulations without icons.

On the theoretical side, our research shows that comprehension was improved when iconic representations of key information were 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 in order 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.

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 also need to be replicated in both the more controlled setting of a laboratory and in authentic educational settings. Further work should also look at how icons influence learning with simulations over longer durations (e.g., over time in an actual chemistry class). In addition, research should examine the effects of exposure to a series of related simulations and should include measures of cognitive load other than learning outcomes.

In summary, the findings from the two studies presented here further support the idea that icons can facilitate learning and increase self-efficacy in visual learning environments, particularly for low prior knowledge learners, and especially under high cognitive load conditions. This provides an example of a design principle for effective simulations for science learning, which suggests that the design of simulations must take into account the representation type used for key concepts of the content.
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REFERENCES


**ENDNOTE**

1 Peirce (1955) identified indices, which obtain meaning from temporal or spatial proximity to their referent, as a third type of sign. We did not include them in the review, as they did not apply to our research.

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