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Learning from multiple representations: An examination of fixation patterns in a science simulation

Paul A. O'Keefe [a,b,*], Susan M. Letourneau [a,b,1], Bruce D. Homer [b], Ruth N. Schwartz [a,2], Jan L. Plass [a,*]

[a] *Department of Administration, Leadership, and Technology, New York University, United States*
[b] *The Program in Educational Psychology, CUNY Graduate Center, United States*

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ABSTRACT

The present study examined how the integration of multiple representations in a multimedia simulation was associated with learning in high school students ($N = 25$). Using eye-tracking technology, we recorded fixations on different representations of the Ideal Gas Laws, as well as transitions between them, within a computer-based model that included a gas container with animated gas molecules, control sliders to adjust different gas variables, and a graph depicting the relations between the variables. As predicted, fixation transitions between conceptually related parts of the simulation were associated with different learning outcomes. Specifically, greater transition frequency between the gas container and the graph was related to better transfer, but not comprehension. In contrast, greater transition frequency between the control sliders and the graph was related to better comprehension, but not transfer. Furthermore, these learning outcomes were independent of learners' prior knowledge, as well as the frequency and duration of fixations on any individual simulation element. This research not only demonstrates the importance of employing multiple representations in multimedia learning environments, but also suggests that making conceptual connections between specific elements of those representations can have an association with the level at which the information is learned.

1. Introduction

How do learners construct knowledge from a computer-based high school chemistry simulation with multiple representations of key information? In particular, how do the different representations in a simulation contribute to learning, and how do learners integrate these representations to construct knowledge? Answers to these questions are of significance to the design of related learning environments, such as simulations and games, and have the potential to improve instruction and learning of scientific topics as well as advance the development of theoretical models of learning with multiple representations. Our first question is concerned with determining which components of science simulations are associated with student learning, and focuses on different modes of representing information in a visual explanatory model and a corresponding graph. Our second question is concerned with the issue of how learners integrate multiple representations while engaging in a science simulation and how that integration relates to different types of learning. To address these questions, we examined fixation patterns across multiple representations in a chemistry simulation and their relation to measures of learning.

The main goal of this study was to begin investigating specific aspects of the process by which learners construct knowledge when presented with learning environments that include multiple representations of complex subject matter. We aimed to extend research on learning from multiple representations, which has been primarily concerned with learning outcomes, by also focusing on the process of connecting multiple representations. In our study, high school students explored a simulation about the Ideal Gas Laws that contained multiple representations of key information (see Fig. 1). One representation was an explanatory model based on the Kinetic Molecular Theory of Matter. The representation depicted a container with moving gas molecules (depicted as spherical particles), and included control sliders that learners used to manipulate values of three variables: the pressure of the gas, the temperature of the gas, and the volume of the container. The other

* Corresponding authors. Present address: Department of Psychology, Jordan Hall, Building 420, 450 Serra Mall, Stanford University, Stanford, CA 94305, United States. Tel.: +1 9192592270 (P.A. O'Keefe). Address: CREATE Lab, 196 Mercer St., Suite 800, Steinhardt School of Culture, Education, and Human Development, New York University, New York, NY 10012, United States (J.L. Plass).

E-mail addresses: paul.okeefe@stanford.edu (P.A. O'Keefe), jan.plass@nyu.edu (J.L. Plass).

[1] Present address: Department of Cognitive, Linguistic, and Psychological Sciences, Brown University, United States.

[2] Present address: School of Education, Quinnipiac University, United States.

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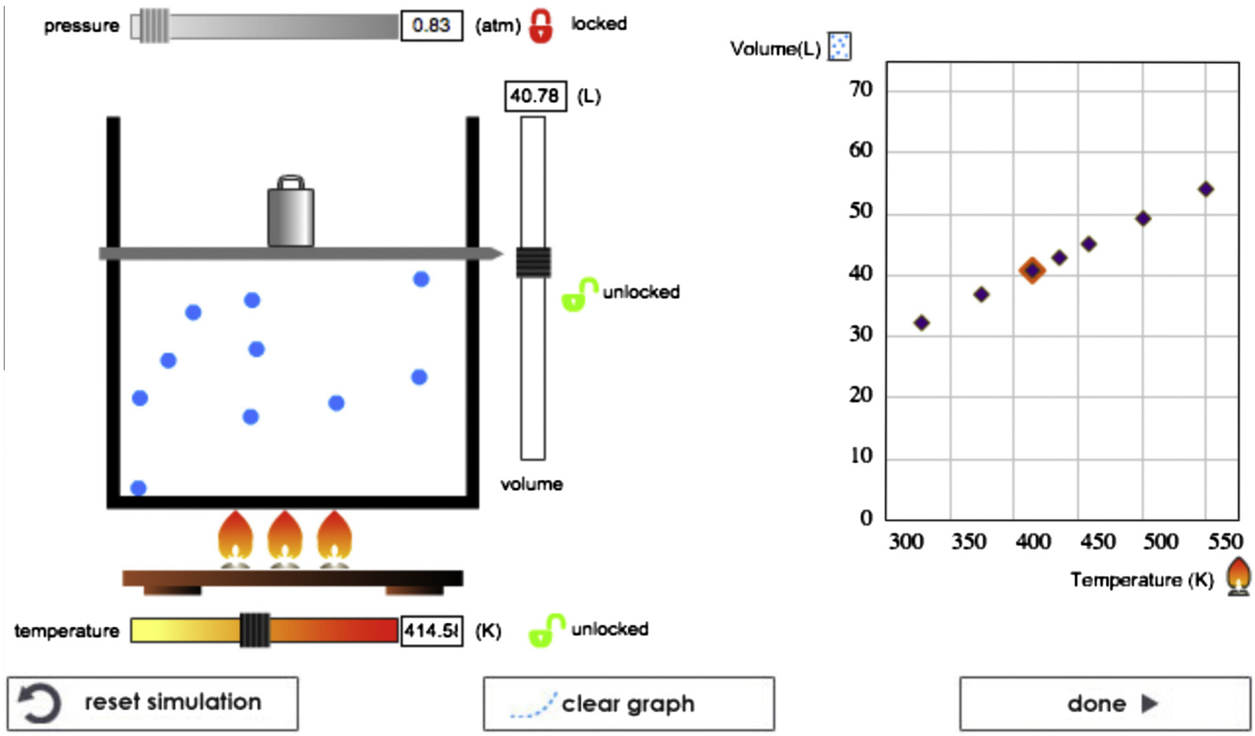

Fig. 1. Interactive model of the Ideal Gas Laws (left) with graphical representation (right).

representation, a graph, was a symbolic representation of the systematic relations between the variables that used a diagram to display all data points generated by the user's manipulation of the simulation. Using eye-tracking technology, we examined the frequency of fixation transitions between conceptually related elements of the simulation. Furthermore, we measured learning in two ways, using separate tests for comprehension (i.e., were learners able to connect key concepts from the simulation?) and knowledge transfer (i.e., can learners apply knowledge to novel situations?).

In this paper, we first describe the exploratory simulation environment used for the present research. We then review extant research on learning with multiple representations and outline the theoretical framework for the present work, which consists of elements from the Cognitive Theory of Multimedia Learning (CTML) (Mayer, 2005; Moreno & Mayer, 2007), the DeFT framework for learning with multiple representations (Ainsworth, 1999), as well as some elements related to cognitive load (Plass, Moreno, & Brünken, 2010; Sweller, 1988), from which we will derive the hypotheses for our research. Finally, we will detail the design of the present study.

2. An exploratory simulation environment for learning high school chemistry

The simulation used for the present research was designed for high school science students (see Fig. 1). It presents a model of the Ideal Gas Laws, which describe how pressure, volume, and temperature predict the behavior of gases for which all collisions between particles (i.e., atoms or molecules) are perfectly elastic and in which there are no attractive forces between them; that is, an ideal gas.

The left panel of the simulation consists of a container with moving gas particles as well as corresponding sliders that allow users to adjust the three variables: pressure, volume, and temperature. Taken together, these visual elements, the simulation engine, and associated variables constitute an explanatory model for the Ideal Gas Laws (Plass et al., 2012). For example, a student might hypothesize that an increase in gas temperature would result in higher pressure of the gas when the volume is kept constant. When the student modifies the temperature to test this hypothesis, the simulation responds by showing the impact of this temperature increase on the pressure of the gas. The increase in temperature is shown through the position of the slider and the numeric value for temperature on the slider, and through the increase of the number of Bunsen burner icons below the gas container. Higher temperature also leads to faster movement of the particles in the container. The corresponding increase in pressure is shown through the position of the pressure slider and the value for pressure on the slider, and through the increase of the number of weights on top of the gas container, and the student would be able to observe this change and compare it with his or her hypothesis.

The right panel of the simulation shows a graph that displays all data points generated by the users when they manipulate the variables of the simulation. The graph constitutes a symbolic representation of the systematic relations between pairs of the variables (Bertin, 1983). Each time the learner modifies a variable by moving the slider in the simulation, the corresponding value pair is added to the graph. Students were asked to explore the relations among pressure, volume, and temperature of an ideal gas by manipulating two of the variables of the simulation at a time, while keeping the third variable constant.

The design of the simulations and the instructions for learners that accompany them are the result of an extensive program of research in which we have investigated cognitive load effects of different simulation designs (Lee, Plass, & Homer, 2006), studied the effects of the icons used to represent pressure and temperature (Homer & Plass, 2010; Plass et al., 2009), and verified the efficacy of the simulations in the high school classroom (Plass et al., 2012). We will next describe the theoretical foundation for the simulation design and the present research.

3. Learning from multiple representations of dynamic content

3.1. Function and benefits of multiple representations for learning

The argument for the use of multiple types of representations is based on findings showing that learning is facilitated when information is available in more than one format (Mayer, 2001; Moreno & Durán, 2004; Paivio, 1986; Schnotz, 2005; Schnotz & Bannert, 2003). There has been strong interest in using multiple representations in science and math education in particular (Cheng, 1999; Carpenter & Shah, 1998; Harrison & Treagust, 2000; Kozma, 2000; Kozma & Russell, 1996; Schank & Kozma, 2002; Wu, Krajcik, & Soloway, 2001; Wu & Shah, 2004; Yerushalmy, 1991). In these contexts, integrating individual pieces of information across multiple representations can allow learners to understand complex scientific processes more deeply (i.e., deepending their comprehension) and to apply their knowledge to new situations (i.e., facilitating knowledge transfer) (Mayer, 1999), because each representation provides a unique and different view (Spiro, Feltovich, Jacobson, & Coulson, 1992).

The specific benefits of using multiple representations depend on the function of the representations, which Ainsworth and colleagues (Ainsworth, 1999; Ainsworth & Van Labeke, 2001, 2004) summarized in the Design, Functions, Tasks (DeFT) framework. The DeFT framework describes the design parameters unique to learning with multiple representations, the pedagogical functions that these multiple representations can play, and the tasks in which learners must engage when processing multiple representations.

One function of multiple representations is that they can be complementary—for example, providing complementary information or facilitating complementary processing—due to the different representational and computational efficiencies they support (Ainsworth & Van Labeke, 2004; Larkin & Simon, 1987). In the case of our simulation, the multiple representations used to illustrate chemical and physical processes that are otherwise invisible to the naked eye have such a complementary function. The visual simulation model is designed to provide a pictorial representation of the relations among variables that learners can manipulate: the pressure, volume, and temperature of an ideal gas. This visual model serves two different functions in the learning process. The sliders with numeric (symbolic) values of each gas property aim to facilitate a quantitative understanding of the exact changes to one variable as a result of manipulating the other. By highlighting the relations among different properties of the gas, this representation is designed to support the comprehension of the subject matter. The container with gas particles and icons (weights and burners), on the other hand, provides an iconic representation of the simulation content that aims to give learners a more qualitative understanding of the relations among the simulation variables. This representation is designed to support the development of memory structures that enable learners to transfer their knowledge to other situations (Plass et al., 2009).

Complementing the visual model is the graph, which shows all data points collected by the learner. These points are automatically plotted as learners interact with the simulation. The graph, therefore, reduces cognitive demands by providing a memory aid that displays key information that is no longer available in the visual model. Here, learners benefit from the perceptual advantages of diagrams, which support the processes of visual search and recognition by grouping related information (Larkin & Simon, 1987; Tufte, 1990).

Another function of multiple representations is that they can support the process of deep knowledge construction when learners integrate information across representations and construct dynamic mental models (Hegarty, 1992; Schank & Kozma, 2002). In particular, our simulation was designed to support knowledge construction through the process of abstraction. The exploration of real-life phenomena by manipulating input parameters of the visual model and inspecting the resulting output allows the learner to investigate relations between pairs of variables, supporting comprehension of these relations and the later transfer of that knowledge. This process is supported by the graph, which plots multiple data points taken by the student and integrates them into a visualization of the relations between each pair of variables in the Ideal Gas Laws. This allows learners to abstract from these individual data points to generalize the relation between the respective variables (pressure, volume, and temperature).

3.2. Learning from dynamic multiple representations

The cognitive processes involved in learning from a simulation with multiple representations are described by the Cognitive Theory of Multimedia Learning (CTML; Mayer, 2001). Based on the dual channel assumption of Dual Coding Theory (DCT; Paivio, 1986), CTML describes how multimedia information is processed in separate channels for visual and verbal information. Learning is considered a generative process in which learners select relevant visual and verbal materials, organize these visual and verbal representations into coherent structures in working memory, and integrate the visual and verbal representations with one another and with prior knowledge (Mayer, 2005). The outcomes of these processes are frequently assessed using measures of comprehension and of knowledge transfer (Plass, Homer, & Hayward, 2009; Plass & Schwartz, 2014; Mayer, 2005). Specific elements in a multimedia simulation can support these learning processes. For example, sliders with numeric (symbolic) values of each gas property in our simulation allow learners to organize information in working memory, and as a result, they support the comprehension of the material. The container with gas particles and icons (weights and burners) provides an iconic representation of the simulation content, and as a result, it facilitates the integration of the different representations, which supports the construction of mental models that allow for knowledge transfer. However, research has shown that many learners are not able to integrate multiple representations effectively (van Someren, Reimann, Boshuizen, & de Jong, 1998). This is especially true of those with low levels of prior knowledge (Kozma & Russell, 1996; Seufert & Brünken, 2004; Yerushalmy, 1991). These studies suggest that learners may vary greatly in their ability to attend to and integrate multiple sources of information.

The causes for these differences between learners are described by Cognitive Load Theory (CLT), a capacity model of multimedia learning (Plass et al., 2010; Sweller, 1988), which has been integrated into CTML. CTML distinguishes *essential processing*, which refers to mental effort invested by the learner in processing materials that are essential for learning, and *non-essential processing*, which refers to mental effort invested in processing materials that are not essential for the learning task (Mayer, 2005), and which are a result of the instructional design of the materials (Kalyuga, 2010).

Applying CTML to learning from multiple representations, learners first have to form an understanding of the syntax of the representations (i.e., the format and operators used to represent information; van der Meij & de Jong, 2006). In the case of our simulation, this involves understanding the function of the sliders, the meaning of icons, and the format of the graph. The next step is to understand which parts of the domain are represented. In our simulations, learners have to comprehend how pressure, volume, and temperature are visualized in the simulation model and represented on the axes of the graph. Next, learners have to relate the representations to one another and integrate them in order to construct a coherent mental model of the subject matter (Lee et al., 2006; Schnotz & Bannert, 1999; Seufert, 2003). In our simulation, this involves linking the visual explanatory simulation model and the graph. Finally, learners have to translate between the representations; that is, they have to identify similarities and differences among related elements of the representations (van der Meij & de Jong, 2006). In the case of our simulation, this involves relating a change made to a gas property, such as an increase in temperature, to the corresponding change in the graph. The simulation dynamically links related elements of the representations, such that a change in one representation dynamically affects the other representation; this dynamic connection has been shown to facilitate learning (van der Meij & de Jong, 2006).

Despite these benefits, a primary concern in learning from multiple representations is the non-essential processing of extraneous information that such learning environments may require. For example, information processing in visualizations often involves re-inspection of parts of the display (Carpenter & Shah, 1998; Hegarty, 1992); yet in dynamic visualizations, information presented at an earlier time is not available for re-inspection at a later time, increasing non-essential processing requirements and reducing the utility of the visualization as an external memory aid (Hegarty, 2004). In addition, adding representations such as diagrams to a visual simulation model may introduce a split-attention effect when the two representations are spatially separated rather than integrated, which can increase non-essential processing demands (Chandler & Sweller, 1991; Mayer, 1997, 2001; Tarmizi & Sweller, 1988). Finally, in the case of computer simulations, controls allow the learner to manipulate input parameters, inspect the response of the simulation, compare this outcome with the response they predicted based on their mental model, and then either confirm or correct their model if necessary. However, operating the interactive features of the simulations, and engaging in the deep processing required to form and test hypotheses about the simulation model, places additional demands on working memory (Hegarty, 2004). Therefore, learning from multiple representations places demands on working memory and creates challenges for learners (van Someren et al., 1998), especially those with low prior knowledge (Kozma & Russell, 1997; Yerushalmy, 1991), and these challenges can cause students to interact with simulations in a random rather than a systematic fashion (de Jong & van Joolingen, 1998).

Although some researchers argue that learning is facilitated when two representations are integrated with one another (Chandler & Sweller, 1991; Tarmizi & Sweller, 1988), such an integration of representations is not always possible, depending on the nature of the learning materials or specific learning goals. In fact, some studies found benefits in spatially separating the representations. For example, in a study with high school science students, Gutwill, Frederiksen, and White (1999) found that those who had to construct their own connections between different models of electricity that were not integrated with one another performed better on a battery of post-tests than students who received support in making these connections.

The present study, therefore, asks whether the mental effort expended by learners to integrate multiple representations in a simulation is indeed non-essential processing, which would result in reduced learning, or whether it is essential processing, resulting in increased learning. We operationalize this mental effort as the frequency of fixation transitions between different representations of the content of the simulation, as suggested by the DeFT framework (Ainsworth & Van Labeke, 2004). We ask whether these fixation transitions relate to learning outcomes; that is, whether the effort required to connect different representations enhances learning and should therefore be considered essential processing, or whether it represents non-essential processing that detracts from learning. This is a significant question, as essential processing supports mental model construction and enhances learning (as suggested by Gutwill, Frederiksen, & White, 1999).

3.3. The present study

In the present study, we examined fixation patterns between conceptually related representations in a chemistry simulation and their association with different levels of learning: comprehension and knowledge transfer. We expected that fixation transitions would be associated with learning because they suggest that users integrated multiple representations, each of which contained unique and vital information that together explained a phenomenon. Therefore, learning should be associated with fixation transitions and not with fixations on any individual representation.

To this end, we used eye-tracking methodology to record fixation patterns while students used the simulation. Fixation transitions between each of the key representations were recorded, as well as the frequency and duration of fixations on each individual representation. Although there is not always a direct one-to-one correspondence between the location of fixations and the location of attention (Posner, 1980), eye movements typically involve simultaneous shifts in selective attention (Hoffman & Subramaniam, 1995; Shepherd, Findlay, & Hockey, 1986). The frequency and duration of fixations on different elements of a dynamic simulation can therefore provide a measure of the location of learners' attention. Likewise, fixation transitions between these elements can provide valuable information about shifts in attention across visual space. Therefore, by recording fixation patterns while students used a chemistry simulation, we could obtain a quantitative measurement of students' shifts in attention among various elements within a dynamic multimedia environment.

We first examined the relation between fixations on individual simulation elements and learning outcomes. In particular, we examined the total fixation time and total number of fixations on key areas of the simulation, namely the gas container, control sliders, and the graph (i.e., the graph area and its axes). We predicted that the frequency and duration of fixations on these individual simulation elements would not be uniquely related to learning outcomes. Rather, we expected that learning outcomes would be related to the tendency to connect those elements through fixation transitions. To test this hypothesis, we examined fixation transitions between conceptually related parts of the simulation. We predicted that frequent fixation transitions between related representations in the simulation would have a positive relation with learning outcomes. Such transitions would reflect learners' integration of multiple representations of the simulation content.

With this in mind, we identified two types of fixation transitions. The first transitions were between the control sliders and the graph. The control sliders contain quantitative information about the individual variables involved in the Ideal Gas Laws, and transitions connecting them to the graph allow learners to understand how those values and the relations between the variables are represented in graphical form. Furthermore, because the value of each variable can be manipulated, the learner is able to connect those manipulations to changes in the graph. The second transitions were between the gas container and the graph. The gas container is filled with molecules that behave differently depending on the relations between the variables; thus making it a qualitative representation. Transitions between the container and the graph allow learners to understand how the behavior of gas molecules is graphically represented under different conditions. We were particularly interested in transitions involving the graph because our instructions to participants required them to plot several points on the graph; therefore, they had good reason to transition between the graph and other elements in the simulation.

We also predicted that different types of transitions would be associated with different learning outcomes. Because transitions between the control sliders and the graph connect quantitative representations of individual variables in the simulation, we predicted that these transitions would be especially related to *comprehension* (i.e., the extent to which learners understand individual concepts within the simulation environment). In contrast, because transitions between the gas container and the graph connect more qualitative depictions of the behavior of gas particles under different conditions, we expected that these transitions would be related to *transfer* (i.e., the extent to which knowledge can be applied to novel situations).

4. Method

4.1. Participants

Twenty-six students (14 females) enrolled in a chemistry course in three New York City public high schools participated as part of class field trips to a university in New York City. Participants' ages ranged from 16 to 20 ($M = 17.52$, $SD = .90$). As part of each class trip to the laboratory, all students were provided with lunch and were given a tour of the university; no specific incentive was offered in exchange for participation. Assent forms for participating students and consent forms for their parents or guardians were provided prior to each field trip and collected at the time of the visit. Background information forms were also distributed to students and their guardians. One participant scored unrepresentatively high on the pre-test (above 3 *SD*) and was consequently omitted from the analyses. Furthermore, no statistically significant sex or school differences were found for any of the variables tested in the present study, and therefore, these characteristics will not be discussed further.

4.2. Procedure

Upon arrival to the laboratory, participants were randomly assigned unique identification numbers and began the experiment, one at a time, in sequential order. Each participant first entered a computer lab and was seated at a computer where he or she logged in with the assigned identification number and worked individually to complete a chemistry pre-test. Subsequently, the participant was escorted to a separate room for the eye-tracking portion of the experiment. Each participant was seated approximately 28 inches (71.12 cm) from the stimulus monitor and eye-tracking cameras, and completed a 5-point calibration to ensure accurate readings. The gaze position accuracy for eye-tracking recordings was within 0.4° visual angle following the calibration procedure.

Participants first read a short narrative on the computer screen, designed to introduce the concepts associated with the simulation in a familiar context. The narrative involved a bicycle tire that became flat when exposed to cooler weather, which introduced participants to an everyday application of the Ideal Gas Laws. Next, participants read a short set of instructions for using the simulation itself. The instructions explained how to manipulate each variable using the control sliders and how to select a pair of variables to test, while the third would be held constant. It also explained that new data points would be dynamically added to the graph with every manipulation of the variables. The instructions ensured that participants began with the same level of knowledge regarding the functionality of the simulation, allowing them to engage with it immediately. The experimenter then instructed participants to graph at least five data points while using the simulation, after which the participant worked with the simulation for five minutes. During this time, participants engaged with the simulation in an unstructured manner and the experimenter was present to answer any questions. At the end of the 5-min period, each participant was asked to stop working and was escorted back to the original room to complete a chemistry post-test, which included tests of comprehension and transfer.

4.3. Materials and apparatus

Ideal gas laws simulation. The simulation used was one in a series of interactive multimedia simulations designed to facilitate high school chemistry students' understanding of complex chemistry concepts. This particular simulation, developed using Macromedia Flash MX 2004, visualizes the interrelations of the temperature, pressure, and volume of an ideal gas. The body of the simulation displays a representation of a container with gas particles; control sliders that allow the participant to independently manipulate the pressure, volume, and temperature of the gas; and a graph (see Fig. 1). As the user interacts with the simulation by adjusting the variables, the display updates dynamically. For example, when a user raises the temperature, the representations of particles move more quickly. Simultaneously, the data point generated by changing this value is entered on the associated graph to the right of the simulation.

Eye-tracking data acquisition and analysis. Eye fixations and transitions were recorded using a SensoMotoric Instruments (SMI) RED eye-tracking system at a 60 Hz sampling rate. The sessions were run using SMI's proprietary software, Experiment Center, and fixation data were processed using BeGaze2. A fixation was defined as gaze resting in one location on the display (with a spatial resolution of 0.03° visual angle) for 100 ms or longer.

In preparation for data analysis, several areas of interest (AOI) were defined on the simulation screen (see Fig. 2). These AOIs included the portions of the screen occupied by the gas container, graph, and control sliders for volume, pressure, and temperature. These parts of the simulation were stationary, although some contained smaller moving parts (e.g., the particles within the container). Using these AOIs, three types of fixation statistics were calculated for each participant: the total fixation time on each AOI, the total number of fixations on each AOI, and the total number of fixation transitions between the relevant pairs of AOIs. A fixation transition was defined as an immediate shift in fixation from one AOI to another.

4.4. Measures

Pre-test. The test of prior knowledge included eight multiple-choice items designed to assess students' understanding of the relations among pressure, temperature, volume and the behavior of gas particles (e.g., "If the temperature is held constant, what happens to the pressure of a gas sample if the volume of its container is decreased?"). Questions were designed to conform to the New York State core curriculum on chemistry and were reviewed in advance by subject matter experts in chemistry and in high school chemistry instruction. Scores were calculated by summing the total number of correct responses for each participant (see Table 1).

Post-test. The post-test included 29 items designed to measure comprehension and transfer. Twenty-five multiple-choice items, similar to the pre-test items, were designed to assess students' comprehension of the material directly presented in the simulation—the relations among the behavior of gas molecules and the pressure, temperature, and volume within the container. For example, one comprehension question asked, "If pressure remains

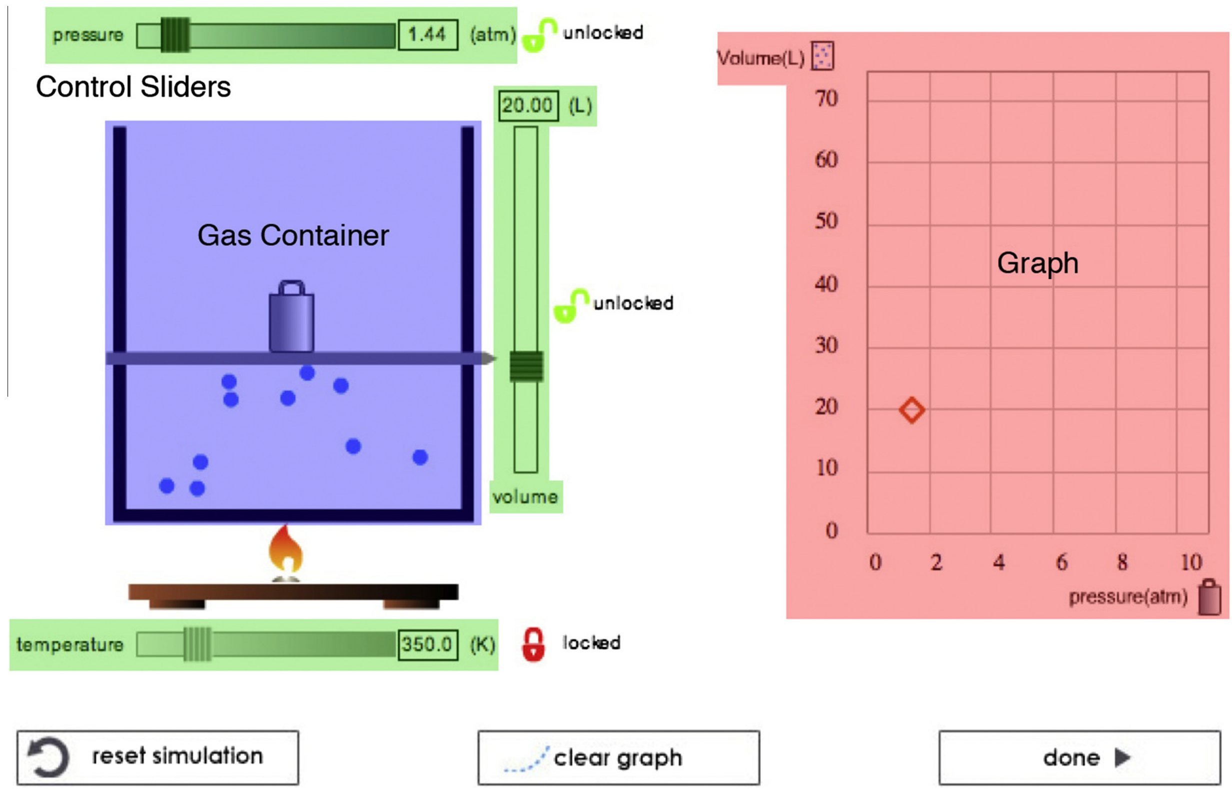

Fig. 2. Areas of interest (AOIs) defined for eye-tracking analyses.

Table 1
Descriptive statistics for dependent and independent variables.

	M	*SD*
Pre-test	2.92	1.29
Post-test comprehension	13.80	5.30
Post-test transfer	3.74	3.23
Container fixation frequency per pixel	.0032	.0015
Control sliders fixation frequency per pixel	.0048	.0017
Graph fixation frequency per pixel	.0020	.0010
Control Sliders Fixations	129.00	44.01
Container Fixations	133.24	60.68
Graph Fixations	133.40	68.76
Container dwell time per pixel (ms)	1.44	.78
Control sliders dwell time per pixel (ms)	2.51	1.17
Graph dwell time per pixel (ms)	1.08	.65
Container-graph transitions frequency	35.88	18.33
Control sliders-graph transitions frequency	39.60	22.01

constant, what happens to the volume of a gas sample when its temperature is decreased?'' Comprehension scores were calculated by summing the total number of correct responses (see Table 1).

Four additional items probed students' ability to transfer their understanding of the gas laws to novel problems. These items required students to type extended responses rather than choose an answer from a list. For example, one transfer question posed the following problem: ''On a very hot day, your friend realizes that he has left an aerosol can in his car. It was exposed to the sun, and it is now very hot. Describe as many ways as you can think of to keep the can from exploding. Explain your answers using the gas laws.'' Students were provided with space to enter a response about what they would do and how they would support this solution based on what they learned in the simulation. Transfer items were scored using a common rubric. For each transfer question, students received one point for choosing a correct prediction or action, one point for explaining their answer with respect to the Ideal Gas Laws, and one point for providing supporting evidence based on what they observed in the simulation. Transfer scores were calculated by summing the number of points participants earned across all four questions (see Table 1).

5. Results

Two sets of analyses were conducted. Preliminary analyses were conducted to determine whether the duration or frequency of fixations on individual representations had any impact on learning. Our main hypotheses, however, concerned the conceptual connections made by learners transitioning from one representation to another, rather than the frequency or duration with which learners focused their attention on any one representation. Therefore, we examined the fixation transitions between key representations hypothesized to contribute to learning.

Pre-test scores were included as a covariate in all analyses for two reasons. Statistically, it allows for an examination of the relations between each variable and the two learning outcomes regardless of participants' prior knowledge. Practically, however, computer-based simulations, such as the one employed in this study, should require little to no prior knowledge. Users should be able to effectively engage with the simulation and learn from that engagement without having prior experience with the content. Therefore, statistically controlling for variations in pre-test scores allows us to address both of these issues.

5.1. Preliminary analyses: frequency and duration of fixations on individual AOIs

Our first set of analyses examined whether the overall frequency or duration of fixations on any individual AOI were related to post-test scores. Because fixations might fall on large AOIs more often or for longer durations than small AOIs, we controlled for differences in size by dividing the total fixation time and total number of fixations by the surface area of each AOI in pixels. In the first set of analyses, comprehension and transfer post-test scores were individually regressed onto the total fixation time per pixel for each of the three AOIs (i.e., gas container, graph, and control sliders) with pre-test scores included as a covariate. In the second set of analyses, comprehension and transfer post-test scores were individually regressed onto the total number of fixations per pixel for each of the three AOIs with pre-test scores included as a covariate.

As predicted, none of the twelve analyses were significant. In fact, none of the models themselves were significant. The results supported our initial hypothesis that neither the amount of time nor the number of fixations on any individual representation would predict learning outcomes. We expected that the information contained within each representation would not be sufficient for increasing comprehension or transfer. Instead, we expected that the conceptual integration of multiple representations through fixation transitions would be beneficial for learning; a question we address in the following analyses.

5.2. Fixation transitions

We conducted a series of analyses to examine whether fixation transitions between key simulation elements predicted comprehension and transfer. Specifically, fixation transitions in either direction between the gas container and the graph, and between the control sliders and the graph were included in the analyses. These transitions were chosen because they both connect the two representations depicted in the simulation (the pictorial representation of the animated gas particles and the variables that students could manipulate, and the graphical representation of the relations between these same variables), but link different, conceptually related elements of those representations. Furthermore, both transitions included the graph because participants were instructed to plot several points during their interaction with the simulation.

The first set of analyses examined the effect of transitions between the control sliders and the graph on post-test comprehension and transfer. In two separate analyses, comprehension and transfer scores were regressed onto the number of slider-graph transitions, controlling for pre-test scores. As predicted, there was a significant effect for comprehension ($\beta = .41$, $t(22) = 2.12$, $p = .046$), but not for transfer (the omnibus test was also nonsignificant). Pre-test scores were also nonsignificant in both models. These results suggest that a greater frequency of transitions between the control sliders and the graph was associated with better comprehension of the Ideal Gas Laws. In the second two models, comprehension and transfer scores were regressed onto transitions between the gas container and the graph, controlling for pre-test scores. These analyses yielded a significant effect for transfer ($\beta = .48$, $t(22) = 2.66$, $p = .01$), but not comprehension (the omnibus test was also nonsignificant). Pre-test scores in both models were also nonsignificant. These results suggest that a greater frequency of transitions between the gas container and the graph was associated with an increased ability to transfer knowledge about the Ideal Gas Laws.

Together, these results supported our hypothesis that fixation transitions between conceptually related elements of the simulation would be associated with particular learning outcomes. Specifically, transitions between the control sliders and the graph were associated with better comprehension but not transfer, while transitions between the gas container and the graph were associated with better transfer but not comprehension. Importantly, there was no significant correlation between the two types of visual transitions ($r(25) = .31$, $p = .14$; see Table 2). A significant negative correlation would have suggested that one type of fixation transition came at the cost of the other; however, no such relation was found. Furthermore, pre-test scores were not correlated with either type of transition (sliders-graph transitions: $r(25) = -.24$, $p = .26$; container-graph transitions: $r(25) = -.13$, $p = .53$), suggesting that prior knowledge was not associated with learners' attempts to conceptually connect particular pairs of representations. This was also evidenced by their nonsignificance as covariates in the regression analyses.

6. Discussion

In the present study, our goal was to gain a greater understanding of how learners integrate multiple representations in a computer-based simulation environment, and whether attention to specific elements of the simulation, or visual transitions between them, would be related to higher essential processing that leads to comprehension and knowledge transfer. To that end, we examined fixations on and transitions between related representations within a computer simulation, and their relation to learning outcomes.

Our data supported the hypothesis that the frequency with which students transitioned their fixations between multiple representations would be related to their levels of learning of chemistry content. Importantly, different types of fixation transitions were associated with different types of learning outcomes. While fixation transitions between the control sliders and the graph were related to students' comprehension of individual concepts illustrated in the simulation (e.g., their understanding of the effect of a change in temperature on the gas particles), transitions between the gas container and the graph were related to students' transfer (i.e., their ability to predict the behavior of gas particles in a novel situation outside of the simulation environment). These results suggest that fixation transitions between representations may indicate successful learning of the complex scientific concepts in this simulation, and that transitions between specific elements of the simulation can be implicated in aspects of the knowledge construction process that facilitate either comprehension or transfer. Together, these findings also suggest that the presence of multiple representations in this simulation may have facilitated learning, rather than adding unnecessary demands of non-essential processing.

These results are also compelling because of the short exposure learners had to the simulation. The simulation was designed to convey the Ideal Gas Laws in a simple and clear manner that minimized cognitive load and allowed learners to autonomously explore the relations among temperature, pressure, and volume. The 5-min period learners were given to interact with the simulation provided them with ample time to fully explore all of the relations many times over. Although they were instructed to plot only five points on the graph, all participants plotted many more. It is encouraging that simulations such as the one used in the present study appear to be engaging learning environments that have the potential to convey a substantial amount of information in a short period of time. They may be especially valuable when used in classroom settings, where time is limited, or when used outside of the classroom, where it might be difficult to sustain attention amidst distractions. Future research will need to examine the effect of longer and repeated interactions on the learning process.

The present study has a few shortcomings that limit the generalizability of our findings. The number of participants in this research is relatively low, although the sample size is typical for eye-tracking studies. Also limiting is the focus on one particular science topic and one particular type of simulation. In addition, although the analyses reported here allowed us to examine immediate transitions from one area of the screen to another, we do not

Table 2
Correlations for test scores, transitions, and fixation frequencies.

Variable	Correlations							
	1	2	3	4	5	6	7	8
1. Pre-test score	–							
2. Comprehension post-test score	.27	–						
3. Transfer post-test score	.27	.60**	–					
4. Control slider-graph transitions	−.24	.32	.29	–				
5. Container-graph transitions	−.13	.16	.44*	.31	–			
6. Number of control sliders fixations	−.06	.20	.07	.19	−.28	–		
7. Number of container fixations	.01	.08	.25	−.34†	.44*	.22	–	
8. Number of graph fixations	−.25	.23	.11	.59**	.46*	−.38†	−.38†	–

† $p < .10$.
* $p < .05$.
** $p < .01$.

yet know how the sequence of these fixations relates to learning. For example, Will transitions to the gas container only enhance learning if students fixated on the graph earlier in the session, or if they already made a transition between the graph and the controllers? How quickly after manipulating the control sliders do students tend to make the types of fixation transitions that are related to beneficial learning outcomes? While the transition analyses reported here were limited to two fixations at a time, follow-up studies might benefit from coding longer sequences of fixations in more detail in order to characterize fixation behavior with more subtlety. Furthermore, our correlational design limited our ability to make causal inferences. Future research will need to examine similar types of transitions experimentally.

Nevertheless, our results have significant implications for the design of educational simulations that include multiple representations of information. Simulation environments allow users to freely explore interactive depictions of complex scientific concepts. The efficacy of these simulations for learning, however, depends on users' ability to integrate multiple sources of dynamic information. By investigating visual attention patterns during the use of simulations, our study may help designers to structure these environments in ways that guide learners' exploration without external intervention. Specifically, designers might alter, add, or connect visual elements within a simulation in order to draw attention to specific conceptual links between representations (thereby guiding fixation transitions that are related to learning outcomes). Furthermore, designers may be able to use multiple representations more strategically in simulation environments by making informed decisions about which representations to include and which conceptual connections to emphasize, perhaps allowing them to engineer particular types of learning (comprehension or knowledge transfer, or both) based on the needs of a particular curriculum.

On the theoretical side, our study contributes to a body of research that suggests that the active integration of multiple representations is an important cognitive process that should not be considered non-essential processing, but that it is, in fact, essential processing. The complementary functions of the two representations within our simulation facilitated learning, and different elements of the simulation supported comprehension and knowledge transfer.

7. Conclusion

The current study provides evidence that students may integrate multiple representations through sequential fixations across related elements of a simulation, and that transitions between different simulation elements are related to different learning outcomes. Furthermore, our results support a broader theoretical assertion: in scientific disciplines where it is crucial for students to connect different levels of representation in order to grasp fundamental principles, fixation transitions between individual pieces of information may play an important role in establishing meaningful links between multiple representations employed in learning materials.

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