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Using Just-in-Time Information to Support Scientific Discovery Learning in a Computer-based Simulation

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Students encounter many obstacles during scientific discovery learning with computer-based simulations. It is hypothesized that an effective type of support, that does not interfere with the scientific discovery learning process, should be delivered on a “just-in-time” base. This study explores the effect of facilitating access to knowledge and skills through just-in-time information. An experiment was conducted in which a group of students who worked with a computer simulation on geometrical optics had access to “information tips” during learning. Performance of this group was compared with that of a group who had no access to information tips. Results showed that the first group showed a better learning gain than the second group. The implications of the results are shortly discussed.

Introduction

While computers continue to advance into virtually all aspects of our culture, their effective use in education is still surrounded by controversy (Stoll, 1999). Although considerable progress has been made in understanding of the opportunities and potential that computers offer for educational practice, some aspects remain problematic. A review by Angrist and Lavy (2002) of the Israeli Tomorrow-98 programme, a billion-dollar venture aimed at creating an environment supportive of integrating information technologies in the classroom, showed very little beneficial short-term effects of increased computer use. This led the authors to conclude that “money spent on CAI [Computer Aided Instruction] in Israel would have been better spent on other inputs” (p. 761). Viewed on a large scale, there exist many factors that impede successful implementation of computers in educational situations. On a smaller scale, much research has been devoted to studying the circumstances under which computers can be effective learning tools, usually by

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comparing different types of computer-based instruction to more traditional forms of
learning. One type of instruction that fully exploits the potential of computer-regulated
learning is known as scientific discovery learning (De Jong & Van Joolingen, 1998). In
scientific discovery learning, the content of a domain is not explicitly stated to learners.
Instead, learners have to “discover” the material for themselves using techniques that
can be compared to the behavior of a scientist who explores a domain. A technique
that has proven useful in eliciting inquiry learning processes is by the use of computer
provides a virtual environment in which students can design and perform different
types of experiments, and observe the effect of manipulating variables. When used as
an instructional tool, students’ task is to induce the relations between variables in the
simulated domain through exploration, experimenting, and discovery. In scientific
discovery learning, information is not delivered to students in a piecemeal fashion.
Instead, students are required to gather evidence themselves and accordingly
construct, shape, and modify hypotheses. The complete process of experimenting
and inducing rules should gradually lead to understanding of the model that underlies
behavior of the simulated system. From the point of view of conversation theory,
scientific discovery learning has the potential of being an effective type of learning.
Conversation theory is a general conceptualization of learning and educational
technology developed by Gordon Pask (Scott, 2001). In conversation theory, a
distinction is made between two levels of learning: learning about “how” (also called
“operation learning”) and learning about “why” (also known as “comprehension
learning”). Full comprehension of a topic means the ability to explain both the how
and why. The “conversation” between student and computer that forms a central part
of the discovery learning process implies that computer simulations may provide the
type of learning environment that is suitable for learning both the “how” and “why” of
a topic.

In an information-processing description of scientific discovery learning processes,
two main processes can be distinguished: transformative and regulative processes
(Njoo & De Jong, 1993). Transformative processes include all the reasoning and
decision-making that guide manipulating a computer simulation and extracting
information from it. These involve orientation, hypothesis generation, hypothesis
testing, and drawing conclusions. The goal of transformative processes is to produce
new information. Regulative processes are meant to control the discovery learning
process on a metacognitive level. This involves monitoring one’s own behavior,
keeping track of progress, and planning in advance what steps to undertake.

Since scientific discovery learning involves many different processes that need to
occur simultaneously on different levels of cognition, it is perhaps not surprising that
it has been difficult to prove its effectiveness (Mayer, 2004). The problems students
encounter during scientific discovery learning can be classified into four components:
hypothesis generation, design of experiments, interpretation of data, and regulation of
learning (De Jong & Van Joolingen, 1998). Proper performance of all the component
tasks that make up the learning process requires both (partial) knowledge, and skills
necessary to execute and complete each task. At least four factors have been shown to
influence the effectiveness of scientific discovery learning: prior domain-specific knowledge, generic knowledge of quantitative and qualitative relations between variables, discovery skill, and metacognition (De Jong et al., 2005). Domain-specific knowledge and generic (domain-general) knowledge are partially independent entities. Discovery skill refers to student’s aptitude at performing and interpreting experiments. Metacognition refers to the generic ability to regulate discovery learning processes. Knowledge and skills contribute differently to the process of transformation and regulation. Here, a description is given of the way knowledge and skill influence scientific discovery learning.

Knowledge plays a key role in determining the steps that learners undertake in the process of experimenting with a simulation and discovering information. Transformative processes yield knowledge, but to function they need at least some prior knowledge. For example, lack of prior domain-specific knowledge makes the process of orientation difficult, since learners who lack knowledge will have trouble separating relevant from irrelevant variables, which will cause them to overlook potentially interesting relations (Veermans, Van Joolingen, & De Jong, 2004). Knowledge not only should help students in making sense of a learning situation, but should also influence the discovery learning process itself. Although the claim that prior knowledge affects rule discovery to a large extent is supported by empirical data, it is uncertain if this notion can be extrapolated to include scientific discovery learning in the type of complex learning environment that a computer simulation entails. In an earlier study, we found only limited effects of prior knowledge on scientific discovery learning. Not only was prior knowledge about the simulated domain (geometrical optics) poor in general, also students did not improve from pre-test to post-test. The implication is that scientific discovery learning can be severely hampered by students’ lack of prior knowledge.

In addition to knowledge, students’ level of discovery skills is assumed to influence the type of experiments a student performs in a simulation, especially the sequence in which experiments are performed. For scientific discovery learning to be successful, experiments should be performed in such a way that enough cognitive resources needed to make inferences from observation of the experiment data are available. However, many students show shortcomings in their approach to experimenting. Tschirgi (1980) observed that students tend to change more than one variable from one experiment to another, which in most cases is a suboptimal strategy. Klahr and Nigam (2004) compared the effect of direct instruction on learning to use the “control of variables” strategy with scientific discovery learning about it. The results were in favor of direct instruction: not only did more children in the “direct instruction” condition learn about the strategy, they also were better able to make better scientific judgements. Klahr and Nigam explain this by pointing out that the main difference between direct instruction and scientific discovery learning lay in the information and feedback that was given to students: whereas students in the direct instruction condition received ample feedback and information, students in the discovery learning condition were shown no examples, nor given explanations.

Given that many students appear to lack the knowledge and skills that are required for successful discovery learning, the implication seems clear: scientific discovery
learning can not be as effective as direct instruction, because many students lack either or both the knowledge or skills necessary to guide transformative and regulative learning processes. However, there are a number of ways in which the situation can be remedied. Structuring a computer simulation, for example by starting with a simple simulation and gradually moving on to more complex situations, supports self-regulation. Also, by adding “support tools” to a computer simulation transformative processes (orientation, hypothesis generation and testing, and drawing conclusions) are fostered. Still, not all forms of support are effective. Some forms of support even degrade performance (Pieters & Van der Meij, 1994). For example, Van Jooolingen and De Jong (1993) used a structured hypothesis scratchpad to help students in making hypotheses explicit. It was expected that students who had this scratchpad at their disposal would come up with more and better hypotheses than students who did not. The actual result was that students who had the hypothesis scratchpad available conducted fewer experiments and stated fewer hypotheses than students who did not. Clearly, the addition of a hypothesis scratchpad did not support students in conducting experiments and generating hypotheses. The problem may have been that the learning situation was complex. Adding the tool meant an extra task to learners, which, given the relatively short time for the experiment, was difficult to conduct.

When the process of discovery learning is considered, it appears that support tools such as the hypothesis scratchpad are created to support the process of hypothesis testing. However, successful orientation is a prerequisite for successful hypothesis testing. To support the orientation process, learners may need sufficient knowledge. Indeed, Shute (1993) found that the availability of an on-line hypertext containing definitions and explanations had a positive effect on scientific discovery learning. Shute argues that support tools may interfere with scientific discovery learning, disrupting the compilation of new knowledge. To minimize interference, providing information should be carefully timed (Leutner, 1993). Providing information too early (that is, before a learning session) does not help students in making sense of a learning situation. Berry and Broadbent (1987) also argue that timing is crucial. They suggest that the most effective way to provide information is on a “just-in-time”-base, that is, when it is made available to students the moment they need it.

The discussion earlier leads to two hypotheses about effective support for scientific discovery learning. Firstly, support should be delivered on a just-in-time base. This means that support should be available the moment that students require it. It should not be provided too early (in which case students may be confused by it) or too late (in which case the support has lost its relevancy). Secondly, interference with the learning process should be kept to a minimum. Support should scaffold the scientific discovery learning of students, not replace it.

The present research attempts to answer two questions. First, is it possible to provide the type of just-in-time support to students in the context of discovery learning with a computer simulation? Second, is such support effective, compared to a situation in which it is not available? To answer these questions, a special type of “information tips” support was created. Information tips consisted of a number of short text blocks that contained domain-specific and general information.
The content of information tips is described in the Method section. Information tips were made available to students on a just-in-time base. Also, the support measure did not interfere with the learning process: students were not required to access information at any time during learning, and information tips were short and succinct. Information tips were studied in the context of the “Optics” computer simulation. The simulation (on geometrical optics) allowed for free exploration of the relations underlying the behavior of light through a lens.

It was expected that access to information tips would foster scientific discovery learning with Optics. Students who access information tips during learning should show a higher learning gain than students who do not. Further, it was expected that the support measure would not interfere with the learning process. With respect to interaction with the simulation, only minimal differences between students who used information tips and students who did not were expected. Finally, it was expected that students with different levels of domain-specific prior knowledge would differ in the number of information tips accessed during learning: students with poor domain-specific prior knowledge were expected to make less use of information tips than students with high domain-specific knowledge. This expectation is in accordance with a finding by Hasselerharm and Leemkuil (1990), who found that students with little prior domain-specific knowledge made less use of an optional support tool than students with high ability.

Method

Participants

There were 32 participants in the experiment, all students in technical vocational education, with a mean age of 19 years. Students came from two school classes, both in the same year of their curriculum. A physics course was a required part of the curriculum for all. Students received a financial compensation of $25 for participating.

Design

A two-group pre-post-test design was applied. Students were randomly assigned to either an experiment condition or a control condition. Both conditions worked with the Optics simulation environment. In the experiment condition, prior to working with the learning environment, students were handed information on paper, which described in a few sentences the possibility to access information tips. Students in the control condition did not receive this information.

Learning Environment

The learning environment used in the experiment was the Optics computer simulation (De Jong et al., 2005). Optics simulates basic geometrical optics.
The simulation allowed students to experiment with a virtual optical workbench, in which the properties of light and different kinds of lenses could be explored. Figure 1 shows an example screen from the simulation.

Figure 1 shows a complex but typical situation that students could produce. The simulation is divided into two areas. At the top, icons indicate the operations students select. In the bottom part, called the “working area”, students manipulate objects, such as different types of lamps and lenses. In Figure 1, a large lamp on the left is sending light in all directions. Light passes through a surface filled with holes that together form an L-shape. Divergent light rays that originate from the holes in the surface pass through a lens (marked “C”). Because the surface is within the focal length of the lens, no image is projected on the screen at the right. Instead, a virtual image is formed. This virtual image can be made visible by the use of the “eye”-tool (positioned at the right). The virtual image is marked by a blue circle. It was possible to measure properties of the virtual image, as if it were a normal projected image. In Figure 1, the top row shows on the left three different lenses that were available to experiment with (the lenses had different focal distances). In addition to the large lamp, a lamp with one light beam, one with three divergent light beams, and one with three parallel light beams were available. Horizontal and vertical distances could be measured, and also the angle with which light beams entered or exited the lens. Light beams could be rotated a specific number of degrees. As an extra aid, light beams could be virtually extended by adding help lines. Participants were allowed to make notes on paper while working with the simulation.
Information Tips

In the experiment condition, nine information tips were available to students. Table 1 shows two tips that were used in the experiment.

Tips could consist of multiple parts. Each tip contained domain-specific information on some concept of geometrical optics. Another part could contain general advice on how experiments could be used in Optics to show the information given in the first part. Objects to use in performing experiments were listed. Finally, some tips gave information on the expected outcome of experiments. Information tips could be accessed at any time by participants in the experiment condition, but they were not required to do so. The bottom line of the Optics simulation contained a set of nine icons, one for each tip. Clicking an icon opened a tip. Tips were not all immediately accessible: every 3 min a new tip would be available. The first tip was available after 3 min, the second after 6 min, and so on until the ninth (after 27 min). When a tip became available, the icon would be highlighted; it could then be accessed. Available tips could be accessed as many times as participants preferred.

Tests

Three pre-tests were administered: one test for domain-specific knowledge about geometrical optics, one for generic knowledge about mathematical relations, and one for experimentation skills. At the end of the experiment, a domain-specific knowledge post-test was administered.

A 30 item multiple-choice test for domain-specific knowledge was used. Two example items are shown in Figure 2. Test items asked for conceptual knowledge. Some items required a prediction of how changes in a situation would affect light propagation through a lens. The test made use of situations similar to those in the Optics simulation.

| Table 1. Two example information tips (#1 and #6), used in the experiment |
|---|---|
| Tip | Content |
| 1. | a) A thin lens is a *weak* lens, a thick lens is a *strong* lens.  
   b) *Advice:* Compare different lenses with each other and observe differences.  
   c) *Appropriate object to use:* lamp with one light beam.  
   d) *Expected outcome:* Light beams are refracted more through a thick lens than through a thin lens. |
| 6. | a) When an object is standing within the focal distance of a lens, the projected image becomes *virtual.* This means that the image will lie at the left of the lens  
   b) *Advice:* The “eye” was developed for this program to show you the position and shape of the virtual image. Put the eye somewhere to the right of the lens. When the object gets near to the lens, you will see the virtual image appear.  
   c) *Appropriate object to use:* Surface with L-shaped holes, screen, lamp with three divergent light beams, distance measures, eye. |
A 32 item test for generic knowledge was used, 29 multiple-choice items and 3 items that required a short written explanation (for example, a formula). Figure 3 shows two example items.

Study the picture. If the lens is moved a little to the left, where will the light beam cross the base line?
- Closer to the lens
- At the same distance from the lens
- Further away from the lens

If, in the same picture, the light beam is aimed a little up, where will it cross the base line?
- Closer to the lens
- At the same distance from the lens
- Further away from the lens

Figure 2. Example items from the domain-specific knowledge test

The table shows for some values the relation between variables A and B. Which description on the right best summarizes this relation?

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>4</td>
<td>□ The more A increases, the slower B increases</td>
</tr>
<tr>
<td>20</td>
<td>8</td>
<td>□ When A is zero, B is also zero</td>
</tr>
<tr>
<td>30</td>
<td>16</td>
<td>□ The more A decreases, the faster B decreases</td>
</tr>
<tr>
<td>60</td>
<td>64</td>
<td>□ The more A increases, the faster B increases</td>
</tr>
<tr>
<td>100</td>
<td>1024</td>
<td></td>
</tr>
</tbody>
</table>

What type of function describes a line that goes through all the points in the graph on the left?
- A quadratic function
- A function with an asymptote
- A monotonic decreasing function
- A logarithmic function

Figure 3. Example items from the generic knowledge test (slightly modified for legibility)
The test for discovery skills used a combination of a computer task and a written test. The computer task was an adapted version of the FILE task (described in detail in Hulshof, Wilhelm, Beishuizen, & Van Rijn, 2005; also see Wilhelm, Beishuizen, & Van Rijn, 2005). Participants worked for a maximum of 30 min with FILE. After that, a test of six items was administered. Test items required participants to state the effect of each of the five variables in the FILE task. Based on the answers, participants were classified in one of four different levels. Participants in level 1 did not find correct main effects, and no interaction effect; level 2 did find correct main effects but no interaction effect; level 3 found correct main effects and the correct interaction effect, but also other incorrect effects; finally, level 4 found correct main effects and the correct interaction effect, and no other effects. The category a participant was classified in is a measure of the level of discovery skills, with level 1 being the lowest, and level 4 the highest level of discovery skills.

Procedure

The experiment was divided over two sessions, about 1 week after another. The sessions lasted about 80 min. In the first session the pre-tests were administered. First the generic knowledge test was administered, then the domain-specific knowledge test, and finally the discovery skills test. The second session was spent working with Optics. Participants were informed at the start of the session that they would be tested afterwards. All participants received a general instruction set which contained an explanation of specific buttons and tools in the Optics computer simulation. Students in the experiment condition received additional instructions on the use of information tips. In both conditions, students were given the general assignment to perform experiments with Optics, and to use the tools they had at their disposal in the virtual environment. The instruction encouraged students to make use of the clues given by the simulation, and to make notes. Students who got stuck would always be referred to the assignment and the instructions. No further guidance was given. All operations participants performed in Optics were registered by the computer. This made possible analysis of the actions participants performed while working with the simulation. After working with the simulation for approximately 50 min, the knowledge post-test was administered.

Results

The results focus on performance on the pre-tests and the post-test and on process data. Analysis showed no difference between the two school classes that participated in the experiment, so only results for the two conditions will be described.

Test Measures

The test for generic knowledge showed a mean score of 21.1 (standard deviation, SD = 4.10) out of 32. Test reliability (as measured by Cronbach’s α) was 0.71. Test
scores ranged from 11 to 28. The results showed no statistically significant difference between the two conditions ($t_{23} = 1.46$; not significant; n.s.).

Figure 4 shows performance on the domain-specific pre-test and post-test, split for the experiment and control condition.

A repeated measures analysis with the test as the within-subject factor shows that there is a statistically significant interaction between condition and test moment ($F_{1,23} = 4.99; p < 0.05; \eta^2 = 0.18$). This interaction is caused by the combination of a decrease from pre-test to post-test for the control condition, and an increase for the experiment condition. Both main effects are not statistically significant: the control condition shows a small decrease from an average test score of 15.71 (SD = 4.46) on the pre-test to 13.86 (SD = 4.64) on the post-test ($F_{1,13} = 2.41$; n.s.; $\eta^2 = 0.16$). The experiment condition shows a small increase from an average test score of 13.82 (SD = 3.10) on the pre-test to 16.45 (SD = 3.64) on the post-test ($F_{1,10} = 2.45$; n.s.; $\eta^2 = 0.20$). A one-tailed $t$-test comparing the two conditions on the pre-test shows no statistically significant differences; ($t_{23} = 1.25$; n.s.). On the post-test, there is a statistically significant difference ($t_{23} = -1.57; p < 0.1$), which means the experiment condition performed better than the control condition on the post-test. Both the pre-test and the post-test were moderately reliable: Cronbach’s $\alpha$ was 0.51 and 0.61, respectively. It can be concluded that the random assignment of participants to one of the two conditions influenced their knowledge gain from pre-test to post-test.

Dependent on the results of the FILE test for discovery skills, participants were classified into one of four different levels. Of the 32 participants, 8 were classified on level 1 (the lowest level), 17 as level 2, 3 as level 3, and 4 as level 4 (the highest level). That means that 78% of the subject group was not able to discover an interaction effect in the FILE task.

In Table 2, correlations between the four knowledge measures are shown (generic knowledge, domain-specific prior and post-test knowledge, and discovery skills), split for the experiment and control condition.
Table 2 shows a statistically significant correlation between the domain-specific pre-test and post-test score for the control condition. For the experiment condition, this correlation is moderately negative. This result replicates earlier findings. Without support, there is a direct relation between prior domain-specific knowledge and post-test performance. The addition of a support tool in the experiment condition appears to modify this relation. The results indicate that there is a positive relation between generic knowledge about mathematical relations and discovery skills. This may be explained by the fact that generic knowledge about the type of relations that can occur in a learning environment fosters the induction of these relations in the FILE environment.

**Process Measures**

In the second session there were 27 participants, 15 in the control condition and 12 in the experiment condition. In the experiment condition, one person did not access any tips at all. Because results for this participant could not be assigned to any of the two conditions, process results were discarded from the analysis. All operations participants performed in the simulation were registered. For the present study, two results are especially relevant: differences between the experimental conditions with regard to interaction with Optics, and the use of information tips by participants in the experiment condition.

**Interaction with Optics.** The analysis of interaction with Optics focused on a subset of all possible operations: the “basic operations”. Basic operations are those that are central to the process of experimentation. Together, the basic operations constitute more than three quarters of all operations that participants performed in the simulation. Three different operations were examined: addition of objects to the working area in the simulation, removal of objects from the working area, and movement of objects in the working area. On average, participants in the control condition performed 70.3 (SD = 43.4), and in the experiment condition 60.1 basic operations (SD = 37.5). The difference is not statistically significant. In Figure 5, a comparison between the experimental conditions is shown for each of the basic operations.
As can be seen from Figure 5, there are small but consistent differences between participants in the two conditions for all three basic operations. The finding that the control condition performed more basic operations than the experiment condition can be explained by the availability of information tips in the experiment condition: the fact that accessing and reading information tips takes time influenced participants’ activity level.

Because most participants in both conditions scored close to the mean on the different knowledge tests, a comparison of participants with low or high knowledge or skill could only be carried out on a selected number of cases. Only participants who scored more than one standard deviation below or above the mean were included. For generic knowledge, this meant that two groups were formed of participants who scored below 17 \((n = 4)\) or above 25 \((n = 4)\). Results are shown in Figure 6.

![Figure 5](image1.jpg)

**Figure 5.** Comparison of control and experiment conditions for basic operations in Optics

![Figure 6](image2.jpg)

**Figure 6.** Comparison on basic operations for low and high generic knowledge
As can be seen, participants with high generic knowledge were more active in working with the Optics simulation than participants with poor generic knowledge. For domain-specific knowledge, the groups were formed of participants who scored below 12 ($n = 6$) or above 19 ($n = 5$). Results are shown in Figure 7.

The results are similar to the findings for generic knowledge: participants with more knowledge about optics showed more activity for all basic operations. For discovery skills, the groups were formed of participants who were classified at the lowest level ($n = 6$) or at the highest level ($n = 3$). Results are shown in Figure 8.

The results differ from the other comparisons. Both groups performed a similar amount of Add and Delete operations, but participants with high discovery skills performed much more Move operations than participants with low discovery skills.

![Figure 7](image7.png)

**Figure 7.** Comparison on basic operations for low and high domain-specific knowledge

![Figure 8](image8.png)

**Figure 8.** Comparison on basic operations for poor and high discovery skills
Use of tips. In the experiment condition, participants could access information tips when they wished. The minimum number of tips viewed was one, the maximum all nine tips. On average, six tips were accessed (SD = 2.6). Table 3 shows correlations between performance on the different test measures and the number of tips accessed by participants.

There is a statistically significant correlation between domain-specific prior knowledge and the number of tips accessed in the simulation: more competent participants accessed more information tips than others. Although not statistically significant, it can be observed that there is also a positive relation between the level of generic knowledge and the number of accessed tips.

Discussion

This study examined the effect of facilitating access to domain-specific and generic information during scientific discovery learning with a computer simulation. Interaction behavior with the “Optics” learning environment and knowledge acquisition of two randomly assigned groups of students were compared: one group worked with Optics without support (control condition), the other was supported by the use of a small set of “information tips”. The tips contained factual information and hints on successfully experimenting with the simulation. The tips were not used to guide students while they explored and experimented with the scientific discovery learning environment. Instead, students could decide for themselves whether or not they wanted to make use of them. Information was available to students on a “just in time”-base, which means that it was designed to be available neither too soon nor too late (Berry & Broadbent, 1987). It was expected that the interaction behavior with Optics would be similar for participants in the control and the experiment condition: the presence of information tips should not interfere with learning. The expectation was confirmed. Participants in the control condition were more active than participants in the experiment condition, but this difference can be explained by the time taken by participants in the experiment condition to access and read the information tips. Differences in knowledge gain were found between conditions. Participants in the experiment condition showed a learning gain from pre-test to post-test, in contrast

<table>
<thead>
<tr>
<th>Knowledge measure</th>
<th>Accessed tips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generic knowledge</td>
<td>0.39</td>
</tr>
<tr>
<td>Discovery skills</td>
<td>−0.24</td>
</tr>
<tr>
<td>Domain-specific prior knowledge</td>
<td>0.66*</td>
</tr>
<tr>
<td>Domain-specific post knowledge</td>
<td>−0.36</td>
</tr>
</tbody>
</table>

*p < .01.
to participants in the control condition. This confirms the expectation that participants in the experiment condition would benefit from the availability of tips. It should be pointed out that the test items used to administer domain knowledge did not ask for information contained within the information tips. The control condition showed a positive correlation between performance on the pre-test and post-test, which indicates that the effect of working with Optics yielded similar effects for all participants in this condition. In contrast, the experiment condition showed a negative correlation, which can be explained by the performance of a number of participants who did poorly on the pre-test but showed a large increase from pre-test to post-test. It appears that the participants who benefited most from the availability of tips were those who showed poor prior understanding about optics. A positive correlation between the number of tips accessed during the experiment and domain-specific prior knowledge indicates that participants with low prior knowledge accessed fewer information tips than participants with higher prior knowledge. This result indicates that accessing only few information tips may result in a large performance increase. It may be concluded that persons with little background knowledge will benefit from a little extra knowledge. In the experiment we used nine knowledge tips, but it may have been sufficient to have only three or four tips available.

The other tests administered in the experiment show mixed results. There was low variation in performance on the generic knowledge measures: participants had no trouble understanding the qualitative and quantitative relations that occur in Optics. The high level of generic knowledge may have facilitated understanding of the information tips. On the test for discovery skills most participants showed relatively poor performance. Scoring of the test was based on the number and type of rules participants were able to discover in the FILE task (Hulshof et al., 2005). Seventy-eight percent of the participants were unable to discover an interaction effect. Given the fact that FILE is relatively simple because its experiment space is small, any learning gains found after working with the complex Optics simulation may come as a surprise. Optics is not just a complex version of FILE, however, since FILE deals with an artificial topic and Optics deals with the real-world topic of optics. This explains the absence of a relation between performance on the discovery skills test and knowledge gain from working with Optics.

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