Do students benefit equally from interactive computer simulations regardless of prior knowledge levels?

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1. Introduction

Recent technological developments have made computer simulations more feasible for promoting adaptive learning in students, as computers can provide visualization of dynamic phenomena. In this context, some researchers (e.g., de Jong & van Joolingen, 1998; Lee, Plass, & Homer, 2006; Rieber, Tzeng, & Tribble, 2004) have pointed out that the use of computer simulations is particularly promising for the learning of complex tasks and the study of phenomena that are not easily observable in real space, impossible to realize in a traditional learning situation, or not inherently visual objects.

Visualization of complex concepts is not, however, the only feature of computer simulations. Computer simulations are 'interactive' software programs that allow students to explore complex interactions among dynamic variables that model real-life situations. Computer simulations can provide benefits over printed graphics if the system reacts according to a student's input. Mayer and Chandler (2001) demonstrated the importance of interactivity in computer simulations. They found that students who had partial or full control over a computer simulation performed better on a post-simulation test than students who had no control. This phenomenon has been labeled the interactivity effect (Betrancourt, 2005). According to the interactivity effect, the information depicted in a simulation is more easily comprehended if the device gives students some control over the pace of the simulation. This is due to the fact that it allows students to integrate information before proceeding to the next stage and divides the simulation into digestible chunks of information.

Despite the widespread belief that interactive computer simulations are useful instructional devices, it is still uncertain what types of interactive computer simulations have the greatest effect on enhancing learning outcomes based on the learner's level of expertise. The expertise reversal effect, suggested by Kalyuga (2005), assumes that design principles intended to help students with low prior knowledge levels might provide no benefit to or even hinder students with high prior knowledge levels. This indicates that the same set of design principles applied to students with low prior knowledge levels cannot always be applied to students who have previously acquired substantial knowledge in a specific domain. This expertise reversal effect was observed through a series of empirical studies (e.g., Kalyuga, Chandler, & Sweller, 2000; Kalyuga, Chandler, & Sweller, 2001) that revealed a relationship between the modality effect, the worked-example effect, and student prior knowledge levels. According to the modality effect, students understand narrated explanations and pictures more effectively than on-screen textual explanations and pictures. However, Kalyuga et al. (2000) demonstrated that, for students with...
high prior knowledge levels, narrated explanations become redundant and reduce learning effectiveness. Also, according to the worked-example effect, well-designed worked-examples accompanied by full instructional guidance are often more effective than instructional methods with no or limited guidance, such as problem solving or discovery learning. Kalyuga et al. (2001) found that inexperienced mechanical trainees benefited from computer-based worked-examples rather than from problem solving practice. However, as trainees became more experienced, the comparative effectiveness between worked-examples and problem solving became indistinguishable.

Little research has been done to investigate whether there is a relationship between the interactivity effect and the expertise reversal effect that is similar to the relationship among the modality effect, the worked-example effect, and the expertise reversal effect. According to Betrancourt (2005), few studies have been performed on the effectiveness of computer simulations that take into account individual differences in domain expertise. He has emphasized that more studies are needed to confirm any relationship between the interactivity effect and the expertise reversal effect in a variety of learning tasks.

2. Interactive computer simulations

Interactivity in computer simulations consists of two different dimensions: control (low interactivity) and interactive behavior (high interactivity) (Betrancourt, 2005). Whereas ‘control’ is defined as the ability of the student to determine the pace of the succession of frames (e.g., pause-play, rewind, forward), ‘interactive behavior’ involves learning activities where the content in successive frames is determined by the student’s actions regarding a given parameter in the current frame.

2.1. Low interactivity

Low interactivity allows students to control the pace of frame succession. The example frame in Fig. 1 represents one segment in a presentation on the concept of ‘speed’. In the low-interactive (LI) simulation group, buttons numbered 1, 2, and 3 appear in the upper right corner of the screen. When the student presses on a button, the computer presents one of three segments corresponding to the number of the button pressed. In this way, the user controls the pace of the presentation based on his/her input. For example, when a student clicks on button 1, the narration states: the slope of the time–distance graph changes as the car moves. When the car starts with a steep slope, the car moves quickly, but it begins to move slowly as the slope approaches zero, and later resumes speed as the slope again becomes steeper”.

Low interactivity allows students to overcome the limitations of memory capacity, since the clicking of buttons in the simulation enables students to process the presented information without perceptual and conceptual overload. Since human working memory is limited with respect to the amount of information that can be held and the number of operations that can be performed on that information (van Gerven, Paas, Jeroven et al., 2003), the clicking of buttons in the low-interactive simulation should reduce students’ cognitive load.

Mayer and Chandler (2001) demonstrated that presenting information in small segments, with low-interactive control over progressing from one part to the next, reduces the risk of cognitive overload in computer-based simulations. In each segment, students received 10 s of visual simulation and a sentence of narration. This allowed students to devote their full mental capacity to processing the given learning material. Thus, when information is presented in parts, rather than in a continuous manner, students have more opportunities to process and to create connections among related information.

When new information is presented, inexperienced students generally experience a heavy cognitive load (Kalyuga, Chandler, & Sweller, 1999; Kirschner, 2002; Sweller, 1994). Since this type of cognitive load has a negative effect on the process of acquiring new information, instructional techniques that reduce working memory load are required (van Gog, Ericsson, Rikers, & Pass, 2005). Accordingly, students with low prior knowledge levels may benefit from a learning program that includes a low-interactive simulation, since it allows them to overcome perceptual limitations. However, little research has been done to investigate whether all students benefit equally from the low-interactive simulations regardless of their prior knowledge levels.

![Fig. 1. Example of a screenshot of the time–distance graph of low-interactive computer simulation.](image-url)
2.2. High interactivity

When students learn using a high-interactive simulation program, they can predict how the time–distance graph will change in a simulated environment. They can verify their predictions on the time–distance curve by changing simulation parameters, and they can observe the way in which the simulation responds to the changing parameters. A screenshot of a high-interactive simulation (HI) is shown in Fig. 2. In this simulation, students can control the slope of the line of the time–distance graph. If students move the points on the line on the time-distance graph, the slope of the graph will change accordingly. Once a parameter is set, pressing the ‘Run’ button will show how the car’s speed direction.

High-interactive simulations can help students understand concepts, even though the simulations do not ask students to predict specific outcomes. For example, in the simulation of speed (i.e., the relationship between time and distance traveled by a car), students might hypothesize that increasing or decreasing the slope of the line in the time–distance graph will result in increased or decreased car speed. Students can subsequently input different parameters for the slope of the line in the time–distance graph into the simulation. The interactive computer simulation will respond by displaying the corresponding changes in the car’s speed. Students can then observe these changes and compare them with their hypotheses.

Some researchers (e.g., Byrne, Catrambone, & Stasko, 1999; Hegarty, Kriz, & Cate, 2003; van Joolingen & de Jong, 1991) have stressed the importance of encouraging students to make their own hypotheses. Byrne et al. (1999) found that simulation itself might accelerate the learning of procedural knowledge by encouraging students to predict the algorithmic behavior of the simulation. They suggested that prediction, rather than simulation, might be a key factor in enhancing learning. In this vein, van Joolingen and de Jong (1991) discovered that the hypothesis scratch pad, designed as interactive simulations supporting hypothesis generation, was beneficial to students. Hegarty et al. (2003) further showed that participants who learn by predicting the behavior of a system gain a better understanding of the system than those who do not.

Students with high prior knowledge levels may benefit from high-interactive simulations more than from low-interactive simulations. This is because learning tasks with high interactivity encourage students to use high level thinking skills, to generate hypotheses, and to test hypotheses by manipulating simulation parameters. Although low interactivity can allow students to overcome perceptual constraints, this interactivity can be redundant once students gain sufficient understanding. High interactivity may facilitate further learning for students with high prior knowledge levels by giving them more options to explore. Similarly, Tuovinen and Sweller (1999) revealed that worked-examples became redundant and that exploratory learning was more effective for students with high prior knowledge levels.

Thus, while prior research (e.g., Byrne et al., 1999; Hegarty et al., 2003; van Joolingen & de Jong, 1991) has found that supporting hypothesis generation was beneficial to students, little research has been conducted to investigate whether all students benefit equally from the high-interactive simulations regardless of their prior knowledge levels. As such, considering both the high-interactive and the low-interactive simulations, the most efficient simulation type may be partly determined by students’ prior knowledge levels. We therefore examined the effects of interactivity with respect to simulation design. The purpose of this study was to investigate whether students’ prior knowledge levels show any relationship with the interactivity effect and the expertise reversal effect. Specifically, our research problem was to investigate how students’ prior knowledge levels and how interactive computer simulations affect comprehension of concepts, cognitive load, and learning efficiency. We hypothesized that, for students with high prior knowledge levels, the high-interactive simulation would be more effective for learning than the low-interactive simulation. We also hypothesized that, if students have low prior knowledge levels, the low-interactive simulation would be more effective than the high-interactive simulation.

![Fig. 2. Example of a screenshot of the time–distance graph of high-interactive computer simulation.](http://scienceall.com/)
3. Methods

3.1. Participants and experimental design

Participants were seventy-two 5th grade students from two elementary schools in Seoul, Korea. Thirty-seven participants were male, and 35 participants were female. Participants were divided into two groups based on their scores from a prior knowledge level test: high prior knowledge levels (HP) and low prior knowledge levels (LP). A 2 × 2 subject factorial design was applied. Participants in each group (HP and LP) were further randomly assigned to two experimental programs: a low-interactive simulation program (LI) and a high-interactive simulation program (HI). There were 16 participants in the HP-LI group, 18 in the HP-HI group, 18 in the LP-LI group, and 20 in the LP-HI group. There were no significant differences in prior knowledge scores between the two high prior knowledge groups \((F(1, 32) = .22, p = .63)\), and there were no significant differences in prior knowledge scores between the two low prior knowledge groups \((F(1, 36) = .93, p = .34)\).

3.2. Materials and instruments

A prior knowledge level test, a cognitive load test, and a comprehension test regarding the concept of speed were conducted. The prior knowledge level test (Cronbach \(\alpha = .74\)) was a multiple-choice test consisting of 10 questions designed to assess students’ basic knowledge of speed (e.g., “A boy travels 100 km in 5 h. What is his average speed in km/h? (a) 10 km/h, (b) 20 km/h, (c) 500 km/h, (d) 5 km/h”). Each question was worth 1 point, with a maximum total score of 10 points for all 10 questions. This test was developed by the researchers in cooperation with two science teachers in the elementary school.

The comprehension test regarding the concept of speed (Cronbach \(\alpha = .85\)) was a multiple-choice test, consisting of 10 questions designed to assess students’ understanding of the science concepts presented in the simulation (e.g., “The total traveled distance can be derived from a time–distance graph by figuring out (a) the square of the slope, (b) the length of the line, (c) the degree of the points, (d) the area under the line”). This test was also developed by the researchers in cooperation with two science teachers in the elementary school.

Cognitive load was measured on a 9 point rating scale. The cognitive load measures developed by Paas (1992) ranged from extremely low mental effort (1 point) to extremely high mental effort (9 points). The reliability coefficients of the cognitive load test were Cronbach \(\alpha = .91\).

Learning efficiency \((E)\), developed by Paas and van Merriënboer (1994), reflects the ratio between cognitive load scores and comprehension scores. The raw scores from the cognitive load test and the comprehension test were converted into standardized scores. The standardized means of cognitive load and comprehension were then combined to give an indication of learning efficiency. Learning efficiency \((E)\) was determined as the perpendicular distance between the coordinate point given by the two standardized values and the diagonal \((E = 0)\), where cognitive load scores and comprehension scores are equal.

Based on the computer-based science learning program installed by the Korea Science Foundation, two types of interactive simulation programs (a low-interactive simulation and a high-interactive simulation, shown in Figs. 1 and 2, respectively) were developed by researchers to achieve the research goals.

3.3. Procedure

Experiments were conducted in science classrooms where all participants could use individual computer terminals. Participants were informed that the purpose of this experiment was to investigate the effectiveness of interactive computer simulations in teaching science concepts. Participants were also informed that all the collected information would be kept confidential. Detailed directions on how to use the interactive computer simulation programs were given to the participants. Participants took the prior knowledge level test before learning to use the interactive computer simulations. After completing the learning activities contained in the interactive simulation programs, participants took a cognitive load test and a comprehension test on the concept of speed.

4. Results

Table 1 shows the mean scores and standard deviations of the comprehension test on the concept of speed and the cognitive load test in each experimental group. To examine the effects of prior knowledge levels and of the two types of interactive computer simulations on the comprehension test and the cognitive load, a two-way analysis of variance (ANOVA) was conducted. Prior knowledge levels (HP vs. LP) and the two types of interactive computer simulations (LI vs. HI) served as factors.

| Two types of interactive simulations | HP group | | LP group | |
| --- | --- | --- | --- | --- | --- |
|  | N | M | SD | N | M | SD |
| Comprehension test | | | | | | |
| LI | 16 | 62.25 | 12.38 | 18 | 42.38 | 23.79 |
| HI | 18 | 76.22 | 16.32 | 20 | 28.70 | 18.29 |
| Cognitive load test | | | | | | |
| LI | 16 | 3.93 | 1.65 | 18 | 3.61 | 1.71 |
| HI | 18 | 2.72 | 1.31 | 20 | 5.30 | 1.97 |

Note: LI, low-interactive; HI, high-interactive; HP, high prior knowledge; LP, low prior knowledge.
4.1. Comprehension

A two-way ANOVA on the comprehension test scores demonstrated that there was a statistically significant difference between high and low prior knowledge groups ($F(1, 68) = 60.51, \text{MSE} = 335.53, p < .001, \eta^2_p = .47$). The comprehension scores of students with high prior knowledge levels ($M = 69.64, \text{SD} = 16.03$) were higher than those of students with low prior knowledge levels ($M = 35.18, \text{SD} = 21.90$). There was no significant difference between the two types of interactive computer simulations ($F(1, 68) = .00, \text{n.s.}$). The results also showed interaction effects between students’ prior knowledge levels and the two types of interactive computer simulations ($F(1, 68) = 10.19, p < .01, \eta^2_p = .13$): students with high prior knowledge levels received higher comprehension scores after learning with the HI program than with the LI program, and students with low prior knowledge levels received lower comprehension scores after learning with the HI program than with the LI program (see Fig. 3).

4.2. Cognitive load

A two-way ANOVA on cognitive load scores showed that there was a statistically significant difference between the high prior knowledge group and the low prior knowledge group ($F(1, 68) = 7.90, \text{MSE} = 2.86, p < .01, \eta^2_p = .10$). Students with high prior knowledge levels ($M = 3.29, \text{SD} = 1.58$) received lower cognitive load scores than students with low prior knowledge levels ($M = 4.50, \text{SD} = 2.02$). However, there was no significant difference between the two types of interactive computer simulations ($F(1, 68) = .35, \text{n.s.}$). The results also showed that there was an interaction effect between students’ prior knowledge levels and the two types of interactive computer simulations on cognitive load scores ($F(1, 68) = 13.15, p < .001, \eta^2_p = .16$). Students with high prior knowledge levels demonstrated lower cognitive load scores with the HI program than with the LI program. In contrast, students with low prior knowledge levels showed lower cognitive load scores with the LI program than with the HI program (see Fig. 4).

4.3. Learning efficiency

As shown in Fig. 5, students with high prior knowledge levels demonstrated higher learning efficiency ($E = 1.11$) after learning with the HI program and lower learning efficiency ($E = 0.28$) after learning with the LI program. Students with low prior knowledge levels demonstrated higher learning efficiency ($E = -0.13$) after learning with the LI program and lower learning efficiency ($E = -1.11$) after learning with the HI program. The results showed that the HI program was a more efficient instructional strategy than the LI program for students.
with high prior knowledge levels, and that the LI program was a more efficient instructional strategy than the HI program for students with low prior knowledge levels.

5. Discussion and conclusion

The goal of this study was to investigate the effects of students' prior knowledge levels and of the two types of interactive computer simulations on the comprehension of the concept of speed, cognitive load, and learning efficiency. The findings of this study present several implications for the design of computer-based interactive learning environments.

First, previous studies on interactive simulation have suggested that interactive simulation could be beneficial. For instance, Mayer, Dow, and Mayer (2003) found that students performed better on a problem solving transfer test when students were able to ask questions and receive answers interactively rather than receive the same information as a non-interactive multimedia message. Evans and Gibbons (2007) also found that students using interactive simulation outperformed those using non-interactive simulation in the problem solving test and needed less time to complete both memory and problem solving tests. These studies showed that interactive systems facilitate deep learning by actively engaging the learner in the learning process.

However, little research has been done to investigate whether all students benefit equally from the interactive computer simulations regardless of their prior knowledge levels. The results of our study showed that there was a significant interaction effect between prior knowledge levels and the two types of interactive computer simulations. This result supports the notion of assigning a particular function to interactive simulations used in physics, and confirms the variant effects of high and low-interactive simulations. Therefore, our study could serve as the evidence of variant effects in interactive computer simulations according to the student’s prior knowledge levels.

Second, this finding also supports the expertise reversal effect suggested by Kalyuga (2005) and Kalyuga, Ayres, Chandler, and Sweller (2003), which can be observed by variations in the interactivity effect. In agreement with the predictions of the expertise reversal effect, our results showed that the effectiveness of the interactive computer simulations varied depending on the levels of prior knowledge. Students with high prior knowledge levels benefited more from the HI program than from the LI program, since the HI program allowed students to obtain high comprehension scores and low cognitive load scores. This result implies that high-interactive computer simulations, which allow students to actively manipulate parameters, enhance learning for students with high prior knowledge levels, and especially for those who have the necessary schema and sufficient working memory capacity. Although low-interactive computer simulations allow students to fully understand concepts by presenting information in smaller segments with control over the simulation progress, these simulations could be detrimental to students with high prior knowledge levels who can generate their own mental simulation.

Students with low prior knowledge levels showed less cognitive load after using the LI program than after using the HI program. This result implies that, since low-interactive computer simulations allow students to control the pace at which information is presented, it enables students with low prior knowledge levels to fully understand each segment. On the other hand, since students with low prior knowledge levels might not have the necessary schema required to guide them through the process of comprehending concepts (Moreno & Valdez, 2005), interactivity in e-learning and two-way communication between students and the computer system might prevent these students from generating their own mental models of phenomena and might result in higher overall cognitive loads.

Third, the results of this study highlight the need to consider learning efficiency in the design of instructional materials. In this study, students with high prior knowledge levels demonstrated higher learning efficiency using the HI simulation and lower learning efficiency
using the LI simulation. Furthermore, students with low prior knowledge levels showed higher learning efficiency using the LI simulation and lower learning efficiency using the HI simulation. These differences in learning efficiency, resulting from complex interactions between mental effort and performance, can be used to compare the effectiveness of instructional conditions. Moreover, students' learning can be more efficient if performance is higher than expected on the basis of a given amount of invested mental effort, as asserted by Paas and van Merrienboer (1994). Researchers and instructional designers, therefore, could identify efficient instructional conditions by assessing learning efficiency.

Fourth, while Betancourt (2005) theoretically suggested the two kinds of interactive simulations, our research showed practical application of these two kinds of interactive simulations (high and low) and examined their effects. More specifically, low-interactive simulation supports the learning environment, enabling the student to determine the pace of the succession of frames. In addition, high-interactive simulation involves learning activities determined by the student's actions regarding a given parameter in the current frame. As such, this software suggests two kinds of interactive simulations, which demonstrate two-way communication between the learner and the computer system.

Fifth, this study could give an implication to designers of computer-based interactive learning environments that it is important to make learners' cognitive loads lighter during their ongoing study, since their cognitive loads and the level of interactive simulations interact with each other. Some researchers might think that interactive computer simulations will generally enhance learners' achievements without considering the learners' cognitive ability levels. Such ideas seem to overlook the fact that learners' achievement levels might be improved, according to the instructional design of interactive computer simulations, by considering learners' prior knowledge levels. Therefore, it is necessary to monitor the learning process and the cognitive state of the learner. In this sense, one of the valuable guides to designers of computer-based interactive learning environments could be to identify the learners' different knowledge levels and then to provide learners with different types of interactive simulations.

Sixth, it can be interesting to relate the present study to four learning styles as such activists, reflectors, theorists, and pragmatists (Honey & Mumford, 1982), also to adaptive hypermedia (Brusilovsky, 1996), in an attempt to explore adaptive contents selection and adaptive recommendation based on user interests. These approaches could provide interactive learning environments, when the students learn the interactive simulations, and thus the system could adaptively select, and prioritize the more relevant simulations based on student's prior knowledge levels as well as learning styles.

Finally, this study was conducted with concepts in physics and 5th grade students in elementary school. Therefore, in order to make additional improvements, and in order to make the findings of this study more generalizable, we suggest that future researchers experiment with different student grade levels and investigate various concepts from other subject areas.

References