Hsu, Y., Gao, Y., Liu, T. C., & Sweller, J. (2015). Interactions Between Levels of Instructional Detail and Expertise When Learning with Computer Simulations. *Educational Technology & Society, 18* (4), 113–127.

Interactions Between Levels of Instructional Detail and Expertise When Learning with Computer Simulations

Yuling Hsu[1], Yuan Gao[2], Tzu-Chien Liu[3*] and John Sweller[4]

[1]Institute of Education, Tzu Chi University, Taiwan // [2]Smart Learning Institute, Beijing Normal University, China // [3]Department of Educational Psychology and Counseling, National Taiwan Normal University, Taiwan // [4]School of Education, University of New South Wales, Australia // eileenhsu2010@gmail.com // yuangao0304@gmail.com // tzuchien@ntnu.edu.tw // j.sweller@unsw.edu.au

[*]Corresponding author

ABSTRACT

Based on cognitive load theory, the effect of different levels of instructional detail and expertise in a simulation-based environment on learning about concepts of correlation was investigated. Separate versions of the learning environment were designed for the four experimental conditions which differed only with regard to the levels of written instructional detail. One hundred and forty Grade 10 (lower-expertise) and Grade 11 (higher-expertise) students participated in this experiment. In accord with the expertise reversal effect, the results supported the hypothesis that higher levels of instructional detail benefited learning for lower-expertise learners, whereas lower levels of detail facilitated learning for higher-expertise learners. It was concluded that the level of instructional guidance needed to match learners' levels of expertise.

Keywords

Cognitive load theory, Expertise reversal effect, Simulation-based learning environment, Levels of instructional detail, Expertise levels

Introduction

In recent years, computer-assisted learning in a simulation-based environment has become increasingly available in many areas of education (e.g., Kolloffel, Eysink, de Jong, & Wilhelm, 2009; Liu, Lin, & Kinshuk, 2010; Morris, 2001; Renken & Nunez, 2013; Rutten, van Joolingen, & van der Veen, 2012; van der Meij & de Jong, 2006). Simulation-based learning attempts to model a real-life situation with dynamically linked multiple representations on a computer so that complex concepts can be visualized or modelled (Lee, Plass, & Homer, 2006; van der Meij & de Jong, 2006). Learning with computer simulations can be considered to have similarities with discovery learning (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011; Mayer, 2004). It provides a platform for learners to construct their own mental models about the concepts or knowledge to be learned by interacting with the environment.

Although the advantages of using simulation-based discovery learning have been confirmed by some empirical studies (e.g., Jaakkola, Nurmi, & Lehtinen, 2010; Lindgren & Schwartz, 2009; Urban-Woldron, 2009), many have argued that learning with minimal guidance (Kirschner, Sweller, & Clark, 2006) in a simulation-based environment often has proved to be ineffective (Eckhardt, Urhahne, Conrad, & Harms, 2013; Kanar & Bell, 2013; Mayer, 2004; Swaak & de Jong, 2001). Mayer (2004) reviewed a number of studies conducted from 1950 to the late 1980s comparing guided and unguided learning and suggested that learning was more effective using guided rather than unguided forms of instruction. In another study with two meta-analyses based on a sample of 164 research studies of discovery learning (Alfieri et al., 2011), the findings suggested that unassisted discovery failed to benefit learning unless the instructional supports in the form of feedback, work examples, scaffolding, and elicited explanations were provided.

In light of these results, how to design appropriate guidance for learning in simulation-based environments is critical (Rutten et al., 2012). Van der Meij and de Jong (2011) found that using step-by-step guidance for self-explanations to relate and translate between representations resulted in better learning outcomes than using general guidance in a simulation-based learning environment. Another study examining the sequential effects of high and low instructional guidance on children's acquisition of experimentation skills within a discovery learning environment (Matlen & Klahr, 2013), indicated that learning and transfer were promoted whether high guidance instruction consisting of a combination of direct instruction and inquiry questions was received before or after low guidance that included inquiry questions only. A study by Lazonder and Egberink (2014) found that using segmented inquiry questions to scaffold learning procedures facilitated children's acquisition and use of the control-of-variables strategy as much as directly providing instruction prior to investigating a multivariable inquiry task in a simulation-based learning environment.

These studies indicated how learning guidance can be designed to improve learning processes and outcomes in a simulation-based environment; however, few studies have been conducted based on individual differences of learners. In studies based on cognitive load theory, optimal instructional designs have been found to interact with levels of expertise (Kalyuga, 2007; 2009a, 2009b; Kalyuga, Ayres, Chandler, & Sweller, 2003; Kalyuga, Chandler, & Sweller, 2000, 2001). Cognitive load theory has been associated with learning with technology in recent years (e.g., De Koning, Tabbers, Rikers, & Paas, 2009; 2011; Lee et al., 2006; Liu, Lin, & Paas, 2013; Liu, Lin, Tsai, & Paas, 2012; Rey & Fischer, 2013).

Cognitive load theory

Cognitive load theory describes different sources of cognitive load when information is transited between working memory and long-term memory (Sweller, 1994, 2003, 2004, 2010, 2011, 2012; Sweller, Ayres, & Kalyuga, 2011). Three types of cognitive load are distinguished in cognitive load theory. Intrinsic cognitive load is generated by the level of complexity of the essential information involved in a learning task. Extraneous cognitive load is caused by an inappropriate format of instruction. Germane cognitive load refers to effective learning processes in which individuals use their cognitive resources to deal with the intrinsic cognitive load induced by learning tasks. Cognitive load theory suggests that instruction should be organized so that limited working memory resources are devoted to dealing with intrinsic and not extraneous cognitive load.

From the perspective of cognitive load theory, when learning with computer simulations, learners need to search, select, and manipulate related information from the multiple representations displayed in the simulation-based environment, which imposes an extraneous cognitive load because it is not directly related to learning and understanding. When the information is appropriately searched, selected, and manipulated, the learners are able to process and encode the selected information in working memory with the aid of prior knowledge stored in long-term memory. The processed information, integrated with existing knowledge in the form of schemas, must be stored in long-term memory. These processes are intrinsic to any learning task and so impose an intrinsic cognitive load whose level depends on the nature of the task. Cognitive load theory suggests that extraneous cognitive load should be minimized by optimal instructional design (Sweller et al., 2011). For this reason, in a simulation-based learning environment, learning how to search and select appropriate representations as well as how to manipulate the representations correctly is critical. If these processes are not provided with an adequate degree of guidance, novice learners will need to discover the processes themselves generating an extraneous cognitive load. If we vary instructional guidance indicating which representations should be selected for manipulation and how to manipulate them in an effective way, learners should experience different levels of cognitive load resulting in different learning outcomes. For less knowledgeable learners, more detailed instructional guidance on representation selection and manipulation should decrease extraneous cognitive load and benefit learning. Novices dealing with complex information must process many elements simultaneously in working memory due to the high element interactivity associated with a high intrinsic cognitive load (Sweller, 2010).

However, what constitutes element interactivity associated with cognitive load also depends on learners' prior knowledge (Kalyuga, 2007, 2009a, 2009b; Kalyuga et al., 2000, 2001; Sweller, 2010). Experts can retrieve very complex, sophisticated schemas from long-term memory into working memory to assist understanding. Those schemas can act as a single element. As a consequence, high element interactivity for novices may not result in a high cognitive load for more knowledgeable learners if sufficient prior knowledge has been attained to treat many interacting elements as a single element for information processing (Gao, Low, Jin, & Sweller, 2013). The cognitive load caused by learning in a complex, simulation-based environment with less detailed instructional guidance may be tolerable for experts. Indeed, additional guidance providing more expert learners with information that they already have may have negative rather than positive consequences due to the redundancy effect (Sweller et al., 2011). Thus, additional guidance required by novices and so having a positive effect may be redundant for more expert learners resulting in a negative effect. This contrast leads to the expertise reversal effect with additional guidance being beneficial for novices but having negative consequences for more expert learners.

Overview of the present study

The present study investigated the effects of levels of instructional details when learning about concepts of correlation in a simulation-based learning environment for learners with different levels of expertise. Specifically, the consequences of guidance varying in levels of detail on both higher- and lower-expertise learners were explored. The level of instructional detail for the current experiment was determined by two factors related to learning in a simulation-based environment: (1) what representations (parameters) could be selected for manipulation within the simulation settings (dynamically linked multiple representations, e.g., “r value” and “paired x and y number table” in this study), and (2) how these representations should be manipulated for effective learning, reflecting the learning procedure. There were four conditions. (1) A High Detail Representation-High Detail Learning Procedure condition in which the learners explored the simulation-based learning environment with given values for setting the parameter representations and with given procedures. (2) A Low Detail Representation-High Detail Learning Procedure condition in which no exact value was provided for setting parameter representations and so the learners had to select appropriate values from a given range. However, the learners were still provided with given procedures to explore the simulation-based environment. (3) A High Detail Representation-Low Detail Learning Procedure condition in which the learners were provided with exact values for parameter representations, but they were not provided with detailed procedures for learning. (4) A Low Detail Representation-Low Detail Learning Procedure condition in which neither exact parameter values nor learning procedures were provided in detail.

The High Detail Representation-High Detail Learning Procedure condition provided the highest level of instructional guidance whereas the Low Detail Representation-Low Detail Learning Procedure condition provided the lowest level of guidance in the current study, with both the Low Detail Representation-High Detail Learning Procedure condition and the High Detail Representation-Low Detail Learning Procedure condition providing intermediate levels of guidance. Within the theoretical framework of cognitive load theory, an interaction between levels of instructional detail and learner expertise was hypothesized. More specifically, it was expected that the highly detailed learning guidance would be of benefit for learners with little expertise in the domain. With higher expertise, the benefits of more detailed instructional guidance were predicted to disappear or even reverse.

Method

Participants

One hundred and fifty-two (male = 97; female = 55) students participated in the current experiment. All students attended a public high school in northern Taiwan. Twelve (male = 3; female = 9) did not finish the whole experiment and therefore 140 participants were included in the final analyses period. Sixty-nine (male = 46; female = 23) were in grade 10 and had no tuition on the concepts of correlation in school before the experiment except some basic tuition about simple probability and statistical charts such as bar charts, pie charts, etc. These students were classified as lower-expertise, less knowledgeable students in the present study. In contrast, seventy-one participants (male = 44; female = 27) in grade 11 had learned the concepts of correlation in the final term of grade 10, and were classified as higher- expertise, more knowledgeable students. Within both expertise levels the participants were assigned to the four experimental conditions balanced according to their average scores of the previous two midterm mathematics exams.

Experiment environment

The experiment was conducted in the third version of the Simulation-Assistant Learning Statistic environment developed by Liu and his colleagues (Liu et al., 2010) to assist students to learn the basic concepts associated with correlation and revised based on the design of the present experiment and the results of a pilot study conducted one week before this experiment (See Figure 1 for a screenshot of the Simulation-Assistant Learning Statistic III).
The Simulation-Assistant Learning Statistic III included two major areas in its interface: a learning guidance area on the left side and a dynamic linked multiple representation area on the right side. Except that the learning guidance varied between conditions, the environment was identical for all learners. The dynamically linked multiple representation area contained a blank for setting up and presenting the correlation coefficient value (*r* value), a table for displaying and manipulating the two dimensions of each of the sample numbers on the X and Y axes, and a

scatter plot for showing the distribution of data points corresponding to the sample numbers. These three representations presented the concepts associated with correlation in different formats. If the students manipulated any of these representations, the corresponding changes would occur in the other representations simultaneously. All manipulation activities by the students in the current experiment were conducted in this dynamically linked multiple representations area. The learning guidance area included textual instructions varying between conditions. It instructed the learners to set appropriate values for the specific representation and to explore the concepts using appropriate procedures. Specifically, the High Detail Representation-High Detail Learning Procedure and the High Detail Representation-Low Detail Learning Procedure conditions had highly detailed guidance on setting values for specific representations. These values were provided with exact *r* values (e.g., input 0.8, 1, -0.8, and -1 in this study) and paired x, y values (e.g., five pairs of numbers) while the other conditions with low detailed guidance for the representation settings were only instructed to enter any number between a range of -1 and 1 in the blank for r value and to make any changes for the values of the paired x, y variables. An example of the learning guidance for the four conditions is presented in Appendix A. Similarly, the High Detail Representation-High Detail Learning Procedure and the Low Detail Representation-High Detail Learning Procedure conditions with highly detailed guidance on the way to explore the environment were provided with detailed steps for observing each relation between dynamically linked multiple representations, whereas the other conditions with low detailed guidance on learning procedures were only provided a general direction to explore the relations between dynamically linked multiple representations.

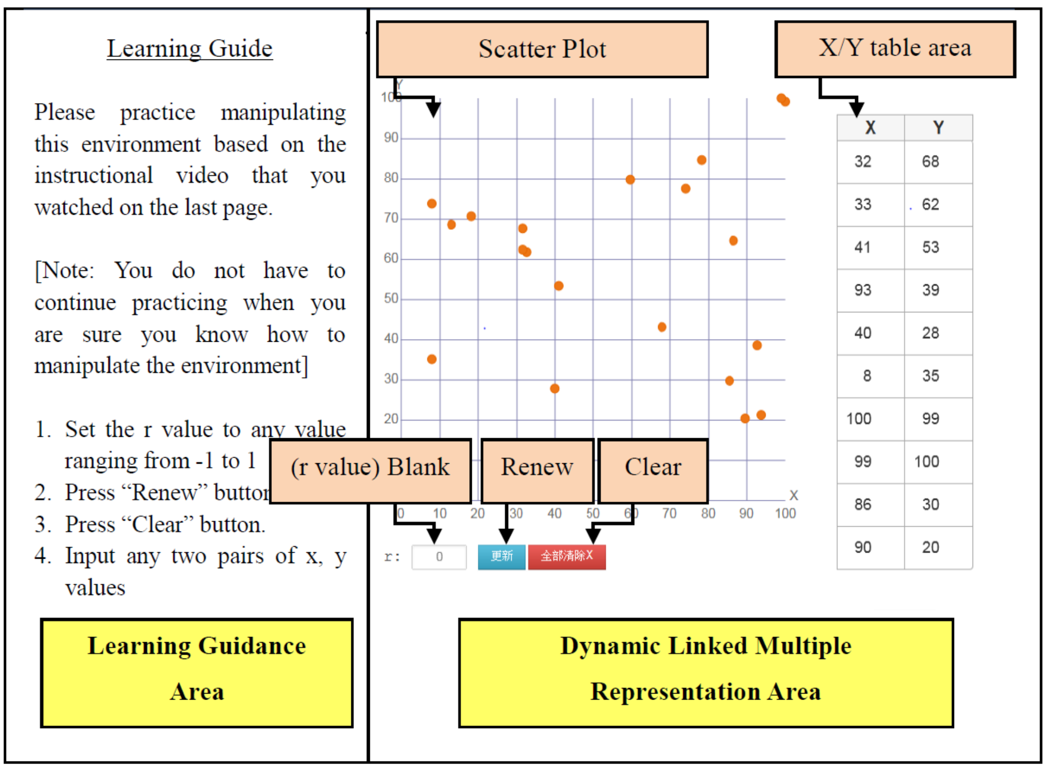

Figure 1. A screenshot of the simulation-assistant learning statistic

Materials and procedure

The experimental materials used in the current experiment were compiled according to the Taiwan National Syllabus Program Requirements designed for Grade 10, Semester 2 mathematics. Three units with two tasks related to three major concepts associated with correlation were selected as the learning materials in the current study, including positive and negative correlations (Unit 1), correlation degree (Unit 2), and perfect correlations (Unit 3). Each unit contained two tasks in which the relations between the dynamically linked multiple representations in the simulation-based learning environment were explored separately by manipulating the r value (Task 1) and the values of the x and y variables (Task 2).

The experimental procedures involved a pre-experimental phase, a learning phase, and a test phase, being executed on two days with an interval of one week. On the first day, only the pre-experimental phase was scheduled, lasting fifteen minutes. On the second day, the learning phase (50 minutes) and the test phase (10 minutes) were administrated using a computer assigned to each participant (see Figure 2, for a schematic representation of the procedure).

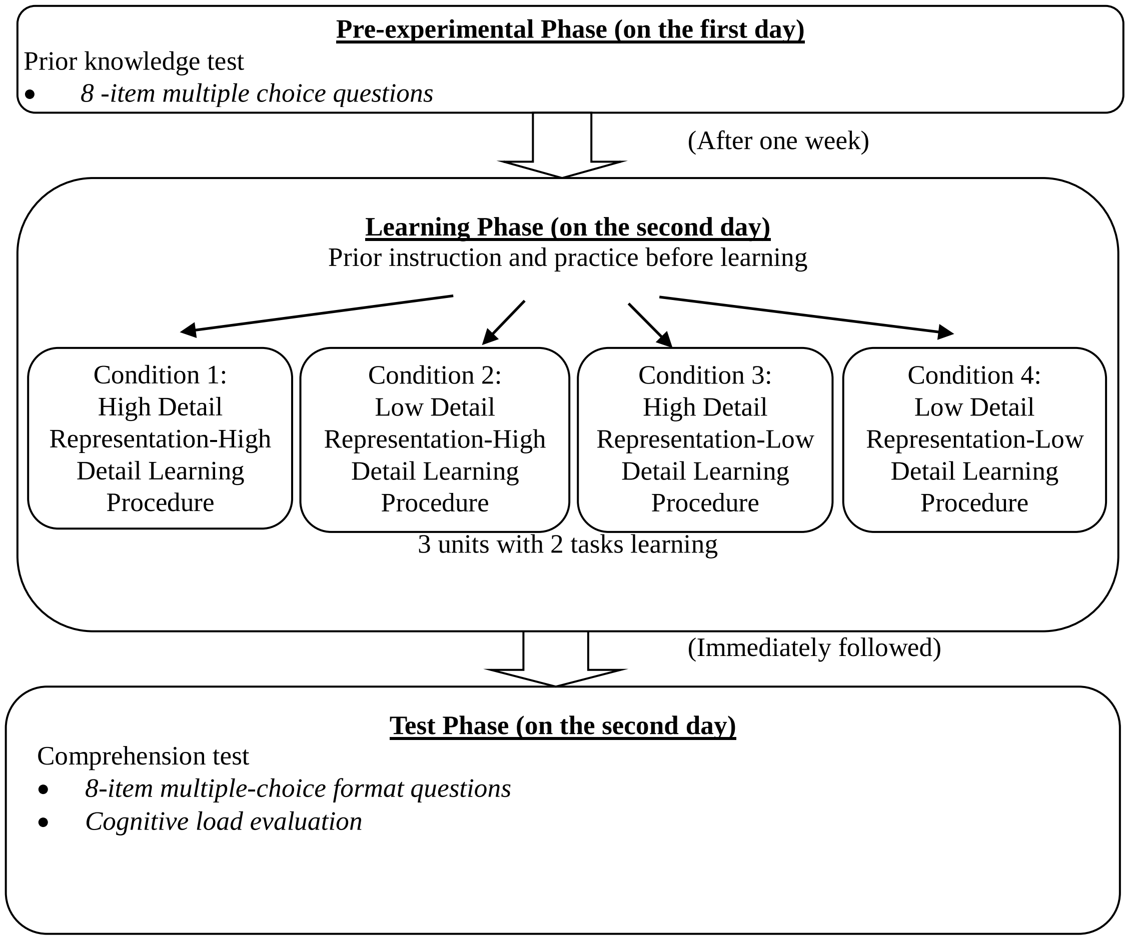

Figure 2. The procedure over the experiment

Pre-experimental phase

A prior knowledge test was carried out one week before conducting the experiment in order to verify the classification of higher- and lower-expertise learners and also to ensure an equivalent initial understanding of the concepts of correlation between experimental conditions within expertise levels. The students were given fifteen minutes to answer eight multiple-choice questions on a sheet of paper. One point was given for a correctly answered question, and full marks for the prior knowledge test were therefore 8 points.

Learning phase

In the learning phase, every student was provided with a computer with the software of Simulation-Assistant Learning Statistic III installed. One page of instruction about basic knowledge of the key concepts associated with correlation (e.g., *r* value, sample size, category of correlation, etc.) was presented to the students on the computer screen for learning at the beginning of the learning phase. No time limit was required for basic knowledge acquisition, and the students could move to the next page when they finished reading.

After basic knowledge acquisition, the students were introduced to the representations involved in Simulation-Assistant Learning Statistic III as well as their functions by a three-minute video. The video showed how to manipulate the different representations, such as an *r* value and the values of the x, y variables. When the video ended, the students were allowed to practice manipulating the representations on their own for a limit of 1 minute. This time limit was adequate for students to finish their practice. The students were also given opportunities to ask questions after practice.

The students were then presented with the simulation-based learning environment with the learning guidance varying corresponding to their own experimental condition. They were presented with identical learning tasks and an identical simulation-based learning environment except that the amount of detail in the learning guidance varied according to the experimental condition.

Test phase

The test phase immediately followed the learning phase and was conducted on the same computer as used in the learning phase. The ten minute comprehension test consisted of 8 multiple-choice items (see Appendix B, for an example question of the comprehension test). The internal consistency of the comprehension tests was 0.61. At the end of the comprehension test, a nine-point Likert rating scale originally designed by Paas, Van Merrienboer and Adam (1994) was presented on the computer screen. Students were asked to indicate their cognitive load in completing the task, with 1-9 being “very very low,” “very low,” “low,” “slightly low,” “neither high nor low,” “slightly high,” “high,” “very high,” and “very very high,” respectively.

Results

Statistical significance for all tests was set at the .05 level except when otherwise indicated. Partial η^2 was used as the effect size index. Accordingly, .01, .06, and .14 are considered as the partial η^2 values reflecting small, medium and large effect sizes (Cohen, 1988).

Prior knowledge test

A 4 (Experimental Condition: High Detail Representation-High Detail Learning Procedure condition, High Detail Representation-Low Detail Learning Procedure condition, Low Detail Representation-High Detail Learning Procedure condition, Low Detail Representation-Low Detail Learning Procedure condition) × 2 (Expertise Level: lower-expertise learners, higher-expertise learners) analysis of variance (ANOVA) was conducted on the prior knowledge test accuracy scores (*see* Table 1, for the means and standard deviations of the test accuracy scores of the prior knowledge test). The results demonstrated a significant main effect of expertise level, $F(1, 132) = 89.41$, $MSE = 2.51$, $p < 0.001$, partial $\eta 2 = .40$, indicating that the division of learners into higher- and lower-expertise levels was valid. Neither a main effect of the experimental conditions, $F(3, 132) = 1.95$, $MSE = 2.51$, $p = .13$, nor an interaction between the experimental conditions and expertise levels was found, $F(3, 132) = 1.62$, $MSE = 2.51$. $p = .19$, verifying the equivalent initial understanding of the concepts of correlation between the experimental conditions within expertise levels. Based on these results, it was decided not to use the prior knowledge test scores in any other analyses of the present study.

Table 1. Means and standard deviations on the prior knowledge test

Learner expertise	Conditions											
	High Detail Representation-High Detail Learning Procedure			Low Detail Representation-High Detail Learning Procedure			High Detail Representation-Low Detail Learning Procedure			Low Detail Representation-Low Detail Learning Procedure		
	N	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
Lower	18	3.61	1.54	18	2.28	1.71	16	2.63	1.20	17	3.06	1.30
Higher	19	5.16	1.64	17	5.00	1.70	18	5.67	1.75	17	5.88	1.69

Comprehension test

Table 2 shows the means and standard deviations for the four experimental conditions on the comprehension test. We conducted a two-way analysis of covariance (ANCOVA), with four experimental conditions (High Detail Representation-High Detail Learning Procedure condition, High Detail Representation-Low Detail Learning Procedure condition, Low Detail Representation-High Detail Learning Procedure condition, Low Detail Representation-Low Detail Learning Procedure condition) and two expertise levels (lower-expertise learners, higher-expertise learners) as between-subjects factors. The average scores of the two previous midterm examinations in mathematics used to allocate students evenly to the four experimental conditions were used as a covariate.

Table 2. Means and standard deviations for the four experimental conditions on the comprehension test

	Conditions											
Variables	High Detail Representation-High Detail Learning Procedure			Low Detail Representation-High Detail Learning Procedure			High Detail Representation-Low Detail Learning Procedure			Low Detail Representation-Low Detail Learning Procedure		
	N	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
Lower-expertise												
Performance	18	5.50	1.43	18	4.94	1.63	16	4.56	1.90	17	3.94	1.60
Cognitive load	18	6.17	1.98	18	6.28	2.24	16	6.50	1.93	17	6.76	1.95
Higher-expertise												
Performance	19	5.05	1.72	17	6.24	1.25	18	6.11	0.96	17	6.24	0.56
Cognitive load	19	4.11	1.76	17	3.82	1.98	18	3.72	1.78	17	4.76	1.64

Before analyzing the data using the two-way ANCOVA, the homogeneity of regression coefficients was tested. The results indicated that neither the interaction between the covariate variable and experimental conditions, F (3, 130) = .55, p = .65, nor the interaction between the covariate variable and expertise levels, F (1, 130) = 1.60, p = .21, was significant. Thus, neither homogeneity assumptions were violated.

The ANCOVA revealed no main effect of experimental conditions, F(3, 131) = .72, MSE = 2.06, p = .54. A significant main effect of expertise level was found, F(1, 131) = 14.87, MSE = 2.06, $p < .001$, partial $\eta^2 = .10$, indicating a better test performance for the higher-expertise learners than for the lower-expertise learners. A significant interaction between expertise level and experimental condition was also obtained, F(3, 132) = 5.89, MSE = 2.06, p = .001, partial $\eta^2 = .12$ (*see* Fig. 3., for a representation of the significant interaction).

Simple effects tests were used following the significant interaction on the comprehension test performance. For lower-expertise learners, a significant effect of experimental conditions on the comprehension test question accuracy scores was obtained, F(3, 131) = 3.52, MSE = 2.06, p = .02, partial $\eta^2 = .08$. Post hoc LSD tests showed that the High Detail Representation-High Detail Learning Procedure condition and the High Detail Representation-Low Detail Learning Procedure condition significantly outperformed the Low Detail Representation-Low Detail Learning Procedure condition. There were no other significant differences between experimental conditions.

For higher-expertise learners, there was also a significant effect of experimental condition on the comprehension test accuracy scores, F(3, 131) = 3.08, MSE = 2.06, p = .03, partial $\eta^2 = .07$. Post hoc LSD tests indicated the High Detail Representation-High Detail Learning Procedure condition performed significantly worse than any of the other conditions with no other significant differences.

For the cognitive load self-ratings during the comprehension test. The homogeneity of variance assumption was again tested before conducting the ANCOVA. The results indicated neither a significant interaction between the covariate variable and experimental conditions, F(3, 130) = 1.22, p = 0.31), nor a significant interaction between the covariate variable and expertise level, F(1, 130) = 0.84, p = 0.36), revealing a plausible assumption of homogeneity of regression coefficients. . ANCOVA only revealed a main effect of expertise level, F(1, 131) = 33.54, MSE = 3.50, $p < .001$, partial $\eta^2 = .20$. Inspection of the means indicated that the lower-expertise learners found the test harder than the higher-expertise learners. The results failed to indicate either a main effect of experimental conditions, F(3, 131) = 1.05, MSE = 3.50, p = .37, or an interaction between expertise level and experimental condition, F(3, 131) = .38, MSE = 3.50, p = .77.

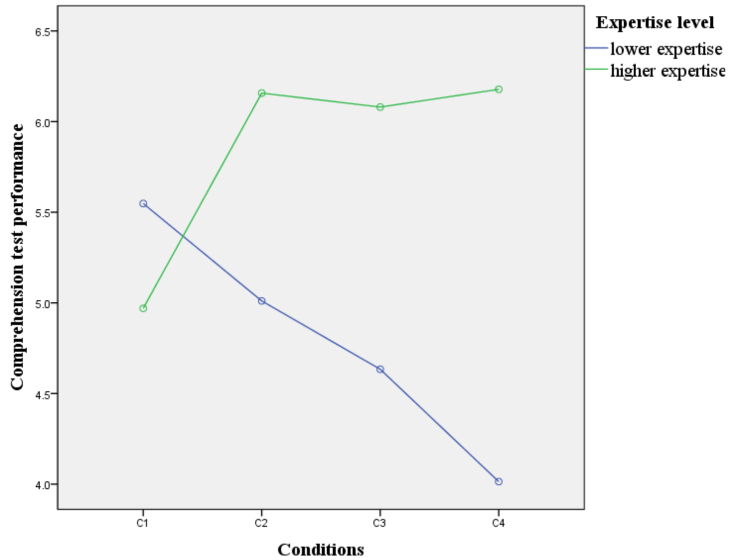

Figure 3. The performance of comprehension test. *Note*. 1, 2, 3, and 4 on the abscissa axis (Conditions) represent: 1. High Detail Representation-High Detail Learning Procedure condition; 2. High Detail Representation-Low Detail Learning Procedure condition; 3. Low Detail Representation-High Detail Learning Procedure condition; 4. Low Detail Representation-Low Detail Learning Procedure condition.

Discussion

The aim of this study was to examine the effects of levels of instructional detail in supporting learners in a simulation-based environment. Four varying levels of details in guidance embedded in the same simulation-based learning environment were compared. It was expected that highly detailed guidance would be helpful for lower-expertise learners while lower levels of details in guidance would be beneficial for higher-expertise learners. Overall, the hypothesis was supported by a significant, disordinal interaction of test performance between experimental condition and expertise level on the comprehension test.

A simulation-based learning environment can provide learners with a platform in which learners' own mental model or schemas can be constructed by independently interacting with the environment. In such a relatively free learning environment, determining what should be dealt with (representation selection) in the environment and how to deal with the selected representation (learning procedure) is critical for effective learning (Kirschner, Sweller, & Clark, 2006). From a cognitive load theory perspective, free exploration of a highly complex environment may result in heavy demands on working memory (Sweller et al., 2011). If minimal details in guidance are provided, learners without sufficient prior knowledge need to devote a large amount of their working memory resources to search for problem solutions, leaving few working memory resources available for learning. The present results supported this hypothesis by demonstrating a positive learning effect using more detailed guidance when learners' expertise levels were low. Although the High Detail Representation-High Detail Learning Procedure condition did not show a statistically significant superiority on comprehension test performance over the two conditions with intermediate levels of detailed guidance (High Detail Representation-Low Detail Learning Procedure condition & Low Detail Representation-High Detail Learning Procedure condition), the means revealed the expected trend using lower-expertise learners. A significant difference was found between the High Detail Representation-High Detail Learning Procedure condition and the Low Detail Representation-Low Detail Learning Procedure condition. The benefit of more detailed guidance on learning in a simulation-based learning environment was further confirmed by the significantly better comprehension test performance for the High Detail Representation-Low Detail Learning Procedure condition than for the Low Detail Representation-Low Detail Learning Procedure condition.

However, such learning effects due to highly detailed guidance were absent for higher-expertise learners. On the one hand, more knowledgeable learners had sufficient prior knowledge to process multiple elements as a single element when searching and selecting representations, resulting in the cognitive load associated with exploring a complex simulation-based environment being manageable. For example, higher-expertise learners previously had learned the concepts of correlation and they were likely to know which manipulations would be most beneficial to further advance their understanding. Learning may therefore have been facilitated using a relatively free mode of exploration with few details during guidance. In contrast, highly detailed guidance that provided exact values for setting parameter representations and specific procedures for manipulating the representations already were likely to be part of the prior knowledge base of higher-expertise learners. The cognitive load associated with reading and following guidance was therefore redundant and imposed an extraneous cognitive load for higher-expertise learners, impairing learning.

These results are consistent with previous cognitive load theory studies on worked examples (Kalyuga et al., 2001; Kalyuga, Chandler, Tuovinen, & Sweller, 2001; Sweller, Van Merrienboer, & Paas, 1998; Tuovinen & Sweller, 1999) that found that worked-out examples instruction, which was effective for novices, lost its advantage and became redundant as the knowledge level of learners was raised as a consequence of intensive training. For example, Kalyuga et al. (2001) presented either a series of worked examples or a less guided, exploratory-based environment to mechanical trade apprentices. The results showed that when dealing with complex tasks, inexperienced trainees clearly benefited most from the worked examples procedure but the advantage disappeared after two training sessions as participants became more experienced in the domain. Despite the differences in procedure, the current results may be interpreted in the same way as that of the worked example studies: discovery with minimal guidance imposes a heavy cognitive load on less knowledgeable learners, limiting effective learning, especially in complex simulation-based learning environment. The disadvantages of discovery learning disappeared and reversed with higher expertise. These results provide a clear example of the expertise reversal effect (Kalyuga, 2007, 2009a, 2009b; Kalyuga et al., 2003), demonstrating a reversal of cognitive load effects with expertise. The present study, by examining the effects of instructional guidance when exploring a simulation-based environment, demonstrated that whether the instructional guidance imposed a germane or extraneous load on learners was determined by learners' expertise.

One limitation of the present study lies in the cognitive load evaluations. On the comprehension test, except for the significant difference of the cognitive load self-ratings between higher- and lower-expertise learners, no other effects related to subjective measures of cognitive load were found. The failure to find subjective ratings effects was inconsistent with the test performance where differences between conditions were found. A possible reason for the absent main effects of subjective ratings of cognitive load was that the complex simulation technology imposed some cognitive load by itself and learners may have found it quite hard to differentiate how much cognitive load was imposed by the learning tasks rather than from dealing with the technology. This limitation in cognitive load measurement may be a challenge for all studies investigating technology-assisted learning. Future research on simulation-based learning environment may need to measure the cognitive load by more specific questionnaires that, for example, ask students to rate how much mental effort was spent on the learning tasks separately from how much mental effort was spent on using the technology. Alternatively, repeatedly measuring mental effort after each question of a test may provide a more accurate measurement of cognitive load (Van Gog, Kirschner, Kester, & Paas, 2012).

The relatively low internal consistency for the comprehension test (.61) constituted a second limitation of the present study. The small number of test questions is a possible reason for the reduced Cronbach's alpha value (Nunnally & Bernstein, 1994). Although the comprehension test questions had been used in previous research with high internal consistency values (Liu, Kinshuk, Lin, & Wang, 2012; Liu et al., 2010), this study only selected eight questions from the previous tests. More test questions should lead to higher internal consistency values.

Another limitation of the present study was its failure to clearly distinguish between the Low Detail Representation-High Detail Learning Procedure condition and the High Detail Representation-Low Detail Learning Procedure condition, which had highly detailed guidance on either representation selection or learning procedures. As a consequence, it is unknown whether representations selection or learning procedure is more important in instructional guidance. Future research may explore this question by further analyzing the cognitive processes during learning, for example, by analyzing the learning performance recorded in the log file or measuring the cognitive load during the learning stage.

In conclusion, individual differences in learner expertise in a domain should be taken into account when selecting user-adapted levels of guidance for simulation-based discovery learning. For novice learners without sufficient prior knowledge, highly detailed guidance should be presented first. After learners become more knowledgeable in the domain, the guidance can be less detailed in line with the guidance fading effect (Renkl & Atkinson, 2003; Renkl, Atkinson, & Große, 2004; Renkl, Atkinson, & Maier, 2000; Renkl, Atkinson, Maier, & Staley, 2002). These findings may provide a reason for the diverse results in previous research on the effects of guidance for simulation-based learning. For example, van der Meij and de Jong (2011) found a positive effect of learning guidance during computer simulation while Chang, Chen, Lin, and Sung (2008) obtained a negative effect. These apparent contradictions may be explained by the current findings.

Acknowledgments

The authors would like to thank the assistance of Wang-Shen Lu in developing the experiment environment. Moreover, we would like to thank the Ministry of Science and Technology, Taiwan, R.O.C. for financially supporting this research under Grant no. MOST 101-2511-S-003 -061 -MY3, and MOST 103-2511-S-003 -058 -MY3. Finally, we would like to thank the support of the "Aim for the Top University Project" of National Taiwan Normal University (NTNU), sponsored by the Ministry of Education, Taiwan, R.O.C. and the "International Research-Intensive Center of Excellence Program" of NTNU and Ministry of Science and Technology, Taiwan, R.O.C. under Grant no. MOST 104-2911-I-003-301.

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Appendix A

An example of the learning guidance for the four experimental conditions with different levels of detail

<table>
<tr><th colspan="5">Unit 1: The concepts of positive and negative correlations</th></tr>
<tr><td colspan="5">The default sample size is 20 in this study (n = 20).
Please complete tasks 1 & 2 using the following procedures.
At the same time, please observe the changes that occur in the r values, paired x and y values, and data points of the scatter plot as well as the relations between them.</td></tr>
<tr><td colspan="5">Learn about positive and negative correlations by setting different correlation coefficients (r values)</td></tr>
<tr><td></td><td>Condition 1:
High Detail Representation-
High Detail Learning Procedure</td><td>Condition 2:
Low Detail Representation-
High Detail Learning Procedure</td><td>Condition 3:
High Detail Representation-
Low Detail Learning Procedure</td><td>Condition 4:
Low Detail Representation-
Low Detail Learning Procedure</td></tr>
<tr><td>Representations
Procedure</td><td>Given
r value</td><td>No given
r value</td><td>Given
r value</td><td>No given
r value</td></tr>
<tr><td>Step 1</td><td>Set the r value to 0.7</td><td>Set the r value to any value ranging from -1 to 1.</td><td rowspan="7">Try to observe the changes and the relations between the r values, paired x and y values, and data points of the scatter plot when setting the r value to 0.7, -0.7 as well as pressing the reordering key on the x, y table.
Once again, reset the r values to 0.9 and -0.9, and observe the changes and relations.</td><td rowspan="7">Try to observe the changes and the relations between the r values, paired x and y values, and data points of the scatter plot when setting the r value to any pair of inverse numbers ranging from -1 to 1 as well as pressing the reordering key on the x, y table.
Once again, reset the r value to another pair of inverse numbers, and observe the changes and relations.</td></tr>
<tr><td>Step 2</td><td colspan="2">Press the reordering key on the x, y table and observe the relations between the paired x, y values and the r value.</td></tr>
<tr><td>Step 3</td><td colspan="2">Observe the relations between the distribution of data points on the scatter plot and r values.</td></tr>
<tr><td>Step 4</td><td colspan="2">Observe the relations between the distribution of data points on the scatter plot and paired x, y values.</td></tr>
<tr><td>Step 5</td><td colspan="2">Observe the relations between the r values, paired x and y values, and data points of the scatter plot</td></tr>
<tr><td>Step 6</td><td>Reset the r value to -0.7 and repeat procedures 2-5.</td><td>Reset the r value to its inverse number and repeat procedures 2-5.</td></tr>
<tr><td>Step 7</td><td>According to the same procedure as above, reset the r values to 0.9 and -0.9, and observe the relations between the r values, paired x and y values, and data points of the scatter plot</td><td>According to the same procedure as above, reset the r values to another pair of inverse numbers ranging from -1 to 1, and observe the relations between the r values, paired x and y values, and data points of the scatter plot</td></tr>
<tr><td colspan="5">Task 2: Learn about positive and negative correlations by setting different paired x and y values</td></tr>
<tr><td></td><td>Condition 1:
High Detail Representation-
High Detail Learning Procedure</td><td>Condition 2:
Low Detail Representation-
High Detail Learning Procedure</td><td>Condition 3:
High Detail Representation-
Low Detail Learning Procedure</td><td>Condition 4:
Low Detail Representation-
Low Detail Learning Procedure</td></tr>
<tr><td>Representations
Procedures</td><td>Given
paired x, y values</td><td>No given
paired x, y values</td><td>Given
paired x, y values</td><td>No given
paired x, y values</td></tr>
<tr><td>Step 1</td><td colspan="2">Press “clear” to remove all the data.</td><td rowspan="2">After pressing “clear” to remove all the data, try to observe the changes and relations between the r values, paired x and y values, and data points of the scatter plot by</td><td rowspan="2">After pressing “clear” to remove all the data, try to observe the changes and relations between the r values, paired x and y values, and data points of the scatter plot by</td></tr>
<tr><td>Step 2</td><td>Input six pairs of x, y values that are positively correlated as shown in the following table.</td><td>Input any six or more pairs of x, y values that are positively correlated.</td></tr>
</table>

<table>
<tr>
<td></td>
<td colspan="2">
<table>
<tr><th>X</th><th>Y</th></tr>
<tr><td>10</td><td>15</td></tr>
<tr><td>20</td><td>30</td></tr>
<tr><td>30</td><td>33</td></tr>
<tr><td>40</td><td>52</td></tr>
<tr><td>50</td><td>48</td></tr>
</table>
</td>
<td>inputting five pairs of x, y values with a positive correlation and then another five pairs of x, y values with a negative correlation as shown in the following tables.</td>
<td>inputting any five or more pairs of x, y values with a positive correlation and then repeat with a negative correlation.</td>
</tr>
<tr>
<td>Step 3</td>
<td colspan="2">Observe the ranking orders of x and y values (whether the x and y values increase or decrease).</td>
<td rowspan="7">
<u>Positive</u>
<table>
<tr><th>X</th><th>Y</th></tr>
<tr><td>10</td><td>15</td></tr>
<tr><td>20</td><td>30</td></tr>
<tr><td>30</td><td>33</td></tr>
<tr><td>40</td><td>52</td></tr>
<tr><td>50</td><td>48</td></tr>
</table>
<u>Negative</u>
<table>
<tr><th>X</th><th>Y</th></tr>
<tr><td></td><td></td></tr>
<tr><td>20</td><td>49</td></tr>
<tr><td>30</td><td>41</td></tr>
<tr><td>40</td><td>29</td></tr>
<tr><td>50</td><td>20</td></tr>
<tr><td>60</td><td>13</td></tr>
</table>
</td>
<td rowspan="7"></td>
</tr>
<tr>
<td>Step 4</td>
<td colspan="2">Observe the changes of r values and think about the relations between the paired x, y values and an r value.</td>
</tr>
<tr>
<td>Step 5</td>
<td colspan="2">Observe the relations between paired x, y values and the distribution characteristics of data points on the scatter plot.</td>
</tr>
<tr>
<td>Step 6</td>
<td colspan="2">Observe the relations between the r value and the distribution characteristics of data points on the scatter plot.</td>
</tr>
<tr>
<td>Step 7</td>
<td colspan="2">Observe the relations between the r values, paired x and y values, and data points of the scatter plot.</td>
</tr>
<tr>
<td>Step 8</td>
<td colspan="2">Press “update” to obtain another six pairs of x, y values with the same r value, and repeat procedures 3-7.</td>
</tr>
<tr>
<td>Step 7</td>
<td>Using the same procedure as above, input five new pairs of x, y values with a negative correlation as shown in the following table and observe the changes and relations between the r values, paired x and y values, and data points of the scatter plot.
<table>
<tr><th>X</th><th>Y</th></tr>
<tr><td>20</td><td>68</td></tr>
<tr><td>30</td><td>59</td></tr>
<tr><td>40</td><td>57</td></tr>
<tr><td>50</td><td>48</td></tr>
<tr><td>60</td><td>50</td></tr>
</table>
</td>
<td>According to the same procedure as above, input six or more new pairs of x, y values with a negative correlation, and observe the changes and relations between the r values, paired x and y values, and data points of the scatter plot.</td>
</tr>
</table>

Appendix B

An example question from the comprehension test

5. A researcher using a sample size of 9 collected data about how much students' read literature and their literature test results in order to find the correlation between the two variables. The results indicated a positive correlation but not a perfect positive correlation between the amount of literature reading (X) and the literature test results (Y). Can you please indicate which of the following four sets of data about X and Y represent the data collected in this research?

I	X	23	32	39	43	48	52	61	67	72
	Y	23	32	39	43	48	52	61	67	72
Ⅱ	X	31	33	39	41	43	48	53	62	71
	Y	42	49	51	53	51	55	52	66	79
Ⅲ	X	68	69	72	73	81	92	110	113	120
	Y	71	72	79	76	89	96	94	96	99
Ⅳ	X	67	71	74	79	81	84	91	92	99
	Y	56	61	63	68	77	81	89	91	93

A. I, IV
B. I, Ⅱ, Ⅲ, Ⅳ
C. Ⅱ, Ⅲ
D. I
E. IV