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Encountering the expertise reversal effect with a computer-based environment on electrical circuit analysis

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Abstract

This study examined the effectiveness of a computer-based environment employing three example-based instructional procedures (example–problem, problem–example, and fading) to teach series and parallel electrical circuit analysis to learners classified by two levels of prior knowledge (low and high). Although no differences between the instructional procedures were observed, low prior knowledge learners benefited most from traditional example–problem pairs while their high prior knowledge counterparts benefited most from problem–example pairs. Overall, this study provides empirical support for the expertise reversal effect, which suggests that the effectiveness of certain instruction procedures in example-based learning environments depends upon the learners' level of prior knowledge.

Keywords: Worked-out examples; Fading; Expertise reversal effect; Engineering education

Computer-based instructional modules teaching electrical circuit analysis techniques have received a significant amount of interest over the last decade, see for instance (Ahmed & Bayoumi, 1994; Al-Holou & Abdallah, 1996; Al-Holou & Clum, 1999; de Coulon, Forte, & Rivera, 1993; Doering, 1996; Hanrahan & Caetano, 1989; Harris & Black, 1995; Jones & Conner, 1994; Nahvi, 1990; Oakley, 1993, 1994, 1996; Pota, 1997; Shaffer & Mabry, 2000; Shannon, 1994; Yoshikawa, Shintani, & Ohba, 1992). This literature contains a wide variety of computer-based instructional modules that are designed to teach circuit analysis techniques.

Both worked examples and practice problems are commonly employed in these modules. A *worked example* is a fully solved example problem that allows the students to examine the full sequence of steps leading to the solution of a problem. A *practice problem*, on the other hand, provides the students with the problem statement and it is the students' responsibility to fill in the individual solution steps. In some computer-based implementations, upon filling in the individual solution steps, the learners are given feedback on the accuracy of their input. The study by Trafton and Reiser (1993) indicates that learning is improved when worked examples are paired with practice problems compared to when only worked examples are provided to the learners. Similarly, the study by Sweller and Cooper (1985) has found that the pairing of worked examples with practice problems is more effective than providing the learners

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only with practice problems. Overall, a significant number of studies performed by Sweller and his colleagues (for an overview see Sweller, Van Merrienboer, & Paas, 1998) have established strong empirical support for this type of *example–problem* pairing, where isomorphic worked examples and practice problems are paired in an instructional activity.

Although learning from worked examples is effective, research indicates that this approach is critical when learners are in the preliminary stages of acquiring a cognitive skill in well-structured domains such as mathematics, physics, and computer programming (Anderson, Fincham, & Douglass 1997; VanLehn, 1996). In particular, Anderson and his colleagues proposed that the importance of learning from examples was limited to the first stage and the beginning of the second stage within a cognitive skill acquisition framework consisting of four overlapping stages (Anderson et al., 1997). According to this framework, learners in the initial stage solve problems by referring to specific examples and attempting to relate them to the problem to be solved. Learners in the second stage begin to develop abstract declarative rules—verbal knowledge that guides their problem solving—through problem-solving practice. After sustained practice, learners move to the third stage where proceduralised rules begin to form and problem-solving performance becomes more efficient, requiring fewer attentional resources. Finally, by the fourth stage, learners have encountered many different types of problems, often committing to memory specific examples that they can retrieve quickly and directly from memory. Although learning from examples is critical in the initial stages of cognitive skill acquisition, it is not the ideal instructional approach when learners are in the third stage, where problem-solving practice is paramount.

In light of this cognitive skill acquisition framework, a hybrid approach has recently been proposed that lies between the use of worked examples and practice problems referred to as the completion strategy (Van Merriënboer, 1990), or the *fading approach* (Atkinson, Renkl, & Merrill, 2003; Renkl, Atkinson, & Große, 2004; Renkl, Atkinson, & Maier, 2000; Renkl, Atkinson, Maier, & Staley, 2002), which has received virtually no attention so far in engineering education. In the fading approach, the learner is initially presented with a fully worked example while in the next example all but one of the problem subgoals are worked out and the learner is required to independently solve (anticipate) the solution of the missing problem subgoal. In the subsequent example, all but two problem subgoals are worked out and the learner is required to anticipate the solutions to the two missing problem subgoals, and so on, until the learner is required to anticipate the solutions for all problem subgoals (independent problem solving). More specifically, with the *backward-fading* design, the last solution step is omitted first, then the last two, and so on. Recent studies conducted for the knowledge domain of elementary probability theory and statistics found indications that backward fading has a positive effect on learning (Atkinson et al., 2003; Renkl et al., 2002, 2004).

Considering the fading approach in light of the stages of cognitive skill acquisition, it is clear that this type of instructional procedure is designed to ensure a smooth transition from example study (in the initial stages of skill acquisition) to working on incomplete examples (in the early-to-middle stages of skill acquisition) to problem solving (in the middle-to-final stages of skill acquisition). Accordingly, the fading approach, with its reliance on worked examples at the outset of instruction, is most relevant for learners with little domain expertise since they are likely in the initial stages of cognitive skill acquisition.

On the other hand, both the traditional example–problem approach and the fading approach to example-based instruction are not well-suited for learners with sufficient domain expertise since these learners are in the latter stages of cognitive skill acquisition where examples have less utility. In fact, recent research indicates that learning by solving problems is superior to studying examples when learners have amassed a reasonable degree of domain expertise as denoted by the learners' relative level of domain knowledge (Kalyuga, Ayres, Chandler, & Sweller, 2003; Kalyuga, Chandler, & Sweller, 2000; Kalyuga, Chandler, Tuovinen, & Sweller, 2001). Kalyuga et al. (2001) analysed mechanical trade apprentices' learning about relay circuits and their programming over an extended training experience. While they found that learning from examples was superior to problem solving for inexperienced learners in the initial stages of cognitive skill acquisition, this advantage disappeared over time as the participants developed more content expertise and moved into the latter stages of cognitive skill acquisition. Hence, there was a reversal of the worked-example effect when learners have substantial prior knowledge, a phenomenon referred to as the expertise reversal effect (Kalyuga et al., 2003). In sum, while learners with low prior knowledge—that is, in the initial stages of skill acquisition as evidenced by little-to-no domain expertise—benefit from worked examples, learners with high prior knowledge—that is, in the middle-to-final stages of skill acquisition as evidenced by moderate-to-high domain expertise—no longer benefit from studying examples and, instead, profit from solving practice problems. In light of the expertise reversal effect, it seems prudent to consider an instructional procedure that is sensitive to high prior knowledge learners, one where practice problems are provided first with an accompanying worked example for reference if needed, which we refer to as a *problem–example* pairing.

Against this background, we conducted a study where we systematically examined the impact of the instructional procedure, that is, the arrangement of worked examples and practice problems, in a computer-based instructional module for electrical circuit analysis under two levels of prior knowledge (i.e., expertise) on the learner performance and attitudes. In particular, we compared the following three example-based instructional procedures: (a) *example–problem*: the learner is first presented with a worked example, followed by an isomorphic practice problem; (b) *problem–example*: the learner is first presented with a practice problem, followed by an isomorphic worked example; and (c) *fading*: the learner is presented with backward faded solution steps.

In sum, our study entailed a 3×2 design with instructional procedure as the first independent variable (example–problem, problem–example, and fading) and prior knowledge (low and high) as the second independent variable. Against this background, our study was designed to explore several hypotheses. First, we predicted that learners provided with a fading instructional procedure would outperform their peers provided with example–problem pairs on performance measures. Second, we predicted that learners with high prior knowledge would outperform their low prior knowledge peers on performance measures. Third, we also expected an interaction between instructional procedure and level of prior knowledge. Specifically, we predicted that learners in the early stages of cognitive skill acquisition, that is, with low prior knowledge, would benefit more from the example–problem and fading instructional procedures than from the problem–example pairs and that learners in the latter stages of cognitive skill acquisition, that is, with high prior knowledge, would benefit more from problem–example pairs than from example–problem and fading instructional procedures.

1. Method

1.1. Participants

The participants of this study were 185 students from the ECE100 introductory engineering courses at Arizona State University. The experimental sample consisted of 20% females and 80% males. The average age of the participants was 20.77 years (SD = 4.85). The participants had a mean grade point average (GPA) of 3.26 (SD = .54) out of a maximum of 4.0. Approximately 60% of the participants had been exposed to some form of instruction on electrical circuits before participating in this study. Based on a pretest administered one week prior to the learning phase, the participants were blocked by prior knowledge and were randomly assigned to one of the three treatment conditions: (1) example–problem instructional procedure, where participants encounter a worked example first followed by a practice problem; (2) problem–example instructional procedure, where the participants first encountered a practice problem followed by a worked example; and (3) fading instructional procedure, where the solution steps were backward faded. Each condition contained identical instructional content, but varied in the structure in which the content was delivered.

1.2. Apparatus and materials

1.2.1. Computer-based learning environment

The computer-based learning environment (see Fig. 1) was developed using Director MX (Macromedia, 2002) software, which is an authoring tool for creating rich multimedia programs. The learning environment was originally developed by Renkl (1997), modified by Stark (1999), modified for a second time by Renkl et al. (2002) before finally being adapted to the present needs by the first author. The module was programmed to operate in one of three modes that corresponded to the three treatment conditions of the current study, namely, example–problem, problem–example, and backward fading.

The goal of the computer-based learning environment was to deliver instruction on the principles of calculating the resistance in the two fundamental types of electrical circuits, namely, parallel and series electrical circuits. The environment presented these two types (parallel and series) of electrical circuit analysis, each with four worked examples/practice problems, constituting a total of eight instructional items. Each item for a given type of circuit analysis had the same underlying structure (i.e., solution rationale), and all items differed in their surface features (i.e., cover stories, values). The following is the cover story from one of the instructional examples that were shown to the participants on the computer screens during the learning phase:

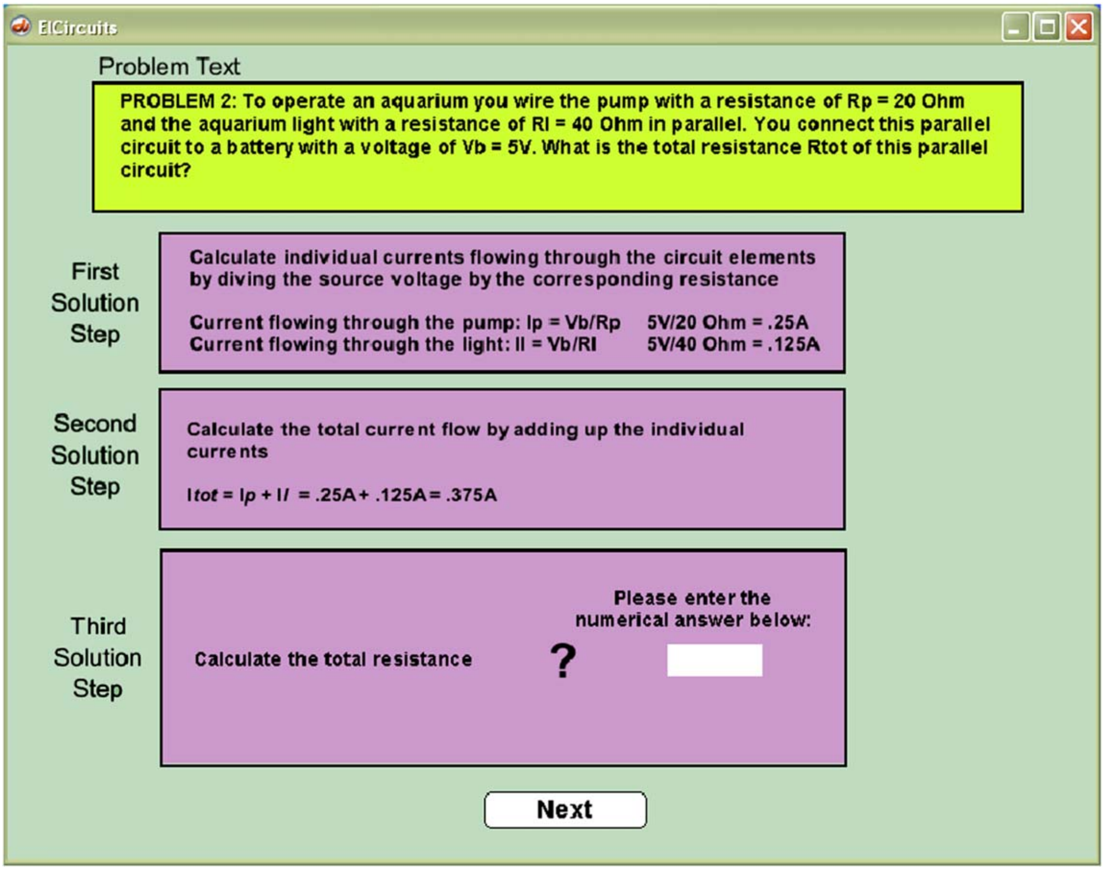

Fig. 1. Screen shot of computer-based learning environment showing a faded example with first two steps worked out and last step awaiting a solution attempt by the learner.

> To operate an aquarium you wire the pump with a resistance of $R_p = 20\ \Omega$ and the aquarium light with a resistance of $R_l = 40\ \Omega$ in parallel. You connect this parallel circuit to a battery with a voltage of $V_b = 5$ V. What is the total resistance R_{tot} of this parallel circuit?

For each type of circuit analysis, the learning environment provided two example−problem pairs in the example−problem condition, two problem−example pairs for the problem−example condition, and one set of four examples with backward faded solution steps for the fading condition.

All the worked examples and practice problems consisted of exactly three solution steps or subgoals. Each step was clearly labelled and visually distinguished from the other steps. The computer module revealed one step at a time after the participants clicked the ‘‘Next’’ button, thus allowing the participants to control the pace of their learning. For each unsolved solution step the students entered their solution. The computer-based learning environment then revealed the correct solution for the solution step. The participants were given a single attempt at solving each missing step. The solved step(s) remained visible on the screen after the final answer was presented, allowing the participants to study the entire solution (worked example). The participants proceeded through the module by clicking on the ‘‘Next Problem’’ buttons after inspecting all three steps in each problem. The navigation was linear and the participants could not return to previous steps and problems once they finalized their answers.

The computer-based learning module automatically recorded the en route practice (accuracy of solving the missing steps or problems depending on the treatment group) and instructional time during the learning (computer) phase. There were a total of 12 unsolved steps in each condition in the computer-based learning environment. Each question could only be answered once before the solution was automatically revealed (single solution attempt or anticipation). For each correctly solved step, one point was awarded, thus producing a maximum score of 12.

1.2.2. *Pencil–paper materials*

The participants were administered a set of pencil–paper materials consisting of a demographic questionnaire, a pretest, an overview of parallel and series electrical circuits, and a posttest.

1.2.2.1. Demographic questionnaire. The questionnaire collected basic demographic data (grade level, gender, ethnicity). It also asked the participants whether they had ever learned about electrical circuit analysis before.

1.2.2.2. Pretest. The pretest was designed to assess the participants' prior knowledge in the area of electrical circuit analysis. It was composed of two parts, with each part consisting of six questions, resulting in a maximum achievable total pretest score of 12 points. The first part contained six multiple-choice questions relating to the basic physical meaning of electrical current, voltage, and resistance, and elementary properties of electrical circuits. The participants could select from four response choices for each question. For instance, the participants were asked "What is electrical current?" and were offered the choices (a) flow of electrical particles in a wire, (b) speed of electrical particles in a wire, (c) total number of electrical particles in a wire, (d) density of electrical particles in a wire, whereby (a) was the correct solution. The second part consisted of six open-response elementary circuit problems that required a single application of Ohm's Law or the basic principles of current and voltage in parallel and series circuits, i.e., a single solution step. For instance, the participants were given the problem "You connect a lamp with a resistance of $R_1 = 5\ \Omega$ to a 9 V battery. How large is the current flow through the lamp?". The maximum obtainable score for the pretest was 12, one point for each correctly answered question.

1.2.2.3. Introductory overview. The four-page overview of parallel and series electrical circuits introduced the participants to (i) the physical meaning and units of electrical current and voltage, (ii) electrical circuit elements and their graphical representations, such as light bulbs and batteries, and the way circuit elements are connected with wires in the two main forms of electrical circuits, namely parallel and series circuits, (iii) the physical meaning and units of resistance as well as Ohm's Law, (iv) the calculation of the resistance of a parallel circuit, and (v) the calculation of the resistance in a series circuit.

The participants were taught to calculate the total resistance from basic principles, namely Ohm's Law and the properties of current and voltage in the electrical circuits. In particular, for the series circuit, the participants were presented with the resistance values of the individual resistors in the circuit and with the value of the current emitted by the battery into the circuit. The participants were then instructed to abide by the following three steps in the calculation of the total resistance of the series circuit. First, the participants studied that the current flowing through each of the circuit elements is equal to the current emitted by the battery and the calculation of the voltage over each individual resistor is done using Ohm's Law. Second, the participants were shown examples where the calculation of the total voltage over the series arrangement of resistors is carried out by summing up the voltages of the individual resistors. Third, the examples presented the calculation of the total resistance of the series circuit by applying Ohm's Law to the entire circuit, i.e., the calculation of the total resistance of the series circuit as the sum of the voltages determined in step 2 divided by the current emitted by the battery.

For the parallel circuit, the participants were presented with the voltage provided by the battery and resistance values of the individual resistors. For the calculation of the total resistance of the parallel circuit, the participants were instructed to proceed through the following three steps. First, the participants observed that the voltage is the same over each individual resistor and were presented with the calculation of the value of the current flowing through each individual resistor using Ohm's Law. Second, an example showed the calculation of the total current flowing in the circuit by summing up the currents flowing through the individual resistors. Third, the total resistance of the parallel circuit was calculated by dividing the voltage provided by the battery by the sum of the currents determined in step 2.

Note that these last two sections on calculating the resistance of series and parallel circuits were not focused on deriving the formulas for calculating the total resistance of the circuit from the resistance values of the individual circuit elements (i.e., $R_{\text{tot}} = R_1 + R_2 + \ldots$ for series circuit and $1/R_{\text{tot}} = 1/R_1 + 1/R_2 + \ldots$ for parallel circuit).

1.2.2.4. Posttest. The posttest contained eight complex problems; more specifically, four problems (two for each type of the electrical circuits, parallel and series) were designed to measure near-transfer performance and four problems (two for each type of the electrical circuits, parallel and series) to assess the far-transfer learning.

The near-transfer problems had the same underlying structure as the practice problems encountered during the learning (computer) phase but different surface characteristics. Specifically, they required the participants to perform the same tasks (e.g., calculating the individual voltage or current, respectively, determining the total voltage or current, respectively, and finally computing the total resistance) as they have learned in the computer-based module. The near-transfer problems provided the participants with the battery current and the individual resistance values for the series circuit problems. For the parallel circuit problems, the participants were given the battery voltage and the individual resistance values. For all of the near-transfer problems, the participants were expected to calculate the total resistance of the electrical circuit. Despite having the same structure and requiring the same solution steps as the practice problems from the learning phase, the near-transfer problems appeared different since they had different cover stories and current, voltage, and resistance values.

The far-transfer problems had different underlying structure and surface features as compared to the computer-based practice problems. In particular, in the far-transfer series circuit problem, the participants were given the individual resistance values and the voltage over one of the resistors. The far-transfer series circuit problem asked the participants to calculate the battery voltage. The following is one of the far-transfer series circuit posttest problems:

> To make your bicycle safe for riding at night, you equip it with a front light that has a resistance of $R_f = 5\ \Omega$ and a rear light with a resistance of $R_r = 5\ \Omega$. You wire the two lights in *series* and connect the series circuit to a battery. To ensure sufficient front lighting, the voltage over the front light must be at least $V_f = 5$ V. How much voltage V_b must the battery at least provide to ensure sufficient lighting?

To solve this problem, the participants had first to use Ohm's Law to calculate the current in the series circuit from the resistance value of the one resistor for which the voltage was given ($I_f = V_f/R_f = 6\ \text{V}/5\ \Omega = 1.2$ A). The participants then had to notice that the current is the same in all resistors and had to calculate the voltages over the other resistors in the circuit from the current determined in the first step and the values of the individual resistors using again Ohm's Law ($V_r = I_f \times R_r = 1.2\ \text{A} \times 10\ \Omega = 12$ V). In the third and final solution step, the participants had to sum up the voltages over the individual resistors to obtain the total voltage (battery voltage) over the circuit ($V_b = V_f + V_r = 6\ \text{V} + 12\ \text{V} = 18$ V). In the far-transfer parallel circuit problems, the participants were provided with the resistance values of the individual resistors and the current flow through one of the resistors and were asked to calculate the total current in the parallel circuit (battery current). To solve this problem, the participants first had to apply Ohm's Law to the resistor for which the current was provided to determine the voltage over the resistor. The participants then had to observe that the voltage is the same over all resistors and had to calculate the currents through the other resistors by applying Ohm's Law to each individual resistor. Finally, the participants had to sum up the individual currents to determine the battery current.

In summary, the far-transfer problems required the participants to apply the same basic principles (Ohm's Law, basic properties of voltages, and currents in parallel and series circuits) as in the practice problems, but the sequence in which these principles were applied and the circuit element to which Ohm's Law was applied differed from those of the practice problems (and the solution steps presented in the introductory overview).

The eight posttest problems had three distinctive solution steps each, thus resulting in a maximum score of three points for each correctly solved problem. Therefore, a maximum total score of 24 (12 points each were associated with the performance on the near- and far-transfer problems) was attainable on the posttest.

1.3. Procedure

Experimental sessions were held during regular class time. This resulted in groups consisting of 30–45 student participants in each of the experimental sessions. The pretest and the demographic questionnaire were administered one week before to the learning phase of the experiment. The average duration of each of the second sessions was approximately 60 min. The participants took part in the study in a computerized classroom or a computer lab at Arizona State University. Each participant was seated in front of a Windows-based desktop computer. The experimenter instructed the participants to work independently of their peers. The participants proceeded to study the introductory overview on electrical circuits. After studying the introductory instructional text, the participants worked through the problems in the computer-based learning environment. During this phase the experimental variation took place. Immediately after completing the computer-based instructional program, the participants were administered the posttest. Finally, they indicated their responses on the attitudinal survey.

2. Results

This section presents the results for the pretest, en route practice in the computer-based learning module, instructional time, and achievement (posttest performance on near- and far-transfer problems). Unless otherwise noted, a 3 (example−problem, or problem−example, or backward-fading instructional procedure) × 2 (low or high prior knowledge) analysis of variance (ANOVA) with a significance level of .05 was used in the analyses. For the ANOVAs, Cohen's f statistic was used as an effect size index where f values of .10, .25, and .40 correspond to small, medium, and large values, respectively (Cohen, 1988).

2.1. Pretest

As previously mentioned, the pretest—a content specific measure of the participants' prior knowledge—was administered to all participants one week prior to learning phase with the goal of creating two levels of prior knowledge (low and high) before randomly assigning the participants at each level to one of the three instructional procedures. Out of a possible 12 points, participants' average score was 7.17 (SD = 3.07) on the pretest with a median score of seven. In light of these measures of central tendency, we elected to use seven as a cut-off and categorized participants as either high prior knowledge (pretest score seven points and higher) or low prior knowledge (pretest score below seven points). This permitted us to create two groups of approximately equal size but with statistically significant differences in their levels of prior knowledge. The high prior knowledge participants ($N = 93$) scored $M = 9.78$ (SD = 1.82) on the pretest, while their low prior knowledge counterparts ($N = 92$) achieved an average score $M = 4.53$ (SD = 1.30). The resulting independent samples t test was significant, $t(183) = 22.61$, $p < .001$. Cohen's d statistic for these data yields an effect size estimate of 3.33, which can be interpreted in terms of the percent of non-overlap between the two distributions of scores associated with the groups. According to Cohen (1988), a d of 3.33 indicates a non-overlap of approximately 95% in the two distributions, which suggests that the distribution of scores for the low prior knowledge participants displayed virtually no overlap with distribution of scores for the high prior knowledge participants.

There was no statistically significant difference between the average pretest scores of the participants assigned to the three treatment groups, $F(2,179) = .45$, MSE = 2.50, $p > .05$. No statistically significant interaction was observed between prior knowledge and instructional procedure factors, $F(2,179) = 1.37$, MSE = 2.50, $p > .05$.

2.2. Practice

Participants' performance on the practice problems presented within the computer-based learning environment was tracked automatically by the program. The mean scores and standard deviations for the accuracy of solving the practice problems are reported by treatment group and participant prior knowledge in Table 1. There were no statistically significant differences in the ability to solve the practice problems among the three different treatment groups, $F(2,179) = 1.31$, MSE = 1.98, $p > .05$, or by prior knowledge, $F(1,179) = .86$, $p > .05$, and there was no statistically significant interaction between the two variables, $F(2,179) = .05$, $p > .05$

2.2.1. Instructional time

Table 1 reports the mean and standard deviation of the instructional times by treatment group and participant prior knowledge. The overall average time the participants spent on the initial paper-based training was 13.89 min (SD = 6.17). An ANOVA found a main effect on the prior knowledge factor, $F(1,179) = 19.90$, MSE = 34.86, $p < .01$. Cohen's f statistics for these data yields an effect size estimate of .33, which corresponds to a medium effect. The high prior knowledge participants spent significantly less time on the initial knowledge acquisition than their low prior knowledge counterparts. There was no significant main effect for the instructional procedure on the time spent studying the paper-based introductory training packet, $F(2,179) = .97$, $p > .05$ and no significant interaction of the two factors, $F(2,179) = .08$, $p > .05$.

An ANOVA revealed that the high prior knowledge participants were able to learn statistically significantly faster from the examples presented by the computer-based module than their low prior knowledge counterparts, $F(1,179) = 3.83$, MSE = 52.29, $p < .05$. Cohen's f statistics for these data yields an effect size estimate of .15, which corresponds to a small effect. No statistically significant differences were found on the instructional procedure factor,

Table 1
Time spent on the initial knowledge acquisition (studying the introductory overview), practice performance on computer-based module, and time spent in the computer environment by treatment group and participant prior knowledge

Condition	Prior knowledge		Study time (minutes)	Computer performance (max. 12)	Computer time (minutes)
Example–problem	Low	*M*	16.12	10.73	18.88
	($N = 33$)	SD	4.87	1.07	9.70
	High	*M*	12.04	10.86	15.54
	($N = 28$)	SD	7.46	1.04	6.05
	Total	*M*	14.25	10.79	17.34
	($N = 61$)	SD	6.47	1.05	8.33
Problem–example	Low	*M*	16.62	10.55	18.34
	($N = 29$)	SD	5.79	1.48	6.18
	High	*M*	12.47	10.72	16.81
	($N = 32$)	SD	6.63	2.02	8.83
	Total	*M*	14.44	10.64	17.54
	($N = 61$)	SD	6.54	1.77	7.66
Fading	Low	*M*	14.80	10.90	17.87
	($N = 30$)	SD	5.28	1.19	6.08
	High	*M*	11.39	11.18	16.48
	($N = 33$)	SD	5.22	1.38	5.01
	Total	*M*	13.02	11.05	17.14
	($N = 63$)	SD	5.48	1.29	5.55
Total	Low	*M*	15.85	10.73	18.38
	($N = 92$)	SD	5.30	1.24	7.54
	High	*M*	11.96*	10.92	16.31*
	($N = 93$)	SD	6.39	1.55	6.78
	Total	*M*	13.89	10.83	17.34
	($N = 185$)	SD	6.17	1.40	7.22

*Denotes statistically significant difference at $p < .01$ level between high and low prior knowledge learners.

$F(2,179) = .06$, $p > .05$. The interaction between prior knowledge and instructional procedure was also non-significant, $F(2,179) = .35$, $p > .05$.

2.3. Near-transfer posttest achievement

Participant achievement on the posttest is reported in Table 2, which shows the mean scores and standard deviations for each treatment condition and prior knowledge on near- and far-transfer posttest problems. While there was no main effect for instructional procedure on near transfer, $F(2,179) = .06$, $\text{MSE} = 2.30$, $p > .05$, participants with higher levels of prior knowledge scored statistically significantly better than the low prior knowledge participants, $F(1,179) = 5.36$, $p < .05$. Cohen's f statistics for these data yields an effect size estimate of .17, which corresponds to a small effect. More importantly, there was a significant prior knowledge by instructional procedure interaction on the near-transfer posttest problems, $F(2,179) = 3.24$, $p < .05$. This interaction is shown in Fig. 2. The prior knowledge by instructional procedure interaction effect was analysed using a simple main effect analysis. The participant prior knowledge level influenced the performance on the near-transfer problems for the problem–example instructional procedure, $F(1,59) = 6.63$, $\text{MSE} = 2.70$, $p < .01$, where the high knowledge participants outperformed their low knowledge counterparts. However, the prior knowledge factor did not influence the participants performance for the example–problem structure, $F(1,59) = .60$, $\text{MSE} = 1.79$, $p > .05$ and the fading structure, $F(1,61) = 3.50$, $\text{MSE} = 2.41$, $p > .05$.

To explore for the possibility that the interaction was due to fluctuations in initial levels of knowledge among learners assigned to each instructional procedure rather than due to the instructional procedures themselves, we conducted an analysis of covariance (ANCOVA) with prior knowledge (pretest scores) as a covariate. The results of the ANOCOVA confirm the presence of the interaction, $F(2,178) = 3.19$, $p < .05$, and the same pattern of results.

Table 2
Near- and far-transfer posttest scores by treatment group and prior knowledge

Condition	Prior knowledge		Near transfer (max. 12)	Far transfer (max. 12)
Example–problem	Low	*M*	11.52	5.64
	($N = 33$)	SD	1.06	4.80
	High	*M*	11.25	9.21
	($N = 28$)	SD	1.60	3.92
	Total	*M*	11.39	7.28
	($N = 61$)	SD	1.33	4.74
Problem–example	Low	*M*	10.76	5.10
	($N = 29$)	SD	2.33	4.32
	High	*M*	11.84	8.63
	($N = 32$)	SD	.52	4.13
	Total	*M*	11.33	6.95
	($N = 61$)	SD	1.72	4.55
Fading	Low	*M*	10.93	3.70
	($N = 30$)	SD	2.08	3.47
	High	*M*	11.67	7.97
	($N = 33$)	SD	.82	4.37
	Total	*M*	11.32	5.94
	($N = 63$)	SD	1.58	4.48
Total	Low	*M*	11.09	4.84
	($N = 92$)	SD	1.89	4.29
	High	*M*	11.60*	8.57*
	($N = 93$)	SD	1.07	4.14
	Total	*M*	11.35	6.71
	($N = 185$)	SD	1.55	4.60

*Denotes statistically significant difference at $p < .01$ level between high and low prior knowledge learners.

2.4. Far-transfer posttest achievement

The better achievement of high prior knowledge participants was also found in the analysis of the far-transfer posttest performance, wherein the high prior knowledge participants achieved statistically significantly higher scores than the low prior knowledge participants, $F(1,179) = 37.43$, $MSE = 17.68$, $p < .01$. Cohen's f statistics for these data yields an effect size estimate of .46, which corresponds to a large effect. There was no statistically significant difference among the three different instructional procedures on the far transfer, $F(2,179) = 2.28$, $p > .05$, and no interaction between prior knowledge and instructional procedure, $F(2,179) = .15$, $p > .05$.

3. Discussion

This study focused on the impact of the instructional procedure—that is, the arrangement of worked examples and practice problems—in a computer-based learning environment on electrical circuit analysis. In particular, it explored the influence of presenting worked examples and practice problems in three different instructional procedures (example–problem, problem–example, and fading) on the performance and attitudes of learners with two different levels of prior knowledge (low and high), as assessed by a content-specific pretest one week prior to the learning phase of the experiment.

Although we predicted that learners provided with a fading instructional procedure would outperform their peers provided with example–problem pairs on performance measures, we did not find any significant differences between the participants who had been exposed to either the example–problem, problem–example, or fading structure in the computer-based learning environment. More specifically, there was no difference in learning time spent in the computer-based learning environment, neither the near-transfer, nor the far-transfer posttest problem performance. This result is in contrast to previous studies (Atkinson et al., 2003; Renkl et al., 2002, 2004), which were conducted in

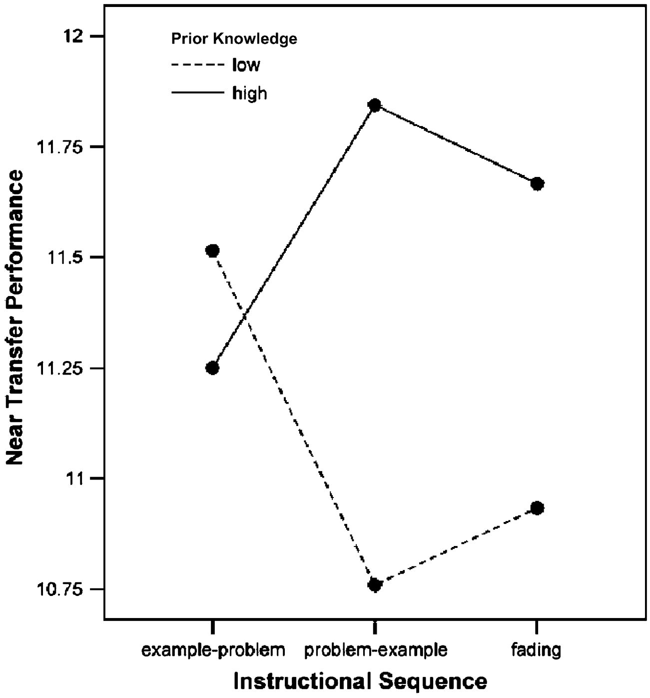

Fig. 2. Illustration of prior knowledge by instructional procedure interaction.

the content domain of elementary probability theory and found backward fading to result in statistically significantly higher posttest performance on both near- and far-transfer problems, without increasing the instructional time.

We also predicted that learners with high prior knowledge would outperform their low prior knowledge peers on performance measures. This prediction was confirmed. We did observe that high prior knowledge learners spent less time studying the introductory overview on electrical circuits and the computer-based learning environment than their low prior knowledge peers. We also found a statistically significant difference (small-to-medium sized effect) for the near-transfer performance when comparing all lower prior knowledge participants with all high prior knowledge participants. For the far-transfer problems, the mean score of all low prior knowledge participants was 4.84 (out of a maximum of 12 points) and the mean score for all high prior knowledge participants was 8.57. This statistically significant difference corresponds to a large effect, one of with unequivocal practical relevance. Overall, these results for the different prior knowledge levels of the participants indicate that higher prior knowledge participants, that is, participants with a higher level of prior knowledge and skills in circuit analysis, need less time to complete the instructional module and achieve higher posttest scores compared to learners with a lower level of prior knowledge.

We also predicted an interaction between the three levels of the instructional procedure factor and the two levels of prior knowledge. Specifically, we expected that the two instructional procedures with worked-out examples providing guidance at the outset (example–problem pairs and fading) would be more beneficial to low prior knowledge learners than problem–example pairs. We also expected the opposite outcome for high prior knowledge: the instructional procedure that emphasized practice problem solving (problem–example pairs) would be more beneficial to high prior knowledge learners than procedures that emphasize the use of examples (example–problem and fading). This proposed interaction was partially confirmed for the near-transfer problems. Interestingly, we found that low prior knowledge learners provided with example–problem pairs performed comparably to their high knowledge counterparts assigned to the same instructional procedure. The virtually equivalent performance we observed between the learners with low and high prior knowledge provides evidence that example–problem pairs were more beneficial to those with low prior knowledge, particularly since their high knowledge peers in general produced more conceptually accurate answers on this measure. Not surprisingly, we also observed that high prior knowledge learners benefited significantly more from the problem–example pairs procedure than their low prior knowledge peers. While we predicted that high prior knowledge learners would benefit most from this type of instructional procedure, we also expected their low prior knowledge peers to benefit least from it.

Several caveats remain, however, regarding this interaction. As Fig. 1 indicates, high prior knowledge participants in the fading condition produced more accurate responses to the near-transfer items than their low prior knowledge counterparts despite the fact that this instructional approach is more comparable to the example—problem approach than the problem—example instructional procedure. Thus, one would expect that the low prior knowledge participants assigned to the fading condition would to produce more conceptually accurate solutions to transfer problem than their high prior knowledge peers. Oddly enough, the low prior knowledge participants assigned to this condition performed worse than their counterparts in the example—problem approach. This unforeseen finding clearly needs to be addressed in future research. In particular, it seems prudent to explore whether the pace at which the fading occurred in this particular implementation was detrimental to learners with low prior knowledge. Perhaps the fading occurred before the low prior learners were able to transition out of the initial stages of cognitive skill acquisition.

Another aspect of this significant interaction that remains challenging to explain is why the particular pattern of results observed for near transfer did not also appear on the far-transfer measure. In other words, the interaction effect was observed only for the posttest items with same underlying structure but difference surface stories than the practice problems presented during the learning phase, whereas the far-transfer items differed from the practice problems in terms of both underlying structure and surface characteristics. Arguably, only learners who have progressed to the fourth and final stage of cognitive skills acquisition can solve these items that appear structurally and superficially unfamiliar. As evidence, we did observe a large, statistically significant effect in favour of the high prior knowledge learners on far transfer. Perhaps the learners' level of prior knowledge was more critical to solving these items than the particular instructional procedure they encountered, particularly since the solutions to these items required a more flexible representation of knowledge, one where many examples are stored and can quickly be retrieved.

This study has opened up several other questions involving the effectiveness of the different structures of computer-based learning environments, which should be addressed in future research. Especially relevant for electrical engineering education is the issue of investigating the unique characteristics of this knowledge domain in contrast to the knowledge domains typically considered in studies of educational strategies, e.g., elementary probability theory, in order to uncover the design principles of highly effective electrical engineering instructional modules. Are there any inherent underlying differences between these two knowledge domains that would give rise to the observed differences in the results? Future research needs to carefully address the impact of the specific characteristics of the various knowledge domains on the effectiveness of the different learning environment structures.

In summary, this study replicates and extends the growing literature documenting the existence of an expertise reversal effect in example-based instruction by capturing this effect among learners interacting with a computer-based learning environment electric circuit analysis, which presented instruction on how to conduct series and parallel electrical circuit analysis. This effect was evident in a significant interaction found on the near-transfer measure where the low prior knowledge participants benefited more from example—problem pairs than from the other instructional procedures. In accordance with this effect, this pattern of results reversed itself on the problem—example instructional procedure where the high prior knowledge participants appeared to benefit most, particularly in relationship to their low prior knowledge peers provided with the same instructional procedure.

References

Ahmed, M., & Bayoumi, M. M. (1994). An artificial intelligent instructor for electrical circuits. In Magdy A. Bayoumi, & W. Ken Jenkins (Eds.), *Proceedings of the 37th Midwest symposium on Circuits and Systems* (pp. 1362—1365). Piscataway, N.J.: IEEE Standards Office.

Al-Holou, N., & Abdallah, M. M. (1996). Teaching introduction to electric circuits using computer-based instruction for manufacturing engineering students. In Magdy F. Iskander (Ed.), *Proceedings of the ASEE/IEEE Frontiers in Education (FIE) conference* (pp. 23—26). Piscataway, N.J.: IEEE Standards Office.

Al-Holou, N., & Clum, J. A. (1999). Teaching electroscience using computer-based instruction. In Dan Budny (Ed.), *Proceedings of the ASEE/IEEE Frontiers in Education (FIE) conference* (pp. 13C13/24—13C13/29). Piscataway, N.J.: IEEE Standards Office.

Anderson, J. R., Fincham, J. M., & Douglass, S. (1997). The role of examples and rules in the acquisition of a cognitive skill. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *23*, 932—945.

Atkinson, R. K., Renkl, A., & Merrill, M. M. (2003). Transitioning from studying examples to solving problems: Effects of self-explanation prompts and fading worked-out steps. *Journal of Educational Psychology*, *95*, 774—783.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

de Coulon, F., Forte, E., & Rivera, J. M. (1993). Kirchhoff: An educational software for learning the basic principles and methodology in electrical circuits modeling. *IEEE Transactions on Education*, *36*, 19—22.

Doering, E. D. (1996). Circuit viz: A new method for visualizing the dynamic behavior of electric circuits. *IEEE Transactions on Education*, *39*, 297–303.

Hanrahan, H. E., & Caetano, S. S. (1989). A knowledge-based aid for dc circuit analysis. *IEEE Transactions on Education*, *32*, 448–453.

Harris, J. G., & Black, B. (1995). Six tutorial computer modules for non-linear circuit analysis and design. In Dan Budny (Ed.), *Proceedings of the ASEE/IEEE Frontiers in Education (FIE) conference* (pp. 2a6.24–2a6.26). Piscataway, N.J.: IEEE Standards Office.

Jones, J. R., & Conner, D. A. (1994). The development of interactive tutorials for introductory circuits. In M. Aldeen (Ed.), *Proceedings of the IEEE first international conference on Multi-Media Engineering Education* (pp. 108–114). Piscataway, N.J.: IEEE Standards Office.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist*, *38*, 23–31.

Kalyuga, S., Chandler, P., & Sweller, J. (2000). Incorporating learner experience into the design of multimedia instruction. *Journal of Educational Psychology*, *92*, 126–136.

Kalyuga, S., Chandler, P., Tuovinen, J., & Sweller, J. (2001). When problem solving is superior to studying worked examples. *Journal of Educational Psychology*, *93*, 579–588.

Macromedia (2002). *Director MX*. San Francisco, CA: Macromedia.

Nahvi, M. (1990). A computer based intelligent synthetic tutor–tester for electrical engineering. In M. Aldeen (Ed.), *Proceedings of the IEEE international conference on Systems, Man and Cybernetics* (pp. 742–744). Piscataway, N.J.: IEEE Standards Office.

Oakley, B., II. (1993). Use of the Internet in an introductory circuit analysis course. In Lawrence P. Grayson (Ed.), *Proceedings of the ASEE/IEEE Frontiers in Education (FIE) conference* (pp. 602–606). Piscataway, N.J.: IEEE Standards Office.

Oakley, B., II. (1994). Implementation of a virtual classroom for an introductory circuit analysis course. In Lawrence P. Grayson (Ed.), *Proceedings of the ASEE/IEEE Frontiers in Education (FIE) conference* (pp. 279–283). Piscataway, N.J.: IEEE Standards Office.

Oakley, B., II. (1996). A virtual classroom approach to teaching circuit analysis. *IEEE Transactions on Education*, *39*, 287–296.

Pota, H. R. (1997). Computer-aided analog electronics teaching. *IEEE Transactions on Education*, *40*, 22–35.

Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. *Cognitive Science*, *21*, 1–29.

Renkl, A., Atkinson, R. K., & Große, C. S. (2004). How fading worked solution steps works: A cognitive load perspective. *Instructional Science*, *32*, 59–82.

Renkl, A., Atkinson, R. K., & Maier, U. H. (2000). From studying examples to solving problems: Fading worked-out solution steps helps learning. In Lila R. Gleitman, & Aravind K. Joshi (Eds.), *Proceedings of the 22nd annual conference of the Cognitive Science Society* (pp. 393–398). Mahwah, N.J.: Lawrence Erlbaum Associates.

Renkl, A., Atkinson, R. K., Maier, U. H., & Staley, R. (2002). From example study to problem solving: Smooth transitions help learning. *The Journal of Experimental Education*, *70*, 293–315.

Shaffer, E. C., & Mabry, F. J. (2000). A student designed, web-based learning program for circuit analysis. In Dan Budny (Ed.), *Proceedings of the ASEE/IEEE Frontiers in Education (FIE) conference* (pp. T2D/17–T2D/22). Piscataway, N.J.: IEEE Standards Office.

Shannon, G. F. (1994). Multi-media computer based teaching—A case study. In M. Aldeen (Ed.), *Proceedings of the IEEE first international conference on Multi-Media Engineering Education* (pp. 398–402). Piscataway, N.J.: IEEE Standards Office.

Stark, R. (1999). *Lernen mit Loesungsbeispielen. Der Einfluss unvollstaendiger Loesungsschritte auf Beispeilelaboration, Motivation und Lernerfolg*. [*Learning by worked-out examples. The impact of incomplete solution steps on example elaboration, motivation, and learning outcomes*]. Bern, CH: Huber.

Sweller, J., & Cooper, G. A. (1985). The use of worked examples as a substitute for problem solving in learning algebra. *Cognition and Instruction*, *2*, 59–89.

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*, 251–296.

Trafton, J. G., & Reiser, B. J. (1993). The contributions of studying examples and solving problems to skill acquisition. In Cognitive Science Society (Ed.), *Proceedings of the 15th annual conference of the Cognitive Science Society* (pp. 1017–1022). Mahwah, N.J.: Lawrence Erlbaum Associates.

VanLehn, K. (1996). Cognitive skill acquisition. *Annual Review of Psychology*, *47*, 513–539.

Van Merriënboer, J. J. G. (1990). Strategies for programming instruction in high school: Program completion vs. program generation. *Journal of Educational Computing Research*, *6*, 265–285.

Yoshikawa, A., Shintani, M., & Ohba, Y. (1992). Intelligent tutoring system for electric circuit exercising. *IEEE Transactions on Education*, *35*, 222–225.