Optimizing Worked-Example Instruction in Electrical Engineering: The Role of Fading and Feedback during Problem-Solving Practice

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Abstract

How can we help college students develop problem-solving skills in engineering? To answer this question, we asked a group of engineering freshmen to learn about electrical circuit analysis with an instructional program that presented different problem-solving practice and feedback methods. Three findings are of interest. First, students who practiced by solving all problem steps and those who practiced by solving a gradually increasing number of steps starting with the first step first (forward-fading practice) produced higher near-transfer scores than those who were asked to solve a gradually increasing number of steps but starting with the last step first (backward-fading practice). Second, students who received feedback immediately after attempting each problem-solving step outperformed those who received total feedback on near transfer. Finally, students who learned with backward-fading practice produced higher near- and far-transfer scores when feedback included the solution of a similar worked-out problem. The theoretical and practical implications for engineering education are discussed.

Keywords: fading, feedback, worked examples

I. Introduction

One promising technique for helping students develop problem-solving skills in engineering is worked-example instruction. A worked example presents students with a problem statement, the worked-out solution steps that are necessary to solve the problem, and the final solution. Worked examples have been shown to help novice students' initial cognitive skill acquisition in several domains (Atkinson et al., 2000). A major challenge of worked-example instruction, however, is to find methods that can help learners transition from studying fully worked-out problems to solving problems independently (Paas and van Gog, 2006).

In an attempt to overcome this challenge, Renkl and colleagues (Renkl, Atkinson, and Große, 2004) tested the effects of asking students to gradually solve an increasing number of solution steps after being presented with a fully worked-out problem example. This method has been called *fading*. With fading, learners are initially presented with a fully worked-out example to study and then presented with subsequent problems in which an increasing number of problem subgoals needs to be completed. In *backward fading* (BF) students complete the last solution step of the first practice problem, the last two solution steps of the second practice problem, and so on, until they solve all steps. In *forward fading* (FF) students complete the first solution step of the first practice problem, then the first two solution steps of the second practice problem, and so on, until all steps are solved.

Past studies show that the practice of fading the number of worked-out steps during problem-solving practice can effectively promote students' problem solving near transfer in mathematics and physics (Renkl et al., 2002, 2004). The first goal of this research was to examine whether asking a group of engineering freshmen to learn about electrical circuit analysis with the help of a computer-based program that included fading as a problem-solving practice method would promote their problem solving transfer.

Another important area of research on worked-example instruction consists of examining the learning effects of different feedback methods. Feedback is one of the most powerful influences on student learning (Hattie and Timperley, 2007). The presence of feedback raises students' awareness of errors, increases behaviors that reduce errors, and facilitates the problem solving process (Zumbach, Reimann, and Koch, 2006). The second goal of this study was to investigate two promising conditions for effective computer-based feedback during problem-solving practice. First, we were interested in examining whether providing students with step-by-step feedback as they independently solved multi-step problems would promote learning as compared to providing summative, total feedback after students complete each problem. Second, we were interested in examining whether feedback that encouraged students to compare their solutions to those of a worked-out problem (which we call meta-level feedback), would promote deeper learning than providing students with explanatory feedback.

Little research on worked-example instruction, fading, and feedback has been conducted in the area of engineering education. An exception comes from the work of Reisslein and colleagues

(2005), who only recently started examining the conditions for effective worked-example instruction in the area of electrical circuit analysis. Two recent studies are most relevant to the present research. In the first study, BF practice was compared to example-problem (EP) practice, where students were given a worked-out problem example followed by a practice problem (Reisslein et al., 2006). The findings of this study showed that BF resulted in significantly lower near-transfer performance for high prior-knowledge learners compared to EP. In the second study, the researchers examined the retention effects of using three different backward fading speeds (i.e., slow, fast, no fading) for learners with three different levels of prior knowledge (Reisslein, Sullivan, and Reisslein, 2007). The results indicated that the high prior-knowledge participants performed best under the fast and no fading conditions whereas the low prior knowledge participants performed best under the slow fading condition.

The present study builds on the existing worked-example research in two important ways; first, by examining how BF and FF practice methods affect engineering students' learning as compared to traditional problem-solving practice methods. Past studies have only used the EP practice method as a comparison group and the few that include comparisons between BF and FF methods showed mixed results (Renkl et al., 2002, 2004).

The second contribution of this research is to provide an empirical basis for the design of computer-based feedback in engineering education. Although presenting summative feedback during problem solving is a common practice, to our knowledge, no research has examined its effectiveness as compared to presenting students with step-by-step feedback methods. Moreover, a challenge in worked-example instruction has been to find methods that promote the far transfer of the principles learned. The vast majority of research has found that the effectiveness of worked-examples is limited to promoting the application of principles learned to solve very similar problems (Ward and Sweller, 1990). The present study examines whether including meta-level feedback, where students are prompted to compare their solutions to those of a worked-out problem example, may overcome this limitation. In sum, this work is motivated by the following four research questions:

(1) Does fading the number of worked-out steps during problem solving-practice promote the near and/or far transfer of the principles learned?
(2) Does presenting step-by-step feedback during problem-solving practice promote students' problem-solving transfer?
(3) Does meta-level feedback during problem-solving practice promote students' problem-solving transfer?
(4) Do the different fading and feedback methods affect students' cognitive-load perceptions?

To answer these questions, we asked a group of college students who were enrolled in an Introduction to Engineering Design course to learn about parallel electrical circuit analysis with the help of an instructional computer program in one of the following conditions: problem solving with step-by-step feedback (PS-S), problem solving with total-problem feedback (PS-T), backward fading with step-by-step feedback (BF-S), forward fading with step-by-step feedback (FF-S), and backward fading with meta-level feedback (BF-M). To answer our first research question, we compared the learning outcomes of the fading groups (BF-S and FF-S) to those of the PS-S group. To answer our second research question, we compared the learning outcomes of the PS-S and PS-T groups. To answer our third research question, we compared the learning outcomes of groups BF-S and BF-M. Finally, we compared students' cognitive perceptions by asking them to rate the perceived level of difficulty after learning in each treatment condition.

Learning was measured by a near-transfer test—where students were asked to solve a set of problems that had the same structure as those presented during the practice session but which differed in their surface characteristics; and a far-transfer test—where students were asked to apply the electrical engineering principles learned to solve a set of problems that had a different underlying structure than those presented during the practice session. In the next sections, we summarize the theoretical framework and research that guided our study and derive a corresponding set of hypotheses.

A. What is Known about Worked-Example Instruction

A significant amount of research has examined the benefits of using worked-out examples to promote students' problem-solving transfer ability. For example, Sweller and colleagues found that, compared to learning how to solve problems by the traditional method of solving problems in their entirety (i.e., means-ends analysis practice), EP practice increased students' near transfer (Mwangi and Sweller, 1998; Tarmizi and Sweller, 1988; Ward and Sweller, 1990). Near problem-solving transfer is the ability to apply learned principles to solve isomorphic problems—problems that share the same structure as the worked-out examples presented during instruction yet differ on their surface characteristics (i.e., cover story). For example, two isomorphic problems from our studies were: "You wire a subwoofer speaker with resistance $R_s = 16\ \Omega$ and a regular speaker with a resistance of $R_r = 8\ \Omega$ in parallel and operate this electrical circuit with a $V = 6$ V battery. What is the total resistance of this electrical circuit?" and "The electrical system of a remote controlled toy helicopter consists of a motor with resistance $R_m = 4.5\ \Omega$, and a control unit with resistance $R_c = 72\ \Omega$. These two components are wired in parallel and are connected to a $V =$ 9 V battery. What is the total resistance of this parallel electrical circuit?"

The superiority of studying worked example problems as compared to independently solving problems has been called the *worked example effect* (Sweller, van Merrienboer, and Paas, 1998). Cognitive load theory explains this effect as the result of the more efficient use of students' limited cognitive resources (Sweller, 1999). Specifically, cognitive load theory argues that students who study examples can use their limited cognitive resources most effectively to induce generalizable problem-solving schemas that can be applied to solve future problems. In contrast, engaging in means-ends analysis is less efficient because it requires an extensive search process to produce the correct solution, which may overwhelm the novice learner. The means-ends analysis method demands a substantial portion of students' cognitive capacity due to the need to simultaneously attend to many aspects of the problem (i.e., the current problem state, the final goal state, the differences between these states). Consequently, there is relatively little capacity available to engage in deeper learning processes—such as the abstraction of underlying principles, which in turn will hinder the development of problem solving schemas that can be used to solve similar problems (Cooper and Sweller, 1987).

The worked-example effect is quite robust (Renkl, 2005). Nevertheless, recent research, such as the present work, has focused on the optimal conditions for learning from worked examples (Renkl et al., 2002). Among this research are studies that examined the effects of presenting more or less information within the worked-out steps; presenting more or less integrated verbal and graphic representations within the worked-out steps; presenting one or multiple ways to solve the worked examples; highlighting the problem subgoals; and using mixed modalities (auditory and visual) to explain problem solutions (see Moreno, 2006, for a review). Additional studies examined the role of presenting more or less worked examples; more or less variability of surface and structure features across worked examples; and different sequencing of worked example and practice problems (Paas and van Merrienboer, 1994; Quilici and Mayer, 1996; Trafton and Reiser, 1993). Our work extends the body of research on worked-example instruction by investigating fading and feedback methods in engineering education.

B. The Role of Fading in Worked-Example Instruction

Fading methods are aimed at transitioning students between studying worked-out problems to independently solving problems. Fading prompts students to think about what they have learned from the previous scaffolds and implement their knowledge to complete the current task (McNeill et al., 2006). According to cognitive load theory (Sweller, 1999), fading diminishes the abrupt increase of load that would result from having students move from studying worked examples to engaging in independent problem solving.

Studies in computer-based instruction show that fading can promote near transfer as compared to EP practice, where learners are given a worked-example followed by a problem to-be-solved. Specifically, in one of three studies, Renkl and colleagues (2002) found that a classroom that learned to solve physics problems with a BF method outperformed a classroom that learned to solve the same problems with EP on near-transfer measures. Likewise, the second study showed that students who learned basic probability principles with the FF method outperformed those that learned to solve the same problems with EP on near-transfer measures. There was no significant fading effect on far-transfer in either of these studies. The third study reported in the cited article, however, showed that students in both BF and FF groups outperformed a group that learned with EP on both near and far transfer measures, although the main effect on far-transfer was stronger for the BF group. More recently, Renkl and colleagues replicated the near- and far-transfer advantage of the BF method over the EP practice method (FF was not included in the research design) and, in an additional study, documented that the position of the faded steps (BF versus FF) did not influence learning outcomes (Renkl et al., 2004). The researchers showed that students learned most about the principles that were faded; whether a backward or forward method was employed did not affect learning outcomes. Atkinson and colleagues (2003, Experiment 1) also compared BF to EP and found a near and far transfer advantage for the BF group.

To some extent, the fading method resembles the chaining method that is typically used to teach humans and animals a long sequence of behaviors or routines. In forward chaining, individuals practice the first behavior of a set of behaviors first, then the first and second behaviors of the set, and so on. Backward chaining is the opposite: individuals practice the last behavior of a set of behaviors first, then the next to last along with the last behavior of the set, and so on. Smith (1999) compared whole-task training to forward chaining and backward chaining methods for a sequence of step-movements in two studies where the difficulty level of the sequence was manipulated. The results showed that when the sequence of behaviors was of high difficulty, there were no overall differences between forward chaining and backward chaining, but both procedures gave better performance than whole-task training. In contrast, whole-task training and forward chaining resulted in better performance than backward chaining when the sequence consisted of an easier string of behaviors. Earlier studies on chaining had shown that forward chaining and whole-task training result in better performance than backward chaining (Watters, 1992) and that forward chaining results in better performance than both whole-task training and backward chaining (Ash and Holding, 1990).

In sum, as can be seen from this literature review, some issues regarding the effectiveness of BF and FF are still open. First, all past studies have compared fading methods to EP practice; therefore, comparisons between fading and traditional problem-solving practices such as the ones used in the present study are warranted. Second, the vast majority of the research has examined forward- and backward-fading methods separately and the few exceptions show mixed results. One study showed that BF may be better at promoting far transfer than FF (Renkl et al., 2002, Experiment 3), a later study showed that the order of fading does not affect learning outcomes (Renkl et al., 2004), and the research on chaining suggests that the effectiveness of any specific practice method depends on the difficulty of the material to learn, with BF and FF being more effective than whole practice for learning difficult materials, but FF and whole practice being more effective than BF for easier materials (Smith, 1999).

In the present study we were interested in testing a cognitive-load hypothesis of fading according to which fading groups would outperform students who are asked to solve problems with no fading on measures of near and far transfer and report lower levels of perceived cognitive load. However, cognitive-load theory does not offer specific predictions for differences between FF and BF. Nevertheless, based on past chaining findings and evidence from a preliminary study that showed that the materials used in the present study with a similar student population were low in difficulty (Moreno, Reisslein, and Delgoda, 2006), we expected the FF group to outperform the BF group on measures of near and far transfer.

C. The Role of Timely Feedback in Worked-Example Instruction

Past research has examined how variations in feedback timeliness and content influence learning (Mory, 2004). For instance, a cognitive-load perspective of feedback suggests that just-in-time information to repair or correct errors during problem solving is more efficient than presenting summative feedback after a problem solving session is over (Kester, Kirschner, and Van Merriënboer, 2006). By presenting feedback immediately after a student attempts one step in a multi-step problem, students are more likely to make meaningful connections between their answer and the feedback information because both pieces of information are being held in their working memory at the same time (Moreno and Mayer, 2007). Past feedback studies support these assumptions by showing that immediate delivery of a feedback message provides the best instructional advantage to the learner (Azevedo and Bernard, 1995; Bangert-Drowns et al., 1991; Mason and Bruning, 2001). In the present study we were interested in testing a cognitive-load hypothesis of feedback according to which students who are given step-by-step feedback would outperform students who are given total feedback on measures of near and far transfer and report lower levels of perceived cognitive load.

D. The Role of Meta-Level Feedback in Worked-Example Instruction

Even when feedback is immediate, simply giving the learner the correct answer may only promote the rote recall of the information (Aleven and Koedinger, 2000; Hattie and Timperley, 2007; Narciss and Huth, 2004). Additional elaborations that prime students' metacognition, such as asking students to provide a self-explanation for their answers (Atkinson, Renkl, and Merrill, 2003; Chi, 2001), presenting an explanation of why students' response is not correct (Moreno, 2004; Moreno and Valdez, 2005), or providing students with elaborative feedback on correct responses (Clark and Dwyer, 1998; Hsieh and O'Neil, 2002), may be necessary to encourage the active construction of knowledge (Moreno and Mayer, 2007). Presumably, these methods induce learners to reflect on their understanding and use the explanations to restructure their knowledge (Butler and Winne, 1995).

The need to promote metacognition during learning is consistent with feedback models that emphasize the mindful, rather than automatic, processing of feedback information (Bangert-Drowns et al., 1991). In other words, feedback is argued to be effective to the extent that it promotes the active processing of strategically useful information, thus supporting students' self-regulation and metacognition (Coutinho et al., 2005; Kluger and DeNisi, 1996).

In the present study we examine one way to promote metacognition during problem solving which we call meta-level feedback. In this type of feedback, students with an incorrect solution attempt are shown the worked-out correct solution for an identical step in a problem that has a different cover story. Meta-level feedback should promote learning by prompting students to reflect on their problem-solving process and thereby deepening their understanding (Corbett and Anderson, 2001). Consequently, we hypothesized that students who learned with meta-level feedback would outperform those who learned with step-by-step corrective feedback alone on near transfer, but especially on far transfer, the learning measure that is most sensitive to deep understanding. Because past research has found that the benefits of BF are mostly limited to promoting near transfer, we were particularly interested in examining whether adding meta-level feedback to BF would promote far transfer as compared to the regular step-by-step feedback BF method. Because meta-level feedback is aimed at increasing cognitive processing, we expected group BF-M to report higher levels of perceived cognitive load than group BF-S.

II. Method

A. Participants and Design

The participants were 232 college students who were enrolled in an introductory engineering design course at a southwestern university in the United States. There were 185 males and 47 females with a mean age of 20.30 years ($SD = 3.92$). The reported ethnicities were 137 White Americans, 30 Hispanic Americans, 22 Asian Americans, 13 Native Americans, 9 African Americans, 1 Pacific Islander, and 20 other or mixed ethnicities. There were 48 participants in the PS-S group, 46 participants in the PS-T group, 46 participants in the BF-S group, 45 in the FF-S group, and 47 in the BF-M group. Comparisons were made among the groups on measures of near transfer, far transfer, and cognitive-load ratings.

B. Materials and Apparatus

1) Computerized Materials: For each participant, the computerized materials consisted of an interactive program that included the following sections: (1) a demographic information questionnaire in which students were asked to report their gender, age, and ethnicity; (2) an instructional session providing a conceptual overview of electrical circuit analysis; (3) a pre-test; (4) a problem-solving practice session, including a worked example and three practice problems; and (5) a cognitive-load questionnaire. Next, we describe each of these sections in detail.

The instructional session presented the students with the meanings and units of electrical current, voltage, and resistance. Furthermore, the session presented how to calculate the total resistance of a parallel circuit when given source voltage and individual resistance values using the fundamental properties of voltages and currents in parallel circuits and Ohm's Law in three steps: (i) note that the voltage is the same over each individual resistor and calculate the value of the current flowing through each individual resistor using Ohm's Law, (ii) calculate the total current flowing in the circuit by summing up the currents flowing through the individual resistors, and (iii) calculate the total resistance of the parallel circuit by applying Ohm's Law to the entire circuit.

The pre-test consisted of 6 questions on parallel circuits (internal reliability of 0.73). Each question could be solved with one application of Ohm's Law or one application of the fundamental behaviors of currents and voltages in parallel circuits, i.e., that the currents through parallel branches add up and that the voltage is the same over all branches. (In contrast, the solution of each post-test question required three applications of Ohm's Law or the fundamental current/voltage behaviors.)

The practice session presented one worked example and three electrical circuit problems in which students were asked to compute the total resistance of a parallel circuit by applying the three solution steps taught in the instructional portion of the program. The practice session was self-paced. After completing each solution step, participants could click on the "Continue" button to move to the next solution step and, after all three steps in each problem were completed, students could click on the "Next Problem" button to move to the next practice problem. Once the participants had submitted their answers, they were not allowed to return to previous steps or problems.

The practice session portion of the program had five different versions, one for each of the five treatments used in the study, which are illustrated in Figure 1. In all conditions the participants were presented with one fully worked out example (WE) and three problems (P1, P2, and P3) that required three solution steps to be solved. As can be seen from the figure, the fading groups were presented with a gradually increasing number of steps to be solved, whereas the problem-solving groups were asked to solve all three steps for all problems. Therefore, the number of steps that the participants had to solve independently varied according to the treatment condition. Students in problem solving conditions were required to solve a total of nine solution steps whereas students in the fading conditions were required to solve a total of six solution steps.

All students were given explanatory feedback about their answers with the following differences. The PS-S group received explanatory feedback after each submitted solution step. More specifically, students submitted the solution for the first solution step. If the solution was correct, the program confirmed the correctness of the solution.

Instructional Sequence of Examples/Problems

Condition			Problem Number		
		WE	P1	P2	P3
	Step	1	S1-ef	S1-ef	S1-ef
PS-S	Step	2	S2-ef	S2-ef	S2-ef
	Step	3	S3-ef	S3-ef	S3-ef
			Problem Number		
		WE	P1	P2	P3
	Step	1	S1	S1	S1
PS-T	Step	2	S2	S2	S2
	Step	3	S3	S3	S3
			ef	ef	ef
			Problem Number		
		WE	P1	P2	P3
	Step	1	1	1	S1-ef
BF-S	Step	2	2	S2-ef	S2-ef
	Step	3	S3-ef	S3-ef	S3-ef
			Problem Number		
		WE	P1	P2	P3
	Step	1	S1-ef	S1-ef	S1-ef
FF-S	Step	2	2	S2-ef	S2-ef
	Step	3	3	3	S3-ef
			Problem Number		
		WE	P1	P2	P3
	Step	1	1	1	S1-mf
BF-M	Step	2	2	S2-mf	S2-mf
	Step	3	S3-mf	S3-mf	S3-mf

Figure 1. The problem solving practice session consisted of one worked example (WE) and three practice problems (P1, P2, and P3), which varied according to the five treatment conditions. Steps denoted by the numerals 1, 2, or 3 were worked out and steps denoted by S1, S2, and S3 required a solution attempt by the learner. "ef" stands for explanatory feedback and "mf" denotes meta-level feedback.

If the solution was incorrect, the program presented an explanation about how to solve the step correctly as well as the correct solution. After studying the explanatory feedback, students could click on the "Continue" button to proceed to the next solution step while the correct solution for the preceding step remained on the screen.

In the PS-T condition, students received total feedback after attempting all three solution steps. In particular, once the last solution step was submitted, the program indicated which steps had been solved correctly and presented explanatory feedback on all incorrectly solved steps similar to the case of the PS-S condition.

In the BF-S condition, students were presented with the worked-out solution for the first two steps/subgoals for the first problem and asked to attempt solving the third step/subgoal. In the second problem, only the first solution step/subgoal was worked out and students were asked to solve the second and third solution steps/subgoals. In the third problem, students were asked to solve all three solution steps/subgoals independently.

The FF-S condition was identical to the BF-S condition but required the learners to attempt the first solution step in problem 1, the first two steps in problem 2, and all three steps in problem 3. In both fading conditions, students received feedback after each individual attempted solution step, analogous to the PS-S condition. If a solution attempt was correct, the correctness was confirmed. If a solution attempt was incorrect, the learning environment provided explanatory feedback and the correct solution.

Lastly, the BF-M condition had an underlying backward fading structure, similar to the BF-S condition, but presented step-by-step feedback in the following way. If a solution attempt was correct, the learning environment confirmed the correctness of the attempt. If the attempt was incorrect, then the learner was shown the worked example studied with the incorrectly attempted step highlighted and with a note instructing the learner to study how to solve the step correctly. Then, the learner was taken back to the incorrectly attempted solution step and given another chance at solving the step.

If this second attempt was correct, then the learning environment provided corrective feedback. If the attempt was incorrect, then the learning environment provided the same explanatory feedback provided to the other treatments.

The last section in the computer program included a cognitive-load questionnaire, which asked participants to rate the perceived difficulty of the instructional program on a 5-point scale which ranged from 0 to 4 (internal reliability of 0.94).

2) Paper and Pencil Materials: The paper and pencil materials consisted of a near transfer test and a far transfer test. The near transfer test was designed to assess students' ability to transfer their problem solving skills to solve an isomorphic set of problems. In particular, the near transfer test consisted of four problems that had the same underlying structure but different surface characteristics than the problems presented during the practice session of the program. Two engineering instructors scored the transfer test questions (inter-rater reliability 98.5 percent).

The far transfer test was designed to assess students' ability to transfer their problem solving skills to solve a novel set of problems. It consisted of four electrical circuit problems which had different underlying structures and different surface features than the practice problems within the computer-based learning environment. Specifically, given the individual resistance values and the current through one of the resistors, the students were asked to calculate the total current in the parallel circuit. In order to solve the far transfer problems the participants had to apply the same basic principles as in the practice problems (Ohm's Law, basic properties of voltages and currents in parallel circuits), but the sequence in which these principles were arranged and the circuit element to which Ohm's Law was applied varied from the practice problems and from the solution steps presented in the instructional session. Two engineering instructors (inter-rater reliability 99.8 percent) scored the far transfer test questions.

3) Apparatus: The computer programs used in the study were developed using Dreamweaver MX software, an authoring tool for creating web-based multimedia programs. The apparatus consisted of a set of PC desktop computer systems, which each included a 17-inch monitor.

C. Procedure

Participants were randomly assigned to a treatment group and seated in front of a Windows-based desktop computer. Then, the experimenter started the respective version of the computer program and instructed participants to work independently on all sections of the program (demographic survey, instructional session, pre-test, practice session, and cognitive-load questionnaire). Once the computer program was over, participants completed the paper-based post-test.

D. Results

In all statistical tests, alpha was set at 0.05 and an appropriate adjustment was made (i.e., Bonferonni) when conducting multiple tests. Table 1 shows the mean scores and corresponding standard deviations for the five groups on measures of pre-test, near transfer, far transfer, and cognitive-load ratings. An analysis of variance verified that the treatment groups did not significantly differ on the mean pre-test score, $F(4, 227) = 0.34$, $MSE = 1.37$, $p = 0.85$. However, to remove extraneous variability from the transfer measures, we used students' pre-test scores as a covariate in our analyses. The pre-test showed a significant correlation with the near transfer scores ($r = 0.14$, $p < 0.05$) and far transfer scores ($r = 0.25$, $p < 0.01$). The next sections present the results of the analyses that were conducted to answer each one of our four research questions.

1) Research Question 1: *Does fading the number of worked-out steps during problem solving-practice promote the near and/or far transfer of the principles learned?* To answer this question, the data were subjected to a multivariate analysis of covariance (MANCOVA) using treatment condition as the between-subjects factor (BF-S, FF-S, and PS-S), students' near and far transfer scores as the dependent measures, and students' pre-test score as a covariate. The analysis revealed significant differences on the dependent variables between treatment conditions, Wilks' $\lambda = 0.84$, $F(4, 268) = 6.27$, $p < 0.0001$, partial $\eta^2 = 0.09$. Separate ANCOVAs were conducted on each dependent variable as follow-up tests. A significant treatment effect was found on near transfer, $F(2, 135) = 13.01$, $MSE = 114.24$, $p < 0.0001$, partial $\eta^2 = 0.16$. Post-hoc Tukey tests revealed that students in the FF-S and PS-S groups outperformed students in the BF-S group on near transfer. On the other hand, no significant differences among groups were found on far transfer.

2) Research Question 2: *Does presenting step-by-step feedback during problem-solving practice promote students' problem-solving transfer?* To answer this question, the data were subjected to a MANCOVA using treatment condition as the between-subjects factor (PS-S and PS-T), students' near and far transfer scores as the dependent measures, and students' pre-test score as a covariate. The analysis revealed a marginally significant difference on the dependent variables between treatment conditions, Wilks' $\lambda = 0.95$, $F(2, 90) = 2.44$, $p = 0.09$, partial $\eta^2 = 0.05$. Separate ANCOVAs showed a significant treatment effect on near transfer, $F(1, 91) = 4.62$, $MSE = 32.04$, $p < 0.05$, partial $\eta^2 = 0.05$. Students in the PS-S group outperformed students in the PS-T group on near transfer but no significant differences between groups were found on far transfer.

3) Research Question 3: *Does meta-level feedback during problem-solving practice promote students' problem-solving transfer?* To answer this question, the data were subjected to a MANCOVA using treatment condition as the between-subjects factor (BF-S and BF-M), students' near and far transfer scores as the dependent measures, and students' pre-test score as a covariate. The analysis revealed a significant difference on the dependent variables between treatment conditions, Wilks' $\lambda = 0.81$, $F(2, 89) = 10.25$, $p < 0.0001$, partial $\eta^2 = 0.19$. Separate ANCOVAs showed a significant treatment effect on near transfer, $F(1, 90) = 16.26$, $MSE = 158.39$, $p < 0.0001$, partial $\eta^2 = 0.15$ and far transfer, $F(1, 90) = 13.16$, $MSE = 186.02$, $p < 0.0001$, partial $\eta^2 = 0.13$. Students in the BF-M group outperformed students in the BF-S group on both transfer measures.

4) Research Question 4: *Do the different fading and feedback methods affect students' cognitive-load perceptions?* To answer this question, we compared students' cognitive-load perceptions with an ANOVA, using treatment condition as the between subject factor and students' average cognitive-load ratings as the dependent variable. There were no significant differences between treatment groups on perceived cognitive-load.

	Type of Measure							
	Pre-test		*Near transfer*		*Far transfer*		*Cognitive load*	
Group	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
PS-S	4.19	2.14	10.98	2.21	4.82	4.30	1.68	0.86
PS-T	4.22	2.03	9.81	2.99	4.92	4.00	1.58	0.99
BF-S	3.96	2.03	8.29	3.96	3.45	3.88	1.82	0.93
FF-S	4.44	1.94	11.13	2.39	4.54	4.23	1.62	1.08
BF-M	4.21	2.01	10.99	2.07	6.34	3.65	1.55	0.85

Note: Scores ranged from 0 to 6 for the pre-test, from 0 to 12 for the near and far transfer tests, and from 0 to 4 for the cognitive load ratings. PS-S stands for problem solving with step-by-step feedback, PS-T stands for problem solving with total feedback, BF-S stands for backward fading with step-by-step feedback, FF-S stands for forward fading with step-by-step feedback, and BF-M stands for backward fading with meta-level feedback.

Table 1. Mean scores and corresponding standard deviations on pre-test, near and far transfer post-test scores, and cognitive load ratings for five groups.

III. Discussion

The goal of the present study was to examine the effects of fading, step-by-step feedback, and meta-level feedback on freshman engineering students' learning and cognitive-load perceptions. To this end, we compared the following problem-solving practice methods respectively: backward and forward fading versus no fading; step-by-step feedback versus total feedback; and step-by-step feedback versus meta-level feedback. The following sections summarize the hypotheses raised in the introduction, discuss the theoretical and practical implications of our findings, and offer suggestions for future research under the light of the limitations of the study.

A. The Impact of Fading Practice on Students' Transfer (BF-S vs. FF-S vs. PS-S)

First, we tested a cognitive-load hypothesis of fading. According to cognitive-load theory (Sweller, 1999), fading methods promote learning by diminishing the abrupt increase of load that results from studying worked examples to engaging in independent problem solving. Therefore, we expected both BF-S and FF-S groups to outperform group PS-S on measures of near and far transfer and to report lower levels of cognitive load. The results, however, did not support this hypothesis. Instead, we found that the FF-S and PS-S groups outperformed the BF-S group on near transfer and no differences in far transfer or cognitive-load perceptions were noted. The fact that the fading methods failed to promote far transfer is consistent with the patterns of prior research and suggests that the cognitive capacity that is presumably freed up by gradually incrementing the number of steps to-be-solved is not necessarily used by learners in a productive way (Atkinson, Renkl, and Merrill, 2003).

In addition, the near-transfer findings support the alternative hypothesis suggested by chaining research that the effectiveness of any specific fading method (forward or backward) depends on whether the problems to-be-learned are of high difficulty-in which case BF and FF are more effective than whole problem-solving practice, or low difficulty-in which case FF and whole problem-solving practice are more effective than BF (Smith, 1999). Although we did not manipulate the difficulty of the materials, we found evidence that the type of problems used in this study were low in difficulty. Specifically, students reported very low levels of cognitive load during learning and produced high scores on the near transfer test immediately after learning across all conditions (over 60 percent of the students had perfect scores on this test).

Taken together, these findings suggest that, for relatively easy materials, the delay in prompting students to engage in problem solving in BF may have limited their cognitive activity during problem-solving practice and, in turn, hindered near transfer. This interpretation, however, should be empirically tested. Unfortunately, the research investigating fading methods in worked-example instruction has only used example-problem practice as a comparison group and the two studies that included both FF and BF conditions show contradictory results (Renkl et al., 2002, 2004). Moreover, the difficulty level of the materials used in past studies has not been reported. Therefore, our attempts to generalize theoretical and practical implications for using FF or BF methods are challenged. Nevertheless, we believe that one of the strongest contributions of this work is to emphasize the need to control for the difficulty of the problem-solving task in future research to better understand whether and how FF and BF methods promote near transfer.

B. The Impact of Means-Ends Practice on Students' Transfer (PS-S vs. PS-T)

Step-by-step feedback has the benefit of allowing the learner to immediately verify the correctness of a solution attempt while the corresponding problem step is still in working memory (Moreno and Mayer, 2007). In contrast, total feedback forces the learner to hold the entire problem in working memory at once. Consistent with cognitive load theory and similar to the case of fading, we hypothesized that this cognitive load reduction would promote transfer as compared to practicing with total feedback (Sweller, 1999). However, this hypothesis was only supported for the near-transfer measure. Group PS-S and PS-T did not differ in cognitive-load ratings or measures of far transfer.

A possible interpretation for this pattern of results is that worked-example instruction that solely includes opportunities to practice isomorphic problems does not effectively promote the deep understanding that is necessary to transfer the underlying principles to novel problems that are structurally different from the practice problems. This interpretation is consistent with past research showing that the effectiveness of worked-example instruction is limited to near transfer unless methods that foster high-order thinking during problem solving are present (Ward and Sweller, 1990). The direct practical implication of this finding is that human tutors and tutoring programs should provide students with step-by-step informational feedback as they solve problems independently to promote near transfer. This guideline should be most important for solving problems that are more intrinsically difficult or that include a larger number of sub-goals or steps (Ayres, 2006).

C. The Impact of Meta-Level Feedback on Students' Transfer (BF-M vs. BF-S)

One of the most promising findings of this research is to show the learning benefits of using meta-level feedback during problem solving. This was demonstrated by the large positive effect on both near and far transfer when comparing meta-level and step-by-step feedback during BF practice. Based on past research, we hypothesized that feedback can effectively promote both near and far transfer to the extent that it promotes the active processing of information, thus supporting students' metacognition (Coutinho et al., 2005; Kluger and DeNisi, 1996).

The benefits of meta-level feedback found in the present study are consistent with the reflection principle in instructional design and according to which the ability to transfer depends on the degree to which students invest their cognitive resources to reflect on their actions and feedback (Moreno and Mayer, 2007). For example, a study that examined the effects of different feedback methods on transfer, showed that only when the instructional program was modified to prompt students to evaluate their responses before submitting them for feedback did it promote students' transfer (Moreno and Valdez, 2005, Experiment 3). We believe that switching back and forward between problems that share structural characteristics but differ in surface characteristics may have promoted a deeper understanding of the electrical engineering principles learned in the computer lesson. Similar to past research in other domains, comparing the solution of a problem to that of a new problem seems to promote the understanding of the underlying structure of the problems without a significant increase in cognitive load (Quilici and Mayer, 1996; Scheiter, Gerjets, and Schuh, 2004).

Another reflection method that has the potential to promote far transfer in worked-example instruction consists of prompting students' self-explanations (Chi, 2001; Moreno and Mayer, 2005). Similar to the case of asking students to compare their solutions to those of a worked-problem, when students are asked to identify the underlying principle illustrated in worked-out problems during BF practice, both near and far transfer are promoted as compared to using the traditional BF-S method (Atkinson, Renkl, and Merrill, 2003). A productive area for future research is to examine whether the meta-level feedback and self-explanation effects found using the BF method would extend to FF methods.

D. Limitations

It is important to note that the findings of this study are limited because we chose to focus on one specific student population (i.e., college freshmen enrolled in an introductory engineering design course), domain (i.e., electrical circuit analysis), and learning environment (i.e., instructional program). Moreover, the fact that students' far transfer scores were relatively low on average, suggests that the flexibility to transfer engineering principles might be compromised not only by the examined methods but also by the brief experimental conditions used in this research. According to cognitive flexibility theory, instructional environments should present new concepts with a variety of examples and contexts to increase students' ability to transfer their knowledge to novel scenarios (Spiro and Jehng, 1990). An important limitation of our study is that we used few examples that were very similar in structure to learn how to apply electrical circuit analysis principles to solve novel problems. The question of how much more influential the methods used in this research would be if we had presented students with a larger number and variety of examples needs further investigation. Importantly, the present study only focused on outcome learning measures (i.e., near and far transfer scores). Measures of students' thinking processes such as the number of impasses, errors, and type of errors that students make as they solve problems are necessary to better understand the mechanisms underlying the facilitating/inhibiting effects of different problem-solving practice methods.

Finally, a promising area of research is to examine the effects that prior knowledge may have on different fading and feedback methods. According to the so-called expertise-reversal effect, the instructional effects found for novice students may disappear or even revert as they acquire expertise in the problem-solving domain (Kalyuga et al., 2003). For instance, although studying examples is productive in the initial stages of skill acquisition, as learners develop a sufficient knowledge base, they are better served by engaging in independent problem solving (van Merriënboer and Kester, 2005). In a similar fashion, it is possible that FF and PS methods are more efficient for learners of high expertise (for whom problems are easier) whereas backward methods are more efficient for novice learners (for whom problems are more difficult). The work of Reisslein and colleagues (2005, 2006) provides evidence for an expertise-reversal effect on the speed of BF, yet no research has examined the role of prior knowledge on learning with FF as compared to BF. In sum, future studies in engineering education should extend on this work by testing the effects of different fading and feedback methods using outcome and process learning measures for a variety of students and problem types.

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