# Toward a Fundamental Understanding of Worked Example Instruction: Impact of Means-Ends Practice, Backward/Forward Fading, and Adaptivity

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*Abstract*— **Recent research has demonstrated that worked example based instructional designs can effectively foster learning of engineering concepts and are supported by contemporary educational theories, including cognitive load theory. However, a number of interrelated fundamental questions, which have neither been addressed in the educational psychology nor in the engineering education literature, remain open including: (A) What is the impact of means-ends practice? (B) What is the effect of backward vs. forward fading of worked example steps? and (C) What is the effect of adaptivity to learner performance? The goal of the present study was to answer these questions by comparing the learning and perceptions about learning of engineering college freshman who learned how to solve electrical circuit problems in five different computer-based learning conditions: (1) problem solving with step-by-step feedback, (2) means-ends problem solving with total feedback, (3) backward fading, (4) forward fading, and (5) adaptive feedback. Forward fading and adaptive feedback practice promoted more students' near problem solving transfer ability than backward fading practice. Furthermore, the adaptive feedback practice group outperformed students in the backward fading practice group on measures of far problem solving transfer.**

*Index Terms*— **Adaptivity, cognitive load, electrical circuit analysis, fading, problem solving, worked examples.**

## I. Introduction

Instructional designs based on worked examples, which consist of the problem statement, the individual solution steps, and the statement of the final solution, can be effective in initial cognitive skill acquisition [1], [2]. One main challenge in these instructional designs is to foster the acquisition of problem solving skills so that the learners can efficiently advance from studying worked examples to solving problems independently [3]. Recent cognitive load research has found evidence that *fading* the solution steps of worked examples (as described in Sec. II.B.c) during practice helps students transition from studying whole worked examples to solving problems on their own. A smooth transition from studying worked examples to problem solving through fading of worked solution steps has been recently proposed as an effective method to reduce cognitive load during learning [4].

While the fading instructional design has started to demonstrate its potential in efficiently fostering skill acquisition, a number of fundamental, interrelated questions about worked-example instructional designs have has not yet been addressed, especially in the engineering education literature. These open questions include: (A) What is the effect of means-ends practice, where students attempt to solve an entire problem and later receive summative feedback at the end, compared to step-by-step practice, where students are asked solve one step at a time and receive feedback after each individual attempted solution step? And, how do these practices compare to fading? (B) What is the effect of backward fading, where the last solution steps are faded first (and attempted by the learner first), compared to forward fading, where the first solution steps are faded first? (C) Does feedback adaptivity increase learning performance?

We answer these research questions with a rigorous experimental study with five conditions that represent each one of the practice methods of interest: problem solving with total feedback (PS-T), problem solving with step-by-step feedback (PS-S), backward fading (BF), forward fading (FF), and adaptive feedback (A). While much of the existing research on worked-example based instructional designs has been conducted with social science students learning probability or mathematics, we conducted our study with *engineering students* learning electrical circuit analysis.

### A. Related Work

In this section we briefly review the existing research that is closely related to our study. A significant amount of cognitive load 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 by solving problems with a means-ends method, learning with example-problem pairs–where a worked-out example is followed by an isomorphic problem to-be-solved, increased near transfer [1], [5]–[7]. This finding has been called in the cognitive load literature the worked example effect [8]. The goal of more recent research, such as the present study, is to extend research on worked example effects by focusing on the optimal conditions for learning from examples [9]. Some of the existing studies include examining practice methods that either present more or less information in the solution steps, one or multiple solutions, subgoal highlighting, more or less integrated verbal and visual representations of the problem solutions, and mixed modality representations of problem solutions [10]. Additional research has also been conducted to examine the role of presenting more or less worked examples during a practice session, more or less variability of surface and structure

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features, and different sequencing of worked example and practice problems [11]–[13].

Despite this prolific work, relatively little research on worked-example design has been conducted in the area of engineering education. For example, Reisslein and colleagues only recently started extending this line of research to the area of electrical circuit analysis learning. In one study, they examined the effect of the format (textual or graphical) and presentation (automatically provided by the learning environment or requested by the learner) of worked examples for high school students [14]. The findings showed that the textual format and automatic presentation are more effective. In a second study, backward fading practice was compared to example-problem pair practice, where students were given a worked-out problem example followed by a practice problem [15]. Finally, a third study examined different speeds of backward fading the worked solution steps [16].

The present study, therefore, extends the existing research on worked-example effects in three ways: $(a)$ By examining how the traditional means-ends practice method (where students are given summative feedback after completing an entire problem), affects engineering students learning and perceptions about learning. Although means-ends practice is commonly used in engineering education, to our knowledge, there is no research that examined its effectiveness as compared to other practice methods. $(b)$ By examining how backward and forward fading practice methods affect engineering students learning and perceptions about learning. The effectiveness of these methods was only tested with freshman psychology students learning probability theory [4], [9]. $(c)$ By examining how an adaptive feedback method combined with fading practice affects engineering students learning and perceptions about learning. Although recent research in engineering education examined the role of adaptivity of the fading speed [17], the effects of adapting the type of feedback provided to students, based on their errors, is still unknown.

## II. Method

### A. Participants and design

The participants were 99 undergraduate freshman students enrolled in an introductory engineering course at a southwestern university (17 females and 82 males).

### B. Materials and apparatus

*1) Computer-Based Learning Environment:* A computer-based learning environment served as a platform for the delivery of the instructional content on the principles of calculating the total resistance in parallel electrical circuits and for allowing the participants to practice their newly acquired electrical circuit analysis skills. The program had four main sections, (1) an Introductory Overview, (2) a Pretest, (3) Practice, and (4) Attitude Survey.

The introductory overview contained basic instruction on the fundamental concepts of electrical circuits, such as electrical current, voltage, and resistance. This instructional material also presented the participants with steps for calculating the electrical current, voltage, and resistance in parallel electrical circuits. The information contained in this material was concise and was presented on four screens. It introduced the participants to (a) the physical meaning and units of electrical current, voltage, and resistance, (b) electrical circuit elements, such as light bulbs and batteries, and the way circuit elements are connected with wires in parallel electrical circuits, (c) the physical meaning and units of resistance as well as Ohm's Law, and (d) the calculation of the total resistance in a parallel circuit.

The program explained how to calculate the total resistance for the parallel circuits from basic principles, namely Ohm's Law and the properties of currents and voltages in the electrical circuits. The program presented the resistance values of the individual circuit elements (resistors) in the electrical circuit and the value of the voltage provided by the battery into the circuit. It also instructed the participants to abide by the following three steps in the calculation of the total resistance of the parallel circuit. First, it showed that the voltage is the same over each individual resistor and that the calculation of the value of the current flowing through each individual resistor is done using Ohm's Law. Second, it showed that the calculation of the total current flowing in the circuit is carried out by summing up the currents flowing through the individual resistors. Third, the total resistance of the parallel circuit is calculated using Ohm's Law as the voltage provided by the battery divided by the sum of the currents determined in step two.

After the Introductory Overview section, the participants completed the pretest, see Section II-B.2.a. After completing the pretest, the participants proceeded to practice the steps in solving parallel electrical circuit analysis. The computer-based instructional environment presented a set of instructional examples/problems, with three distinct solution steps each, on computing the total resistance in parallel circuits. Each step was clearly labeled and visually distinguished from the other steps. The program allowed the participants to linearly navigate through the individual examples/problems, revealing one step at a time. This navigation permitted the participants to control the pace of their learning. The program allowed the participants to proceed through the module by clicking on the "Next Problem" buttons after all three steps in each problem had been displayed. The participants were not allowed to return to previous steps and problems once they had finalized their answers.

The module had been programmed to operate in one of five modes that corresponded to the five experimental conditions, which are illustrated in Table I. In all conditions the participants first had the opportunity to study one worked example (WE). They then worked through three problems (P1, P2, and P3) with a varying number of worked solution steps (denoted by the step number) or steps to be solved (denoted by an "S" followed by the step number) according to the different experimental conditions. The number of problems was held constant across the five treatment conditions, while the number of steps that the participants solved independently varied: nine in the problem solving conditions, six in the fading conditions, and six or

TABLE I
INSTRUCTIONAL SEQUENCE OF EXAMPLES/PROBLEMS

| | | Problem number | | | |
|---|---|---|---|---|---|
| Condition | | WE | P1 | P2 | P3 |
| Problem Solving | Step | 1 | S1-ef | S1-ef | S1-ef |
| with step-by-step | Step | 2 | S2-ef | S2-ef | S2-ef |
| feedback (PS-S) | Step | 3 | S3-ef | S3-ef | S3-ef |

| | | Problem number | | | |
|---|---|---|---|---|---|
| Condition | | WE | P1 | P2 | P3 |
| Problem Solving | Step | 1 | S1 | S1 | S1 |
| with total | Step | 2 | S2 | S2 | S2 |
| feedback (PS-T) | Step | 3 | S3 | S3 | S3 |
| | | | ef | ef | ef |

| | | Problem number | | | |
|---|---|---|---|---|---|
| Condition | | WE | P1 | P2 | P3 |
| Backward | Step | 1 | 1 | 1 | S1-ef |
| Fading (BF) | Step | 2 | 2 | S2-ef | S2-ef |
| | Step | 3 | S3-ef | S3-ef | S3-ef |

| | | Problem number | | | |
|---|---|---|---|---|---|
| Condition | | WE | P1 | P2 | P3 |
| Forward | Step | 1 | S1-ef | S1-ef | S1-ef |
| Fading (FF) | Step | 2 | 2 | S2-ef | S2-ef |
| | Step | 3 | 3 | 3 | S3-ef |

| | | Problem number | | | |
|---|---|---|---|---|---|
| Condition | | WE | P1 | P2 | P3 |
| Adaptive | Step | 1 | 1 | 1 | S1-af-ef |
| Feedback (A) | Step | 2 | 2 | S2-af-ef | S2-ef |
| | Step | 3 | S3-af-ef | S3-ef | S3-ef |

Note: The steps denoted by the numerals 1, 2, or 3 were provided worked out. The steps denoted by S1, S2, and S3 required a solution attempt by the learner. Feedback was in the form of explanatory feedback (ef) or adaptive feedback (af).

more according to correctness of solution steps in the adaptive feedback condition. The feedback was generally in the form of explanatory feedback (ef), except for the adaptive transitioning condition, which employed both corrective and explanatory feedback as detailed shortly.

*a) Problem solving with step-by-step feedback (PS-S):* The learner was only presented with one instructional example (WE) in the practice section of the program. All subsequent three problems required the learner to attempt an independent solution of all three problem steps. The learner received explanatory feedback after each entered solution step. More specifically, the learner typed in the solution for the first solution step and clicked "Enter". In case the entered solution was correct, the learning environment confirmed the correctness of the entered solution. If the entered solution was incorrect, the learning environment explained how to solve the step correctly and provided the correct solution. The learner then was given an opportunity to study the explanatory feedback and the correct solution and clicked on "Continue" to proceed to the next solution step. The correct solution for the preceding step remained on the screen.

*b) Problem solving with total feedback (PS-T):* In the PS-T condition the learner received feedback after attempting all three solution steps (means-ends solution attempt). In particular, after entering all three solution steps the learner was provided with corrective feedback on all correctly solved steps and explanatory feedback on all incorrectly solved steps.

*c) Backward Fading (BF) and Forward Fading (FF):* With backward fading, the learners first studied a worked out example, i.e., the learners only viewed the three solved problem steps/subgoals. As illustrated in Figure 1, in the first problem (P1), the first two steps/subgoals were solved and the learners had to attempt solving the third step/subgoal. In the second problem (P2), only the first solution step/subgoal was worked out and the learners had to attempt solving the second and third solution step/subgoal. In the third problem (P3), the learners had to attempt solving all three solution steps/subgoals independently.

Forward fading was analogous 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. Throughout, the learners 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.

*d) Adaptive Feedback (A):* This condition was similar to the backward fading condition in that the learners were required to attempt the last solution step in problem 1, the last two solution steps in problem 2, and all three steps in problem 3. In contrast to the backward fading condition, however, the navigation through the worked example and the three problems adapted to the correctness of the solution attempts of the leaner. In particular, if a solution attempt was correct, the learning environment confirmed the correctness of the attempt and proceeded as in the static backward transitioning condition.

If the learner was asked to solve a solution step for the first time, i.e., step 3 in problem 1, step 2 in problem 2, and step 1 in problem 3, and the attempt was incorrect, then the learning environment proceeded as follows. The learner was first provided with corrective feedback, i.e., only a note that the solution attempt was incorrect, but neither the correct solution, nor an explanation how to obtain the correct solution. Then, the learning environment showed the worked example (WE) once more to the learner, this time 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 explanatory feedback and proceeded as in the static backward transitioning condition to the next solution step or problem.

If the learner attempted a solution step that s/he had had the opportunity to attempt independently before, i.e., step 3 in problem 2, and steps 2 and 3 in problem 3, and the attempt was incorrect, then the learning environment proceeded as in the static backward fading condition. That is, if the solution attempt was correct, then the learning environment provided corrective feedback, whereas it provided explanatory feedback if the attempt was incorrect.

*2) Criterion Measures:*

*a) Pretest:* The pretest contained 6 problems (internal reliability of .73) and was designed to measure the participant's knowledge of the topic.

*b) Near transfer posttest:* 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 items that required the participants to engage in the same problem-solving tasks as in the learning (computer) phase. Two engineering instructors scored the transfer test questions (inter-rater reliability 98.5 %).

*c) Far transfer posttest:* The far transfer test was designed to assess students' ability to transfer their problem solving skills to solve a novel set of problems. Four far-transfer problems were included which had different underlying structure and different surface features than the practice problems within the computer-based learning environment. The far transfer problems contained only the individual resistance values and the current flowing through one of the resistors. The participants were required to calculate the current provided by the battery. In order to solve the transfer problems the participants had to apply the same basic principles (Ohm's law, basic properties of voltages and currents in parallel circuits) as in the practice problems, but the sequence in which these principles were deployed and the circuit element to which Ohm's Law was applied varied from the practice problems and from the solution steps presented in the introductory overview. Two engineering instructors (inter-rater reliability 99.8 %) scored the far transfer test questions.

*d) Attitude Survey:* The program rating questionnaire was a 16-item instrument asking participants to rate their learning perceptions on a 5-point scale which ranged from 0 (Strongly disagree) to 4 (Strongly agree) and had an internal reliability of .94. Using principal axis estimation, a factor analysis was conducted to reduce and validate the ratings for the 16 questionnaire items into an aggregated factor-based scale. Three factors were extracted using Kaiser's criterion accounting for 73% of the variance of students' ratings. The first factor consisted of three items about the interest in the engineering domain (factor coefficients .77, .92, and .89). The second factor consisted of two items (factor coefficients .92 for both) about the perceived difficulty of the instructional program, an indirect measure of cognitive load. The third factor assessed students' general perceptions about the helpfulness of the instructional program (factor coefficients ranging from .57 to .89). The internal reliability of the interest, cognitive-load, and helpfulness scales was .88, .83, and .80, respectively.

## III. Procedure

The participants were randomly assigned into one of the five different conditions. Each participant was seated in front of a Windows-based desktop computer and instructed to work independently of her/his peers. First, the participants studied the initial training materials within the computer-based learning environment, and then completed the pretest. Subsequently the participants studied one worked-out example and worked through three problems in the computer module. During this phase the experimental variation took place. After finishing the practice problems, the participants were administered an attitude survey by the computer-based learning environment. The paper-based posttest requiring independent problem solving of eight problems was handed out last.

## IV. Results

Statistical assumptions were evaluated using graphical plots and statistical tests. Only minor and statistically non-significant departures from the assumptions of normality and homogeneity of variances were noted. Alpha was set at .05 for all statistical tests and an appropriate adjustment was made (i.e., Bonferonni) when conducting multiple tests. Table II shows the mean scores $M$ and corresponding standard deviations $SD$ for the five groups (each consisting of around $N$ = 20 subjects) on measures of pretest, near and far transfer tests, and interest, cognitive-load and helpfulness ratings.

### A. Near- and Far-Transfer Achievement

The achievement data were subjected to a multivariate analysis of covariance (MANCOVA) using treatment condition as the between-subjects factor, near and far transfer scores as the dependent measures, and students' pretest score as a covariate. The analysis revealed significant differences on the dependent variables between treatment conditions, Wilks' $\lambda = .81$, $F(8, 184) = 2.55$, $p = .01$. Separate ANCOVAs using treatment condition as between-subject factor and students' pretest score as a covariate, were conducted on each dependent variable as follow-up tests to the MANOVA.

A significant treatment effect was found on near transfer, $F(4, 93) = 2.82$, $MSE = 32.53$, $p < .05$, partial $\eta^2 = .11$, and far transfer, $F(4, 93) = 2.55$, $MSE = 48.31$, $p < .05$, partial $\eta^2 = .10$. Post-hoc Tukey tests revealed that students who learned with forward fading and adaptive feedback outperformed students who learned with backward fading on measures of near transfer and that students who learned with adaptive feedback outperformed those who learned with forward and backward fading on far transfer measures.

### B. Attitudes

We compared students' perceptions about learning in the three scales with a MANOVA, using treatment condition as the between subject factor and students' scores on the three program-rating scales (interest, cognitive load, and helpfulness) as the dependent variables. The MANOVA revealed no significant difference between treatment groups on any of the three scales, Wilks' $\lambda = .94$, $F(12, 241) = .51$, $p = ns$.

## V. Discussion

### A. Impact of Means-Ends Practice

This study did not find a significant difference between step-by-step feedback (PS-S condition) and total feedback (PS-T condition) during practice. This result is contrary to what cognitive load theory would predict. From a cognitive

TABLE II

MEAN SCORES AND CORRESPONDING STANDARD DEVIATIONS ON PRETEST, NEAR AND FAR TRANSFER TESTS, AND INTEREST, COGNITIVE LOAD, AND HELPFULNESS RATINGS FOR FIVE GROUPS

| | Type of Measure | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pretest | | Near Transfer | | Far Transfer | | Interest | | Cogn. Load | | Helpfulness | |
| Groups | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ |
| PS-S ($N$ = 21) | 5.29 | 1.38 | 10.20 | 3.04 | 6.90 | 4.29 | 2.51 | 1.22 | 1.24 | 0.80 | 2.94 | 0.65 |
| PS-T ($N$ = 19) | 4.58 | 1.84 | 9.11 | 3.53 | 6.42 | 4.63 | 2.39 | 1.21 | 1.22 | 0.88 | 2.90 | 0.88 |
| BF ($N$ = 20) | 4.40 | 1.82 | 7.58 | 4.86 | 4.25 | 4.62 | 2.22 | 0.76 | 1.30 | 0.68 | 2.66 | 1.06 |
| FF ($N$ = 20) | 5.05 | 0.95 | 11.05 | 2.78 | 5.05 | 5.08 | 2.58 | 0.84 | 1.35 | 0.81 | 2.79 | 0.55 |
| A ($N$ = 19) | 4.74 | 1.56 | 10.84 | 2.74 | 8.44 | 4.34 | 2.09 | 0.98 | 1.18 | 0.75 | 2.86 | 0.47 |

Note: Scores ranged from 0 to 6 for the pretest, from 0 to 12 for the near and far transfer tests, and from 0 to 4 for the interest, cognitive load, and helpfulness scores. PS-S stands for problem solving with step-by-step feedback, PS-T stands for problem solving with total feedback, BF stands for backward fading, FF stands for forward fading, and A stands for adaptive feedback.

load perspective, the 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. On the other hand, total feedback forces the learner to hold the entire problem in working memory at once. Consistent with this view, we expected that step-by-step feedback would promote learning for two reasons. First, it reduces cognitive load as compared to practicing with total feedback. Second, it provides students with immediate rather than delayed feedback, which is one of the identified characteristics of effective feedback in educational research. More specifically, in the total feedback condition, if a student makes an error in an early step, then the subsequent solution steps—and thus the final answer to the problem—will necessarily be incorrect because the error will carry on to the subsequent solution steps.

However, the alleged differences in either amount of cognitive load and promptness of feedback did not have a significant impact on students problem solving transfer in our study. Although the near and far transfer scores were somewhat lower in the PS-T condition than the PS-S condition, this difference was not statistically significant.

A possible interpretation of this finding is that the materials were not challenging enough to show significant differences between these two practice treatments. This hypothesis is also supported by the lack of significant differences between treatments on students perception about learning. As can be seen from Table II, students reported very similar levels of interest in the domain (with above average mean scores), very similar levels of cognitive load (which had low mean values for all conditions), and gave very similar ratings of program helpfulness (which had high mean values for all conditions). The easiness of materials can, at least, help explain the lack of differences on the near transfer measure, where students are presented with problems that have an identical underlying structure and solution as the problems with which they practice. In terms of far problem solving transfer, we can only observe that the direction of the scores favors both groups who were asked to produce a solution before being shown the correct response (PS-T and PS-S) compared to the two groups that were shown the correct response before attempting a solution (FF and BF). This tendency is consistent with the interactivity principle in instructional design, which supports the design of instructional technologies that engage students in hypothesis testing and manipulation of new information [18]. In sum, the materials may not have been difficult enough to have taxed students' limited cognitive resources. Unless cognitive load is high, methods aimed at reducing cognitive load, such as fading, will be ineffective and methods aimed at increasing students cognitive activity, such as problem solving, will be effective.

### B. Impact of Backward and Forward Fading

The result that forward fading outperformed backward fading may also be explained as due to the fact that the materials were easy to learn. For example, according to the expertise reversal effect [19], once a learner has acquired some basic skill, further skill acquisition is more effectively fostered by engaging in problem solving and receiving feedback rather than by studying worked examples. In the context of this study, the learners may have had sufficient initial knowledge after completing the introductory overview and the worked example. Hence, they benefited more from own practice and receiving feedback rather than being presented with the worked solution. The fact that forward fading engages learners in problem solving at the very first step of each new problem may have been the cause of their enhanced learning. Conversely, backward fading practice presents the solution steps for the first steps of a problem and only asks students to engage in problem solving for the final steps. This delay in prompting students to engage in their own problem solving may have limited the cognitive activity of learners in the backward fading condition and therefore, hurt learning.

### C. Impact of Adaptive Feedback

One of the most interesting findings of this research is that feedback adaptivity provided a significant learning advantage that extended over both, near- and far-problem solving transfer. The benefit of adaptivity may arise from seeing the problem step that the learner just missed in the context of a different example that is completely worked out. 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. The transfer of the correct worked solution to the missed problem step apparently leads to a deeper understanding of the underlying structure of the problems [12]. This deeper understanding in turn enabled the learners in the adaptive feedback condition to perform significantly better on the far-transfer posttest problems, which required the transfer of the principles learned during the practice phase to entirely different solution step sequences.

## VI. Conclusion

This study has important theoretical and practical implications for engineering education. Theoretically, it supports cognitive load theory by showing that forward fading, a practice method that engages students in solving and mastering the initial steps of problems first, promotes near transfer. According to cognitive load theory, when students are learning how to solve problems of moderate to low difficulty, because the intrinsic load of the materials is low, there is sufficient working memory capacity to engage students in higher cognitive activity levels, such as when they are asked to first attempt a solution before receiving feedback [19]. In this regard, our study replicates the findings of past research in botany science, where students who were given the opportunity to attempt a solution before being given principle-based feedback, outperformed those who were given a model solution on problem solving transfer [18].

Likewise, cognitive load theory would explain the near and far problem solving transfer benefits for the adaptive practice condition as the result of the additional cognitive activity that students engaged in during practice. More specifically, cognitive load theory would argue that asking students to compare their solution to a model solution to learn from their mistakes, may have created "germane" load, a type of load that is necessary to promote deeper learning [20]. However, it is important to note that more research with materials of low and high difficulty levels is needed to confirm our conclusions further.

The practical implications of this research are clear. First, our results suggest that the total feedback method provided in typical in-class practices, may be as effective as providing feedback after each individual problem step is attempted by the learner, especially if the problems to-be-learned are not too complex. Second, the findings suggest that, when new instructional materials have low intrinsic cognitive load, once the principles to-be-learned and a worked out example are presented, it is most efficient to ask students to attempt the first steps of isomorphic problems to promote near transfer. Third, our research also suggests that if the instructional objective is to help students transfer the principles learned to solve novel problems with different underlying structures (far transfer), then, asking students to compare the solution of a target problem to that of a given worked example may be most effective. Future research in engineering education should investigate further the promising method of adaptive feedback by testing problem solving practice conditions for a variety of topics and difficulty levels.

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