Comparing Static Fading with Adaptive Fading to Independent Problem Solving: The Impact on the Achievement and Attitudes of High School Students Learning Electrical Circuit Analysis

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ABSTRACT

This study compared conventional static fading, where the problem solving responsibility of the learner increases at a fixed sequence, with a novel adaptive fading design in which the learner assumes more problem solving responsibility only if her or his previous solution attempt is successful. This study was conducted in the engineering knowledge domain of introductory electrical circuit analysis with high school students. A 2 (static or adaptive fading) $\times$ 2 (lower or higher academic ability) Analysis of Variance (ANOVA) yielded a significant main effect on retention and transfer performance: with adaptive fading the participants scored significantly higher on retention and transfer than with static fading, while not requiring more learning time or learning material.

Keywords: cognitive load, fading, worked example

I. INTRODUCTION

Recent research has examined the role of both worked examples (consisting of problem formulation, individual solution steps, and final solution) and practice problems (consisting only of the problem formulation, and requiring a solution attempt by the learner) on learning. It was found that pairing worked examples and practice problems improves learning [1, 2]. It has also been found that worked examples are critical for the initial learning stages in well-structured domains [3], such as algebra [1] or statistics [4].

Worked examples for initial skill acquisition are supported by the cognitive load theory [5–7], which posits that there are three types of cognitive load, namely intrinsic load, germane load, and extraneous load, that put demands on the limited human cognitive resources. Intrinsic load captures the inherent difficulty of the learning material, while germane load reflects the mental effort to process, comprehend, and gain an understanding of the instructional material. Extraneous load arises due to mental effort that is expended to process the instructional material, yet does not directly contribute to learning. For instance, when a novice learner is faced with a practice problem, he or she cannot yet effectively apply the specific rules for the problem domain. Instead, the novice learner has to rely to a large extent on the general strategy of comparing the starting state provided by the problem formulation (i.e., the given variables, quantities, etc.) with the goal state (i.e., the desired quantities, characterizations, etc.) and trying to resolve the difference between these two states. This so-called means-ends problem solving strategy typically requires significant cognitive resources for keeping track of the starting state, the goal state, the differences between the states, and attempts to overcome the differences, but does not usually directly foster understanding [8]. As a result, the problem solving demands arising from being faced with a practice problem result in high extraneous load in novice learners. This in turn leaves typically very little cognitive resources for germane cognitive load, i.e., questioning and developing a deepened understanding of the material. On the other hand, worked examples limit the extraneous cognitive load due to problem solving demands in the initial skill acquisition and foster the initial learning [4].

Recently, a new structure for instruction, which lies between worked examples and practice problems, has been proposed [8, 9]. This instructional sequence first presents the learner with a fully worked out example, i.e., all solution steps are shown to the learner. Next, the learner is presented with a problem, which has all but the last solution step worked out. The learner is expected to solve this last step. Next, the learner is presented with a problem, which has all but the last two solution steps worked out; whereby these last two steps require solution by the learner. This process of reducing (fading) the worked solution steps by one with every new problem continues until all the worked solution steps are faded away and the learner has to independently solve the entire problem. The described structure where the worked solution steps are faded starting with the last step is referred to as backward fading. In contrast, in a forward fading design, the worked solution steps are faded beginning with the first solution step. It has been found that backward fading results generally in higher learning performance [8, 10].

To the best of the authors' knowledge, all previous studies on fading have considered a *static fading* sequence, that is the worked solutions steps were faded away and the learners asked to solve more steps themselves at a predetermined, rigid sequence. No attention was paid to whether or not the learner could keep up with the increasing problem solving demands and correctly solve the problem steps she or he was asked to solve independently. Therefore, it appeared worthwhile to design and investigate an *adaptive fading* scheme that adapts the fading of the worked solution steps to the learner's successes and failures in solving problem steps: If the learner successfully solves a problem step, the fading away of worked steps continues, whereas if he or she fails, the missed step is presented once more as a worked example step.

A. Related Work

Adaptive educational systems have received some attention in the context of the development of adaptive hypermedia systems. Brusilovsky [11] provides an overview of the literature on adaptive navigation support in educational hypermedia. He notes that empirical studies have provided evidence that learners with different knowledge levels appreciate different navigation support technologies. In the study by Kashihara, Kinshuk, and Opperman [12] the size of the exploration space was adapted according to the ability levels of the learner in an effort to control the cognitive load on the learner. More recently, the study by Azevedo, Gromley, and Seibert [13] compared three scaffolding conditions, namely adaptive scaffolding, fixed scaffolding, and no scaffolding. It was found that adaptive scaffolding facilitated the construction of mental models significantly more effectively than the other conditions. An adaptive engineering learning module has been developed by Khandan [14]. In this computer-based module, the students are presented with practice problems whose solutions require a varying number of underlying concepts. When the solution attempt of a learner is correct (incorrect), then he or she is next presented with a practice problem requiring more (less) concepts. The module of Khandan [14] is thus complementary to the present study in that the adaptive transitioning from studying worked examples to solving practice problems examined here could be followed by adaptively presenting the learners with practice problems of varying difficulty.

The investigation of adaptive fading is especially relevant for the engineering education domain, which has so far received relatively little attention in worked example research in general and in fading research in particular. Worked examples have recently been employed in the research by Leland et al. [15, 16] on fostering the problem solving skills of engineering students. Leland et al. solicited self-explanations of the worked steps from the learners to encourage the active processing of the worked examples. Similarly, the electrical circuit tutorials by McDermott and Shaffer [17–19] are designed to foster the active processing of the presented concepts. The present study complements this existing research in that it examines one approach for encouraging active processing of and engagement with the concepts, namely by asking the learners to solve progressively larger portions of the problems.

The authors are only aware of the studies regarding fading in the engineering domain [20–22], which are complementary to this study. The study [20] focused on the presentation and format of the feedback in a fading based engineering learning module (the underlying fading structure was static fading). Static fading was compared to abruptly switching from worked examples to practice problems [21]. The study [22] considered different fixed paces of static fading, i.e., no attention was paid to the learner successes or failures in solving practice problem steps.

II. Purpose and Research Questions

The purpose of this study was to investigate the impact of the adaptation of the fading of worked solution steps on learner performance and attitudes. The study included two treatment conditions. In the static fading condition the worked solution steps were faded at a fixed pace of one solution step for every two problems. In the adaptive fading condition the learning environment "probed" the learner's ability for solving solution steps; if the learner's solution was correct, the number of steps requiring solution by the learner was increased by one, otherwise the learner was next provided with a problem that had the incorrectly solved step worked out. These two fading conditions were investigated under two levels of academic ability.

The primary research questions for this study were:

1. What is the effect of the fading condition (static or adaptive) on learner retention and transfer achievement?
2. What is the effect of the academic ability on the navigation pattern in the adaptive fading condition and on learner performance on in-program practice items?
3. What is the effect of the fading condition and the academic ability on learner attitudes?

III. Method

A. Participants

The participants of this study were 65 high school freshmen from a large public high school in the Southwest. The evaluation of adaptive fading in the context of a computer-based module with high school students was motivated by the need to develop effective instructional techniques and modules that expose high school students to engineering in an effort to attract students to engineering programs at universities and colleges [23]. The experimental sample consisted of 33 males and 32 females. The age of the participants ranged from 13 years to 16 years, the average age of the participants was M = 14.60 years (standard deviation SD = 0.58). The participants had no content-specific prior knowledge and were randomly assigned to one of the two fading conditions. The Grade Point Average (GPA) of the participants ranged from 2.0 to 4.0, with a mean of M = 3.59 (SD = 0.43). The participants were grouped according to a mean split of their GPA into a lower academic ability group (GPA of 3.6 or less) and a higher academic ability group (GPA higher than 3.6). According to this grouping there were 29 participants with lower academic ability and 36 participants with higher academic ability. Following Cohen [24], the resulting per sample cell size was sufficient to detect a large effect (Cohen's $f = 0.40$), which was deemed to be substantively significant in the present study based on a conventional alpha level of 0.05 (two-tailed) and statistical power of 0.80.

B. Materials

A computer-based learning environment served as a platform for the delivery of the engineering 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 computer-based module was developed using Dreamweaver MX software [25], an authoring tool for creating web-based multimedia programs. The program had two main sections, (1) an Introductory Overview, and (2) Practice. The program also included questions that collected basic demographic data on participant gender, age, GPA, and content-specific prior knowledge.

The introductory overview to the program contained basic instruction on the fundamental electrical engineering 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. It introduced the participants to: (a) the physical meaning and units of electrical current, voltage, and resistance, (b) electrical circuit elements and their graphical representations, 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 resistance and voltage 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. 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 the calculation of the value of the current flowing through each individual resistor is done using Ohm's Law. Second, it showed examples where 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 examples demonstrated the calculation of the total resistance of the parallel circuit by applying Ohm's Law to the entire circuit, i.e., the calculation of the total resistance of the parallel circuit 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 proceeded to practice the steps in solving parallel electrical circuit analysis problems. The computer-based instructional environment presented a set of eight 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 by clicking the "Continue" button while revealing one step at a time. The program allowed the participants to proceed through the module by clicking on the "Next Problem" buttons after all three steps in each problem were displayed. The participants were not allowed to return to previous steps and problems once they finalized their answers.

The computer program presented the participants with instances requiring independent solving of one or more of the problem's individual solution steps. The participants were asked to enter a solution for each unsolved solution step. The computer-based learning environment then revealed the correct solution for the solution step. Only a single attempt at solving each missing step was given to the participants. Feedback followed each participant's solution attempt. If the solution of the missing solution step was correct, the feedback confirmed the accuracy of participant's practice performance. In the case of inaccurate solution, the computer module automatically presented the participant with the correct answer in textual format, which has been found to be beneficial for novice learners [20]. The solved step(s) remained visible on the screen after the final answer was presented, allowing time for the participants to study the entire solution.

The module had been programmed to operate in one of the two modes that corresponded to the two fading conditions. In both treatment conditions, the participants studied worked examples and independently solved practice problems within the computer-based learning environment. The instructional sequence of the examples/problems and steps requiring independent problem solving from the participants varied according to the experimental fading condition.

1) Static Fading Condition: In this condition the first problem was fully solved (worked out) and the learners only viewed the three solved problem steps/subgoals. All three solution steps in the second problem were also worked out. In the third and fourth problems, the first two solution steps were worked out and the learners had to solve the third solution step. In the fifth and sixth problems, only the first solution step/subgoal was worked out and the learners had to solve the second and third solution step/subgoal. In the seventh and eighth problems, the learners had to solve all three solution steps/subgoals independently.

2) Adaptive Fading Condition: In this condition, the first problem was also fully worked out. In the second problem, the first two steps/subgoals were solved (worked-out) and the learner had to solve the third step/subgoal. The number of worked/to-be-solved solution steps in the next (third) problem and all the following problems depended on the correctness of the solutions. Specifically, if the solution of the third step in the second problem was correct, the learner was next presented with a problem where the first solution step was worked out and the last two solution steps were to be solved by the learner. If the solution was incorrect, the learner was next presented with a problem where all three solution steps were worked out.

In general, the learner was only allowed to advance to a problem with $n + 1$, $n = 1, 2$, missing worked solution steps after she or he had correctly solved all the n missing solution steps in the current problem. Whenever the learner incorrectly solved a particular solution step k, $k = 1, 2, 3$, then the learner was next presented with a problem where the solution steps up to and including step k were worked out and the remaining steps $k + 1, 2, 3$, required solution from the learner. In other words, the learning environment "probed" whether the learner was able to correctly solve a solution step k. If so, the learner was permitted to advance to solving one additional solution step herself or himself. Otherwise, the program demonstrated the correct solution of step k once more with a worked out solution of step k.

In the adaptive fading condition, the sequence of problems that a learner encountered was not pre-determined, but rather a function of the solutions of the learner. To ensure the validity of the comparisons on the dependent variables across the two experimental conditions, the learners in both experimental conditions were allowed to spend the same prescribed time limit in the practice section of the computer-based learning environment. The time limit was determined from a pilot study and set to 20 minutes. In addition, the learners in both experimental conditions were exposed to at most eight problems. Each problem consisted of three steps, whereby a given step was either worked out or to be solved by the learner. The learners in both conditions were exposed to at most 24 steps, i.e., each had the same limited amount of learning material.

C. Procedures

The participants took part in the study in a computerized classroom at their high school during regular class time. Each participant was seated in front of a Windows-based desktop computer and the participants were instructed to work independently of their peers.

The participants studied the initial training materials within the computer-based learning environment. Following the introductory self-study of the basic principles of electrical circuit analysis, the participants studied worked-out examples and engaged in independent problem solving in the computer module. During this phase the experimental variation took place. The computer-based learning environment automatically recorded the accuracy of participants' performance on the independent problem solving. After finishing the activities in the computer-based learning environment, the participants were administered a paper-based attitude survey. The post-test requiring independent problem solving of six problems was handed out last.

D. Criterion Measures

The study used two measures intended to evaluate the impact of the two independent variables (fading: static or adaptive; participant level of ability: lower or higher) and their interaction. These measures were a post-test and an attitude survey.

1) Post-test: A six-item paper-based post-test consisting of retention and transfer problems was created to assess the participants' ability to retain and to transfer the knowledge obtained from the instructional environment to novel problems. The problems required the participants to independently solve complex electrical circuit analysis problems. The participants worked out three solution steps in each problem, whereby each step involved reasoning about the behaviors of the currents, voltages, and resistance values in the circuit and carrying out the appropriate calculations. Overall, the participants performed between three and five arithmetic operations (multiplications, divisions, additions) in each problem.

Three post-test items were similar to the problems the participants encountered within the computer-based learning environment in that they had the same underlying structure but different surface features, such as parameter values and cover stories. These post-test items measured retention of participants' knowledge. Their solution required the participants to engage in the same problem-solving tasks as in the learning (computer) phase. The problem statements provided the participants with the battery voltage and the individual resistance values of two to three circuit elements and required the participants to compute the total resistance of the given electrical parallel circuits. For example, the participants were given the following problem to solve, "You wire a subwoofer speaker with resistance $Rs = 16\Omega$ and a regular speaker with a resistance of $Rr = 8\Omega$ in parallel and operate the two speakers with a 6V battery. What is the total resistance of this parallel circuit?".

Three problems measuring transfer performance were also included in the post-test. The transfer problems had different underlying structures and different surface features than the practice problems within the computer-based learning environment. The transfer parallel circuit problems contained only the individual resistance values and the current flowing through one of the resistors. The participants were required to calculate the total current provided by the battery. For example, the participants were asked to solve the following problem, "To illuminate your tent, you wire two light bulbs in parallel and connect the parallel circuit to a battery. The first light bulb has a resistance of $R1 = 10\Omega$. The second light bulb has a resistance of $R2 = 20\Omega$. To ensure sufficient illumination in your tent, the current flowing through the first light bulb must be at least $I1 = 0.5$A. How much total current flow is drained from the battery?".

In solving transfer problems, the participants had to first use Ohm's Law to calculate the voltage in the parallel circuit from the resistance value of the one resistor for which the current was given. Next, the participants had to observe that the voltage is the same over all resistors. The calculation of the currents over the other resistors in the circuit followed. The participants had to use Ohm's Law and the voltage determined in the first step together with the values of the individual resistors to perform this operation. In the third and final solution step, the participants had to add the currents through the individual resistors to compute the total current (battery current) in the parallel circuit. Generally, 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.

2) Attitude Survey: A sixteen-item Likert-type five-choice (5 = strongly agree, 1 = strongly disagree) attitude survey was employed to assess participants': (a) perceptions toward the overall instructional value of the program (assessed with four items, such as "I learned a lot from this computer-based program"); (b) willingness to continue studying in the engineering area (assessed with three items, such as "This program made engineering more interesting for me."); (c) perceptions about the effectiveness of the instructional strategies (assessed with five items, such as "The examples helped me learn.", "The problems helped me learn."); and (d) attitudes regarding the usefulness and instructional value of the different fading conditions (assessed with four items, such as "The way the program selected the problem steps for me to work on was good for my learning").

Enroute measures included the time learners spent on the introductory overview of electrical circuit analysis and the time spent on the in-program practice. A composite measure of the total instruction time spent during the learning phase was then derived. In addition, the computer module automatically recorded the correctness of learner responses when solving the missing solution steps.

IV. Results

A 2 (static or adaptive fading instructional sequence) × 2 (lower or higher academic ability) analysis of variance (ANOVA) was used

Condition	Academic Ability		Retention (max. 100)	Transfer (max. 100)
Static Fading	Lower	M	77.13	2.93
	(N = 15)	SD	15.66	5.04
	Higher	M	95.35	10.41
	(N = 17)	SD	13.18	16.92
	Total	M	86.81*	6.91*
	(N = 32)	SD	16.90	13.18
Adaptive Fading	Lower	M	94.57	12.64
	(N = 14)	SD	10.19	15.02
	Higher	M	95.16	25.68
	(N = 19)	SD	9.53	22.37
	Total	M	94.91*	20.15*
	(N = 33)	SD	9.66	20.40

*denotes a statistically significant difference at the $p < 0.01$ level between static and adaptive fading.

Table 1. Retention and transfer post-test scores by treatment group and ability: Adaptive fading resulted in significantly higher retention and transfer performance.

to analyze all collected data. Cohen's f statistic, defined in terms of the partial eta squared η^2 as $f = \sqrt{\eta^2/(1 - \eta^2)}$, was used as an effect size index whereby f values of 0.10, 0.25, and 0.40 correspond to small, medium, and large effect sizes [24].

A. Achievement

Participant achievement on the post-test is reported in Table 1 that shows the mean scores M and standard deviations SD for each treatment condition and level of academic ability on retention and transfer post-test problems. A 2 $\times$ 2 ANOVA conducted on the retention post-test scores revealed that the participants in the adaptive fading condition (M = 94.91) scored significantly higher than the participants in the static fading condition (M = 86.81); F ratio $F(1,61) = 7.90$, mean square error MSE = 150.75, statistical significance level $p = 0.007$, $\eta^2 = 0.115$. Cohen's f statistic for these data yields an effect size estimate of 0.36, which approaches a large effect, and is, therefore, of practical significance. The ANOVA also revealed that the higher ability participants (M = 95.25, SD = 11.23) significantly outperformed their lower ability counterparts (M = 85.55, SD = 15.80) on the retention post-test problems; $F(1,61) = 9.40$, $p = 0.003$, $\eta^2 = 0.134$.

The ANOVA on the retention revealed that there was a significant academic ability by fading condition interaction on the retention post-test scores; $F(1,61) = 8.27$, $p = 0.006$. A simple main effects analysis revealed that the lower ability learners had significantly higher retention performance in the adaptive fading condition (M = 94.57) than in the static fading condition (M = 77.13); $F(1,27) = 12.43$, MSE = 177.15, $p = 0.002$, $\eta^2 = 0.315$. Cohen's f statistic for these data yields an effect size estimate of 0.68, which corresponds to a large effect. There was no such significant simple main effect for the higher ability learners; $F(1,34) = 0.003$, MSE = 129.78, $p = 0.959$.

A 2 $\times$ 2 ANOVA on the transfer post-test scores uncovered a main effect for fading condition on transfer performance; $F(1,61) = 9.04$, MSE = 276.70, $p = 0.004$, $\eta^2 = 0.129$. In particular, participants in the adaptive fading condition scored significantly higher on the transfer problems (M = 20.15) than participants in the static fading condition (M = 6.91). Cohen's f statistic for these data yields an effect size estimate of 0.38 which corresponds to a large effect and is of practical significance. The ANOVA also revealed a significant main effect for academic ability on transfer performance; $F(1,61) = 6.10$, $p = 0.016$, $\eta^2 = 0.091$. Specifically, the higher ability participants scored significantly higher on the transfer post-test (M = 18.47, SD = 21.17), than their lower ability counterparts (M = 7.62, SD = 11.91). Furthermore, the ANOVA revealed that there was no significant academic ability by fading condition interaction on the transfer performance; $F(1,61) = 0.45$, $p = 0.506$.

B. Practice

The participants' performance on the practice problems presented within the computer-based learning environment was automatically tracked by the program. The corresponding descriptive statistics are reported in Table 2. All learners in the static fading condition viewed all twelve worked example steps contained in the eight-problem static fading sequence, i.e., they all reached and completed at least the first step of the sixth problem in the sequence. A 2 $\times$ 2 ANOVA on the number of viewed worked example steps revealed that the participants in the adaptive fading condition viewed significantly less worked steps (M = 9.61) than the participants in the static fading condition; $F(1,61) = 11.51$, MSE = 7.46, $p = 0.001$. There was no significant difference between the number of worked example steps viewed by the higher ability learners (M = 10.50, SD = 2.98) and the lower ability learners (M = 11.14, SD = 2.92); $F(1,61) = 0.60$, $p = 0.442$.

Condition	Academic Ability		Viewed worked example steps	Practice problem steps worked on	Correctly solved practice problem steps	Total experienced steps (max. 24)
Static Fading	Lower	M	12.00	11.67	9.67	23.67
	(N = 15)	SD	0.00	1.29	2.23	1.46
	Higher	M	12.00	11.18	10.18	23.18
	(N = 17)	SD	0.00	2.04	2.19	2.04
	Total	M	12.00*	11.41	9.94	23.41†
	(N = 32)	SD	0.00	1.72	2.18	1.77
Adaptive Fading	Lower	M	10.21	10.57	8.71	20.79
	(N = 14)	SD	4.08	2.98	3.54	3.64
	Higher	M	9.16	13.16	12.11	22.32
	(N = 19)	SD	3.64	3.72	4.07	3.37
	Total	M	9.61*	12.06	10.67	21.67†
	(N = 33)	SD	3.81	3.61	4.16	3.52

*denotes a statistically significant difference at the $p < 0.01$ level between static and adaptive fading.
† denotes a statistically significant difference at the $p = 0.01$ level between static and adaptive fading.

Table 2. Number of viewed worked example steps, practice problem steps worked on, and total number of experienced steps by treatment group and ability: With adaptive fading, the learners viewed significantly fewer worked example steps and experienced significantly fewer total steps than with static fading.

Neither was there a significant interaction; $F(1,61) = 4.47$, $p = 0.442$.

A 2 × 2 ANOVA on the number of practice problem steps that the learners worked on revealed that there was no significant difference between the number of steps that the learners in the static condition worked on (M = 11.41) and the number of steps that the learners in the adaptive fading condition worked on (M = 12.06); $F(1,61) = 0.42$, MSE = 7.43, $p = 0.518$. Neither was there a significant difference between the number of steps attempted by the higher ability learners (M = 12.22, SD = 3.16) and the lower ability learners (M = 11.14, SD = 2.30); $F(1,61) = 2.37$, $p = 0.129$. However, the ANOVA revealed a significant ability by fading condition interaction on the number of attempted practice problem steps; $F(1,61) = 5.10$, $p = 0.028$. A simple main effects analysis revealed that in the adaptive fading condition, the higher ability learners attempted significantly more practice problem steps (M = 13.16) than their lower ability counterparts (M = 10.57); $F(1,31) = 4.59$, MSE = 11.74, $p = 0.040$.

A 2 × 2 ANOVA on the number of correctly solved practice problem steps showed that there was no significant difference between the learners in the static fading condition, who solved on average M = 9.94 steps correctly, and the learners in the adaptive fading condition, who solved on average M = 10.67 steps correctly; $F(1,61) = 0.38$, MSE = 9.94, $p = 0.538$. However, the ANOVA uncovered that the higher ability learners solved significantly more problem steps correctly (M = 11.19, SD = 3.41) than their lower ability counterparts (M = 9.21, SD = 2.92); $F(1,61) = 6.13$, $p = 0.016$. Furthermore, there was no significant interaction, $F(1,61) = 3.35$, $p = 0.072$.

Finally, a 2 × 2 ANOVA on the total number of steps experienced by the learners (i.e., the number of viewed worked example steps plus the number of practice problem steps worked on) revealed that the learners in the static fading condition experienced significantly more steps (M = 23.41) than their counterparts in the adaptive fading condition (M = 21.67); $F = (1,61) = 6.49$, MSE = 7.75, $p = 0.013$. On the other hand, the ANOVA revealed that there was no significant difference between the total number of steps experienced by the higher ability learners (M = 22.72, SD = 3.17) and the lower ability learners (M = 22.17, SD = 3.01); $F(1,61) = 0.80$, $p = 0.376$, neither was there a significant interaction.

C. Time in Program

Table 3 reports the time that the participants spent on the introductory overview in the program, the time spent on the in-program practice, and the total time spent in the program by treatment condition. A 2 × 2 ANOVA on the time spent on the introductory overview revealed that neither the treatment condition nor the ability level had a significant impact on the time spent on the introductory overview. Neither was there a significant interaction for the time spent on the introductory overview.

A 2 × 2 ANOVA on the time spent on practice uncovered that the participants in the adaptive fading condition spent significantly less time (M = 16 minutes: 20 seconds) on practice than their counterparts in the static fading condition (M = 18 min: 10 sec); $F(1,61) = 5.25$, MSE = 35841.31, $p = 0.025$, $\eta^2 = 0.079$. There was no significant main effect due to the ability level, neither was there a significant interaction.

A 2 × 2 ANOVA on the total time spent in the program (total instruction time) revealed that there was no significant difference

Condition			Introductory overview time (min:sec)	In-program practice time (min:sec)	Total time (min:sec)
				(max. 20 minutes)	
Static Fading	Total	M	8:40	18:10‡	26:51
	(N = 32)	SD	3:56	2:23	4:12
Adaptive Fading	Total	M	8:51	16:20‡	25:11
	(N = 33)	SD	4:19	3:40	6:39

‡ denotes a statistically significant difference at the $p < 0.05$ level between static and adaptive fading.

Table 3. Time spent on introductory overview, in-program practice, and total time in program by treatment group: With adaptive fading, the learners spent significantly less time practicing than with static fading, but there was no significant difference in the total time spent in the learning module.

Condition	Academic Ability		Overall instructional value (4 items)	Continuous motivation (3 items)	Effectiveness of instructional strategies (5 items)	Value of fading condition (4 items)
Static Fading	Lower	M	3.58	3.20	3.75	3.35*
	(N = 15)	SD	0.92	0.97	1.14	1.16
	Higher	M	3.85	3.29	4.34	4.32*
	(N = 17)	SD	0.65	0.90	0.45	0.54
	Total	M	3.73	3.25	4.06	3.87
	(N = 32)	SD	0.79	0.92	0.88	1.00
Adaptive Fading	Lower	M	3.70	3.29	4.10	3.88
	(N = 14)	SD	0.85	1.13	0.74	0.86
	Higher	M	3.83	3.44	4.21	3.96
	(N = 19)	SD	0.83	1.12	0.83	0.78
	Total	M	3.77	3.37	4.16	3.92
	(N = 33)	SD	0.83	1.11	0.78	0.80

*denotes a statistically significant difference at the $p < 0.01$ level between static and adaptive fading.

Table 4. Attitude scores for four main attitudinal categories by treatment group and ability: In the static fading condition, the higher ability learners valued the fading condition significantly more than the lower ability learners. Generally, there were no significant differences between the attitudes of the learners in the adaptive and static fading conditions.

between the participants in the static fading condition (M = 26 min: 51 sec) and the participants in the adaptive fading condition (M = 25 min: 11 sec); $F(1,61) = 1.16$, MSE = 113671.27; $p = 0.286$. Neither was there a significant difference between the total time that the higher ability participants (M = 26 min: 06 sec, SD = 4 min: 44 sec) and the lower ability participants (M = 25 min: 54 sec, SD = 6 min: 36 sec) spent in the program; $F(1,61) = 0.043$, $p = 0.837$. Furthermore, there was no significant interaction; $F(1,61) = 1.23$, $p = 0.272$.

D. Attitudes

The learner attitudes toward the positive survey statements regarding the four attitudinal categories are reported in Table 4 by treatment condition and academic ability. The overall mean attitudinal scores in descending order were M = 4.11 for the effectiveness of the employed instructional strategies, M = 3.90 for the usefulness of the different fading conditions, M = 3.75 for the overall instructional value of the program, and M = 3.31 for the continuous motivation. The Cronbach α across all survey items was 0.94 indicating a high reliability of the survey.

The mean attitudinal scores for each category were analyzed with a 2×2 ANOVA. No main effects or interactions were found for the overall instructional value, continuous motivation, and effectiveness of instructional strategies categories. The 2×2 ANOVA for the usefulness of different fading conditions category revealed that the higher ability learners perceived the fading conditions as significantly more useful (M = 4.13, SD = 0.69) than their lower ability counterparts (M = 3.60, SD = 1.04); $F(1,61) = 6.24$, MSE = 0.72, $p = 0.015$, $\eta^2 = 0.093$. There was no significant main effect for the fading condition. However, the ANOVA uncovered a significant ability by fading condition interaction on the usefulness of the fading conditions attitudinal category; $F(1,61) = 4.39$, $p = 0.040$. A simple main effect analysis revealed that in the static fading condition, the higher ability learners perceived the fading as significantly more useful (M = 4.32) than their lower ability counterparts (M = 3.35); $F(1,30) = 9.72$, MSE = 0.78, $p = 0.004$.

V. Discussion

This study, which was conducted with high school students in the electrical engineering domain, compared static fading, which fades away the worked solution steps at a fixed pace, with adaptive fading, which fades away the worked solution steps according to the accuracy of the solution attempts of the individual learner.

A. Achievement

This study revealed for both retention and transfer performance that (A) the learners in the adaptive fading condition outperformed the learners in the static fading condition, and (B) the higher ability learners outperformed the lower ability learners. In addition there was a significant interaction for the retention performance, while there was no significant interaction for transfer performance. Inspection of the retention results for adaptive fading indicates that both higher and lower ability learners had about the same retention performance of around M = 95. This suggests that there was a ceiling effect in the adaptive fading condition that prevented the higher ability learners from achieving higher retention scores than the lower ability learners. Had the higher ability learners scored higher then there would be no interaction, as is the case for transfer performance, where there is clearly no ceiling effect. In any case, there is a significant main effect due to the examined treatment, namely higher retention and transfer performance with adaptive fading and the following discussion focuses on this main effect.

This empirical main effect finding of this study can be related to the cognitive load theory [5–7]. For a beginning learner, worked examples are beneficial since they free the learner from problem solving demands, allowing the learner to study how to solve the problem. This approach ensures low extraneous cognitive load due to problem solving demands, allowing the learner to allocate cognitive resources to comprehend and gain an understanding of the learning material (i.e., the so-called germane cognitive load dedicated to comprehension is allowed to be large).

The learner advances in the skill acquisition process by formulating declarative and procedural rules for problem solving [26]. Declarative rules are verbalizations of the solution strategy that assist in developing the solution. Procedural rules are more formalized solution strategies that allow for fast problem solving with relatively little mental effort. As the learner advances in the skill acquisition process to formulating these rules, the benefit of worked examples diminishes, and the learner's further skill acquisition is fostered more by attempting to solve increasingly larger parts of problems and eventually complete problems. By practicing the problem solving and receiving feedback on the correctness of the solution the learner can validate correct declarative and procedural rules or repair incorrect rules [27]. It is reasonable to suppose that the individual learners have their own personal successes and setbacks in formulating the declarative and procedural rules, i.e., they advance on their own personal trajectory through the skill acquisition process.

Static fading, however, forces all learners on the same trajectory of continuously increasing problem solving burden at some fixed rate (one new step for every second problem in the present study). Static fading does not pay attention to the individual successes and failures of a learner in formulating rules and verifying them by attempting to solve practice problem steps. On the other hand, adaptive fading monitors the successes and failures of the individual learner in attempting to solve practice problem steps. If the attempt was successful, then adaptive fading increases the problem solving opportunities of the learner, allowing for further advancement of the skill acquisition process to a wider scope of the problem solution. If the attempt failed, then adaptive fading provides the learner with a worked example of the missed step, fostering the repair of the incorrect rules that the learner had formulated.

B. Practice and Time in Program

It is noteworthy that the learners in the adaptive fading condition viewed less worked example steps, experienced less steps overall in the program, and spent less time with the worked examples/practice problems in the program than the learners in the static fading condition. This indicates that the improved learning due to adaptive fading is not due to the learning time or the amount of consumed learning material (total number of experienced steps). The learners in the adaptive condition in fact spent less time learning and went through fewer steps. Rather the personalized instruction with adaptive fading that provides the learners with a worked example to repair rules, or additional practice opportunities just when they need it to best foster their learning is apparently responsible for the improved learning performance with adaptive fading.

The significant interaction found for the number of practice problems that the learners worked on in the adaptive condition is consistent with the cognitive load theory. The interaction shows that higher ability learners worked on more practice problems than their lower ability counterparts. The higher ability learners were more successful in formulating problem solving rules (as indicated by the higher number of correctly solved practice problem steps). Thus they tended to advance faster and reach more advanced stages in skill acquisition which in turn led them to try more solution attempts. In the adaptive fading condition, the higher ability learners also experienced somewhat more total steps than their lower ability counterparts. Conversely, the lower ability learners viewed somewhat more worked example steps than their higher ability counterparts. These differences, although not statistically significant, are consistent with the presented cognitive load interpretation.

C. Attitudes

The attitude results indicate that the learners were positive toward the instructional strategies and fading conditions overall. The uncovered interaction for the usefulness of fading conditions category suggests that the higher ability learners were more positive toward the static fading than their lower ability counterparts. The higher ability learners may have been able to keep up with formulating their declarative and procedural rules and validating those rules as the static fading condition asked them to attempt more problem steps. On the other hand, the lower ability learners may have not been able to keep up in their skill acquisition with the pace dictated by the static fading condition and felt frustrated. No such difference was found for the adaptive fading condition where both higher and lower ability learners felt equally positive about the fading design. This is a reasonable result as the adaptive fading adapted to the individual progress that the learners were making.

VI. Conclusion

This study examined a novel adaptive fading instructional design which fades worked solution steps according to the correctness of solution attempts of problem steps by the learner. This design was compared with conventional static fading which fades worked solution steps at a fixed pace. It was found that adaptive fading results in significantly higher retention and transfer post-test performance than static fading, while not requiring more learning time, nor more learning material. Adaptive fading is a highly personalized instructional approach and appears therefore best suited for individualized instruction through computer-based modules or a personal tutor/instructor. A drawback of the technique is that it does not appear to be suitable for large lecture-type classes.

However, it may be feasible to have a small team of learners jointly interact with a single adaptive fading instructional module. The team members could collaboratively study the worked steps and attempt to solve the required problem steps. The effectiveness of such teaming in the context of adaptive fading would need to be carefully studied in future research. It would also be of interest to validate the results of this study, which was conducted with high school students in the electrical engineering domain, in future research for different learner populations (e.g., college students) and other knowledge domains within engineering and outside of engineering.

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