Pre-college Electrical Engineering Instruction: Do Abstract or Contextualized Representations Promote Better Learning?

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Abstract - **Pre-college students were randomly assigned to learn about electrical circuit analysis with an instructional program that included two problem solving practice conditions. In the first condition, students learned to solve parallel circuit problems that were contextualized around real electrical devices and represented with realistic diagrams. In the second condition, students learned to solve the same problems except that they were de-contextualized and represented with abstract diagrams. To measure learning, students were given near and far transfer problem solving tests. In addition, students' learning perceptions were measured using a program-rating survey that included three subscales: overall program usefulness, problem representation usefulness, and perceived cognitive load. Students who learned with abstract problems produced higher scores on the near transfer test and made better problem representations during problem solving than those who learned with contextualized problems. The contextualized group gave marginally higher ratings for the program representation usefulness. The findings suggest that abstract electrical circuit representations promote better learning because they facilitate thinking about a variety of problem contexts.**

Index Terms – Abstract representation, Cognitive learning theory, Contextualized representation.

INTRODUCTION

The K-12 school audience has been identified as a key target for improving engineering education [1]. Investigating methods that can help increase the performance and enthusiasm of pre-college students in engineering has become a major focus of policymakers in recent years [2]. How can we help pre-college students develop problem-solving skills and positive perceptions towards engineering education? A promising technique that has been shown to promote problem-solving skills in well-structured domains such as physics or mathematics is worked-example instruction [3]. In this instructional method, students learn by studying example problems, the worked-out solution steps that are necessary to solve the example problems, and their final solutions. Worked-example instruction is widely used in the classroom--where instructors demonstrate the solution of problem examples before asking students to engage in independent problem solving; and it is a common method found in textbooks and computer-based instructional programs such as cognitive tutors [4].

In engineering, several studies have shown that worked-example instruction that is followed by guided problem-solving practice can effectively promote freshman students' near problem-solving transfer [5,6]. Near transfer is the ability to apply the problem-solving steps demonstrated in the worked-out examples to solve new isomorphic problems--those that share the same structure as the worked-out examples yet differ on their surface characteristics (i.e., cover story). For example, two isomorphic parallel circuit problems are: "You wire a subwoofer speaker with a resistance of R_s = 16 Ω and a regular speaker with a resistance of R_r = 8 Ω 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 of R_m = 4.5 Ω, and a control unit with a resistance of R_c = 72 Ω. 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?"

A major challenge of worked-example instruction, however, is to find methods that promote the far transfer of the principles learned. Most research has found that the effectiveness of worked-examples is limited to promoting the application of principles learned to solve very similar problems [7]. The goal of the present study was to extend past research in worked-example instruction by examining whether contextualizing worked-out problem examples would promote both students' near and far transfer ability. More specifically, we were interested in testing two contradictory hypotheses. First, according to contextualized learning theory, realistic problem-solving scenarios that are anchored on learners' past experience are more likely to facilitate learning because their meaning can be more readily accessed in long-term memory [8,9]. Although abstract representations attempt to depict a close correspondence between the diagram and the concrete objects that they intend to represent, they rely significantly more on knowledge conventions for their interpretation than contextualized representations [10]. Therefore, contextualized learning theory predicts that students who learn with richly contextualized problems will experience less cognitive load and learn better than those who learn with problems that are not contextualized [11].

In contrast, according to cognitive learning theory, abstract problem cover stories and representations promote better learning because they help learners focus their attention on the relevant structural information underlying all isomorphic problems rather than on the superficial information that changes from problem to problem. Studies have shown that one of the main obstacles to successful problem solving is that problem representations may divert attention to irrelevant details or may highlight some aspects of the problem at the expense of information that is necessary to accomplish the task [12-14].

Cognitive learning theory also suggests that contextualized problem solving may be more difficult than abstract problem solving because it requires the following three translation steps between different symbol systems [15]: (1) translating from the given situated problem setting to a mathematical model; (2) transforming the mathematical model so that desired results can be obtained; and (3) translating the obtained result back into the given problem context [16]. Identical translation steps are involved in solving contextualized engineering problems [17,18].

Therefore, cognitive learning theory predicts the opposite outcomes than contextualized learning theory: students who learn with abstract problem representations will experience lower cognitive load and learn better than those who learn with contextualized problems.

In addition to testing the aforementioned conflicting theories, this research set out to derive practical implications for engineering education. Whereas introductory engineering textbooks for pre-college students typically present problems in the context of real-world examples [19], college-level engineering textbooks present most problems in abstract form, using standard engineering symbols [20]-[21]. The question of whether abstract or contextualized problem-solving instruction better fosters pre-college students' learning of engineering topics is largely unexplored. In sum, this work is motivated by the following research questions:

I. Does contextualizing problems during worked-example instruction promote the near and/or far transfer of the principles learned?

II. Does contextualizing problems during worked-example instruction affect students' ability to represent novel problems?

III. Does contextualizing problems during worked-example instruction affect students' learning perceptions?

To answer these questions, we asked a group of pre-college students to learn how to solve parallel electrical circuit problems with an instructional program that included two problem solving practice conditions. In the first condition, students were given problems that were contextualized around real electrical devices and represented with realistic diagrams. In the second condition, students were given the same problems except that they were de-contextualized and represented with abstract diagrams. To answer our first research question, we gave students near and far transfer paper-and-pencil tests. To answer our second research question, we conducted a qualitative analysis of the representations that students spontaneously produced during the transfer tests. Finally, students' learning perceptions were measured using a program-rating survey that included three subscales: an overall program usefulness subscale, a problem representation usefulness subscale, and a perceived cognitive load subscale.

METHOD

I. Participants and Design

The participants were 86 pre-college students (54 females and 32 males). The mean age of the participants was 15.42 years (*SD* = 1.43 years). Forty-two (48.8 %) of the students reported that they were Hispanic American, 24 students (27.9 %) reported that they were Caucasian, 6 students (7.0 %) reported that they were African American, 2 students each (2.3 %) reported they were Native American and Asian American, and 10 students (11.6 %) reported they were of other ethnicities. Students were randomly assigned to one of two conditions: contextualized (C group) and abstract (A group) problem representations. There were 45 students in group C and 41 students in group A.

II. Materials

Computerized materials. The computerized materials consisted of an interactive instructional program that included the following sections: (1) a demographic information questionnaire; (2) a pretest; (3) an instructional session; (4) a problem-solving practice session, and (5) a program rating questionnaire. The pretest consisting of 3 multiple-choice questions and 3 open-ended problem statements measured the participant's prior knowledge of the topic and was used as a covariate in the statistical analyses. The instructional session presented students with the definitions and units of the electrical current, voltage, and resistance concepts followed by a worked-out example demonstrating how to calculate the total resistance of a parallel circuit 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 practice session presented 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 at their own pace. After completing each solution step, participants received feedback about the correctness of their response. Specifically, if the solution was correct, the program confirmed the correctness of the solution. 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. After all three steps in a 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 instructional and practice sessions for the A and C treatments differed as follows. In the A condition, the electrical circuit elements (i.e., voltage source and resistors) were represented with the abstract symbols that are typically used in electrical engineering (see screenshot in Figure 1). All instructional text and practice problem statements were presented in abstract terms, e.g., "Consider two resistors connected in parallel to a voltage source". In the C condition, the electrical circuit elements were represented by life-like images (see screenshot in Figure 2). All instructional text and practice problem statements were presented in the context of a real-life scenario, e.g., "Consider two light bulbs connected in parallel to a battery".

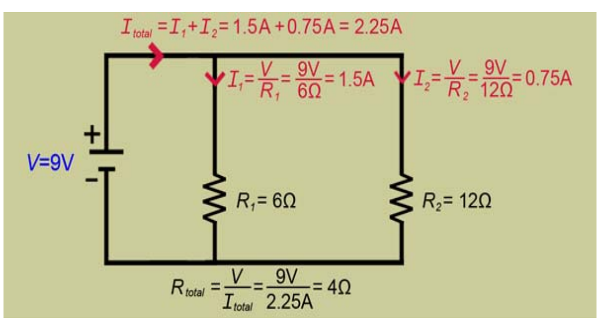

FIGURE 1
SCREENSHOT OF THE INSTRUCTIONAL PROGRAM FOR ABSTRACT (A) GROUP.

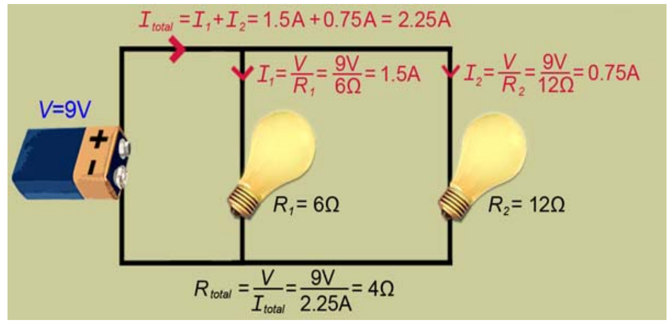

FIGURE 2.
SCREENSHOT OF THE INSTRUCTIONAL PROGRAM FOR CONTEXTUALIZED (C) GROUP.

The last section in the computer program included a program rating survey, which was an 11-item instrument asking participants to rate their learning perceptions on a 5-point scale Likert scale which ranged from 0--strongly disagree to 4--strongly agree. The survey included three subscales. Five items asked students to rate their perceptions about the usefulness of the program in general (i.e., "I learned a lot from the program"); four items asked students to rate the usefulness of the representations in the program (i.e., "The pictures made the lesson easier to understand"), and the cognitive-load subscale included two items asking students to rate the difficulty of the program (i.e., "The lesson was difficult"). The internal reliability for the three subscales was .92, .90, and .83, respectively (Cronbach's alpha).

Paper and pencil materials. The paper and pencil materials consisted of a posttest that included three near transfer questions (Cronbach's alpha reliability .95) and three far transfer questions (Cronbach's alpha reliability .92). The problems were presented as contextualized word problems with no accompanying graphics or illustrations. The near transfer test was designed to assess students' ability to transfer their problem solving skills to solve an isomorphic set of problems. It consisted of three problems that had the same underlying structure but different surface characteristics than the problems presented during the practice session of the program. The far transfer test was designed to assess students' ability to transfer their problem solving skills to solve a novel set of problems that had different underlying structure and different surface features than the practice problems presented in the instructional program. In order to solve the far transfer problems, the participants had to apply the same basic principles learned in the instructional program (Ohm's Law, basic properties of voltages and currents in parallel circuits), but the sequence in which these principles were employed and the circuit element to which Ohm's Law was applied were different than those used during the instructional session. Two engineering instructors who were blind to the participants' condition scored the near transfer test (inter-rater reliability 98.5 %) and far transfer test (inter-rater reliability 99.8 %).

Because we were interested in examining whether one of the two conditions would be more likely to elicit students' spontaneous problem representations, the near and far transfer tests did not explicitly ask the students to draw circuit diagrams. Yet, a few students drew diagrams, which were scored using a rubric developed by an experienced electrical engineering instructor. The rubric assigned points for drawing a closed circuit and for including a voltage source and two resistive elements in parallel. Points were given for appropriately labeling the voltage, currents, and resistors and for assigning their respective numerical values. The maximum score for each circuit diagram was ten points, leading to a maximum score of 60 points for the 6 problem representations. Two instructors (inter-rater reliability 98.9 %) scored the diagrams.

Apparatus. The computer program used in the study was developed using Adobe Flash CS3 software, an authoring tool for creating web-based and standalone multimedia programs. The apparatus consisted of a laptop computer system, with a screen size of 1680 x 1050 pixels, and headphones.

III. Procedure

The research was conducted in the participants' regular classroom. Every student was provided with a laptop, a headphone, and a closed envelope, which contained the paper-based posttest. The envelopes were randomly distributed to the students and included a participant's identification number and condition key. The students started the respective version of the computer program by entering the identification number and condition key from the envelope. They worked independently on all sections of the module. When the computer program was completed, each student was directed to the posttest.

RESULTS

A univariate analysis of variance (ANOVA) using the pretest score as a dependent variable showed that there were no significant differences between the A and C groups in prior knowledge, $F(1, 84) = 0.65$, $MSE = 0.92$, $p = .42$, partial $\eta^2 = .01$. Nevertheless, in order to remove extraneous variability from our analyses of learning measures, we used students' pretest scores as a covariate in the analyses. Table I shows the mean scores and corresponding standard deviations for the two groups on measures of pretest, near-transfer posttest, far-transfer posttest and representation quality. Next, we present the results by research question.

I. Does Contextualizing Problems Promote the Near and/or Far Transfer of the Principles Learned?

We conducted two univariate analyses of covariance (ANCOVA), using treatment condition as between-subject factor, students' near- and far-transfer test scores as a dependent variable, respectively, and the pretest scores as a covariate. The first ANCOVA revealed a significant treatment effect on near transfer, $F(1, 83) = 4.98$, $MSE = 14.51$, $p = .03$, $\eta^2 = .06$, showing that students in group A produced significantly higher scores than those in group C. The second ANCOVA revealed no significant difference between the A and C groups, $F(1, 83) = 1.62$, $MSE = 6.41$, $p = .21$, $\eta^2 = .02$.

II. Does Contextualizing Problems Affect Students' Ability to Represent Novel Problems?

Only 15.12% of the participants spontaneously produced graphic representations of the posttest problems. Six of these students were in the A group and seven were in the C group. We conducted an ANOVA using treatment condition as between-subject factor and the scores yielded by our qualitative analyses of the problem representations as a dependent measure. The analysis revealed that group A produced significantly better representations of the posttest problems than group C, $F(1, 10) = 5.39$, $MSE = 176.63$, $p = .04$, partial $\eta^2 = .35$.

III. Does Contextualizing Problems Affect Students' Learning Perceptions?

We conducted three ANOVAs using treatment condition as the between subject factor and each program survey subscale as the dependent variable. There were no significant differences between the treatment groups on ratings of overall program usefulness ($p = .60$) and cognitive load perceptions ($p = .26$) and only a marginally significant difference for representation usefulness ratings. Group C rated the usefulness of the program representations marginally higher than group A, $F(1, 84) = 2.84$, $MSE = 0.86$, $p = .10$, partial $\eta^2 = .03$.

TABLE I
MEAN SCORES AND STANDARD DEVIATIONS ON PRETEST, NEAR- AND FAR-TRANSFER TESTS AND REPRESENTATION QUALITY

Condition		*Pretest* (max 6)	*Near-transfer* (max 9)	*Far-transfer* (max 9)	*Representation Quality* (max 30)
Abstract	*M*	2.12	4.86	1.61	28.33
(*N=41*)	*SD*	0.87	3.78	2.69	17.52
Contextualized	*M*	2.29	3.09	0.96	9.38
(*N=45*)	*SD*	1.04	3.84	2.37	6.26

DISCUSSION

The present study sought to examine whether contextualizing problems and problem representations during worked-example instruction would promote better learning in engineering education. We compared the learning and learning perceptions pre-college students who were randomly assigned to learn about electrical circuit analysis with the help of an instructional program that included contextualized problems (group C) or identical abstract problems that lacked anchors to real-life scenarios (group A).

I. Theoretical Implications

Theoretically, this research is significant because it tested the conflicting hypotheses stemming from two robust theories of learning, namely, contextualized learning and cognitive learning theories. Although contextualized views of learning posit that realistic problem-solving scenarios and representations are more likely to facilitate learning because their meaning can be more readily accessed in long-term memory [9], cognitive learning theory supports the opposite conclusion. Abstract problem-solving promotes better learning by helping learners focus their attention on the relevant structural information underlying problems rather than on their superficial information and by minimizing translation steps during problem solving.

Our findings support a cognitive theory of learning in several ways. First, students who learned with realistic problems and representations underperformed those that learned with identical abstract problems on measures of near transfer. Although significant differences in far transfer were not noted, this result is consistent with past research. Most studies using worked-example instruction show that the benefits of this instructional method are limited to helping students acquire the schemas that are necessary to solve isomorphic problems that share the same underlying structure [6,7].

Considering that both A and C groups were given an identical posttest where the problem stories were contextualized, it is especially noteworthy that group A outperformed group C on the near-transfer learning measure. According to the well-known psychological phenomenon called encoding specificity [22] retrieval of information is enhanced when the conditions at retrieval (i.e., assessment) match those at encoding (i.e., instruction). Because students who learned with abstract problems were provided with abstract problems during encoding but contextualized problems during the posttest, this group of students was at a disadvantage.

A second way in which cognitive theory of learning was supported by this study relates to the quality of students' problem representations during the posttest. Even though the number of students who spontaneously produced representations while attempting to solve the near- and far-transfer tests was comparable, those in group A produced significantly better representations as measured by the number of relevant information included in the graphics. This difference was very large, suggesting once again that the benefits of using abstract problem representations during instruction is to help students develop a portable schema that can be effectively used to help them think about a variety of isomorphic problems, regardless of differences in cover stories.

Finally, cognitive learning theory was also supported by the results of the program-rating survey. According to contextualized learning theories, the advantage of anchoring learning on realistic scenarios is to reduce the difficulty of understanding abstract problems that are not related to students' past experiences. Moreover, proponents of this theory argue that students who learn with real-life scenarios will perceive the learning experience as more relevant and useful to their lives. Taken together, these arguments predict that group C would produce more favorable ratings for the overall program and problem-representation usefulness subscales and lower ratings for the perceived cognitive load during learning. Yet, students did not differ significantly in their overall perceptions of program usefulness, picture representation usefulness, or cognitive load. The marginal tendency in favor of group C on the picture representation usefulness needs further research. It is possible that because realistic problem representations are typically more interesting than abstract representations, they induced an illusion of understanding in the C group [3]. Many studies have documented the negative effects of using seductive details in the form of interesting but irrelevant words, pictures, music, and videos in learning [23-26].

In sum, the present study strongly supports cognitive learning theory and a coherence principle for worked-example engineering education: Novice students who are in the beginning stage of problem-solving skill acquisition should be presented with abstract problem scenarios and representations to help them focus their attention on relevant problem information and develop effective representation tools [25] The coherence principle is based on research findings showing that student learning is supported when extraneous materials (those that are interesting but informationally irrelevant) are removed from instruction. Studies show that novices in a domain tend to focus on superficial rather than structural problem information which, in turn, hinders their problem solving transfer [27]-[28].

I. Practical Implications and Limitations

In addition, the reported study has important practical implications for engineering education. When reviewing introductory electrical engineering textbooks for pre-college students and college students, we found that those for the younger audience typically present problems in the context of real-world examples [19]. In contrast, college-level textbooks mostly rely on abstract problem representations and only a few selected problems are presented in real-world contexts. Examples are the Comprehensive Problems in [20] and the Application Problems in [21]. To our knowledge, the research base for contextualizing problems for pre-college students is lacking. The findings of the present study, although preliminary, suggest that pre-college engineering instruction should also focus on the development of abstract problem solving before asking students to tackle real-life problems independently. Because pre-college students have reached the cognitive development necessary to engage in abstract thinking, this practical implication is developmentally appropriate for this age [29,30].

Nevertheless, it is important to note that our study is limited because we chose to focus on one specific student population (i.e., pre-college students who were novices in engineering), domain (i.e., electrical circuit analysis), and learning environment (i.e., instructional program). Moreover, the experimental conditions used in this research do not allow us to generalize the results to other, more authentic learning situations in which students spend several days learning with materials that are embedded in their curriculum. Finally, an important limitation of our study is that due to the brief nature of our school intervention, we used few problem examples that were very similar in structure to learn how to apply electrical circuit analysis principles to solve novel problems. More laboratory and field studies using other engineering education materials with pre-college and college students are necessary to extend and generalize our results.

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