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Representation sequencing in computer-based engineering education

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ABSTRACT

Multimedia engineering instruction typically includes verbal descriptions and diagrams, which can be presented in a contextualized format, using descriptions and illustrations of real-life elements (e.g., light bulb and battery), or in an abstract format, using conventional electrical engineering symbols. How the sequencing of these representation formats influences learning of conceptual knowledge has been examined in prior research. The present study examines how the representation sequencing impacts procedural learning of engineering problem solving. The study compared four sequences of representation (abstract → abstract, contextualized → contextualized, contextualized → abstract, or abstract → contextualized) during computer-based learning to determine which of the four sequences best promotes student learning. Learning outcomes were measured with a problem-solving posttest and learner perceptions were assessed using a learner questionnaire. The study results indicated that the abstract → contextualized condition resulted in significantly higher near- and far-transfer posttest scores than the contextualized → contextualized condition and in significantly higher near-transfer posttest scores than the contextualized → abstract condition. Computer-based instruction in engineering problem solving for novice learners should initially employ abstract representations that convey the conceptually-relevant solution procedures shared across similar problems. Providing a variety of problem contexts in later stages of learning can assist learners in transfer of key procedural problem solving principles to novel problem settings with different superficial features.

1. Introduction

Engineering learning is becoming increasingly important for K-12 (kindergarten through 12th grade) students (Brophy, Klein, Portsmore, & Rogers, 2008; Carr, Bennett, & Strobel, 2012). In his 2013 State of the Union address, U.S. President Barack Obama highlighted the need to enhance K-12 education focusing on science, technology, engineering, and mathematics (STEM) disciplines (Obama, 2013). Regrettably, analyses indicate a shortage of qualified science and mathematics teachers and a high degree of teacher turnover in these subjects (Ingersoll, 2001; Ingersoll & May, 2012; Ingersoll & Perda, 2010; Rumberger, 1987). Given the lack of qualified educators as well as the emergence of flipped classroom instruction (Houston & Lin, 2012), there is a consequential need to identify optimal computer-based learning practices and develop computer-based environments to meet the growing demand for effective K-12 engineering education and outreach (Carter, 2002; Fabregas, Farias, Dormido-Canto, Dormido, & Esquembre, 2011; Plant, Baylor, Doerr, & Rosenberg-Kima, 2009; Ozogul, Johnson, Atkinson, & Reisslein, 2013). Moreover, computer-based instruction provides an ideal context for individualized delivery of different representation types. Computer-based delivery allows each student to advance at his/her own pace and provides him/her with immediate feedback for practice problems and is thus generally an effective instructional approach for challenging STEM topics (Baser, 2006; Schoppek & Tulis, 2010; Timmers & Veldkamp, 2011; Yang et al., 2012).

The format of representations used in multimedia instruction contributes to its efficacy in developing conceptual and procedural knowledge (Cheng, 1999). One representational format may be best for a particular task or learner, whereas another type may be optimal for another task or learner (Gerjets, Scheiter, Opfermann, Hesse, & Eysink, 2009; Hwang & Hu, 2013; Kollöfel, 2012; Lowe, Rasch, & Schnotz, 2010; Mina & Moore, 2010; Schnotz & Kurschner, 2008). Many engineering concepts and problems can be represented in a contextualized real-life format using contexts that novice K-12 students are familiar with, such as flashlights, cell phones, and iPads, or conventional

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abstract engineering symbols (Reisslein, Moreno, & Ozogul, 2010). Commonly, introductory instructional materials for K-12 students emphasize familiar real-life problem contexts (Orsak, et al., 2004). In advanced instruction, most engineering learning resources employ abstract representations using standard engineering symbols (Brockman, 2008; Irwin & Nelms, 2011). That is, it is customary in engineering instruction to transition students from contextualized representations at the beginning of the learning experience to abstract representations as the students progress in their learning.

Popular models of learning, such as the Anderson, Fincham, and Douglas (1997) skill acquisition model within the Adaptive Control of Thought-Rational (ACT-R) framework (Anderson, 1993), view learning as a process that evolves over multiple stages. As learners advance through these stages, their needs change. Instructional designs that may help a novice in the initial learning stages may hinder a more advanced learner (Kalyuga, Ayres, Chandler, & Sweller, 2003). Thus, learning models generally support the dynamic transitioning of instructional strategies as learning progresses, which can be readily accomplished using computer-based learning environments.

The purpose of this study was to examine sequencing (transitioning) of representations in computer-based instruction of engineering problem solving for middle-school students. Does transitioning of representations improve learning over a static sequence that uses the same representation type throughout? Which representation transitioning sequence (contextualized → abstract or abstract → contextualized) best supports learning? Specifically, this study compared four fixed representation sequences, namely abstract → abstract, contextualized → contextualized, contextualized → abstract, and abstract → contextualized.

1.1. Theoretical background and representation transitioning hypotheses

We present two conflicting hypotheses on the representation sequence that best supports problem solving learning among the four compared representation sequences. The context fading hypothesis is based on the four stage problem solving learning model (Anderson et al., 1997) within the ACT-R framework and posits that the contextualized → abstract representation sequence best supports problem solving learning. In contrast, the abstract fading hypothesis predicts that the abstract → contextualized representation sequence best supports problem solving learning based on cognitive load theory.

1.1.1. Context fading hypothesis based on four stage problem solving learning model within ACT-R framework

One of the most popular contemporary cognitive models for learning is the four-stage model proposed by Anderson et al., (1997) within Anderson's Adaptive Control of Thought-Rational (ACT-R) framework (Anderson, 1993). In this model, the learner solves problems initially by analogy, that is, by relating problems to known examples (Anderson & Fincham, 1994). With more experience, the learner advances to the second stage where s/he formulates declarative rules, such as verbalizations of the solution strategy that assist in developing a solution. As experience increases, the learner moves to the third stage in the model. In this third stage s/he formulates procedural knowledge for problem solving, which facilitates fast problem solving with relatively little mental effort. After having encountered many different varieties of problems, s/he advances to the fourth stage where s/he may have many different examples in long-term memory, which enables the learner to rapidly retrieve a solution from memory. Extensive empirical studies have found support for a wide range of instructional strategies informed by the outlined four-stage learning model. For instance, several studies have confirmed that novice learners that acquire a new procedural problem solving skill (Eiriksdottir & Catrambone, 2011) generally benefit from initial extensive support from detailed worked examples and subsequent fading (disappearance) of the support as they advance in their learning (Atkinson, Derry, Renkl, & Wortham, 2000; Atkinson, Renkl, & Merrill, 2003; Reisslein, Sullivan, & Reisslein, 2007; Renkl, Atkinson, Maier, & Staley, 2002).

According to a context fading hypothesis, an instructional sequence that progresses from concrete, real-life representations to abstract representations best fosters learning. In particular, instruction should start with richly contextualized real-life engineering scenarios, which are congruent with contextualized models of instruction (Brown, Collins, & Duguid, 1989; Cognition and Technology Group at Vanderbilt, 1993; Lavonen, Meisalo, Lattu, & Sutinen, 2003; Strobel, Wang, Weber, & Dyehouse, 2013; Uttal, Liu, & DeLoache, 1999). These real-life scenarios related to the novice learners' prior experiences may be most conducive to learning by analogies during the first stage of the Anderson, Fincham, and Douglas model (1997). As learners progress to forming declarative and procedural knowledge in the higher stages of the Anderson, Fincham and Douglas model, contextualization may be unnecessary and may induce extraneous processes related to encoding properties of specific engineering problem scenarios.

Abstract engineering representations using symbols that represent the key characteristics of the engineering system may better foster learning at later stages, after students have made meaningful connections between their prior knowledge with concrete electrical devices and the new electrical circuit knowledge. For instance, the abstract resistor symbol in an electrical circuit diagram can represent a wide variety of resistive components. The abstract representation provides a transferable tool for representing a wide variety of real-life engineering contexts and may thus foster the formulation of declarative and procedural knowledge for solving electrical circuit problems.

1.1.2. Abstract fading hypothesis based on cognitive load theory

Cognitive load theory (Sweller, van Merrienboer, & Paas, 1998) builds on the widely-accepted assumption that humans have limited working memory capacity (Baddeley, 1986) and further asserts that each instructional condition imposes on working memory three types of cognitive load: 1) *intrinsic* cognitive load; 2) *extraneous* cognitive load; and 3) *germane* cognitive load. Whereas *intrinsic* cognitive load is determined by the complexity (i.e., "element interactivity") of the learning task itself and *germane* load is associated with conscious, constructive processes used to construct mental representations, *extraneous* load does not contribute to learning. Furthermore, if working memory capacity is fully engaged in processes related to intrinsic and extraneous load, learners will have no remaining cognitive resources to allocate to germane processes, and little learning can occur. According to the Four-component Instructional Design (4C/ID) model, learning tasks should be ordered such that earlier tasks include lower element interactivity (i.e., low intrinsic cognitive load) and as learning tasks become more complex, instructional scaffolds should be provided to reduce extraneous load during transitions to more difficult material (Van Merrienboer & Sluijsmans, 2009).

An abstract fading hypothesis suggests that an instructional sequence progressing from abstract to contextualized representations will best foster learning. Abstract representations avoid the seductive details that may distract novice learners from the important information crucial for solving engineering problems (De Bock, Deprez, Van Dooren, Roelens, & Verschaffel, 2011; Harp & Mayer, 1998; Kaminski, Sloutsky, & Heckler, 2008; Sloutsky, Kaminski, & Heckler, 2005). Thus, abstract representations could best support learning in the initial stages by helping learners focus on underlying principles rather than on superficial information. In particular, abstract representations can promote the selection of relevant information, thereby reducing extraneous processing (Huff & Schwan, 2008; 2012). In comparison to experts, novice learners demonstrate significant difficulty identifying and attending to conceptually relevant, rather than perceptually salient information (Jarodzka, Scheiter, Gerjets, & van Gog, 2010; Lowe, 1999; 2003). As the learner develops mastery in declarative and procedural knowledge, practice with a variety of contextualized problems may help students understand that the underlying principles they learned are transferable across problem contexts (Spiro, Feltovich, Jacobson, & Coulson, 1991; 1992; Spiro & Jehng, 1990).

In concluding the section on cognitive load theory, we note that the present study employed a multimedia presentation consisting of narration/text and graphics as is common for learning materials in engineering, and generally in STEM disciplines (Berthold & Renkl, 2009; Johnson, Ozogul, Moreno, & Reisslein, 2013; Jonassen, Strobel, & Lee, 2006). Although multiple representations can positively impact STEM learning by constraining interpretation and playing complementary roles (Ainsworth, 1999; Ertl, Kopp, & Mandl, 2008), integrating information from two or more sources of information places unique cognitive demands on the learner (Goldman, 2003; Kozma, 2003). Instructional features that reduce extraneous load, such as an abstract representation devoid of seductive, irrelevant details, may therefore initially be helpful. As expertise develops, learners may need to have later practice with a variety of contextualized examples to promote understanding that the principles derived from the early stage of learning apply to problems with varying surface characteristics.

1.2. Related studies

We proceed to briefly review related studies on representations of instructional materials. We first briefly review studies that have compared static representations, i.e., studies without transitioning of representations during an instructional session. Next, in Section 1.2.2, we give a brief overview of studies on the diversity of representations employed in problem solving. In Section 1.2.3, we review in detail the prior studies on representation transitioning and identify the open research area addressed in the present study.

1.2.1. Comparison of static representations

We first briefly review the related research on static representations, i.e., studies that employ the same representation throughout the instruction. In the conceptual knowledge domain of functioning of the human heart, different types of graphical illustrations have been compared (Butcher, 2006; Dwyer, 1969; Joseph & Dwyer, 1984). The impact of abstract and contextualized pictorial representation for conceptual mathematics learning has been examined in a series of studies that found improved learning for abstract representations (De Bock et al., 2011; Kaminski, Sloutsky, & Heckler, 2006; 2007; 2008; Sloutsky et al., 2005).

In the domain of mathematical problem solving, contextualized problems that are grounded in "stories", i.e., problem contexts from real life presented through text, have been compared with abstract problems that are formulated purely with mathematical equations (Koedinger & Nathan, 2004; Nathan, 1998; Nathan, Kintsch, & Young, 1992; Walkington, Petrosino, & Sherman, 2013; Walkington, Sherman, & Petrosino, 2012). A key recent result of this line of research has been that grounded problems lead to improved problem solving for simple single-reference problems that involve the (single) unknown variable only once, whereas abstract problems improve problem solving performance for more complex problems that involve two references to the (single) unknown variable (Koedinger, Alibali, & Nathan, 2008).

In the domain of engineering problem solving, static abstract representations of electrical circuits have been compared with contextualized representations of electrical circuits in the context of multimedia instruction on problem solving involving three solution steps and several unknown variables (Johnson, Butcher, Ozogul, & Reisslein, 2013, 2014; Moreno, Ozogul, & Reisslein, 2011; Reisslein et al., 2010). Static abstract representations have been found to generally improve problem solving learning compared to static contextualized representations. In hands-on lab sessions employing either abstract or contextualized circuit element representation throughout the session, the contextualized representation led to higher perceived enjoyment for elementary school students while no differences in learning were found (Reisslein et al., 2013).

1.2.2. Range of representations employed in problem solving

Problem solving in STEM domains is often facilitated by fluent use of a variety of representations (Johri & Lohani, 2011; Johri & Olds, 2011; Moore, Miller, Lesh, Stohlmann, & Kim, 2013; Nathan, 2008). Specifically, a study on how learners analyze long sequences of interlocking gears discovered that learners tend to switch between depictive representations of the gears with cogs and abstract circles as they reason about the gear systems (Schwartz & Black, 1996). Nathan, Walkington, Srisurichan, and Alibali (2011, 2013), as well as Walkington, Nathan, Wolfgram, Alibali, and Srisurichan (2011) have extensively observed engineering instructors and students during project-based class activities. Their analysis of observed instructor–student interactions indicates that students generally benefit from being exposed to a wide range of representations and perspectives on a problem, including underlying mathematical and scientific laws, engineering design strategies and objects, as well as the social context. The analysis of the observed interactions indicates that coordination of the different representations in a cohesive manner and explicit identification of their relations supports student understanding.

1.2.3. Representation transitioning

In this section, we review prior studies that transitioned representations during an instructional session. Scheiter, Gerjets, Huk, Imhof, and Kammerer (2009) compared four instructional sequences, namely realistic–realistic, where the same realistic video of mitosis was shown twice, realistic-schematic, where first the realistic video and then a computer-generated animation using schematic line drawings of mitosis were shown, schematic-realistic (line drawings followed by video), and schematic–schematic (line drawings shown twice). It was found that the realistic–realistic sequence led to lower scores on a verbal multiple-choice test assessing knowledge of the dynamic staged mitosis process and related definitions than the realistic–schematic and schematic–schematic sequences. Furthermore, the realistic–realistic sequence led to lower scores than the other three instructional sequences on a pictorial test requiring subjects to detect errors in schematic line drawings and to complete partial line drawings.

A study in the domain of competitive specialization showed that the best transfer of principles implicitly demonstrated by a simulation of a specific "food and ants" problem to a specific pattern matching problem resulted when concrete elements became abstracted at a later stage (Goldstone & Son, 2005). Rules governing the simulation were provided to students, but the optimal solution tactic was implicitly demonstrated through the simulation, not explicitly taught to students. That is, the investigation did not examine representation sequencing in the context of explicit problem-solving instruction.

Scheiter, Gerjets, and Schuh (2010) investigated the effect of supplementing traditional text-based worked examples with animations, which transitioned from concrete to abstract visual representations of the problems. Results indicated that learners had better transfer performance after learning with both text worked examples and transitioned animations than from text alone. The study did not utilize experimental conditions using abstract visual representations throughout, concrete visual representations throughout, or transitioning from abstract to concrete visual representations. Thus, the design was not suitable for determining the optimal representation sequence.

More recently, McNeil and Fyfe (2012) examined conceptual mathematics learning from a concrete fading condition; the first eight practice problems were displayed using the same real-life illustrations (measuring cups), the second eight problems were displayed using roman numerals (which have some similarity to their referents), and the last eight problems used arbitrary abstract symbols. Compared to learning conditions using abstract symbols throughout or concrete illustrations throughout, the concrete fading condition led to better learning. McNeil and Fyfe (2012) did not examine transitioning from abstract to concrete representations.

Berlin and White (1986) examined instructional sequences for developing young students' spatial ability using three learning conditions: concrete only (via manipulatives – pegboards and colored cubes); computer simulation only (via simulated pegboards and colored cubes); or concrete followed by computer simulation activities (the sequence condition). The results from the study suggested that the positive impact of including abstract activities (i.e., computer simulations) in later learning stages depends on student individual differences (e.g., gender, age). A similar study in the physics domain demonstrated that physical manipulatives, virtual manipulatives (computer simulation), and the two sequences of manipulatives (physical → virtual; virtual → physical) equally promoted learning (Zacharia & Olympiou, 2011). Manches, O'Malley, and Benford (2010) showed that young children utilize differing learning strategies when given physical or virtual manipulatives.

Summarizing the review of previous studies on representation sequencing we note that the previous studies have primarily considered relatively isolated declarative (conceptual) knowledge domains in which knowledge is represented in propositional statements (facts) about the world (e.g., mitosis is the process of cell division, the first phase of cell division is prophase; Anderson, 1993). Specifically, prior studies have examined representation transitioning for declarative knowledge about specific biological processes or complex system functioning (Goldstone & Son, 2005; Scheiter et al., 2009), pattern recognition or pattern learning (Berlin & White, 1986; Goldstone & Son, 2005), conceptual mathematics (McNeil & Fyfe, 2012), and conceptual physics (Zacharia & Olympiou, 2011). One additional study examined representation transitioning within the domain of algebra (Scheiter et al., 2010).

In summary, the results from prior representation transitioning studies, which have primarily considered declarative knowledge domains, showed: 1) maintaining the realistic representation throughout instruction inhibits learning, in comparison to three other representations (realistic-schematic, schematic–schematic, and schematic-realistic); 2) transitioning from concrete (or contextualized) to abstract representation leads to the best posttest performance in declarative knowledge domains; 3) learners benefit from access to a range of representation types (concrete and abstract); and 4) learners tend to naturally transition from using realistic representations to using abstract representations with greater knowledge of the domain.

Overall, we conclude from the review of prior research that there is relatively little empirical evidence concerning the learning effects of sequences of abstract and contextualized (or concrete) representation types. In particular, there is no prior research on this issue in the procedural knowledge domain of engineering problem solving where a common set of procedures can be adapted to solve a variety of instantiations of real-life problem settings. We note that the engineering domain generally has declarative knowledge components, e.g., definitions of engineering quantities and underlying laws from mathematics and physics, as well as procedural knowledge components, such as procedures for the design of engineering systems and the solution of dimensioning problems of engineering systems. The focus of this study is on engineering problem solving, which can be viewed to a large degree as a procedural knowledge domain (Anderson, 1993; Corbett & Anderson, 1995) in that a common set of abstract symbols and solution procedures can be flexibly adapted (transferred) to represent and solve a wide variety of real-life problems. In the electrical circuits domain, for instance, solution procedures based on Ohm's Law and Kirchhoff's Laws can be applied to solve a wide range of realistic problem settings involving resistive electrical components.

With the exception of one investigation (Berlin & White, 1986) with elementary school students, all previous studies have considered university undergraduate or graduate students. The purpose of the current study was to advance our understanding of optimal sequences of representation types in computer-based engineering problem solving instruction for novice middle school students.

2. Method

2.1. Participants and design

Participants were a total of 343 middle school students (53.4% female) from a local middle school in the Southwestern United States who had no prior formal instruction in electrical circuits. The mean age of the participants was 12.7 years ($SD = 1.1$ years). One hundred and ninety (55.4%) of the students reported that they were Caucasian, 85 (24.8%) reported that they were Hispanic American, 34 (9.9%) reported that they were African American, 16 (4.7%) reported being of other ethnicity, 10 students (2.9%) reported that they were Asian American, and eight students (2.3%) reported that they were Native American. Participants were randomly assigned to experimental condition. There were 87 students in the Abstract (A) condition, 84 students in the Contextualized (C) condition, 84 students in the Abstract → Contextualized (AC) condition, and 88 students in the Contextualized → Abstract (CA) condition. Comparisons were made among conditions on performance on near- and far-transfer posttest scores, performance on practice, and program ratings (learner perceptions).

2.2. Materials

2.2.1. Computerized materials

The computerized materials consisted of an interactive multimedia program that included the following sections: (1) a demographic information questionnaire; (2) a prior knowledge check; (3) instruction with embedded practice; and (4) a program rating questionnaire.

The prior knowledge check consisted of 6 multiple-choice questions designed to assess students' preexisting knowledge of elementary algebra before beginning the instructional session (e.g. What is the value of x if $4x = 32$?). Data from previous experiments indicated that middle school students have very little knowledge of electric circuits prior to interventions (Reisslein et al., 2010). Thus, we employed a pretest assessing existing knowledge of algebra, since algebra is the main relevant prior knowledge for the electrical circuit analysis taught by the multimedia program. The measure had an internal reliability of 0.66 as measured by Cronbach's α.

In all experimental conditions, the computer instruction consisted of an introduction phase, a demonstration phase, and a practice phase. Each phase in the instruction was narrated and a diagram of an abstract parallel circuit or an illustration of a contextualized parallel circuit was displayed, depending on the experimental condition, see Table 1. The introduction phase presented students with the meanings and units of electrical current, voltage, and resistance as well as their elementary relationships based on Ohm's and Kirchhoff's Laws, i.e., the declarative knowledge required for the procedural problem solving. Immediately after the introduction phase, students answered three multiple choice questions in the computer program on the definitions of electrical resistance, voltage, and current (referred to in the results section as 'comprehension check'). After students had provided their answers, the system revealed the correct answers to each question.

Next, the demonstration phase showed students how to calculate the total resistance of a parallel circuit, i.e., presented the procedural knowledge for solving the electrical circuit problem. Specifically, given source voltage and individual resistance values, the students were instructed to proceed in three steps: *(i)* note that the voltage is the same over each individual resistor (electrical device) and calculate the value of the current flowing through each individual resistor (electrical device), *(ii)* calculate the total current flowing in the circuit by summing up the currents flowing through the individual resistors (electrical devices), and *(iii)* calculate the total resistance of the entire parallel circuit.

For all conditions, the embedded computer practice phase consisted of three parallel circuit problems that reinforced and practiced the procedural knowledge presented in the demonstration phase. The practice phase asked students to independently complete an increasing numbers of steps in a backward fading manner (Atkinson et al., 2003; Moreno, Reisslein, & Ozogul, 2009; Reisslein et al., 2007; Renkl et al., 2002). The fading method builds on the worked example effect (Schwonke et al., 2009; Schworm & Renkl, 2006; Sweller, 2006; Van Gog, Pass, & Merrienboer, 2008) and transitions the learner to attempting the solution of an increasing number of problem steps so as to minimize extraneous cognitive load during acquisition of the problem solving procedure (Renkl, Atkinson, & Grosse, 2004). Specifically, the first practice problem provided the first two solution steps worked out and the students were required to solve the last step of the problem, i.e., calculate the total resistance of the parallel circuit ($R_{\text{total}} = V/I_{\text{total}}$). In the second practice problem, the first solution step was worked out, and students were required to solve the last two steps of the problem, i.e., calculate total current ($I_{\text{total}} = I_1 + I_2 \ldots$) and calculate total resistance of the parallel circuit. In the last practice problem, the students solved all three solution steps on their own: calculate the individual currents ($I_1 = V/R_1$, $I_2 = V/R_2 \ldots$), calculate total current, and calculate total resistance.

Students were given one attempt at solving the practice problem steps. Students received immediate feedback after completing each solution step (Schoppek & Tulis, 2010). If the solution was correct, the student was given positive feedback (and received one point towards the practice score); if the solution was incorrect, the program presented an explanation about how to solve the step correctly as well as the correct solution. All solved steps of a given problem remained displayed on the screen to facilitate learning. The practice section of the module was self-paced, that is students could progress to the next solution step or problem by clicking the continue button. As the solution of a problem progressed the equations for the steps were cumulatively added into the circuit diagram or illustration in order to avoid the split-attention effect (Ginns, 2006; Ozogul, Johnson, Moreno, & Reisslein, 2012; Sweller, Chandler, Tierney, & Cooper, 1990). Specifically, in the first solution step only the equations for the individual currents were displayed, in the second solution step the equations for the individual currents and the total current were displayed, and so on.

The instruction with embedded practice section of the computer program had four different versions, one for each of the four treatment conditions used in this study, which are illustrated in Table 1. In the Abstract (A) condition, all diagrams, narrations, and problem texts were presented in an abstract format. Specifically, in the circuit diagrams, the electrical circuit elements, such as voltage source and resistors, were represented using the conventional abstract symbols of electrical engineering, as illustrated in Fig. 1(a). Also, the narration accompanying the instruction and the practice problems used abstract terms, e.g., "voltage source" and "resistor".

Conversely, in the Contextualized (C) condition, throughout the entire instruction with embedded practice section, the graphical depictions, narrations, and problem texts were presented in a contextualized format. Specifically, the electrical circuits were graphically represented with illustrations using real-life settings and circuit components from everyday devices, e.g., battery, light bulb, and fan in a garage setting illustrated in Fig. 1(b). The narration and the problems used contextualized terms, e.g., "battery", "lamp", and "fan" throughout. Each contextualized problem presented a new real-life problem setting.

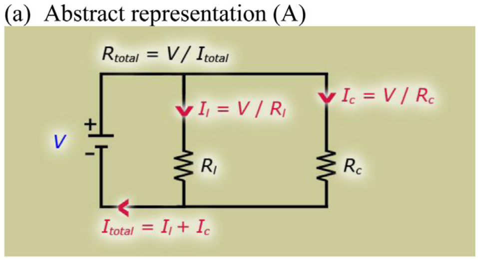
In the Abstract → Contextualized (AC) condition, the introduction and demonstration phases of the instruction section were presented using abstract diagrams and narration, analogous to the abstract (A) condition. During transition, an abstract diagram was presented side-by-side with a contextualized circuit illustration, as shown in Fig. 1(c). To facilitate the transition between abstract representations in the

Table 1
Sequencing of representations in computer instruction for four experimental conditions.

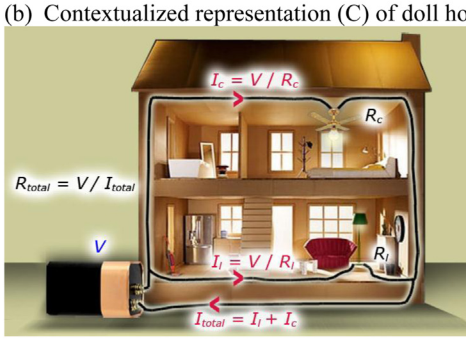
Condition	Introduction	Demonstration	Practice 1 transition problem (student solves last step)	Practice 2 (student solves last two steps)	Practice 3 (student solves all three steps)
A	Abs.[a] Diagram & Abs. Narration	Abs. Diagram & Abs. Narration	Abs. Diagram & Abs. Problem Text	Abs. Diagram & Abs. Problem Text	Abs. Diagram & Abs. Problem Text
C	Cont. Illustration & Cont. Narration	Cont. Illustration & Cont. Narration	Cont. Illustration & Cont. Problem Text	Cont. Illustration & Cont. Problem Text	Cont. Illustration & Cont. Problem Text
AC	Abs. Diagram & Abs. Narration	Abs. Diagram & Abs. Narration	Abs. Diagram and Cont. Illustration & Cont. Problem Text	Cont. Illustration & Cont. Problem Text	Cont. Illustration & Cont. Problem Text
CA	Cont. Illustration & Cont. Narration	Cont. Illustration & Cont. Narration	Cont. Illustration and Abs. Diagram & Cont. Problem Text	Abs. Diagram & Abs. Problem Text	Abs. Diagram & Abs. Problem Text

[a] Note: Abs. = Abstract; Cont. = Contextualized.

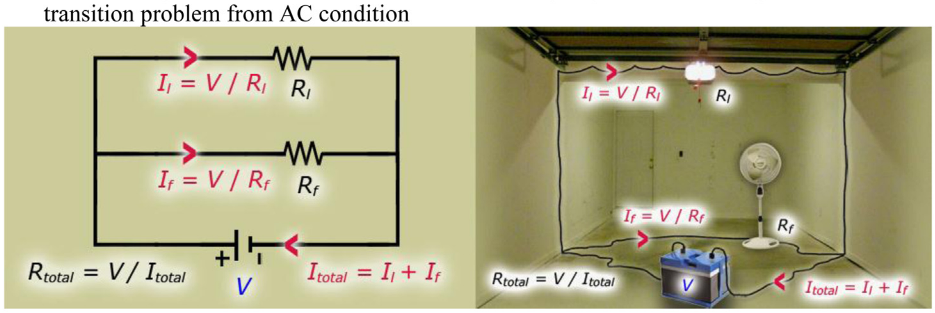
(a) Abstract representation (A)



(b) Contextualized representation (C) of doll house context with ceiling fan, lamp, and battery



(c) Abstract diagram and contextualized illustration (of garage context with light, fan, and battery) of transition problem from AC condition



(d) Contextualized illustration (of garage context with light, fan, and battery) and abstract diagram of transition problem from CA condition

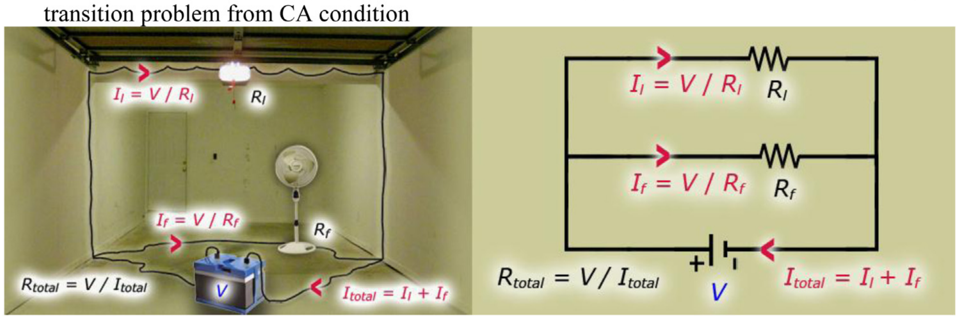


Fig. 1. Sample circuit diagrams and illustrations. (a). Abstract representation (A). (b) Contextualized representation (C) of doll house context with ceiling fan, lamp, and battery. (c). Abstract diagram and contextualized illustration (of garage context with light, fan, and battery) of transition problem from AC condition. (d). Contextualized illustration (of garage context with light, fan, and battery) and abstract diagram of transition problem from CA condition.

preliminary stages of instruction and contextualized representations in the later stages of instruction, a short narration indicated the correspondences between the abstract diagram and the co-present contextualized illustration. Subsequent problems were contextualized, as in the contextualized (C) condition. As summarized in Table 1, the learners in the AC sequence condition experienced twice the abstract diagrams, once the abstract-to-contextualized transition, and twice the contextualized illustrations.

The Contextualized → Abstract (CA) condition conformed to this same transition design, except the introduction and demonstration phases were contextualized and the last two practice problems were abstract. The transition problem presented the contextualized circuit illustration and the abstract circuit diagram arranged side-by-side, as shown in Fig. 1(d) and the narration on the correspondence between contextualized illustration and abstract diagram. As noted in Table 1, the learners in the CA sequence condition experienced twice the contextualized illustrations, once the contextualized-to-abstract transition, and twice the abstract diagrams.

The final section of the computer program was a program rating questionnaire. The questionnaire was a 6-item Likert instrument asking participants to rate their learning perceptions on a 5-point scale, which ranged from 1–strongly disagree to 5–strongly agree. Two items related to overall enjoyment of the computer program (“I liked the lesson”; “I enjoyed learning with the lesson”); two items related to the graphics in the program (“The graphics in the lesson helped me learn”; “The graphics helped me to solve the problems”); two items assessed perceived cognitive load (“The lesson was difficult”; “Learning the material in the lesson required a lot of effort”). The reliability of the questionnaire was examined with a factor analysis using principal axis estimation, which showed that two factors accounted for 63.9 percent of the variance. Two factors emerged from the analysis, namely overall program ratings (including the two enjoyment items and two graphics items; four items, Cronbach’s $\alpha = .86$) and cognitive load ratings (two items, $\alpha = .80$).

2.2.2. Paper and pencil materials

The paper and pencil materials consisted of two near-transfer and two far-transfer posttest problems. The two near-transfer parallel circuit problems (Cronbach’s $\alpha = .85$) were stated in a contextualized format, as is common for real-life engineering problem settings. The problems were designed to assess students’ ability to apply their problem-solving skills to solve an isomorphic set of problems. The near-transfer problems had the same underlying structure as the demonstration and practice problems in the computer program, but different surface characteristics. An example of a near transfer posttest problem was “The electrical system of a remote controlled toy helicopter consists of a motor with resistance $R_m = 4.5$ Ohm, a siren with resistance $R_s = 18$ Ohm, and a control unit with resistance $R_c = 72$ Ohm. All these components are wired in parallel and are connected to a $V = 9$ V battery. What is the total resistance of this parallel electrical circuit?” Two engineering instructors who were blind to the experimental condition scored the near-transfer problems (inter-rater reliability 98.4%).

The far-transfer problems were designed to assess students’ ability to transfer the problem-solving skills learned in the computer program to a novel set of problems with a different underlying structure. The two far-transfer problems (Cronbach’s $\alpha = .90$) were stated in a contextualized format and required the learners to calculate total current given two individual resistance values and the individual current of one of the devices (e.g., “To operate your gameboy you wire the display unit with resistance of $R_D = 30$ Ohm and a speaker with resistance of $R_S = 10$ Ohm in parallel. To ensure satisfactory performance the current flow through the display must be at least $I_D = 0.3$ A. You power this system with a battery. How large is the total current flow drained from the battery?”). In order to solve the far-transfer problems, students had to modify the solution procedure from the problems presented in the computer-based program. Two engineering instructors who were blind to the experimental condition (inter-rater reliability 98.2%) scored the far-transfer problems.

Each of the four problem-solving posttest problems had a three-step solution. Each step solved correctly received one point, resulting in a maximum score of three points for each problem-solving posttest question, and a maximum near-transfer posttest score of 6 points and a maximum far-transfer posttest score of 6 points.

2.2.3. Software and apparatus

The computer-based instructional module used in the study was developed using Adobe Flash CS3 software, an authoring tool for creating web-based and standalone multimedia programs. Adobe Flash was used because it is a very interactive visual programming platform. Adobe Flash allows the programmer to see each screen as the user would and easily create new elements (e.g., an input box) or alter existing elements. Flash also allows for importing many different types of images, videos and sounds. Because of the diversity of Adobe Flash we were able to create a visually pleasing module that was easy to alter for the different experimental conditions. Aside from the visual benefits of Adobe Flash, it permits for traditional programming using Flash’s language “ActionScript”. Through ActionScript we controlled the inner-workings of the module, such as checking user input to practice problem steps and providing appropriate feedback, logging learner interaction data, and controlling the elements in each screen. The apparatus consisted of a set of laptop computer system, with a screen resolution of 1680×1050 pixels, and headphones.

2.3. Procedure

Students participated in the experiment during a regular class session in their normal classroom, providing for high external validity of this study. Each student received a laptop and headphones. In addition, closed envelopes containing the paper-based post-test were randomly distributed to the individual students. The envelopes were labeled with the participant identification number and a letter that represented the experimental condition. The random envelope distribution ensured that the students in a given class session were randomly distributed to the four experimental conditions. For each student, the computerized program was launched with the randomly assigned condition by typing in the participant id number and condition letter from the envelope. The students were instructed to begin the computerized program and to complete all portions of the program at their own pace. Once students had completed the program, they were instructed to open the posttest envelope, answer all questions, and return the test to the envelope. Subsequently, all laptops and posttest envelopes were collected for scoring and data analysis.

3. Results

A preliminary Analysis of Variance (ANOVA) on pretest scores and comprehension check scores indicated no significant differences among conditions (Fs < 1). An ANOVA on time spent on the instruction with embedded practice (recorded by the computer system) demonstrated significant differences among the conditions, $F(3, 339) = 3.60$, $p = .01$. Follow-up pairwise comparisons revealed that the CA condition spent significantly more time on the instructional module than the C ($p = .01$) or A conditions ($p = .01$). No other comparisons were statistically significant. Although mean time on task was also descriptively higher for the CA condition compared to the AC condition, this difference was not statistically significant ($p = .16$). Time on task was not significantly correlated with near-transfer posttest scores, $r(341) = -0.046$, $p = .40$, or far-transfer posttest scores, $r(341) = -0.029$, $p = .59$. Table 2 presents descriptive statistics for the practice scores, posttest scores, program ratings, and cognitive load ratings.

To determine the effect of our experimental conditions on participants’ learning, we conducted two ANOVAs, with near-transfer posttest score and far-transfer posttest score as dependent variables, and experimental condition as independent variable. The analysis of near-transfer performance indicated significant differences among the conditions, $F(3, 339) = 4.42$, $p = .005$. Follow-up Tukey pairwise comparisons showed that the AC condition significantly outperformed both the C condition ($p = .007$; Cohen’s $d = 0.48$) and the CA condition

Table 2
Means and standard deviations for time spent on instruction with embedded practice, near-transfer posttest score, far-transfer posttest score, practice score, and program ratings (learner perceptions), by experimental condition.

Experimental condition	*N*	Instruction time (mins)	Near transfer (max = 6)	Far transfer (max = 6)	Practice score (max = 6)	Program ratings (max = 5)	Cognitive load ratings (max = 5)
		M (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Abstract (A)	87	16.3 (3.8)	4.43 (1.63)	2.68 (2.09)	2.50 (1.91)	3.24 (0.91)	3.59 (0.98)
Contextualized (C)	84	16.3 (3.9)	3.76 (2.30)	2.14 (2.18)	2.52 (1.99)	3.22 (0.83)	3.63 (1.17)
Abstract → Contextualized (AC)	84	16.7 (3.2)	4.73 (1.72)[a,b]	3.01 (2.15)[a]	2.50 (1.95)	3.16 (1.07)	3.28 (1.11)
Contextualized → Abstract (CA)	88	18.0 (4.6)[a,c]	3.96 (2.00)	2.33 (2.07)	2.51 (1.74)	3.17 (0.96)	3.59 (1.13)

[a] Significantly higher than the C condition.
[b] Significantly higher than the CA condition.
[c] Significantly higher than the A condition.

($p = .045$; $d = 0.41$). Thus, the abstract fading hypothesis from Section 1.2.2. was supported by the near-transfer posttest results, in that the AC condition significantly outperformed the CA and C conditions; however, the AC condition did not significantly outperform the A condition. The context fading hypothesis of Section 1.2.1. was not supported.

The analysis on far-transfer scores indicated significant differences among the groups, $F(3, 339) = 2.78$, $p = .041$. Follow-up Tukey tests revealed that the AC condition had significantly higher far-transfer scores than the C condition ($p = .041$; $d = 0.40$). Thus, the abstract fading hypothesis was supported by the far-transfer posttest results to the extent that the AC condition achieved significantly higher far-transfer scores than the C condition. Also, descriptively the AC condition had a non-significant tendency for higher far-transfer scores ($M = 3.01$, $SD = 2.15$) compared to the A condition ($M = 2.68$, $SD = 2.09$) and the CA condition ($M = 2.33$, $SD = 2.07$). Analysis of the posttest scores controlling for time on task (transfer divided by time on task) revealed the same pattern of results.

An ANOVA was run using participants' practice score as dependent variable and experimental condition as independent variable. The analysis did not reveal significant differences among the conditions ($F < 1$). Also, analyses did not indicate significant differences among conditions for overall program ratings ($F < 1$) or cognitive load ratings, $F(3, 339) = 1.83$, $p = .14$. While the overall analysis of the cognitive load ratings did not detect significant differences among the experimental conditions, individual pairwise comparisons of experimental conditions for the cognitive load ratings indicated that the AC condition had significantly lower cognitive load ratings ($M = 3.28$, $SD = 1.11$) than the C condition ($M = 3.63$, $SD = 1.17$), $p < .05$. No other pairwise comparisons were significant, although the AC condition had a non-significant tendency for lower cognitive load ratings compared to the A and CA conditions (both with $M = 3.59$ and $SD = 0.98$ and 1.13, respectively).

4. Discussion

The goal of the current study was to contribute to the developing understanding of optimal sequences of representation types (contextualized and abstract) in computer-based instruction. Specifically, the goal was to address this question in the domain of engineering problem solving instruction for K-12 students. Given prior evidence showing that sequential exposure to a variety of representation types benefits student learning beyond a single representation type (Goldstone & Son, 2005; McNeil & Fyfe, 2012; Scheiter et al., 2009), we predicted that an instructional condition that transitioned from one representation type (contextualized or abstract) to the opposite type (abstract or contextualized) would lead to better learning outcomes than conditions that presented consistent representation types throughout instruction. Two competing hypotheses were offered to predict the optimal sequence among the four examined sequences: 1) the context fading hypotheses predicted that presenting contextualized representations first, followed by abstract representations, would best promote learning; and 2) the abstract fading hypotheses predicted that presenting abstract representations first, followed by contextualized representations, would best foster learning.

Results indicated that participants in the AC (abstract → contextualized) learning condition had both significantly higher near-transfer and far-transfer posttest scores, compared to the C (contextualized → contextualized) condition. In addition, learners in the AC condition significantly outperformed their counterparts in the CA (contextualized → abstract) condition on the near-transfer posttest. The superior performance of the AC condition over the C condition on the entire (near-transfer and far-transfer) posttest is consistent with general findings demonstrating better learning outcomes when varied representation types are sequentially provided to learners (Goldstone & Son, 2005; McNeil & Fyfe, 2012; Scheiter et al., 2009). However, our findings deviate from earlier investigations showing learning benefits for sequencing from concrete (or realistic) to abstract (or schematic) representations. Recall that these earlier studies were conducted for declarative or conceptual knowledge domains, i.e., knowledge of facts or abstract principles (Anderson, 1993). For instance, Scheiter et al. (2009) examined instruction on facts about the biological processes of cell mitosis. McNeil and Fyfe (2012) taught sets of symbols (concrete, partially concrete, or abstract) and parallel sets of rules in order to carry out individual mathematical calculations using the given symbols and rules (e.g., $1 + 2 = 3$). The individual rules taught represented declarative knowledge.

Students from Goldstone and Son's investigation (2005) learned abstract principles within a complex scientific system by exploring the behavior of a dynamic simulation and attempted to transfer the abstract principles to a related domain. The optimal solution steps to the competitive specialization demonstrated were implicitly exhibited through the actions performed by agents in the simulation.

In contrast, in the current experiment, students learned an explicit set of procedures for determining unknown electrical circuit quantities. In order to correctly solve the circuit problems, learners were required to follow an appropriate sequence of steps, each involving at least one mathematical calculation. Prior to the current study, the optimal sequence of representation type had not been examined for the procedural knowledge domain of engineering problem solving.

The results of the current experiment generally support the abstract fading hypothesis for computer-based instruction in procedural engineering problem solving for novice middle school students. Initially providing novice students with abstract representations of electric circuits may assist learners to focus on conceptually-relevant information in visual representations by eliminating unnecessary information associated with concrete elements. When students attend to conceptually relevant information, rather than superficial elements that may change from one real-life problem context to the next (e.g., specific electrical devices), they can more effectively acquire knowledge about the underlying solution steps.

The results of the current experiment can be interpreted in light of cognitive load theory by noting that the abstract representations may help novice learners select information that is conceptually relevant, not simply perceptually salient (Lowe, 1999; 2003). Thus, the initially abstract representations may reduce extraneous cognitive load and free up cognitive resources for applying germane cognitive processes related to constructing internal representations of the solution procedure. Unfortunately, the cognitive load scale employed in the study did not detect a significant overall effect on the cognitive load ratings. This may be due to the limitations of the employed cognitive load scale adopted from Paas and Van Merrienboer (1994), which commonly measures total cognitive load (De Jong, 2010; Schnotz & Kurschner, 2007; Schnotz & Rasch, 2005; Van Gog & Paas, 2008). Since our posttest results indicate significantly improved learning with the AC condition compared to the C and CA conditions, it is likely that similarly to the recent study by Cierniak, Scheiter, and Gerjerts (2009), the AC condition reduced extraneous load compared to the C and CA conditions while increasing germane load such that the total cognitive load remained nearly unchanged. Developing and validating measures that distinguish the different types of cognitive load and employing such detailed cognitive load measures is an important direction for future research on representation sequencing.

Once the initial stage of learning with abstract representations is complete, and students have formed preliminary internal representations, they are better equipped to recognize common problem structure in newly presented problems including contextualized elements. Thus, in the later stages of learning, when subsequent problems are presented in contextualized format, learners can activate relevant schemas necessary to recognize problem structure and observe that the solution procedures can be transferred to a variety of problem settings. Practice with a variety of contextualized problems can assist learners to transfer solution procedures to novel test problems (Spiro et al., 1991, 1992; Spiro & Jehng, 1990). Rau, Aleven, and Rummel (2013) advise that the amount of problem variability should be carefully considered in instructional design. If problem types are too similar, learners will be unable to perceive subtle differences to achieve abstraction. On the other hand, problems may be so dissimilar that they require different problem schemas to solve, diminishing the capacity for abstraction of principles.

Learners in the CA condition required significantly more time to complete the self-paced instruction section than the learners in the C and A conditions. This result for instructional time corroborates the challenges that the CA condition, which is effectively the inverse of the AC condition, presents to the learners. The CA learners may struggle initially due to search processes required to select relevant information in the contextualized problems and to form preliminary internal representations. The search processes within the richly contextualized representations may be interpreted as extraneous cognitive load (cf. Section 1.1.2). When transitioning to the abstract representation, the CA learners may need to extensively compare their internal representations to the provided abstract representations, which can be a time consuming process.

Although mean near- and far-transfer posttest scores were descriptively higher for the AC condition, compared to the A (abstract → abstract) condition, our results did not indicate significant differences between the conditions. Additional participants could lead to the detection of a small effect (Cohen, 1992); however, such a small effect would be of limited interest to instructional practice. Thus, employing only abstract representations appears to be a viable alternative to the AC representation transitioning in instruction on engineering problem solving, especially when the design of contextualized instructional components for an AC sequence would incur large additional production costs.

Before concluding the discussion of the results of the present experiment, we return to the comparison of the present experiment on representation transitioning in learning of procedural problem solving with prior experiments on representation transitioning in learning of conceptual knowledge. We note that the results from the present and prior experiments indicate that the optimal representation transitioning depends on the type of knowledge to be learned. As outlined in Section 4.2 a comprehensive set of empirical studies covering the spectrum from mainly conceptual knowledge to mainly procedural knowledge along with corresponding theoretical model development is required to develop a thorough understanding of the learning phenomena related to representation transitioning. With due caution we outline the following perspectives on possible explanations of the differing representation transitioning results for conceptual versus procedural knowledge.

The prior conceptual knowledge oriented studies typically required subjects to learn facts or rules and to transfer the learned facts/rules to novel representation (symbol) systems. The facts/rules typically only required minimal manipulations with the symbols. For instance, subjects in the McNeil and Fyfe (2012) study learned elementary addition facts and had to transfer these facts to novel abstract symbols but were not required to carry out manipulations with the symbols. Thus, it is likely that the main difficulty for the learners in these conceptual knowledge oriented studies was in learning the conceptual rules/facts and the first learning steps with familiar real-life contextualized representations eased the students' learning by invoking existing schemata of related real-life contexts (Axelrod, 1973; Bartlett, 1932; Rumelhart & Ortony, 1976, pp. 99–135; Sweller et al., 1998). In contrast, in the present experiment, the manipulations with the representations (symbols) were significantly more complex than in the conceptual knowledge studies. The solution procedures in the present experiment required multiple steps, whereby each successive step built on the intermediate results obtained in the preceding step. For novice learners, it is likely that this multi-step solution procedure presented the main learning difficulty. Thus, the reduction of extraneous cognitive load through presentation of abstract symbols (representations) without distracting real-life features (that are irrelevant to acquiring the underlying solution procedure) may have benefited the novice learners. Essentially, the outlined perspective on explaining the different results for conceptual and procedural learning hinges on the relative importance of exploiting the familiarity with real-life contextualized representations versus the "clutter-free" abstract representation of the solution procedure (as per cognitive load theory, see Section 1.1.2) for completing the overall learning task.

Moreover, the abstract representations used in some prior studies shared very little physical similarity (resemblance) to the systems they were depicting. For example, the abstract depictions of ants and food in Goldstone and Son (2005) were little more than splotches. These fully abstracted representations, in which elements do not in any way share physical characteristics with their referents, make grounding to real-life situations nearly impossible. In comparison, the abstract circuit diagrams in our study employed at least similar structural features present in real-life electrical circuits (e.g., wires) which may have alleviated some difficulties identifying familiar elements (e.g., batteries). This may explain why, compared to Goldstone and Son (2005), who found an inhibitor effect of abstract representations, students in our study did not suffer from early learning with abstract representations.

An additional perspective on the explanation of the different results for the prior conceptual knowledge oriented studies versus the present procedural knowledge oriented study is based on the variety of real-life contextualized representations employed in these studies. The prior conceptual knowledge oriented studies employed typically one contextualized real-life representation, e.g., "food and ants" (Goldstone & Son, 2005), measuring cups (McNeil & Fyfe, 2012), or microscope video of mitosis (Scheiter et al., 2009), during the learning phase. In contrast, the present experiment employed a variety of real-life contextualized representations that varied for each contextualized problem in the learning phase. That is, the contextualized representation in the prior studies was consistent across the learning phase and this consistency may have facilitated the learning from the contextualized representations. Essentially, the consistent contextualized representations may have facilitated learning by exploiting the familiarity with real-life objects, while limiting the extraneous cognitive load. In contrast, the variability in the contextualized representations in the present study may have hindered learning of the underlying solution procedure. In essence the extraneous cognitive load through the constantly changing contextualized representations with rich seductive details (cf. Section 1.1.2) may have diminished the benefit from the real-life familiarity of the contextualized representations (cf. Section 1.1.1).

In summary, our results for pre-college computer-based instruction on engineering problem solving for the abstract to contextualized (AC) sequence contradict earlier results showing learning benefits for the contextualized to abstract (CA) sequence. We propose that the domain of engineering problem solving has qualities, which separate it from domains examined in earlier representation transitioning studies. In particular, our instruction was aimed at developing problem-solving competency (procedural knowledge), whereas earlier investigations examined effects on declarative knowledge about functioning and/or behaviors of biological systems or rules of mathematical systems. The abstract → contextualized sequence may be better suited for acquiring procedural knowledge by developing problem-general schemas first, rather than initially emphasizing problem-specific differences in contextualized representation.

4.1. Practical implications

Our results suggest that computer-based engineering education introducing novice students to engineering problem solving procedures should first present abstract representations, then transition in later stages to problems using contextualized formats (or employ abstract representation throughout). We interpret the study results to indicate three primary ways in which the AC sequence of instruction can assist learners: 1) allowing learners to initially focus on the conceptually-relevant information shared across similar problems so they are able to develop preliminary internal representations of problem structure; 2) reducing extraneous cognitive load associated with selecting relevant information in visual representations, freeing cognitive resources for germane processing; and 3) in later stages, exposing learners to a variety of contextualized problems, allowing learners to recognize that there are various specific problem settings, but the general structure of problems remains consistent. All three of these aspects of the AC instructional sequence may ultimately lead to more sophisticated, flexible internal representations necessary to recognize problem structure in novel test problems (transfer problems).

We submit that computer-based engineering education modules applying the AC instructional sequence may offer valuable alternative educational experiences to K-12 schools and students with limited access to qualified engineering educators. Such computer-based modules can maintain fidelity of the instructional approach and can be easily delivered via internet platforms or software applications to schools, community centers, and informal learning settings, such as museums, science and technology centers, and students' homes. This tactic can support the increasing demand for students in STEM disciplines to contribute to the technology-driven U.S. economy (Brophy et al., 2008).

4.2. Limitations and future directions

A limitation of the presented study is that the posttest used only contextualized problems. The contextualized test format could have favored the AC condition in which the learners viewed contextualized problems immediately preceding the posttest. However, we note that the AC condition significantly outperformed the C condition. The C condition also presented contextualized problems immediately before the posttest, but did not result in better posttest performance compared to the A or CA condition. Thus, matching the type of representation at the end of the instruction does not improve learning. Rather, the transitioning from abstract to contextualized representation is critical for achieving the learning gains.

A limitation of the comparison of the AC and CA representation transitioning conditions with the static representation conditions A and C is that the AC and CA conditions showed learners the transition problem (Practice 1, see Table 1) with both representations side-by-side and all other problems with only a single representation. In contrast, the A and C conditions showed all problems with only a single representation. Seeing both representations simultaneously side by side in one of the problems may have assisted the AC and CA learners. However, this limitation does not affect the AC vs. CA comparison, for which we found significantly improved near transfer with the AC condition. Also, the study results did not indicate a significant difference for the comparison of the AC and A conditions, and neither for the comparison of the CA and C conditions.

A limitation of the contextualized representations employed in the present study is that they did not depict full-fledged photographic real-life situations, but rather a hybrid between abstract representations and photographic reality. Specifically, the main circuit elements (voltage sources and resistive elements), for which the abstract engineering symbols have little resemblance to their real-life counterparts, were represented by real-life images. On the other hand, the wires connecting the circuit elements were represented by abstract lines, that have relatively close resemblance to real-life wires. The lines representing the wires were neatly drawn and overall the contextualized representations were laid out to resemble the layout (structure) of the corresponding abstract circuit. It is possible that this neatly arranged, hybrid contextualized representation that closely linked to the structure of the abstract representation supported successful learning in the AC condition. Future studies could vary the degree of realism in the contextualized representations. Also, future studies could examine extended AC representation sequences that increase the degree of realism in multiple stages, e.g., from an abstract representation, to a hybrid contextualized representation (as employed in the present study), and on to full-fledged photographic realism.

The present study was limited to the comparison of fixed representation sequences, i.e., the representations followed fixed schedules that did not dynamically adapt to the characteristics of the individual students. Future research could examine dynamic strategies that monitor the accuracy of the student responses to practice problems and accordingly adapt the representation sequence. For instance, once a student has reached a prescribed accuracy with abstract problems, the representation could be shifted to a variety of contextualized practice problems.

The current experiment examining the effects of representational sequence was conducted using a specific subject population (i.e., middle school students with no prior electric circuit instruction) from one geographical region (i.e., Southwestern U.S.) in a specific instructional domain (i.e., introductory electric circuit problem solving). Accordingly, the conclusions from this experiment may not apply to different developmental levels or domain knowledge levels, other geographical regions, or different engineering topics. Replication studies with different subject populations, geographical regions, and instructional domains may serve to substantiate the present findings and contribute to the growing knowledge base on effective representation sequences. For instance, it is conceivable that advanced learners in a given knowledge domain have so thoroughly acquired the abstract representations that are employed by domain experts and have extensive experience with the wide set of real-life situations that can be represented with the abstract symbols, that they may no longer benefit from any contextualized representations. Instead, their further learning may be hindered by contextualized representations according to the expertise reversal effect (Kalyuga et al., 2003). We furthermore note that the present study was focused on examining representation transitioning in the context of computer-based education. Future research could examine representation transitioning in other educational contexts, e.g., education based on work sheets or presentation by a human instructor.

Unfortunately, our procedures did not involve noting which participants were in each of the class sections. Thus, we were unable to examine whether students in particular classes shared common characteristics which would warrant using hierarchical linear modeling to account for sources of variance due to class. However, by randomly assigning each individual student to experimental condition, we consider the individual student as the correct unit of analysis. Furthermore, the middle school where the study was conducted employs an inclusive enrollment model, i.e., there is *no* deliberate differentiation in student characteristics among the classes. Also, the teachers closely coordinate lesson plans to ensure cohesive state-defined, standards-based education across the class sections. Thus, any differences between classes were likely minimal.

The results on representation transitioning from the current procedural knowledge focused study, along with earlier findings in declarative knowledge domains, suggest that the optimal sequence depends on the type of knowledge the learner is acquiring. Clearly, there exists a wide spectrum of knowledge from mainly conceptual (declarative) knowledge domains to mainly procedural knowledge domains, with knowledge domains that are composed of various levels of conceptual and procedural knowledge in between the extreme ends of the spectrum. The present study along with the prior studies on representation transitioning point to complex dependencies of the optimal representation sequence on the composition of knowledge to be acquired. An extensive set of future studies including both empirically and complementary theoretically oriented studies seems required to comprehensively examine these representation transitioning dependencies.

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