Computer-Based Instruction and Cognitive Load

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Abstract
Following cognitive load theory, we used a computer-based software training paradigm to determining the optimal number of steps or information chunks to present before practice opportunities. Results demonstrating that the size of information chunks presented and the type of practice used individually influenced participants' ability to effectively learn via computer-based instruction. These findings contribute to the literature by showing the importance of practice and optimal segment sizes for learning via a computer.

Introduction
Imagine that you have just been assigned to teach a web-based college course. You have never taught an online class, and besides having access to a pre-designed Blackboard program, you are not given any other resources. Many teachers increasingly find themselves in this situation. The problem that these teachers face, along with anyone else who wants to use computer-based instruction is how to use the technology to foster effective learning.

Fortunately, research studies in computer-based learning are beginning to scientifically determine how to effectively use the technology for teaching purposes, with effective multimedia learning environments incorporate such principles as "guided activity, reflection, feedback, control, and pretraining" (Moreno & Mayer, 2007, p. 309). Despite the recent research efforts in the area of computer-based instruction, more research is needed to determine when such factors as animations, actions, and cognitive and personality differences may increase or decrease students' learning outcomes (Reed, 2006; e.g., Paas & Kester, 2006). In the current study we used a computer-based software training paradigm to determining the optimal number of steps or information chunks to present before practice opportunities. No known research has focused exclusively on the impact of information chunks and practice in computer-based learning. Therefore, the current research contributes to the literature by demonstrating that the size of information chunks presented and use of practice both influence participants' ability to learn the skills being taught to them via computer-based instruction.

Computer-Based Software Training

Three difficulties generally arise when one is trying to learn a new computer program: The incompatibility between one's desire for immediate and meaningful action and one's need for additional learning, numerous mistakes, and simultaneously handling the program (interface), input device, and manual (Carroll, 2000). For example, few people read the manual systematically when learning a computer program, while around a third of people learn only from exploring the interface (Bannert, 2000). Therefore in learning new software programs, individuals typically pursue less effective approaches **(**Clarke, Ayres, & Sweller, 2005).

Another reason why new software users persist in less effective routes of learning may have to do with the tutorial itself. Traditional step-by-step tutorials tend to be confusing to learners. More effective are recent methods based on cognitive load theory in which the focus is on increasing recall, reducing interference, minimizing cognitive load, and enhancing understanding (Bannert, 2000**;** Clarke, Ayres, & Sweller, 2005).

Cognitive Load Theory

A major assumption of cognitive load theory or CLT is that human working memory (active short-term memory) has a limited capacity. Therefore, CLT is concerned with how limited mental resources are used during an instructional task (Sweller, 1988; Clark, Nguyen, & Sweller, 2006).

Cognitive load theorists have identified three sources of cognitive load that can be potentially active during learning: intrinsic, extraneous, and germane. Intrinsic cognitive load refers to the overload placed by the number of cognitive elements that are required to be learned by the new material (Clark et al. 2006); for example, having to memorize a series of different menus in order to know the desired functions in a Microsoft Excel program. Extraneous cognitive load occurs when learners are required to engage in activities not related to learning the new information (Sweller, 2005); for example, having to scan through irrelevant menus in order to find the desired function in a Microsoft Excel program. According to CLT, when a person is under high levels of either intrinsic and/or extraneous cognitive load, learning becomes difficult **(**Clark et al., 2006**)**. Germane load, on the other hand, actually contributes to learning by providing relevant information that facilitates the integration of new information into a more complex schema. Therefore if the goal is to improve learning, then a reduction of either intrinsic or extraneous cognitive load with an increase in germane cognitive load allows for greater efficiency in learning.

Despite the prevalence of extraneous cognitive load reduction techniques in software training research, Van Merriënboer and Sweller (2005) concluded that reducing extraneous load may not significantly reduce total load (i.e., intrinsic + extraneous - germane) imposed by learning tasks.

Therefore even with reduced levels of extraneous load, working memory may still be overwhelmed, leading to less effective learning outcomes.

A more promising direction for increasing positive learning outcomes by using computer-based load reduction techniques may be to focus on reducing intrinsic cognitive load instead (Pollock, Chandler, & Sweller, 2002). Recent research examining intrinsic load has found that this type of load can be reduced by presenting partial task elements in order to reduce element interactivity (Bennert, 2000; Pollock, et al., 2002); nevertheless, the proper way of breaking down or segmenting learning material is still unclear (Van Merriënboer & Sweller, 2005) The current research seeks to directly address this question by varying the number of steps or information chunks presented before practice opportunities.

Practice Effects

Skill acquisition is thought to develop through the cognitive attainment or learning of the following sequence: A single principle or rule, a collection of interacting pieces of knowledge, and finally a skill. In the final stage, practice is essential in developing speed and accuracy (VanLehn, 1996). Generally, practice is considered to be an important factor in the automation of cognitive, affective, and behavioral learning (Moors & De Houwer, 2006), with practice promoting faster knowledge application and increased response accuracy and motivation (Felder & Brent, 2003).

According to CLT, practice can facilitate learning through increasing germane cognitive load. Germane load actually contributes to learning by providing relevant information that facilitates the integration of new information into a more complex schema. Therefore, practice increases germane load by allowing for faster integration of the to-be-learned material (Clark et al., 2006). The current research seeks to directly test the effectiveness of practice vs. no practice in a computer-based software training environment.

Overview and Predictions

In the current experiment, we manipulated the number of steps or information chunks presented before the type of practice opportunities given after each step (practice vs. no practice). Based on research by Nadolski, Kirschner, & Van Merriënboer (2005) it was predicted that the intermediate segment size (6 steps) would be optimal for learning in the present task because receiving too few steps (2 steps) or too many steps (12 steps) may have a similar detrimental influence on learning. In addition, it was predicted that participants in the practice conditions should outperform those in the no practice conditions (Merrill, 2002). No specific prediction was made about a possible interaction between information chunks and practice type.

Method

Participants

One hundred and twenty-eight undergraduates (*M* age = 21.8; 70 female) from a large southwestern university participated for credit in a computer literacy course. The majority of participants reported moderate to high (4+ times a week) computer and Microsoft Excel use. Participants were randomly assigned to one of eight experimental conditions in a 4 (information chunks: two vs. four vs. six vs. twelve) by 2 (practice: yes vs. no) between-subjects factorial design. The reason that the current research did not include an eight or ten chunk size condition is because sizes over six have traditionally been shown to be fairly equal in learning outcomes based on memory limitations of human cognition (Sweller, 2006). The twelve chunking size condition was chosen to maximize potential difference that may exist.

Materials

The experimental materials consisted of (a) twelve tutorial modules, (b) attitude survey, and (c) final assessment questioner.

Tutorial Modules. Twelve tutorial modules presented visual demonstrations (with a verbal narration by a female voice) of various functions in Microsoft Excel. The modules were developed by the authors using Macromedia Captivate (http://www.adobe.com/products/captivate/) which automatically records all onscreen actions and instantly creates an interactive Flash simulation. Each of the 12 tutorial modules proceeded in the following order for all participants: frequency, round function, sort function, rank function, conditional formatting, data validation, auto filter, subtotals, line chart, page number and date, print selected area, and print out formula. Each module included onscreen demonstration, text captions, narration, and scoring feedback. The content of each of the 12 modules consists of 12 steps or information chunks. An information chunks is defined as an event involving a mouse click (e.g., click on menu items, buttons, or cells), drag and drop (e.g., select a specific region), or keyboard input (e.g., key in formula). The default length of each step is four seconds, with the total duration of each module (not including practice) being 48 seconds. The practice conditions included an interactive simulation (i.e., roll-over or pop-up captions) which instructed and guided the participants through what they are to practice. The no practice conditions simply repeat the same demonstrations described above, so that in both treatments learners were exposed to the instructional materials for approximately the same amount of time.

Attitude Survey. This 5-point survey (Strongly agree – Strongly disagree) assessed participants' evaluations and perceptions of the tutorial modules. Sample items included: "I enjoyed studying this Excel tutorial; The text was very readable; I like to listen to the audio narration; and I learned a lot of Excel skills from this tutorial".

Final Assessment Questionnaire (Posttest). Evaluation of post-tutorial performance consisted of 40 multiple choice questions. These multiple choice questions included a flash movie clip to assess how well that student learned from the demonstration. Sample items included: "In the Excel tutorial, the validation function is located on _______; Auto filer function is located on the _______; In the Excel tutorial, we use data validation to avoid _______; In the Excel tutorial, how many criteria are used to sort grades?" Two research proctors recorded individuals' starting time and ending time of the final assessment. All the answers were transmitted into a database and graded by computer.

Procedure

Students (20 – 24 students per session) participated in the experiment by registering for one of eight experimental sessions located in a computer lab containing 25 IBM compatible computers. When participants entered the lab they were informed that they were taking part in a two day study that was exploring how to teach spread sheet software through the computer. Following the second day of the study, all participants received the same credit in their computer course for participating. A research proctor (blind to the experimental conditions) began the study by instructing the participants to turn on their computer monitor and silently read the instruction on the screen. The instructions contained screen-shot pictures and unique paragraphs for each experimental condition. After the participants were oriented to the computer, they were instructed to begin with the first tutorial module.

Prior to participants' arrival, they were randomly assigned to one of the eight treatment conditions that contained the 12 tutorial models. Each module took approximately two minutes to complete. Participants assigned to the practice conditions were visually (not verbally) instructed to repeat each step of the function by typing in and clicking on the appropriate parts of the screen six (after every two steps), three (after every four steps), two (after every six steps), or one time (after all twelve steps) for each of the 12 tutorial models. Participants assigned to the no practice conditions received an exact repeat of each step of the function (including verbal explanations) six, three, two, or one time.

On the second day of the experiment participants once again repeated the exact same treatment condition as before, except at the end of the twelfth tutorial module all participants received the same attitude survey and posttest. The total duration in minutes to complete the posttest divided by the total mean score of the posttest (efficiency) represented the main dependent variable for the study.

Results

In order to investigate the influence of chunk size and practice on learning outcome, a two-way between-subjects ANOVA using duration to complete the posttest divided by total mean score on the posttest (efficiency) as the dependent variable was conducted. Results indicated a significant main effect for information chunk size, $F\ (3,120) = 6.04$, $p = .001$ (see Figure 1), a significant main effect for practice, $F\ (3,120) = 20.50$, $p < .001$ (see Figure 2), with the interaction between chunk size and practice failing to reach significance, $F < 1$. In order to understand the main effect for chunk size, a Tukey HSD procedure was conducted. This procedure reveled that those receiving the six and twelve steps learned at a higher rate than those receiving two steps with pairwise differences among those means significant at the $p < .05$ level. Given the similarity between the two and four steps and the six and twelve steps, a simple contrast was conducted. The simple contrast showed that in combination the six and twelve step conditions learned at a significantly higher rate than the combination of the two and four step conditions, $t\ (124) = 3.23$, $p = .002$. As predicted, examining the means for the significant main effect for practice found those in the practice condition learned at a higher rate than those in the no practice condition.

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In order to investigate the influence of chunk size and practice upon participants' subjective experiences, a two-way ANOVA using the summed attitude survey scores as the dependent variable was conducted. Results indicated a significant main effect for practice, $F\ (1,120) = 6.72$, *p* = .01, with all other effects failing to reach significance, all *F*s < 2. Examination of means reveals that participants had more positive attitudes about the tutorial modules when given practice (*M* = 42.24, *SE* = 0.77) than when not given practice (*M* = 39.43, *SE* = 0.77).

Discussion

The two hypotheses for the current study were that the intermediate segment size (6 steps) will be optimal for computer-based learning and that participants in the practice conditions should outperform those in the no practice conditions. The first hypothesis was partly confirmed given that participants in the 6 and 12 step conditions demonstrated significantly better learning outcomes than participants in the 2 and 4 step conditions; however the 4, 6 and 12 step conditions did not significantly differ from each other in isolation. The second hypothesis was confirmed given that participants demonstrated significantly better learning outcomes when given practice vs. no practice.

In our study, we examined the optimal segmentation of information via computer-based instruction in order to lower intrinsic cognitive load. Results revealed that the greater the steps the better the learning outcome (up to 12 steps); however, receiving 6 to 12 steps seems to be most conducive to effective learning outcomes in the current study. It seems then that small segmentations (in particular 2 steps) hinder schemata building and information integration (Pollock, et al., 2002). In retrospect, the finding that larger segment sizes (12 steps) seems to be as optimal for learning as intermediate segment sizes (6 steps) makes sense given that the majority of participants already have some background in Micosoft Excel, making the task less complex (cf. Nadolski et al., 2005).

We included practice opportunities in order to increase germane cognitive load. Results revealed that despite the amount of steps received at a time, practice facilitated more positive learning outcomes compared to when no practice opportunities were given. It seems then that practice facilitated the automation of mental effort, freeing up working memory. This influence of practice in computer-based instruction is similar to other contexts in which practice effects are found (e.g., Merrill, 2002). Further, unlike segment size, the learning benefits of practice are salient enough that participants consciously recognize greater fluency in learning as evidenced by the results of the survey analysis.

Applying these results to learning objectives in computer-based instruction, it becomes important to present information in segments and to include practice opportunities; for example, presenting no more than 6 to 12 parts of a major concept before using follow-up and application questions (that students are required to answer). Overall, results of the current study are consistent with cognitive load theory and add to the literature by providing a demonstration of an effective way of segmenting learning material in computer-based instruction, while at the same time showing the benefit of practice in a computer-based context.

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