Adaptive Instruction to Learner Expertise with Bimodal Process-oriented Worked-out Examples

Jihyun Si, Dongsik Kim* and Chungsoo Na
Hanyang University, Dept. of Educational Technology, 17 Haengdang-dong, Seongdong-gu, Seoul Korea, 133-791 // jennyhan0306@gmail.com // kimdsik@hanyang.ac.kr // skcjdtm@gmail.com
*Corresponding author

(Submitted December 6, 2012; Revised March 8, 2013; Accepted May 7, 2013)

ABSTRACT

This study investigated the instructional efficiency of adaptive instruction to learner expertise in the domain of C programming language with college students. It also aimed to investigate whether a bimodal process-oriented worked-out example (WOE) could effectively control extraneous cognitive load and further improve instructional efficiency. For this purpose, a learner-paced problem-solving e-learning environment was developed. A total of 112 college students participated and they were randomly divided into four groups (adaptive and bimodal, adaptive and unimodal, fixed and bimodal, and fixed and unimodal) when they logged into the problem-solving e-learning environment. After removing uncompleted or repeated data, data from 96 students were used for a series of ANOVA and ANCOVA. The findings showed that the adaptive instruction groups showed significantly higher instructional efficiency than the fixed instruction groups. Although there was no significant difference between the bimodal and the unimodal WOE groups, the bimodal WOE groups showed lower mental effort, higher knowledge acquisition, and instructional efficiency. In addition, the bimodal WOE condition was more efficient in both adaptive and fixed conditions. Based on these findings, it was concluded that the adaptive instruction method and the bimodal process-oriented WOE effectively controlled cognitive load and thereby successfully and efficiently led to schema construction and automation. The insight gained through this study may inform instructional designers seeking to enhance their understanding of efficient instructional design within the cognitive load theory framework.

Keywords
Adaptive instruction, Cognitive load theory, Process-oriented WOE, Instructional efficiency, E-learning, Learner expertise, Modality effect

Introduction

Adaptive instruction refers to educational interventions intended to effectively accommodate the needs of individual students (Park & Lee, 2003). This educational approach is generally characterized as one that incorporates alternative instructional procedures by providing built-in flexibility to allow students to take various paths to learning (Park & Lee, 2003). The practice of adaptive instructions has had a long history (e.g., aptitude-treatment interactions, Cronbach & Snow, 1977). More recently, researchers in the cognitive load theory (CLT) have investigated methods of adaptive instructions and cast new insight on this important issue.

CLT offers principles and methods to design and deliver instructional interventions that efficiently utilize the limited capacity of human working memory (Sweller, van Merriënboer, & Paas, 1998). If instructional interventions are designed in a way that causes excessive cognitive load, the limited capacity of human working memory can easily be overloaded. This excessively high cognitive load does not contribute to acquisition or automation of schematic knowledge, but rather impedes it (Paas, Renkl, & Sweller, 2004). One of the instructional methods to control excessive cognitive load is worked-out examples (WOE) (Renkl & Atkinson, 2010). WOE provides an experts’ problem solving model for novices to study and emulate, so a substantial amount of unnecessary cognitive load caused by premature problem solving can be reduced by studying with WOE in the early phase of skill acquisition (Sweller, 2006). However, as learner expertise grows, knowledge acquisition from studying WOE becomes a redundant activity that contributes little or nothing to further learning. Instead, problem solving fosters learning more than studying with WOE (Kalyuga, Chandler, Tuovinen, & Sweller, 2001). This reversal of the WOE effect is called the expertise reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003). The instructional implication of this expertise reversal effect is continuous optimization of cognitive load.
Adaptive instruction to learner expertise

To continuously optimize cognitive load, instructional designs need be tailored to an individual trajectory of cognitive skill acquisition in a domain (Kalyuga, 2007, 2008; Kalyuga & Sweller, 2004, 2005). In the traditional learning situations, researchers or instructors pick when to modify instructional techniques typically through interviews or think-aloud procedures or observations as learners gain expertise. However, in e-learning environments, such techniques are inconvenient to use (Kalyuga, 2006a). As an alternative, CLT researchers have utilized efficiency measures to decide the right movement. Such measures were originally developed to measure efficiency of instructional conditions. Pass and van Merriënboer (1993) suggested the following formula to calculate instructional efficiency, $E = \frac{Z_{\text{performance}} - Z_{\text{mental effort}}}{\sqrt{2}}$. Students’ performance and mental effort on the test are first standardized and then mean standardized test performance and test mental effort are entered into this formula to calculate instructional efficiency. According to them, a high performance combined with low mental efforts is called high instructional efficiency while a low performance combined with high mental effort is called low instructional efficiency. However, a combination of performance and mental effort is also indicative of expertise. Learners with more expertise are able to attain equal or higher levels of performance with less investment of mental effort (Kalyuga, 2007). Thus, the efficiency measure is also used to measure levels of learner expertise (van Gog & Paas, 2008).

However, such formula may not be appropriate for e-learning situations. Kalyuga and Sweller (2005) argued that it is not convenient for e-learning applications which require diagnostic assessments of learner expertise for adaptation in real time during an experiment. They defined efficiency as the ratio of the level of performance to rating of mental effort, $E = \frac{P}{R}$ (P: performance measure, R: mental effort rating). They also employed a critical level of efficiency defined as $E_{\text{cr}} = \frac{P_{\text{max}}}{9}$ (as 9-point subjective rating scale was used to assess cognitive load), where $P_{\text{max}}$ is the maximum performance score for a given task level. If the efficiency measure is $E > E_{\text{cr}}$, the cognitive performance is considered efficient. If $E \leq E_{\text{cr}}$, the cognitive performance is regarded as relatively inefficient. Similarly, Kalyuga (2006a) used a simple threshold-based definition for efficiency. In this definition, learners’ performance was considered efficient if they correctly verified all the suggested solution steps up to, but not including, the final numerical answer, and rated a task difficulty as less than 5 on 9-point rating scales. Although these formulas to calculate efficiency are slightly different, they indicates that if similar levels of performance are reached with less mental effort, the efficiency is higher and they are convenient to use in e-learning environments.

Based on the definition of efficiency described above, Kalyuga (2006a) and Kalyuga and Sweller (2004, 2005) investigated the efficiency of adaptive instructions to learner expertise in e-learning environments. They all used a subjective rating of mental effort to measure cognitive load (Paas, & van Merriënboer, 1993). To measure learner performance, two different diagnostic methods were employed, the first-step method (Kalyuga, 2006c; Kalyuga & Sweller, 2004, 2005) and rapid verification method (Kalyuga, 2006a, 2006b). The rationale behind both methods was drawn from a theory of long-term working memory. According to the theory of long-term working memory, “reliance on acquired memory skills enables individuals to use long-term memory as an efficient extension of working memory in particular domains and activities after sufficient practice and training” (Ericsson & Kintsch, 1995, p. 211). That is, when learners encounter a problem in a familiar domain, their available knowledge structures in long-term memory are rapidly activated and corresponding long-term working memory structures created. These schematic knowledge structures are durable and interference-proof enough to observe their immediate traces (Kalyuga, & Sweller, 2004). Such schematic knowledge structures provide necessary executive guidance during problem solving and they are a major feature of learner expertise. (Kalyuga, 2006c, Sweller, 2006, Ericsson & Kintsch, 1995). To probe this knowledge structure, the first-step method asks learners to indicate the first-step toward a solution of a task for a limited time while the rapid verification method asks them to verify rapidly each of the sequentially presented solution steps. If a task is precisely specified in advance, the first step methods may be utilized. However, when the solution procedure requires drawing graphical representations or there are several possible solution paths but only a limited number of steps representing different levels of schema-based problem solutions can be selected, the level of proficiency can be assessed by the rapid verification method. The studies of Kalyuga (2006a, 2006b, 2006c) and Kalyuga and Sweller (2004, 2005) showed that both methods have a sufficiently high degree of external validity to detect differences instantly and adequately in learner knowledge structures.

In both the studies of Kalyuga (2006a) and Kalyuga and Sweller (2005), adaptation occurred based on the efficiency measures described before. The decisions for the initial placements for the training and the adjustment of levels of
instructional guidance during the training were made according to the efficiency measures. Kalyuga and Sweller study (2005) compared the learner-adapted instruction with the non-adapted instruction in the domain of 10th grade algebra. According to their results, the learner-adapted group showed significantly higher efficiency gains and knowledge gains than the control group. With these results, they concluded that the learner-adapted instruction through the first-step method coupled with mental effort ratings proved to be more efficient than non-adapted instruction. Similarly, Kalyuga (2006a) compared two learner-adapted instructions (efficiency-based and performance-based) to non-adapted instruction with vector addition motion problems in the domain of 11th grade kinematics. The results showed that both of these adaptive groups through a verification method coupled with mental effort ratings outperformed the non-adapted group on knowledge gains, spent less mental effort and less instruction time, and showed higher instructional efficiency.

**Bimodal process-oriented WOE**

To reduce unnecessary cognitive load imposed on novices, Kalyuga (2006a) and Kalyuga and Sweller (2005) used a typical WOE as an instructional intervention. A typical or product-oriented WOE provides a problem state, solution steps, and a goal state but does not include the rationale for the solution steps (van Gog, Paas, & van Merriënboer, 2004). In contrast, a process-oriented WOE states not only the solution steps, but also the rationale behind those steps. That is, it includes the “why” information in order to explain functions of operators and the “how” information in order to inform learners of the strategic knowledge used by experts. Such information is useful particularly at the initial training stage when students lack domain knowledge. It increases learners’ understanding of problem solving and encourages schema construction and automation (van Gog et al., 2004).

In designing a process-oriented WOE, the modality effect needs to be considered; otherwise, the effectiveness of learning from the process-oriented WOE could be moderated by inefficient design of WOE. According to Baddeley and Hitch (1974), working memory has two components, the phonological loop and the visual-spatial sketchpad and these two channels partly independently process auditory or visual information. Thus, if the process-oriented WOE is presented as a bimodal WOE, by allocating “why” and “how” information into auditory and visual channels rather than dedicating them to one channel, the learner is able to off-load some of the cognitive processing from the overloaded visual channel to the not-overloaded verbal channel (Mayer & Moreno, 2010). Many empirical studies have provided supports for the superiority of multimodal presentation of information (Moreno & Mayer, 2002; Mousavi, Low, & Sweller, 1995). However, Tabbers, Martens, and van Merriënboer (2004) have shown different results that replacing visual text with spoken text does not always improve learning; they found no modality effect. Tabbers et al. (2004) argued that in a learner-paced system, the visual-only condition was more effective as the learners with the visual-only instructions had more time to relate the text to the picture and could jump back and forth through the text more easily than with spoken text instruction. These mixed results need to be clarified.

**The purpose of the study**

Kalyuga (2006a), and Kalyuga and Sweller (2005) showed the possibility and promising potential of adaptive instructions to learner expertise in e-learning environments, but there is lack of research available to confirm and generalize their findings. Further research in other areas, in particular, complex cognitive skill acquisition, is necessary to generalize their findings. Typical complex cognitive skills have both recurrent and non-recurrent components (van Gog et al., 2004). The solution steps of complex problems are not easy to be specified in advance as recurrent algorithmic skills have a narrow problem space but non-recurrent skills have multiple possible solution paths (van Gog et al., 2004). In these cases, a rapid verification method may be more appropriate to probe changing levels of learner expertise in adaptive e-learning environments.

Their adaptive instructions could be further improved with a bimodal process-oriented WOE. If problems under instructions are complex, a typical WOE is not enough to facilitate schema construction and automation. In contrast, a bimodal process-oriented WOE provides necessary information for schema construction and automation in a cognitively efficient way. According to the modality effect, the utilization of the bimodal process-orientated WOE is expected to effectively expand working memory capacity, thereby resulting in learning enhancement. However, the utilization of the bimodal process-oriented WOE has not been investigated in adaptive instructions in e-learning environments. Furthermore, there is a study reporting that the modality effect was not found in a learner-paced
system as opposed to other studies supporting the modality effect. Theses mixed results need be clarified. Therefore, the purpose of this experimental study is to test the efficiency of adaptive instruction to learner expertise based on efficiency measures in a complex problem-solving e-learning environment. The rapid verification method was utilized for cognitive diagnosis coupled with a subjective mental effort rating to calculate the efficiency measures. In addition, we investigated whether a bimodal process-oriented WOE could effectively control cognitive load and further improve instructional efficiency in the learner-paced e-learning environments. The specific research question for this purpose was “How do the different instruction methods (adaptive and fixed instruction) and the modality of WOE (bimodal and unimodal) affect participants’ knowledge acquisition, mental effort, and instructional efficiency?"  

Method

Participants

One hundred and twelve students who enrolled in one of the four sessions of basic computer programing classes at a four-year teachers college in 2012 spring semester were invited to participate in this study. One instructor taught all the classes. When 112 students logged on to the website developed for this experiment, the system randomly assigned them into one of the four groups, adaptive instruction and bimodal group (AB), adaptive instruction and unimodal group (AU), fixed instruction and bimodal group (FB), and fixed instruction and unimodal group (FU). Each experimental group was expected to have an equal sample size, but random loss of a few subjects caused unequal sample size; 5 students did not complete the experiment, and 9 students participated more than once. Thus, 2 students, one from the AB group and one from the FU group, were randomly deleted to make all the four groups have equal samples. Thus, data from 96 students were prepared for statistical analyses (24 for each group, 71 female, 25 male). Their age ranged from 20 to 39 (M = 23.68) and they were all juniors. Their majors ranged from Music, Mathematics, Science, Physical Education, to Practical Art.

Experimental materials

Task classes and sub-steps of problems

The content area in this experiment was C programming language. The desired exit-behavior of learning was for students to be able to write a basic source program with C programming language appropriately. This complex cognitive skill has both recurrent and non-recurrent components. Since the participants were novices in this area, the overall complexity of the learning materials was adjusted to a very basic level. There were three complexity levels (task classes), if-else statement, if-else compound statement, and while statement with if-else statement. The problems in each task class had three sub-steps: verify an appropriate flow chart; declare variables; and express if-else or if-else compound, or while statements based on the flow chart chosen.

Bimodal and unimodal process-oriented WOE

Two types of process-oriented WOE were constructed, bimodal process-oriented WOE (visual and auditory mode) and unimodal process-oriented WOE (visual-only mode). For the unimodal WOE, all the information including the rationale of the solution steps was visually presented (see Figure 1). For the bimodal WOE, as seen in Figure 2, the rationale coordinated with the flow chart of the unimodal WOE was removed and instead, a control box was presented to play an audio file. Both WOE have three sub-steps and each sub-step was used as a heading as seen in Figure 1and 2. Both the WOE presented all the sub-steps at the beginning of the training session and for smooth transitions from learning from the WOE to problem solving, rather than abrupt changes in cognitive demand from WOE to the to-be-solved problems, their sub-steps were progressively faded backward (see Table 1). Two types of the process-oriented WOE occurred only in the training session. In the learning phase, all the participants studied only with the unimodal process-oriented WOE.
Table 1. Faded WOE during the training session

<table>
<thead>
<tr>
<th>Task Class1</th>
<th>Task Class2</th>
<th>Task Class3</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td>W</td>
<td>W</td>
<td>W</td>
</tr>
<tr>
<td>1.1</td>
<td>2.1</td>
<td>3.1</td>
</tr>
<tr>
<td>1.2</td>
<td>2.2</td>
<td>3.2</td>
</tr>
<tr>
<td>1.3</td>
<td>2.3</td>
<td>3.3</td>
</tr>
</tbody>
</table>

**Note.** P: Problem  W: Worked-Out Example

Subjective mental effort

A 9-point Likert scale rating was utilized to measure mental effort. This subjective rating scale are based on the assumption that participants are able to reflect on and report their mental effort expenditure (Paas, Tuovinen, Tabbers, & van Gerven, 2003). The scale used in this study was the same form employed in the studies of Kalyuga (2006a), and Kalyuga and Sweller (2005). Learners were asked to rate their perceived mental effort with semantically different scales varying from extremely easy (1) to extremely difficult (9) (see Figure 3).

Problem solving e-learning environment

The problem solving e-learning environment was developed and its structure is presented in Figure 4. As seen in Figure 4, it contained pretests, learning phase, initial diagnostic tests, training sessions, mental effort rating for the
whole training session, and final diagnostic tests. The participants could access this learner-paced e-learning environment from IBM compatible PCs, anywhere if they have an Internet access. This whole learning package was developed by the author consulting leading C programming language books and reviewed thoroughly by several graduate students in the field of Computer Education. Then, the whole package was inspected by an instructor who has taught C programming language for the last three years. With this reviewed materials, this problem solving e-learning environment was developed using PowerPoint, HTML, PHP, MySQL, and JSP. Then, it was field-tested with a group of graduate students ($N = 12$). They were also asked to check clarity and wording of the whole package. Their feedback was incorporated and this e-learning environment was finalized.

<table>
<thead>
<tr>
<th>Pretests</th>
<th>Learning phase</th>
<th>Initial diagnostic tests</th>
<th>Training session</th>
<th>Mental effort rating</th>
<th>Final diagnostic tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>adaptive and bimodal WOE</td>
<td>fixed and unimodal WOE</td>
<td>fixed and unimodal WOE</td>
</tr>
</tbody>
</table>

*Figure 4. Structure of the problem-solving e-learning environment*

**Login page**

The login page was developed to collect the participants’ background information such as name, student number, gender, age, major and experience with C programming language.

**Pretests**

The pretest was designed to assess participants’ prior knowledge in C programming language and consisted of 10 multiple-choice questions.

**Learning phase**

In this phase, the learners studied brief explanations of C programming language and if-else statement, if-else compound statement, and while statement with if-else. Each explanation of the three statements was followed with one WOE paired with one conventional problem to practice. All WOE's and conventional problems consisted of a sequence of three sub-steps. The participants were allowed to move back to the previous pages by clicking on the “Prev.” button in this learning phase.

**Initial diagnostic tests**

The initial diagnostic test consisted of three problems (one problem from each task class). Each was designed as a sequence of three sub-steps. The rapid verification method was employed to assess learner expertise as the task involved graphical information and included both non-recurrent and recurrent skills. A 9-point mental effort rating scale was presented to measure mental effort after the participants clicked on an answer for every question (see Figure 3). The first sub-step question for each problem provided a flow chart and asked the learners to choose one of the three options, “correct”, “incorrect” and “don’t knows” (see Figure 5). For the next two sub-steps, four multiple-choice recognition questions were utilized due to the technical difficulty to make verification questions with long source programs. They were asked to choose one of the four alternatives for the blanks in the problem (see Figure 6 and 7). These sub-steps were scored differently. For the first sub-step, score 1 was allocated for a correct response. For the second sub-step, score 2 was allocated and for the third sub-step, score 3 was allocated for a correct answer. As the second and the third sub-steps required the participants to maintain the results of the previous step in working memory to mentally determine the values of the current stage, their scores became cumulative. Thus, if a learner chose correct answers for all the sub-steps, the allocated maximum score was 6 ($1+2+3 = 6$).
The first sub-step of problem 2 in the initial diagnostic tests

The second sub-step of problem 2 in the initial diagnostic tests

The third sub-step of problem 2 in the initial diagnostic tests

Training session

The training session included nine stages and each of three stages corresponded to each task class. Each stage contained a fully or faded worked-out example, one conventional problem solving, one diagnostic test, and a mental effort rating (see Figure 8). In the fixed instruction groups, the participants followed the fixed sequence from stage 1 to stage 9 without any repetition. In contrast, in adaptive instruction groups, the initial placement for an appropriate
training stage occurred according to the efficiency measure based on the simple threshold-based definition discussed before (Kaluga, 2006a). The participants started the training session from the stage corresponding to either the first initial diagnostic question not answered correctly or the first mental effort rating of 5 or above in the initial diagnostic tests. For example, if a learner chose a wrong answer or rated mental effort as 5 or both for problem 1.2 (the second sub-step of problem1) in the initial diagnostic tests, she or he started the training from the stage 2 of the training session. During the training session, repetitions occurred based on the results of the diagnostic test taken at the end of each stage. If participants correctly answered a diagnostic test and rated the mental effort as 4 or below, they advanced to the next stage. However, if they did not select a correct answer, or rated mental effort as a 5 or above, or both, they studied the same stage again. After the second try, the participants advanced to the next stage regardless of their answer and mental effort rating. After checking an answer or rating mental effort, the learners received messages such as “Good job, click on the next button”, “Good job, but it seemed difficult for you. Study the next problem.” If they incorrectly answered the test on the second try regardless of their mental effort rating, a correct answer was provided with the following feedback, “Incorrect. The right answer is ______. Study the next example.” The fixed instruction groups also took all the diagnostic tests and rated all the mental effort, but their results were not used for the adaptation. After the participants finished the training session, a mental effort scale for the whole training session appeared. This mental effort rating was identical to the mental effort rating used before except for the wording. This one point assessment asked the participants to rate the mental effort invested during the entire training session.

![Figure 8. Structures of the stages during the training session](image)

**Final diagnostic tests**

The final diagnostic tests had exactly the same underlying structure as the initial diagnostic tests, but they were different problems containing dissimilar surface characteristics. Similar to the initial diagnostic tests, the final diagnostic tests contained three problems, one from each task class, and each problem has three sub-steps followed by a rating of subjective mental effort.

**Procedures**

This experiment was conducted as an assignment for one week. They individually participated in this experiment whenever and wherever they have an Internet access and computer. They earned 10% of the course credit on the basis of accomplishment of the whole learning package. The URL of the e-learning environment was provided to the participants by one instructor in class with specific instructions. Although there was no time limit controlled by the system, the participants were instructed to complete the whole program in two hours. This instruction was given in order to minimize any possible interruption in the middle of their learning. They were also instructed to try this
program only once, not to share their experience with other students and not to earn any assistance from other books or through the Internet. They were also informed of two types of programs, a text version and a text and audio version. They were instructed that as the system tailored the following questions according to their performance, if they did not know an answer, they had to select the “Don’t know” option. This instruction was given to minimize random selection of answers. All the participants’ responses were automatically recorded into a database created for this experiment. If participants were chosen for the bimodal WOE conditions, when they were on an instruction page for the training session, they could see a speaker icon and words saying, “There are audio files, so please prepare earphones.”

Research design and data analyses

The design of this study is a 2 by 2 factorial design. The two factors are the instruction methods (adaptive and fixed instructions) and the modality of WOE (bimodal and unimodal WOE). The dependent measures under the analyses were the pretest results, knowledge acquisition, mental effort, and instructional efficiency. Knowledge acquisition was computed by subtracting the initial diagnostic test scores from the final diagnostic test scores for each participant. The instructional efficiency was calculated as the ratios of knowledge acquisition to ratings of mental effort for the whole training session. PASW statistics 18 were used to perform ANOVA and ANCOVA. One-way ANOVA was conducted to compare group differences in the pretest results. The pretest mean scores of the four groups were not significantly different \( [F (3, 92) = 0.60, p = .62] \). All dependent variables were initially analyzed with a two-way, between-subjects ANCOVA, taking the pretest results as a covariate. According to the results, the covariate revealed no significant relation to the dependent variables of knowledge acquisition, instructional efficiency, and instruction time, so the results from ANOVA were reported for these dependent variables. On the other hand, as the pretest results revealed significant relation to the dependent variables, the mental effort for the whole training session and during the final diagnostics tests, the results from ANCOVA were reported for those dependent variables.

Results and discussion

Is adaptive instruction more efficient than fixed instruction?

The adaptive instruction groups showed significantly higher instructional efficiency than the fixed instruction groups \( [F (1, 92) = 4.68, p = .03, \eta_p^2 = .048] \) (see Table 2). In addition, there were significant differences in mental efforts for the whole training session and during the final diagnostic tests between the groups \( [F (1, 91) = 6.53, p = .01, \eta_p^2 = .067, F (1, 91) = 7.77, p = .01, \eta_p^2 = .079] \). However, there was no significant difference in knowledge acquisition \( [F (1, 92) = 0.34, p = .56] \). Learner expertise is associated not only with higher levels of performance but also with lower levels of cognitive load. As experts’ available knowledge structures in long-term memory could significantly reduce working memory demands, individuals with more expertise are able to attain equal or higher levels of performance with less investment of mental effort (Sweller, J., Ayres, P., & Kalyuga, S, 2011). Thus, it is likely that the level of expertise of the adaptive instruction groups in the domain of C programming language was higher after training than their counterpart. The significant difference in the mental effort during the final diagnostic tests supports this assumption as well. It implies that the learners who managed to acquire more knowledge during the training as a result of a more efficient instructional format experienced less cognitive load in test situations than learners who received a less efficient instructional format. Therefore, as expected, the effort to optimize the cognitive load according to the individual trajectory of cognitive skill acquisition successfully controlled cognitive load, thereby resulting in schema construction and automation. In addition, the rapid verification method coupled with a subjective mental effort rating seemed to probe the levels of learner expertise instantly and adequately in adaptive e-learning environments.

This result is consistent with the current literature on adaptive instructions within CLT. The study of Kalyuga and Sweller (2005) showed that the learner-adapted group to learner expertise showed significantly higher efficiency gain (Cohen’s \( d \) effect size, 0.69) and significantly higher knowledge gain (Cohen’s \( d \) effect size, 0.55). In addition, in Kalyuga’s (2006a) study, the learner-adapted group to learner expertise demonstrated a significantly lower mental effort and higher instructional efficiency than the non-adapted group, but there were no statistically significant
differences in knowledge acquisition. He argued that this lack of statistically significant differences between the experimental groups in knowledge acquisition could be due to a single training session. Likewise, in this study, the average amount of time the students spent in the training session was 24.4 min. More prolonged instructional events than a single training session may amplify knowledge acquisition of learners. From a slightly different perspective, Camp, Paas, Rikers, and van Merriënboer (2001) and Salden, Paas, Broers, & van Merriënboer, (2004) investigated adaptive instructions. They examined the assumption that the dynamic problem selection through efficiency measures would lead to more efficient training and better transfer than non-dynamic problem selection and dynamic problem selection based on performance or mental effort alone. These studies were primarily concerned with gradual increases in task difficulty rather than determining levels of guidance based on efficiency measures. However, their results also showed that the dynamic problem selection led to more efficient training than non-dynamic problem selection. Overall, the finding of this study provided the evidence that efficiency-based adaptation can be successfully and efficiently used to individualize instructional procedures in the domain of C programming language.

### Table 2. Effects of instruction methods on the dependent variables

<table>
<thead>
<tr>
<th>Knowledge acquisition</th>
<th>Mental effort</th>
<th>Instructional efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>M (TS)</td>
<td>M (FD)</td>
<td>M</td>
</tr>
<tr>
<td>Adaptive</td>
<td>3.81</td>
<td>2.54</td>
</tr>
<tr>
<td>Fixed</td>
<td>3.35</td>
<td>2.19</td>
</tr>
</tbody>
</table>

Note. TS: Mental effort for the whole training session; FD: Mental effort during the final diagnostic tests

---

**Is the bimodal process-oriented WOE more efficient than the unimodal process-oriented WOE?**

There was no significant difference on knowledge acquisition between the bimodal and the unimodal WOE groups ($F(1, 92) = 0.34, p = .56$). There were no significant differences in both mental efforts for the whole training session and during the final diagnostic tests ($F(1, 91) = 0.50, p = .48, F(1, 91) = 3.88, p = .05, \eta^2_p = .041$) and in instructional efficiency, either ($F(1, 92) = 0.38, p = .54$). Although no statistical support was found, as seen Table 3, the bimodal WOE groups acquired more knowledge, invested lower mental effort and showed higher instructional efficiency. In addition, the main effect of the modality of WOE on mental effort during the final diagnostic tests almost reached a significant level. This almost significant difference seems to imply that the learners who experienced less cognitive load and thereby managed to acquire more knowledge during the training experienced less cognitive load in test situations. Thus, it is fair to say that the bimodal WOE is more efficient than the unimodal WOE.

This finding is in line with the literature demonstrating the modality effect (Kalyuga, Chandler, & Sweller, 2000; Moreno & Mayer, 2002; Mousavi et al, 1995). In contrast, Tabbers et al. (2004) found that college students in the visual-only condition performed better than students in the audio condition on both retention and transfer tests and their interpretation for this reverse modality effect was that ecological classroom setting, longer studying time (more than an hour) and more procedure subject matter might have caused a reverse modality effect. In addition, they argued that a bimodal presentation was only advantageous when the instruction was system-paced whereas the visual-only instructions were the preferred format if the learners were in control. However, this study was not conducted in a laboratory setting and the participants spent a relatively longer time during a training session. The contents had both non-recurrent and recurrent components (procedural information) (van Merriënboer, Kirschner, & Kester, 2003) and the e-learning environment used was learner-paced. In spite of these similar experimental conditions, this study showed the modality effect.

### Table 3. Effects of modality of WOE on the dependent variables

<table>
<thead>
<tr>
<th>Knowledge acquisition</th>
<th>Mental effort</th>
<th>Instructional efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>M (TS)</td>
<td>M (FD)</td>
<td>M</td>
</tr>
<tr>
<td>Bimodal</td>
<td>3.81</td>
<td>3.59</td>
</tr>
<tr>
<td>Unimodal</td>
<td>3.35</td>
<td>2.31</td>
</tr>
</tbody>
</table>

Note. TS: Mental effort for the whole training session; FD: Mental effort during the final diagnostic tests
Is there any interaction effect between instruction methods and modality of WOE?

There were no significant interaction effects between two factors on knowledge acquisition \([F (1, 92) = 0.28, p = .60]\), both mental efforts for the whole training session and during the final diagnostic tests \([F (1, 91) = 0.13, p = .72]\), and instructional efficiency \([F (1, 92) = 0.05, p = .83]\). As seen in Table 4, the bimodal process-oriented WOE group in the adaptive instruction showed the highest knowledge acquisition, lowest mental effort, and highest instructional efficiency. On the contrary, the unimodal WOE group in the fixed instruction showed lowest knowledge acquisition, highest mental effort, and lowest instructional efficiency. Thus, as expected, the bimodal process-oriented WOE provided necessary information for understanding in a cognitively efficient way, and as a result, utilization of the bimodal process-oriented WOE further improved the efficiency of the adaptive instruction.

| Table 4. Interaction effect of instruction methods and modality of WOE on the dependent variables |
|-----------------------------------------|---|---|---|---|---|---|---|
|                                      | Knowledge acquisition | Mental effort | Instructional efficiency |
|                                      | M (TS) | SD (TS) | M (FD) | SD (FD) | M | SD |
| adaptive                            |       |         |        |         |   |    |
| Bi                                  | 4.25  | 3.17    | 4.51   | 2.73    | 25.90 | 17.54 |
| Uni                                 | 3.38  | 3.61    | 4.60   | 2.38    | 31.40 | 18.03 |
| fixed                               |       |         |        |         |   |    |
| Bi                                  | 3.38  | 4.15    | 5.47   | 2.36    | 34.22 | 14.29 |
| Uni                                 | 3.33  | 4.38    | 6.05   | 1.99    | 42.12 | 18.57 |

Note. TS: Mental effort for the whole training session; FD: Mental effort during the final diagnostic tests; Bi: bimodal WOE, Uni: unimodal WOE

Conclusions and limitations

This study added evidence that tailoring instruction to the level of learner expertise through efficiency measures can be successfully used in e-learning environments in the domain of C programming language with college students. The adaptive instruction efficiently optimized cognitive load to the level of learner expertise and the efficiency measures based on the rapid verification method and its associated level of cognitive load successfully probed levels of learner expertise. Furthermore, the bimodal process-oriented WOE successfully controlled cognitive load and improved instructional efficiency further even in a learner-paced adaptive e-learning environment. These findings yield some important implications for future study. First, further research in the condition under which the modality effects occur is necessary to uncover more sophisticated design principles in e-learning environments. Second, this study focused on knowledge acquisition (near transfer), but left out a possible effect on far transfer. The bimodal process-oriented WOE may yield effects on efficiency in far-transfer tasks. The issue of near and far transfer should be addressed in forthcoming studies. Third, the effects of the adaptive instruction with the bimodal WOE should be examined over a long extended period. The average amount of time for the training session was 24.4 min in this study. This length seemed too short to cause changes in learner knowledge structure. A prolonged practice may yield effects on knowledge acquisition. Finally, complex problems usually include both recurrent and non-recurrent components and it is not easy to make verification questions for non-recurrent components to probe learners’ knowledge structure activated in their long-term working memory. More research on solid diagnostic tests for non-recurrent components, at the same time appropriate for e-learning environments, is therefore necessary.

As a limitation of this study, the reliability estimates for both initial and final diagnostic tests did not prove to be sufficiently high. Each diagnostic test consisted of 9 questions and the relatively low reliability estimate was probably due to this very small number of test items. In addition, this experiment was conducted as an assignment. Specific instructions were given by the instructor to prevent any possible interruptions during their participation. However, interruptions happening in the middle of participations that could influences experimental results either positively or negatively could not be totally controlled for. The findings of this study are particularly important as excessive cognitive load prohibits a successful learning experience. Therefore, despite the limitations, insight gained through this study may inform instructional designers seeking to enhance their understanding of efficient instructional design within the CLT framework.
References


