Selecting Learning Tasks: Effects of Adaptation and Shared Control on efficiency and task involvement

Open Universiteit
www.ou.nl

Running head: ADAPTIVE TASK SELECTION WITH SHARED CONTROL

Selecting Learning Tasks: Effects of Adaptation and Shared Control on

Learning Efficiency and Task Involvement

Gemma Corbalan*, Liesbeth Kester, Jeroen J. G. van Merriënboer

Educational Technology Expertise Center,

Open University of the Netherlands, Heerlen, The Netherlands

----

* Correspondence concerning this article should be addressed to Gemma Corbalan, Open University of the Netherlands, Educational Technology Expertise Center, P.O. Box 2960, 6401 DL, Heerlen, the Netherlands. E-mail: gemma.corbalan@ou.nl

Abstract

Complex skill acquisition by performing authentic learning tasks is constrained by limited working memory capacity (Baddeley, 1992). To prevent cognitive overload, task difficulty and support of each newly selected learning task can be adapted to the learner's competence level and perceived task load, either by some external agent, the learner herself, or both. Health sciences students ($N = 55$) participated in a study using a 2x2 factorial design with the factors adaptation (present or absent) and control over task selection (program control or shared control). As hypothesized, adaptation led to more efficient learning; that is, higher learning outcomes combined with less effort invested in performing the learning tasks. Shared control over task selection led to higher task involvement, that is, higher learning outcomes combined with more effort directly invested in learning. Adaptation also produced greater task involvement.

KEYWORDS

Selecting Learning Tasks: Effects of Adaptation and Shared Control on Learning Efficiency

and Task Involvement

In addition to incorporating authentic learning tasks, which are based on real-life tasks,

modern educational approaches often aim at adapting a sequence of learning tasks to the

needs of each individual learner (Kalyuga & Sweller, 2005; Renkl & Atkinson, 2003).

Rather than one predetermined pathway for all learners, such approaches allow each

learner to follow her own course through the curriculum. This study addresses the

questions how adaptation of task selection can be realized, and which agent, that is,

computer program or learner should be responsible for it.

Especially for novice learners, the acquisition of complex skills by performing

authentic or real-life tasks is heavily constrained by the limited processing capacity of

working memory because such tasks easily cause cognitive overload (Baddeley, 1992;

Sweller, 1988). Within the framework of cognitive load theory, three types of cognitive load

are identified: intrinsic, extraneous and germane load (Sweller, 1988; Sweller, van

Merriënboer, & Paas, 1998; van Merriënboer & Sweller, 2005). Intrinsic load is inherent to a

learning task and depends on the number of interacting elements that have to be related,

controlled, and kept active in working memory during task performance. For example,

learning vocabulary and speaking in a foreign language cause low and high intrinsic load,

respectively. Extraneous and germane load are the result of the instructional design.

Extraneous load is ineffective load due to poorly designed instructional material, resulting,

for example, from the need to combine information from different sources to complete a

learning task. Germane load occurs when load is imposed by processes that are directly

beneficial for learning. For instance, a high variability in a set of learning tasks may stimulate

learners to construct more integrated cognitive schemata. In the current study, task load is

seen as a combination of intrinsic and extraneous load, that is, all load caused by *performing*

the task but not directly caused by learning processes. In contrast, germane load is caused by *learning* to perform the task.

Cognitive load can be measured in several ways. Paas, Tuovinen, Tabbers, and van Gerven (2003) describe three different techniques including subjective measures, secondary-task methods, and psychophysiological measures. With regard to subjective measures, cognitive load researchers have commonly measured cognitive load as perceived mental effort (Paas et al., 2003). Self-ratings of invested mental effort measured after task performance have been widely used and quickly accepted amongst cognitive load researchers because they are unintrusive, reliable, relatively easy to use and analyze, and provide a good indication of the overall cognitive load a task imposed (Paas & van Merriënboer, 1994; Paas et al., 2003). Possible limitations such as socially desirable ratings and the tendency to keep answering in the same manner (Richman, Kiesler, Weisband, & Drasgow, 1999) are usually overcome through randomized or counterbalanced design.

In order to enable the use of authentic tasks in education, and yet prevent overloading the learners' cognitive system, task characteristics should be adapted to the individual needs of learners (Corno & Snow, 1986; Kalyuga & Sweller, 2005; Park & Lee, 2003; Salden, Paas, Broers, & van Merriënboer, 2004; van Merriënboer & Luursema, 1996; van Merriënboer, Schuurman, de Croock, & Paas, 2002). Two approaches to individualization that aim to cope with increasingly complex learning situations are program control, in which a computer program is responsible for the process of selecting new learning tasks, and learner control, in which the learner controls the selection of tasks (Corbalan, Kester, & van Merriënboer, 2006).

The issue of the locus of instructional control, whether it is external (i.e., program control) or internal (i.e., learner control), has been a primary concern in the upsurge of computer-assisted instruction (Lawless & Brown, 1997; Tennyson & Buttery, 1980). First,

according to models of *program-controlled instruction*, learning is influenced by the characteristics of the learners (Zimmerman, 2002) and the learning tasks (Lawless & Brown, 1997). Intelligent Tutoring Systems (ITS) are adaptive problem-solving environments which make a distinction between: (a) a domain model representing the domain that must be learned, (b) a student model representing what the learner is already able to do or not yet able to do, and (c) a computer program which makes instructional decisions in response to input from the learner (Corbett, Koedinger, & Hadley, 2001; Park & Lee, 2003). Using ITS may reduce both training time and costs, which is particularly interesting for domains in which these aspects are of great importance, as in aviation and industry (Camp, Paas, Rikers, & van Merriënboer, 2001). In addition, technology-based instruction has the potential to become an important resource to improve learning in K-12 classrooms. However, still few ITSs have become successfully implemented products to enhance learning, especially in K-12 settings (Wong, Chan, Chou, Heh, & Tung, 2003), probably because they are difficult and costly to develop, although attempts are being made to address these challenges (e.g., Beal, 2004).

Second, besides program-controlled instruction, there is an increasing emphasis on providing learners with control over their own learning path. *Learner-controlled instruction* assumes that learners are able to monitor their own learning processes and that this will accommodate individual differences. Giving learners some control over instructional aspects creates the necessary preconditions for practicing self-regulation skills and is a first step towards teaching those skills (Kinzie, 1990). Technological advances make it possible to implement types of computer-assisted instruction such as simulations and microworlds, which are multimedia learning tools that provide users with dynamic elements that are under their control. Whereas simulations are more aligned with traditional instructional uses of educational software and allow learners to run experiments, microworlds take a more constructivist approach and allow learners, for instance, to design their own experiments

(Rieber, 2005). Both simulations and microworlds provide learners with considerable

freedom in choosing aspects of learning such as the content, the sequence, and the pace of the

instruction (Bell & Kozlowski, 2002).

This study focuses on adaptive task selection with shared control, in which a

computer program and the learner share control over the selection of learning tasks. In this

two-step process, the computer program first selects a subset of learning tasks with

characteristics (difficulty, available support) that are adapted to the needs of the individual

learner (program control). Second, the learner selects from this subset one task to work on

(learner control). We hypothesize that adaptive task selection with shared control will have a

positive influence on both learning efficiency (i.e., computed by the combination of learning

outcomes and task load), due to the task adaptation made by the computer program, and task-

involvement (i.e., computed by the combination of learning outcomes and germane load), due

to the fact that the learner feels to be in control over her own learning. In this introduction,

the advantages and disadvantages of program control and learner control are described first.

Then, adaptive task selection with shared control is discussed.

Adaptive Task Selection with Program Control

Good instruction accommodates relevant individual differences among learners

(Shute & Towle, 2003). A predefined and fixed sequence of learning tasks cannot take the

different levels of competence, misconceptions, interests, and learning styles of a

heterogeneous group of learners into account. But with adaptive task selection with program

control, the program may dynamically adapt the task characteristics of each newly selected

learning task to the characteristics of the individual learner.

With regard to learner characteristics, measuring a learner's competence and

cognitive load is essential for the adaptive selection of new learning tasks. First, competence

refers to the combination of knowledge, skills, and attitudes that allows for the performance

of real-life tasks (Baartman, Bastiaens, Kirschner, & van der Vleuten, 2007; van Merriënboer, 1997). Eraut (1994) stresses that skills cannot be separated from knowledge, as this would exclude the practical know-how to perform real-life operations. Hence, the assessment of competence requires a combination of assessment methods (Baartman et al., 2007). Second, assessing the cognitive load imposed by the performance of a certain task may provide additional insight into the learner's needs. For example, if after one task two learners shows the same competence level but one learner reports higher task load than the other, the first learner is best supported by presenting her with a new learning task which is easier or provides more support than is required by the second learner. The combination of performance and task load has been proposed by Paas and van Merriënboer (1993) as a reliable estimate of the relative *efficiency* of learning. According to this approach, efficiency is high if performance is higher than might be expected on the basis of the invested mental effort required to perform the task. Conversely, efficiency is low if performance is lower than might be expected on the basis of the invested mental effort to perform the task.

With regarding to task characteristics, in a well-designed curriculum learning tasks are ordered from easy to difficult, and learner support decreases as the learners' competence increases (van Merriënboer, 1997; van Merriënboer, Clark, & de Croock, 2002; van Merriënboer & Kirschner, 2007). Accordingly, in this study the *difficulty* and *support* of selected learning tasks are adapted to the characteristics of each individual learner (i.e., level of competence and perceived task load). In terms of cognitive load theory, the difficulty of a task determines the intrinsic cognitive load, which is a direct result of the complex nature of the learning material. Tasks should be selected that are neither too difficult nor too easy for the learner. Two studies in the Air Traffic Control domain which adapted the level of difficulty (Camp et al., 2001; Salden et al., 2004) showed that adaptive task selection based

on competence and cognitive load yielded better learning outcomes than a fixed task
sequence.

Furthermore, the amount of embedded support may determine the extraneous load.
When novices start working on a range of complex tasks, it is essential to provide them with
support, which gradually diminishes in a process of 'scaffolding' as their competence
increases. The 'completion strategy' (van Merriënboer, 1997, van Merriënboer & Kirschner,
2007) is a powerful approach to scaffolding and is commonly used in on-line learning
environments as well as in traditional classrooms. In this approach, tasks with a particular
level of difficulty are organized from worked-out examples, via completion tasks, to
conventional tasks. First, worked-out examples confront learners not only with a description
of a given state and the criterion for an acceptable goal state, but also with a description of all
solution steps. Then, completion tasks provide learners not with all solution steps but with a
partial solution that must be completed by them. Finally, conventional tasks provide learners
with a given state and a criterion for an acceptable goal state only: learners must
independently generate the whole solution. Experienced learners have relevant knowledge
that enables them to approach a conventional task. However, when novice learners in a
domain are confronted with conventional tasks, they use cognitively demanding strategies
such as means-ends analysis and working backward to reach a solution, increasing extraneous
cognitive load because those strategies are not efficient ways to learn (Renkl, Stark, Gruber,
& Mandl, 1998; Sweller, 1988).

The 'expertise reversal effect' (Kalyuga, Ayres, Chandler, & Sweller, 2003) states
that successful instructional techniques for novice learners (e.g., presenting tasks with high
embedded support) often lose their value when used with more experienced learners. For
instance, presenting a diagram with integrated textual explanations may be an effective
technique for novice learners who need the explanations to understand the diagram. However,

experienced learners who already possess the knowledge necessary to understand the diagram must invest cognitive resources unnecessarily before they can determine that the information is redundant. Such redundant cognitive processing constitutes extraneous cognitive load, which may hinder learning. In a study carried out by Kalyuga and Sweller (2005), both the level of difficulty and the level of support were adapted to learner's competence and cognitive load ratings. Learners in the adaptive group showed higher gains in algebraic skills from pretest to posttest, and higher gains in efficiency compared to learners in a control group. The research reported in this article also adapts the level of difficulty and the level of support to the individual learner's competence level and perceived task load. However, we will use another measure of competence and another selection table for choosing tasks, and we provide learners with some control over the - final - selection of learning tasks.

Although adaptive task selection with program control may have positive effects on learning efficiency (i.e., higher learning outcomes combined with lower task load, that is, less effort invested in performing the tasks), it also has clear limitations. Program control over task selection leaves learners with no freedom of choice, which may negatively affect their motivation, specifically their task involvement and interest. One way to overcome this problem is to give learners some control over the selection of learning tasks, which has positive effects on motivation (Kinzie & Sullivan, 1989; Ross, Morrisin, & O'Dell, 1989; Schnackenberg & Sullivan, 2000).

Task Selection with Learner Control

Recent instructional theories advocate on-demand methods of education in which learners are given freedom over their own learning path (Bell & Kozlowski, 2002; Schnackenberg & Sullivan, 2000; Williams, 1996). This is in line with the presented study, in which learner control explicitly refers to control over *task selection*. Merrill (1994) suggested that by providing control, learners will acquire more effective ways of learning and become

better equipped to adapt to diverse situations. Learner control is typically perceived as something which will enhance motivation, and consequently may increase learning outcomes (Reeves, 1993). Motivated learners engage in learning activities and allocate cognitive resources to learning because they derive satisfaction from performing the task (Deci, Vallerand, Pelletier, & Ryan, 1991). The invested mental effort and its associated learning outcomes have been recognized as an indicator of the learners' *involvement* in a task (Paas, Tuovinen, van Merriënboer, & Darabi, 2005). Accordingly, learner control, amongst other elements, is considered as a determinant of intrinsic motivation to learn (Deci & Ryan, 1985). When intrinsically motivated, learners engage in activities out of *interest* (Deci, et al., 1991).

First, with regard to the learner's task involvement, the effort invested in learning processes is a direct indicator of motivation (Keller, 1983). Thus, learner control, amongst other factors, may increase learners' task involvement. Learners involved in learning are more inclined to be engaged in learning processes such as exploration, abstraction, and generalization (van Merriënboer, 1997), and will invest more mental effort in the construction of cognitive schemata (Keller, 1983; Paas et al., 2005). This enhanced engagement may positively influence learning outcomes (Greene & Miller, 1996). If learners attribute 'achieving better outcomes' to 'higher mental effort invested', they will perceive a higher self-efficacy in implementing the required actions to perform such tasks, affecting motivation positively (Bandura, 1997; Keller, 1983; Kinzie, Sullivan, & Berdel, 1988; Zimmerman, 2000). In this study, the effort invested in learning (i.e., germane load) is used to compute task involvement.

Until now, cognitive load theorists have typically focused on comparing instructional formats in terms of their efficiency. However, the importance of motivation for learning has not been sufficiently explored. According to Paas et al. (2005), mental effort and performance have both cognitive and motivational components. Consistent with the efficiency approach,

Paas et al. (2005) proposed a complementary approach to calculate the relative task involvement in instructional conditions. According to this approach, the higher the learner's task involvement, the higher the mental effort directly invested in learning (i.e., germane load), which is likely to enhance learning outcomes.

Second, the learner's level of interest is another important motivational factor (Keller, 1983). When the learning environment gives learners the opportunity to explore, interest is more likely to be retained. Educational researchers have identified two types of interest, namely, personal and situational interest (Alexander & Jetton, 1996; Hidi, 2001, 2006; Hidi & Renninger, 2006). Personal interest develops slowly over time, is internally oriented, and of enduring personal value. Situational interest is transitory, external, and environmentally triggered. Personal interest most likely results from repeated experiences and develops over time, whereas situational interest can be increased by, for instance, emphasizing learners' choices (Schraw, Flowerday, & Lehman, 2001) as is intended in the current study. Accordingly, learner control is expected to make learning more interesting (Fry, 1972; Kinzie & Sullivan, 1989; Lahey, Hurlocj, & McCann, 1973), with potential benefits for learning outcomes (Wolters, 2003; Zimmerman, 2002). A study in the math domain carried out by Cordova and Lepper (1996) revealed that participants in the choice conditions (i.e., participants who were given control over irrelevant aspects of the tasks) reported liking the program significantly more and scored significantly higher than those in the no-choice conditions.

Despite the apparent beneficial effects of learner control on learning, novices generally lack the necessary knowledge to make effective educational decisions and may omit essential aspects of learning (Merrill, 2002). It is also apparent that learner control may introduce potential problems with cognitive load. Even highly experienced task performers with full control may become overwhelmed by a (too) high amount of choice, hampering

their learning (Iyengar & Lepper, 2000; Schwartz, 2004). In addition, Niemiec, Sikorski, and Walberg (1996) argue that as the level of experience increases, it is appropriate to decrease program control and increase learner control (provided that the amount of choice provided is not excessive, for example, by providing hundreds of tasks to choose from). In this respect, several studies (Fry, 1972; Gay, 1986) showed that with learner control, learners with low prior knowledge learned significantly less than learners with high prior knowledge. Hence, giving (perceived) control to learners does not always lead to higher performance, but can positively affect motivation (Fry 1972; Judd, 1972; Lahey, 1976; Lahey et al., 1973). Accordingly, we discuss an alternative approach that combines the benefits of program control and learner control over task selection, namely, adaptive task selection with shared control.

Adaptive Task Selection with Shared Control

Both program control and learner control over task selection may have beneficial effects on learning. However, a high level of program control may negatively affect learners' task involvement and interest. A high level of learner control may overwhelm even expert learners if the number of tasks to choose from is (too) large. The present study combines program and learner control into a task-selection approach with shared control. In this two-step approach, the *program* first uses a measure of the individual learner's competence level and task load ratings to select from an existing database with learning tasks a subset of tasks with an optimal level of *difficulty* and an optimal level of *support*. All the tasks in the selected subset have the same difficulty and the same level of support. They only differ in *surface* features, that is, aspects of the task that are not related to goal attainment, such as the color of the eyes of a person in dietetic problems (i.e., which deal with the relationship between body weight and energy expenditure). In the second step, the learner makes the final selection of one task from the pre-selected subset of tasks. Thus, the learner may select one task with the

surface features she prefers. As an illustration of this two-step process, take a learner who has solved a dietetics task with a particular level of difficulty (e.g., difficulty level 4 of a range of 5 levels) and a particular level of support (e.g., highest support level 1 of a range of 4 levels). The learner performs reasonably well (e.g., 7 out of 10 points) and reports a moderately low task load (e.g., 3 out of 7 points). According to predefined task-selection rules, the program now first presents the learner three tasks which have the same difficulty (e.g., again at difficulty level 4) but a lower level of support (e.g., now *without* support, that is, support level 4 rather than support level 1 as for the previous task). The three pre-selected tasks in the subset have varying surface task features, such as the subject's age and habits. In the second step of the task-selection process, the learner then selects the task with her preferred surface features from the pre-selected subset.

We hypothesize that adapting the difficulty and the embedded support of the learning tasks to the level of competence and invested load of the learner will make learning more effective (i.e., higher learning outcomes) and more efficient (i.e., higher learning outcomes combined with less effort invested in performing the learning tasks). Moreover, it is hypothesized that the greater perceived control offered by shared control will have positive effects on learners' motivation, depicted by increased task involvement, that is, higher germane load combined with higher learning outcomes. This in turn is also expected to positively affect learner interest in the learning tasks and the training program as a whole.

Method

Participants

Fifty-five first year students (13 males and 42 females; mean age = 22.40 years, *SD* = 7.27) in Dutch Vocational Education and Training (VET) in the Health Sciences domain participated in the experiment. Learners had no prior knowledge in dietetics which was the learning domain used in the experiment. All participants were entered into a lottery making

them eligible to win one of 18 music compact disks. Participants were randomly assigned to one of the four experimental conditions in a 2x2 factorial design: adaptation with shared control ($n = 15$); non-adaptation with shared control ($n = 12$); adaptation with program control ($n = 15$), and non-adaptation with program control ($n = 13$).

Materials and Measurements

Training Phase

Learning-task database. The learning-task database contained tasks of five difficulty levels in the dietetics domain. Each difficulty level comprised five levels of embedded support. Each level of support contained three different tasks with varying irrelevant surface features.

There were five *levels of difficulty* (1 to 5), defined in cooperation with three domain experts. Each subsequent, more difficult level included a new element or a combination of new elements increasing the difficulty of the task. In level 1, participants used their *own* data to calculate changes in their body weight over time, taking energy intake and energy expenditure as input variables. This made the task more personally relevant and helped participants to get acquainted with the material. In level 2, participants were required to identify the changes in body weight of a *specific person* over time, based on energy intake and energy expenditure. Subject characteristics were predetermined in the learning task. This required learners to transfer the learned procedures to an unfamiliar situation. In level 3, participants had to investigate the differences in body weight and the factors influencing *fat percentage* (a new element) between a man and a woman of the same age, height, weight and pattern of activities. In level 4, participants had to simulate three *different strategies* for the treatment of obesity which required more solution steps, and concluded which strategy was most appropriate. In addition, participants inferred what happens to body weight when a person on a diet returns to her original habits (a new factor - body adaptation to the new

situation after following a diet - plays a role). In level 5, participants studied the effects of smoking on the body weight of a given person. This implied taking another additional input variable, the increase of the *basal metabolism rate,* into account. Moreover, learners had to simulate the effects on body weight when the same person stopped with smoking, which decreased the basal metabolism rate. This required learners to simulate the same person in the simulator taking body changes as well as the decrease of basal metabolism rate into account.

There were also five *support levels,* differing with regard to the amount of embedded support, and diminishing in a process of 'scaffolding' according to the completion strategy described earlier (van Merriënboer, 1997). The five levels, ordered from high to low support, are: (1) worked-out examples that included both full product support (i.e., all the solution steps and the 'expert' solution are given) and process support (i.e., the 'why' or the rationale behind the solution steps is given), (2) worked-out examples or learning tasks that provided full product support but no process support, (3) completion problems with high support or learning tasks that provided many but not all solution steps, (4) completion problems with low support or learning tasks that provide a few solution steps, and (5) conventional problems or learning tasks that did not provide any support.

Within each level of difficulty (except for difficulty level 1, in which learners used their own data), three different tasks with different *surface features* that did not influence the difficulty or support levels (i.e., different persons with different characteristics, such as age, habits, appearance and background) were included. Figure 1 shows a learning-task database that combines different levels of difficulty, five levels of embedded support, and three task features per support and difficulty level.

[Insert Figure 1 about here]

Electronic learning environment. The learning environment was a Web application written in the popular web scripting language PHP and especially developed for the current

study. A MySQL database connected to the learning environment contained all learning tasks, registered competence and cognitive load measures, a selection table for making a pre-selection of tasks, and various kinds of logging information. In the electronic learning environment participants were presented with (a) a Web application in which the learning tasks in the domain of dietetics were presented, and (b) a simulator called "Body Weight", which allowed learners to retrieve and process the necessary data to perform the presented learning tasks. The learning environment was a Web application connected to the learning-task database and contained the following instruments to gather information on learner behavior: (a) practice multiple-choice questions, (b) performance measures of operating the simulator (i.e., whether learners use the relevant windows in the simulator to reach the solution, such as the 'eating meter' or the 'physical activity meter' to calculate the amount of calories gathered by energy intake or burned by energy expenditure, respectively), and (c) cognitive load measures for task load and germane load. In the Body Weight simulator, participants could look up the energy in kilojoules of a specific drink or type of food, estimate the energy expenditure of a person, or simulate changes in a person's body weight and body composition using energy intake, energy expenditure, and other parameters as input variables.

In the adaptive/program-control condition, the level of difficulty and the level of support of selected tasks were based on the learner's competence and task-load scores, and one task with randomly selected surface features was presented to the learner. In the adaptive/ shared-control condition, the level of difficulty and the level of support of selected tasks were again based on the learner's competence and task-load scores, but now three tasks with different surface features were presented to the learner, so that the learner could make a final selection from these three tasks. In the non-adaptive/program-control condition, each learner was paired (i.e., *yoked*) to one learner in the adaptive/program-control condition and received

exactly the same sequence of tasks as his or her yoked counterpart. In the non-adaptive/shared-control condition, each learner was paired to a learner in the adaptive/shared-control condition and received the same subset of tasks as his or her yoked counterpart.

Competence (C). After each learning task, participants received six multiple-choice questions (with three answering options) to measure acquired knowledge. Each correct answer scored 100 points / 6 questions = 16.67 points. Furthermore, an assessment tool monitored the relevant windows opened in the simulator to assess the accuracy on actual performance. This was calculated by counting the number of opened windows proportional to the number of windows that had to be opened to correctly complete the learning task. Scores could range from 0% of correct windows opened (0 points) to 100% correct windows opened (100 points). For instance, if four windows had to be opened to correctly complete the task and the learner opened only two of them, the score would be $100/4 = 25 * 2 = 50\% = 50$ points. Competence was measured with the formula (60 * score on multiple choice questions) + (40 * score on correct windows opened) / 100), leading to a minimum score of 0 and a maximum score of 100. This measure allows for real-time assessment of a learner's competence, weighting knowledge measures and actual performance. The weight of the knowledge measure is somewhat higher than the weight of the actual performance, because knowledge is seen as a prerequisite for the ability to open the correct windows.

Task load (L). After each learning task, task load was measured with a one-item 7-point rating scale as the 'effort required to perform the task', ranging from a very small amount of effort (1) to a very high amount of effort (7). The internal consistency of the test was $\alpha = .93$ (Cronbach's alpha). The task load is used to make task-selection decisions in the adaptive conditions and to compute the learning efficiency as described in a later section.

Selection table. In the two adaptive conditions, the MySQL database connected to the learning environment contained a selection table (see Table 1). The selection table indicated

the 'jump size' or progression from one level of support to another level of support, and from one difficulty level to another difficulty level. Competence and task load scores are used as a learner variable for dynamic task selection. This approach has also been successfully used in other studies (Camp et al., 2001; Salden et al., 2004). To correct for extreme values, the mean of the competence measure on the last learning task and the previous learning task was computed with a higher weight for the last learning task (70%) than for the previous learning task (30%), leading to a minimum score of 0 and a maximum of 100.

[insert Table 1 around here]

To compute the jump size (J), task load scores (TL) are subtracted from competence scores (C). The higher the competence score and the lower the task load, the larger the positive jump size. For instance, a score of 5 on competence and 2 on task load yields a jump size of +3 (i.e., $5 - 2 = 3$), meaning that the level of support *decreases* three levels (e.g., from a worked-out example with product support to a conventional problem). If there are less than three support levels available at the current difficulty level, the learner will move to the lowest support level (i.e., a conventional task) because the learner is only allowed to progress to the next difficulty level after successful completion of a conventional task (i.e., a task without embedded support). That is, only once the learner has successfully solved a conventional task at a particular difficulty level, s/he is considered to master the required competence level and is allowed to proceed to the next, higher difficulty level. Accordingly, the lower the competence level and the higher the task load, the larger the negative jump size. For instance, a score of 2 on competence and 5 on task load yields a backward jump of 3 steps (i.e., $2 - 5 = -3$), meaning that the level of support *increases* three levels. But, if there are less than three support levels available at the current difficulty level, the learner will move back to the highest level of support (i.e., a worked example with process and product support) at the current difficulty level.

The selection table also applies some additional rules: If the computed jump size is negative *and* the competence score is 5 or higher (rule a), or if the computed jump size is negative *and* the task-load score is 2 or lower (rule b), the learner will not jump backwards (i.e., the adjusted jump size = 0) because an easier task or a task with more embedded support may not be challenging enough. Additionally, if the computed jump size is positive *and* the competence score is 3 or lower (rule c), or if the computed jump size is positive *and* the task-load score is 6 or higher (rule d), the learner will not jump forward (i.e., the adjusted jump size = 0) because a more complex task or a task with less embedded support may overwhelm the learner. In Table 1, these additional rules yield a jump size of 0.

Germane load. After each task, germane load was measured with a one-item 7-point rating scale as the 'effort invested in gaining understanding of the relationships dealt with in the simulator and the task', ranging from minimum effort (1) to maximum effort (7). The participants were not instructed on how to rate task load versus germane load. The reliability of the germane load measures reported during training was $\alpha = .95$ (Cronbach's alpha). Germane load directly reflects the effort a participant has invested in learning and is used to compute task involvement (see below).

Training time. The database connected to the learning environment tracked the time (in minutes) participants spent during training.

Test Phase

Learning outcomes. Learning outcomes were measured with a conceptual knowledge test consisting of 20 multiple-choice questions, administered to the participants after the training. All questions had three alternative answers that were presented in a random order. The test assessed participants' understanding of the dietetics domain (i.e., reasoning with effects of alterations in energy intake, physical activity, and other factors such as gender and smoking on body weight and body composition). An example item is:

Anouk has started smoking. Will her Basal Metabolism Rate (BMR) be affected?

a) Yes, her BMR will increase.

b) Yes, her BMR will decrease.

c) No, her BMR will remain the same.

Three items were not included in the analysis, because one item had an item difficulty value (*p*) of 1 and two items had a negative item-test correlation. Item difficulty (*p)* is defined as the proportion of participants who answer an item correctly (Crocker & Algina, 1986). A *p*-value of 1 means that 100% of the participants answered this item correctly. This means that the correct answer was probably too obvious. The maximum test score was thus 17 points. The internal consistency of the test was $\alpha = .63$.

Learning efficiency. The Paas and van Merriënboer procedure (1993; Marcus, Cooper, & Sweller, 1996; Paas et al., 2003) was used to calculate the efficiency of the instructional conditions. First, learning outcomes (i.e., the score on the conceptual knowledge test) and task-load scores for each participant are transformed into *z*-scores, using the grand mean across conditions. Then, the mean *z*-scores for every condition are represented in a Cartesian coordinate system with task load *z*-scores on the horizontal axis and learning outcomes *z*-scores on the vertical axis The line *LO = TL* through the origin indicates a neutral efficiency. The efficiency, *E,* is calculated as the perpendicular distance from a data point in the coordinate system to the line *LO = TL* (Paas & van Merriënboer, 1993). The formula for calculating this distance is:

$$\text{Learning Efficiency} = \frac{z_{\text{Learning Outcomes}} - z_{\text{Task Load}}}{\sqrt{2}}$$

Task involvement. The computation of task involvement (Paas et al., 2005) was analogous to the computation of learning efficiency. Now, learning outcomes and

germane load (GL) scores are transformed into *z*-scores using the grand mean across conditions. The task involvement is calculated as the perpendicular distance from a data point in the coordinate system to the line *LO = – GL*. The formula for calculating this distance is:

$$\text{Task Involvement} = \frac{z_{\text{Learning Outcomes}} + z_{\text{Germane Load}}}{\sqrt{2}}$$

Interest scale. After each task in the practice session, learners completed a 7-point rating scale that measured *interest-in-task* with the statement 'I found the computer lesson interesting', ranging from strongly disagree (1) to strongly agree (7). In addition, in the test phase participants answered a questionnaire that measured their *interest-in-training*. The questionnaire contained 7 items from the interest/enjoyment subscale of the Intrinsic Motivation Inventory (IMI; Deci, Eghrari, Patrick, & Leone, 1994) (e.g., *"I would describe the computer lesson as very interesting"*, *"While I was carrying out the computer lesson, I was thinking about how much I enjoyed it")*, which was translated from English into Dutch by Martens and Kirschner (2004). The interest questionnaire had a reliability of .92 (Cronbach's alpha).

Procedure

Introduction. One week before the computer session, all participants participated in an oral introductory session in which both the learning environment and the functioning of the simulator "Body Weight" were presented and explained in a Microsoft® PowerPoint® presentation. In addition, participants were given a short introduction to the dietetics domain. During this introduction the participants could ask questions and the experimenter made sure that the whole procedure was clear to all participants before the actual experiment started.

Training phase. During the training phase participants worked in the learning environment on the learning tasks, using the body weight simulator. Participants were not informed on how the tasks were selected or preselected (for the program-control and the

shared-control conditions, respectively). The first learning task at the first level of difficulty was used as a practice task, in which all participants could practice with their own data. Competence and task-load scores for the second task (i.e., a conventional task at difficulty level 1) were assessed and used as the first input for task selection. After each task, competence measures were taken and participants indicated on 7-point rating scales the amount of task load and germane load they perceived while working on the learning task. It was emphasized that they were not allowed to skip any part of the answer of the competence and cognitive load questions. If they did, the program prompted them to answer the questions before they could continue. During the training phase the time spent by the participants was logged.

Test phase. One week after the computer session, participants were presented with the paper-and-pencil conceptual knowledge test to measure learning outcomes and the interest questionnaire to assess their interest in the training phase. During the test phase participants were allowed to work at their own pace.

<div align="center">Results</div>

A significant main effect of adaptation was found on training time (i.e., the total amount of time spent on all learning tasks), $F (1, 51) = 39.59$, $p < .001$, $MSE = 619.42$, $\eta^2_p = .437$. Participants in the adaptive conditions spent more time on training ($M = 129.68$, $SD = 23.29$) than participants in the non-adaptive conditions ($M = 87.30$, $SD = 25.95$). No effects on training time were found for control or the interaction between adaptation and control. Therefore, ANCOVA's with total training time as a covariate are used in the subsequent analyses and estimated marginal means are presented. For all statistical tests a significance level of .05 was maintained. Table 2 provides an overview of the training results.

<div align="center">[Insert Table 2 about here]</div>

Training Phase

Competence scores. A significant main effect of adaptation was found on the competence scores, $F(1, 50) = 16.51$, $MSE = 305.25$, $p < .001$, $\eta^2_p = .248$. Participants in the adaptive conditions achieved higher competence scores ($M = 73.56$, $SD = 15.46$) than participants in the non-adaptive conditions ($M = 47.97$, $SD = 18.87$). No effects on the competence scores were found for control or the interaction between adaptation and control.

Task load. Similarly, a significant main effect of adaptation was found on task load during training, $F(1, 50) = 4.42$, $MSE = 1.04$, $p < .05$, $\eta^2_p = .081$. Participants in the adaptive conditions experienced a lower task load ($M = 3.07$, $SD = 1.14$) than participants in the non-adaptive conditions ($M = 3.85$, $SD = .93$). No effects on task load were found for control or the interaction between adaptation and control.

Germane load. A significant main effect of control on germane load during training was found, $F(1, 50) = 4.46$, $MSE = 0.55$, $p < .05$, $\eta^2_p = .082$. Participants in the shared-control conditions reported higher mental effort in learning ($M = 4.49$, $SD = .77$) than participants in the program-control conditions ($M = 4.07$, $SD = .75$). No effects on germane load were found for adaptation or the interaction between adaptation and control.

Test Phase

Not all participants filled out the conceptual knowledge test. Only the data of participants who completed the conceptual knowledge test and the interest questionnaire ($n = 50$) were used in the analysis. The number of participants that dropped out was evenly distributed over the conditions ($X^2 = .38$, $p = .95$). Table 3 provides an overview of results from the test phase.

[Insert Table 3 around here]

Learning outcomes. A significant main effect of adaptation was found on learning outcomes, $F(1, 45) = 4.28$, $MSE = 4.06$, $p < .05$, $\eta^2_p = .087$. Participants in the adaptive conditions scored higher ($M = 13.55$, $SD = 2.07$) than participants in the non-adaptive

conditions ($M = 11.98$, $SD = 2.27$). No significant effects on the test scores were found for control or the interaction between adaptation and control.

Learning efficiency. A significant main effect of adaptation was found on learning efficiency, $F(1, 45) = 6.25$, $MSE = 0.98$, $p < .025$, $\eta^2_p = .122$. As hypothesized, participants in the adaptive conditions showed higher efficiency scores ($M = .44$, $SD = 1.03$) than participants in the non-adaptive conditions ($M = -.49$, $SD = .91$). No effects on learning efficiency were found for control or the interaction between adaptation and control.

Task involvement. Similarly, a significant main effect of control was found on task involvement, $F(1, 45) = 5.37$, $MSE = 0.70$, $p < .025$, $\eta^2_p = .107$. As hypothesized, participants in the shared-control conditions showed higher task involvement ($M = .25$, $SD = 1.05$) than participants in the program-control conditions ($M = -.30$, $SD = 1.02$). Moreover, a significant main effect of adaptation was found on task involvement, $F(1, 45) = 7.81$, $p < .025$, $\eta^2_p = .148$. Participants in the adaptive conditions showed higher task involvement ($M = .41$, $SD = 0.92$) than participants in the non-adaptive conditions ($M = -.47$, $SD = .84$). No effects on task involvement were found for the interaction between adaptation and control.

Interest

Table 4 presents the mean scores for interest-in-task (measured for each learning task during practice) and the interest-in-training (measured with the interest questionnaire in the test phase). No significant differences between conditions were found.

[Insert Table 4 about here]

Discussion

The first hypothesis of this study that adapting the difficulty and support of the learning tasks to the learners competence scores and perceived task load would make learning more effective and efficient was clearly confirmed by the findings. The learning outcomes of participants who received adaptive training were higher, and they experienced a lower task

load during practice than participants who received non-adaptive training. In addition, competence scores of participants in the adaptive conditions were also superior to competence scores of their yoked counterparts. Adaptive training may have reduced the task load during practice to an acceptable level, and therefore, participants may have used their freed-up cognitive resources for learning.

Some comments should be made with regard to the higher training time for participants in the adaptive conditions. These participants may have noticed the relationship between their performance and the difficulty and/or embedded support of the subsequent tasks, whereas participants in the non-adaptive conditions probably lacked this association, which might have negatively influenced their time investment. Since total training time could have influenced the results, all reported analyses included time as a covariate.

The second hypothesis that shared control has positive effects on learner motivation was partially confirmed by the data. Participants in the shared-control conditions showed higher task involvement. In other words, the choice provided positively influenced the amount of effort invested in learning, combined with higher learning outcomes. An explanation is that these participants perceived that their effort was well invested and were thus motivated to invest germane load. Furthermore, task variability can be seen as a strategy to gain the learner's attention (Keller, 1983). Hence, the relative variability provided by the three tasks presented in the shared control conditions may have further contributed to the positive effect on germane load. However, the absence of a significant effect of shared control on learning outcomes may indicate that the variability of the characteristics of the presented tasks may not have been large enough. A higher degree of variability might have yielded a significant effect on learning outcomes in favor of the shared control conditions. In addition, the fact that learner control did not yield higher learning outcomes seems to support the idea that learners with lower levels of competence in a domain lack the ability to make

productive use of learner control. In this study, learners cannot be considered to have a substantive level of competence, for which longer exposure to the learning materials (e.g., weeks) than provided in this study would be needed. Nevertheless, because in our study shared control was provided over the surface features only, which are irrelevant aspects for goal attainment, any interpretation regarding the potential effects of control on learning outcomes can only be made from a motivational rather than a cognitive perspective.

Another interesting finding pertained to the positive effect of adaptation on task involvement. Providing learners with an appropriate amount of embedded support may have a positive influence on their task involvement, because it prevents the cognitive load of a learning task from becoming too high to perform the task. If this load is too high the learners will lose motivation to continue working on the task (de Croock & van Merriënboer, 2003). In addition, learners provided with an optimum level of task difficulty might be willing to invest effort in learning (i.e., germane load), which in combination with higher learning outcomes indicates higher task involvement. That is, adaptation lowered perceived task load as expected, and prevented learners of being demotivated. This might well explain why the observed differences between perceived task load and perceived germane load ratings seem to be higher for the adaptive conditions than for the non-adaptive conditions. To sum up, our main results are clearly in favor of adaptive instruction with shared control as expected.

Whereas participants in the shared control conditions showed a higher task involvement, they did not report a higher interest in the learning tasks or in the training. A possible explanation is again related to the limited amount of learner control available. Providing learners with a wider range of tasks to choose from could have revealed differences in interest amongst the experimental conditions. Another feasible reason may be that interest is evoked when learners are given more opportunities for exploration within the learning environment. Participants in the shared control condition were presented with three tasks to

choose from, but once the task was selected, the actual performance of the task involved precisely the same activities as the preselected task in the program control conditions. Other studies (e.g., Overskeid & Svartdal, 1996; Reeve, Hamm & Nix, 2003; Schraw, Flowerday, & Reisetter, 1998) reported that when provision of choice is the *only* aspect involved to enhance motivation, this may not positively affect interest in the learning tasks. In contrast, a study by Cordova and Lepper (1996) included other aspects (such as internal locus of control and volition) and found that participants reported liking the training more. Hence, the provision of learner control over task selection may be considered as only one aspect to enhance interest, which needs to be combined with other aspects to become effective. For example, other factors such as the pace of instruction or the learner's background knowledge may influence interest, as well as motivation and perceived task difficulty.

Although shared control did not arouse learners' interest and learners did not report liking or enjoying the instruction more, positive results on task involvement indicate that learners still persisted in investing effort to learn from the tasks. Furthermore, that shared control was beneficial for task involvement but not for interest seems to support Paas et al.'s (2005) argument that combining cognitive load and performance measures offers a supplementary approach to inventories that collect motivational data and, in addition, yields information that is not directly reflected in performance-based data. Whereas in this study the constructs of mental effort and performance are considered to have motivational as well as cognitive components (Paas et al., 2005), one may argue that the fact that no effects were found on task involvement (which is measured by the combination of these constructs) but not on interest may be due to this operationalization of task involvement which relies more on cognitive than on motivational constructs.

Our results are consistent with cognitive load theory, which states that an optimal instructional design should decrease extraneous and intrinsic cognitive load and encourage

learners to use their freed-up cognitive resources for learning (that is, increase germane cognitive load). From a cognitive load perspective, providing learners with tasks that differ on a number of relevant dimensions from previous learning tasks may increase germane load and improve the construction of cognitive schemata. In our study, extraneous and intrinsic load were successfully reduced by adapting the level of difficulty and support to a learner's competence and task-load scores, and task involvement was induced by providing shared control, recognizing the important role of motivation in designing instruction. These findings are consistent with the results of several studies in other domains that have tailored the difficulty level (Camp et al., 2001; Salden et al., 2004) and both the difficulty level and the level of support (Kalyuga & Sweller, 2005) based on performance scores and cognitive load ratings in the domains of Air Traffic Control and algebra. Hence, initial instruction of a complex skill in educational settings can be facilitated by designing and adapting instruction according to cognitive load theory. Future studies may test the applicability of the adaptive approach in other domains, especially in less structured areas, such as language monitoring comprehension in online reading tutors (Kalyuga, & Sweller, 2005).

Assessment of complex performance must include several qualitatively distinct aspects (e.g., breadth and depth of an integrated and organized knowledge base, the possession and implementation of flexible problem-solving strategies, learners' self-monitoring skills, or categorical diagnosis of problems) to obtain valid and reliable information. In our study, learners competence scores were only based on answers to multiple-choice questions and performance measures of operating the simulator. The use of more advanced process-tracking methods, such as concurrent verbal protocols, retrospective reporting, and eye tracking would provide more sensitive indicators of a learner's competence and her understanding of the rationale behind the steps performed, and will thus further refine the basis for adaptive task selection, which in turn may provide superior

learning results. Furthermore, our study used task load and competence measures for task selection purposes. In future research, germane load might be considered as an additional factor for task selection. A high germane load indicates that the learner is investing a substantial part of her available cognitive resources in learning. A selection table that incorporates this type of load should therefore aim to keep it as high as possible. For example, when competence is (relatively) high, a learner who reports a high germane load should not receive a less difficult task or a task with more support, but rather progress to a higher difficulty level or a lower lever of support more rapidly than a learner who reports a low germane load. This guarantees that every subsequent task is challenging for the learner. Such a refined selection table including germane load might be expected to be superior to the selection table used in the current study, in which we tried to keep the subsequent tasks challenging by adding a rule that prescribed not to select a less difficult task or a task with more support when the competence-score was 5 or higher and the task load was 2 or lower.

Concerning the measurement of cognitive load, theorists are faced with the challenge to distinguish the different types of cognitive load through self-reporting instruments. In this respect, Opfermann, Gerjets, and Scheiter (2005) found preliminary differential effects in a study in which cognitive load was measured with six items that assessed the different types of cognitive load on a 9-point Likert scale. Our findings also indicate that learners seem to be able to distinguish between task load, which may be seen as a combination of intrinsic and extraneous load, and germane load.

With regard to the learning outcomes, two remarks should be made. First, the multiple-choice questions might have been relatively easy for the participants who scored moderately high in all conditions. More complex test questions could have increased differences between the experimental conditions. Second, learning outcomes were only

measured with the conceptual knowledge test. In future research, transfer tasks should also be used to measure participants' learning outcomes.

To conclude, the results of this study indicate that adapting the difficulty and support of selected tasks to the learner's level of competence and task load and providing learners with some control over the process of task selection is advisable. Adaptive task selection yielded more effective and efficient learning. In addition, shared control enhanced learners' motivation. Further research is needed to determine ways to control extraneous and intrinsic cognitive load and to optimize germane load, for example, by providing learning tasks that differ on a number of relevant dimensions from previously presented learning tasks to ensure a high variability which helps learners to construct new schemata, with positive effects on learning.

References

Alexander, P. A., & Jetton, T. L. (1996). The role of importance and interest in the processing of text. *Educational Psychology Review,* 8, 89–121.

Baartman, L. K. J., Bastiaens, T. J., Kirschner, P.A., & van der Vleuten, C. P.M. (2007). Evaluating assessment quality in competence-based education: A qualitative comparison of two frameworks. *Educational Research Review, 2,* 114-129.

Baddeley, A. D. (1992). Working memory. *Science, 255,* 556-559.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman.

Beal, C. R. (2004). Adaptive user displays for intelligent tutoring systems. *CyberPsychology and Behavior,* 7, 689-693.

Bell, B. S., & Kozlowski, S. W. J. (2002). Adaptive guidance: Enhancing self-regulation, knowledge, and performance in technology-based training. *Personnel Psychology,* 55, 267-306.

Brna, P., & Cox, R. (1998). Adding intelligence to a learning environment: Learner-centred design? *Journal of Computed Assisted Learning,* 14, 268-277.

Camp, G., Paas, F., Rikers, R., & Van Merriënboer, J. J. G. (2001). Dynamic problem selection in air traffic control training: A comparison between performance, mental effort, and mental efficiency. *Computers in Human Behavior*, 17, 575-595.

Corbalan, G. Kester, L., & van Merriënboer, J. J. G. (2006). Towards a personalized task selection model with shared instructional control. *Instructional Science, 34,* 399-422.

Corbett, A. T., Koedinger, K. R., & Hadley, W. H. (2001). Cognitive Tutors: From the research classroom to all classrooms. In P. S. Goodman, eds, *Technology Enhanced Learning: Opportunities for Change*, pp. 235-263. Mahwah, NJ: Lawrence Erlbaum Associates.

Cordova, D. I., & Lepper, M. R. (1996). Intrinsic motivation and the process of learning: Beneficial effects of contextualization, personalization, and choice. *Journal of Educational Psychology, 88,* 715-730.

Corno, L., & Snow, R. E. (1986). Adapting teaching to individual differences among learners. In M. C. Wittrock (Ed.). *Handbook of research on teaching* (3rd ed.) (pp. 605-629). New York: MacMillan.

Crocker, L, & Algina, J. (1986). *Introduction to classical & modern test theory.* New York: Holt, Rinehart and Winston, Inc.

Deci, E. L., & Ryan. R. M. (1985*). Intrinsic Motivation and Self-determination in Human Behaviour.* New York: Plenum.

Deci, E. L., Eghrari, H., Patrick, B. C., & Leone, D. (1994). Facilitating internalization: The self-determination theory perspective. *Journal of Personality, 62,* 119-142.

Deci, E. L., Vallerand, R. J., Pelletier, L. G., & Ryan, R. M. (1991). Motivation and education: The self-determination perspective. *Educational Psychologist, 26,* 325-346.

De Croock, M., & Van Merriënboer, J. J. G. (2003, April). *TASKI: A system to adapt 4C/ID training programs to a learners' learning capability.* Paper presented at the annual meeting of the American Educational Research Association, Chicago.

Eraut, M. (1994). *Developing professional knowledge and competence.* London: Routledge Falmer.

Fry, J. P. (1972). Interactive relationship between inquisitiveness and learner control of instruction. *Journal of Educational Psychology, 63,* 459-465.

Gay, G. (1986). Interaction of learner control and prior understanding in computer-assisted video instruction. *Journal of Educational Psychology, 78,* 225-227.

Green, B. A., & Miller, R. B. (1996). Influences on achievement: Goals, perceived ability,

and cognitive engagement. *Contemporary Educational Psychology,* 21, 181-192.

Hidi, S. (2001). Interest, reading and learning: Theoretical and practical considerations.

Educational Psychology Review, 13, 191–210.

Hidi, S. (2006). Interest: A unique motivational variable. *Educational Research Review, 1,*

69-82.

Hidi, S., & Renninger, K. A. (2006). The four-phase model of interest development.

Educational Psychologist, 41, 111-127.

Iyengar, S. S., & Lepper, M. (2000). When choice is demotivating: Can one desire too much

of a good thing?. *Journal of Personality and Social Psychology, 79*, 995-1006.

Judd, W. A. (1972). *Learner-controlled computer-assisted instruction*. ERIC #ED 072-635.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect.

Educational Psychologist, 38, 23-31.

Kalyuga, S., & Sweller, J. (2005). Rapid dynamic assessment of expertise to improve the

efficiency of adaptive e-learning. *Educational Technology, Research and*

Development, *53*, 83-93.

Keller, J. M. (1983). Motivational design of instruction. In C. M. Reigeluth (Ed.),

Instructional-design theories and models: An overview of their current status (pp.

383-436). Hillsdale, NJ: Erlbaum.

Kinzie, M. B. (1990). Requirements and benefits of effective interactive instruction: Learner

control, self-regulation, and continuing motivation. *Educational Technology,*

Research & Development, 38, 5-21.

Kinzie, M. B., & Sullivan, H. J. (1989). Continuing motivation, learner control, and CAI.

Educational Technology, Research and Development, 37, 5-14.

Kinzie, M. B., Sullivan, H. J., & Berdel, R. L. (1988). Learner control and achievement in science computer-assisted instruction. *Journal of Educational Psychology, 80,* 299-303.

Lahey, G. F. (1976). *Leaner-control of lesson strategy: A model for PLATO IV system lessons.* ERIC #ED 125-543.

Lahey, G. F., Hurlock, R. E., & McCann, P. H. (1973). *Post-lesson remediation and learner control of branching in computer-based learning*. ERIC #ED 083-797.

Lawless, K. A., & Brown, S. W. (1997). Multimedia learning environments: Issues of learner control and navigation. *Instructional Science, 25,* 117-131.

Marcus, N., Cooper, M., & Sweller, J. (1996). Understanding instructions. *Journal of Educational Psychology,* 88, 49-63.

Martens, R. L., & Kirschner, P. A. (2004, October). *What predicts intrinsic motivation?*. Paper presented at the annual meeting of the Association for Educational Communications and Technology, Chicago.

Merrill, M. D. (1994). *Instructional design theory*. Englewood Cliffs, NJ: Educational Technology Publications.

Merrill, M. D. (2002). Instructional strategies and learning styles: Which takes precedence?. In R.A. Reiser, & J.V. Dempsey, eds, *Trends and Issues in Instructional Technology*. Upper Saddle River, NJ: Merrill Prentice Hall.

Niemiec, P., Sikorski, C., & Walberg, H. (1996). Learner-control effects: A review of reviews and a meta-analysis. *Journal of Educational Computing Research,* 15(2), 157-174.

Opfermann, M., Gerjets, P., & Scheiter, K. (2005, August). Exploration of hypermedia environments: Learner control and adaptive user strategies. Paper presented at the Learning and Instruction (EARLI). Nicosia, Cyprus.

Overskeid, G., & Svartdal, F. (1996). Effects of reward on subjective autonomy and interest when initial is low. *The Psychological Record,* 46, 319-331.

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skills in statististics: A cognitive-load approach. *Journal of Educational Psychology,* 84, 429-434.

Paas, F., Tuovinen, J., Tabbers, H., & Van Gerven, P.W.M. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist,* 38, 63-71.

Paas, F., Tuovinen, J., Van Merriënboer, J. J. G., & Darabi, A. (2005). A motivational perspective on the relation between mental effort and performance: Optimizing learner involvement in instruction. *Educational Technology, Research and Development,* 53, 25-34.

Paas, F., & Van Merriënboer, J. J. G. (1993). The efficiency of instructional conditions: An approach to combine mental-effort and performance measures. *Human Factors,* 35(4), 737-743.

Park, O., & Lee, J. (2003). Adaptive instructional systems. In D. H. Jonassen (Ed.), *Handbook of research for educational communications and technology* (2nd ed.) (pp. 651-684). Mahwah, NJ: Erlbaum.

Reeve, J., Hamm. D., & Nix, G. (2003). Testing models of the experience of self-determination in intrinsic motivation and the conundrum of choice. *Journal of Educational Psychology,* 95, 375-392.

Reeves, T. C. (1993). Pseudoscience in computer based instruction: The case of learner control research. *Journal of Computer Based Instruction, 20(2),* 39-46.

Renkl, A., & Atkinson, R. K. (2003). Structuring the transition from example study to

problem solving in cognitive skills acquisition: A cognitive load perspective.

Educational Psychologist, 38, 15-22.

Renkl, A., Stark, R., Gruber, G., & & Mandl, H. (1998). Learning from worked-out examples:

The effects of example variability and elicited self-explanations. *Contemporary*

Educational Psychology, 23, 90-108.

Richman, W., Kiesler, S., Weisband, S., & Drasgow, F. (1999). A meta-analytic study social

desirability distortion in computer-administered questionnaires, traditional

questionnaires, and interviews. *Journal of Applied Psychology*, 84, 754-775.

Rieber, L. P. (2005). Multimedia learning in games, simulations, and microworlds. In R.

Mayer (Ed.), The Cambridge handbook of multimedia learning (pp. 549-567). New

York: Cambridge University Press.

Ross, S. M., Morrison, G. R., & O'Dell, J. K. (1989). Uses and effects of learner control of

context and instructional support computer-based instruction. *Educational*

Technology, Research and Development, 37, 29-39.

Salden, R. J. C. M., Paas, F., Broers, N. J., & van Merriënboer, J. J. G. (2004). Mental effort

and performance as determinants for the dynamic selection of learning tasks in air

traffic control training. *Instructional Science*, 32, 153-172.

Schnackenberg, H. L., & Sullivan, H. J. (2000). Learner control over full and lean computer-

based instruction under differing ability levels. *Educational Technology, Research*

and Development, 48, 19-35.

Schraw, G., Flowerday, T., & Lehman, S. (2001). Increasing situational interest in the

classroom. *Educational Psychology Review,* 13, 211-224.

Schraw, G., Flowerday, T., & Reisetter,, M. F. (1998). The role of choice in reader

engagement. *Journal of Educational Psychology,* 90, 705-714.

Schwartz, B. (2004). *The paradox of choice: Why more is less.* New York: Ecco.

Shute, V., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist,* 38, 105-114.

Song, S. H., & Keller, J. M. (2001). Effectiveness of motivational adaptive computer-assisted instruction on the dynamic aspects of motivation. *Educational Technology, Research and Development,* 49, 5-22.

Sweller, J. (1994). Cognitive theory; learning difficulty, and instructional design. *Learning and Instruction,* 4, 295-312.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science,* 12, 257-285.

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (1998). Cognitive architecture and instructional design. *Educational Psychology Review,* 10, 251-296.

Tennyson, R. D. & Buttery, T. (1980). Advisement and management strategies as design variables in computer-assisted instruction. *Educational Communication and Technology Journal,* 28, 169-176.

Van Merriënboer, J. J. G. (1997). *Training Complex Cognitive Skills.* Englewood Cliffs, NJ: Educational Technology Publications.

Van Merriënboer, J. J. G., Clark, R., & de Croock, M. (2002). Blueprints for complex learning: The 4C/ID-model. *Educational Technology, Research and Development,* 50, 39-64.

Van Merriënboer, J. J. G. & Kirschner, P. (2007). Ten steps for complex learning: A systematic approach to four-component instructional design. Mahwah, NJ: Lawrence Erlbaum Associates.

Van Merriënboer, J. J. G., & Luursema, J. (1996). Implementing instructional models in computer-based learning environments: A case study in problem selection. In T. Liao

(Ed.), *Advanced educational technology: Research issues and future potential (*pp. 184-206). Berlin, Germany: Springer Verlag.

Van Merriënboer, J. J. G., Schuurman, J., de Croock, M., & Paas, F. (2002). Redirecting learner's attention during training: Effects on cognitive load, transfer test performance, and training efficiency. *Learning and Instruction*, 12, 11-37.

Van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review,* 17, 147-177.

Williams, M. D. (1996). Learner-control and instructional technologies. In D. H. Jonassen (Ed.), *Handbook of research for educational communications and technology* (pp. 957-982). New York: Simon & Schuster Macmillan.

Wolters, C. A. (2003). Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. *Educational Psychologist,* 38, 189-205.

Wong, W. K., Chan, T. W., Chou, C. Y., Heh, J. S., Tung, S. H., (2003). Reciprocal tutoring using cognitive tools. *Journal of Computer Assisted Learning,* 19, 416-428.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology,* 25, 82-91.

Zimmerman, B. J. (2002). Achieving academic excellence: A self-regulatory perspective. In M. Ferrari (Ed.), *The pursuit of excellence through education* (pp. 85-110). Mahwah, NJ: Erlbaum.

Table 1

Selection Table Indicating Jump Sizes Between Learning Tasks

Task Load	Competence						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1	0	0 [c]	0 [c]	+3	+4	+5	+6
2	0 [b]	0	0 [c]	+2	+3	+4	+5
3	-2	-1	0	+1	+2	+3	+4
4	-3	-2	-1	0	+1	+2	+3
5	-4	-3	-2	-1	0	+1	+2
6	-5	-4	-3	-2	0 [a]	0	0 [d]
7	-6	-5	-4	-3	0 [a]	0 [a]	0

[a] Adjusted jump size = 0 because the computed jump size is negative and the competence score is 5 or higher (rule a)

[b] Adjusted jump size = 0 because the computed jump size is negative and the task-load score is 2 or lower (rule b)

[c] Adjusted jump size = 0 because the computed jump size is positive and the competence score is 3 or lower (rule c)

[d] Adjusted jump size = 0 because the computed jump size is positive and the task-load score is 6 or higher (rule d)

Table 2
Overview of Results from the Training Phase

Condition

	Adaptation with program control n = 15		Adaptation with shared control n = 15		Non-adaptation with program control n = 13		Non-adaptation with shared control n = 12	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Training Time (min.)	126.70	29.27	132.65	15.76	88.55	28.01	85.95	24.69
Practice Performance (max. = 100)	71.90	14.86	75.22	16.36	50.08	19.27	45.77	18.99
Task Load (max. = 7)	3.01	1.20	3.14	1.10	3.61	0.86	4.09	0.97
Germane Load (max. = 7)	4.40	0.56	4.63	0.94	3.73	0.83	4.35	0.50

Note: Estimated marginal means are presented with total training time as a covariate.

Table 3

Overview of Results from the Test Phase

Condition

	Adaptation with program control n = 12		Adaptation with shared control n = 14		Non-adaptation with program control n = 12		Non-adaptation with shared control n = 12	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Learning Outcomes (max. = 17)	12.88	2.57	14.21	1.21	11.95	2.67	12.01	1.91
Learning Efficiency	0.29	1.36	0.60	0.66	-0.32	1.05	-0.67	0.76
Task Involvement	0.15	0.81	0.68	0.94	-0.75	0.87	-0.19	0.75

Note: Estimated marginal means are presented with total training time as a covariate.

Table 4

Mean interest-in-task and interest-in-training

	Condition			
	Adaptation with program control	Adaptation with shared control	Non-adaptation with program	Non-adaptation with shared control

	control											
	M	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*
Mean Interest-in-Task (max. = 7)	3.69	1.13	15	3.72	1.30	15	4.01	0.59	13	3.98	1.37	12
Interest-in-training (max. = 7)	3.58	1.20	12	3.38	1.33	14	3.75	1.31	12	3.91	1.58	12

Note: Estimated marginal means are presented with total training time as a covariate.

Figure Captions

Figure 1. Learning-task Database with the Combination of Different Levels of Difficulty, Different Levels of Support, and Different Task Features.

		Task support levels			
	WOE1 [a]	WOE2 [b]	COMP1 [c]	COMP2 [d]	CONV [e]
Difficulty 1	Task 1 [f]	Task 4	Task 7	Task 10	Task 13
	Task 2	Task 5	Task 8	Task 11	Task 14
	Task 3	Task 6	Task 9	Task 12	Task 15
Difficulty 2	Task 16	Task 19	Task 22	Task 25	Task 28
	Task 17	Task 20	Task 23	Task 26	Task 29
	Task 18	Task 21	Task 24	Task 27	Task 30
Difficulty n	Task n	Task n	Task n	Task n	Task n
	Task n	Task n	Task n	Task n	Task n
	Task n	Task n	Task n	Task n	Task n

Figur

Mr. Brown
-English painter
-36 years old
-84 kilos
-Swims 3 hours
per week

Mrs. Van Hout
-Dutch teacher
-51 years old
-67 kilos
-Plays golf 2 hours
every Sunday

[a] WOE1= Worked-out example with full product and process support
[b] WOE2= Worked-out example with full product support
[c] COMP1= Completion task with high product support
[d] COMP2= Completion task with low product support
[e] CONV= Conventional task without support
[f] = Learning task. Each cell contains several (3 in the Table) learning tasks with different task features that belong to one difficulty level and one level of learner support