

# Dynamic Selection of Learning Tasks According to the 4C/ID-Model

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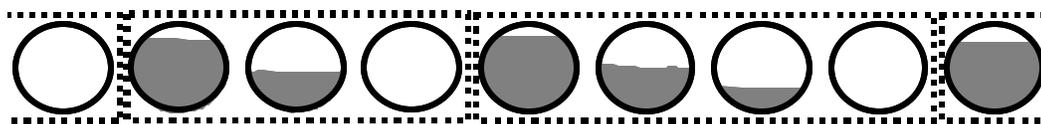
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## Introduction

Recent instructional theories tend to focus on authentic learning tasks that are based on real-life tasks as the driving force for complex learning (Merrill, 2002; van Merriënboer & Kirschner, 2001). The general assumption is that such tasks help learners to integrate the knowledge, skills and attitudes necessary for effective task performance; give them the opportunity to learn to coordinate constituent skills that make up this performance, and eventually enable them to transfer what is learned to their daily life or work settings. This focus on authentic, whole tasks can be found in several educational approaches, such as the case method, project-based education, problem-based learning, and competency-based education. Van Merriënboer's four-component instructional design model (4C/ID-model, 1997; van Merriënboer, Clark, & de Croock, 2002) describes how learning tasks fulfill the role of a backbone for an integrated curriculum (Figure 1: the "circles" represent learning tasks). Two requirements for this backbone are: (a) learning tasks are organized in easy-to-difficult task classes (the dotted boxes around sets of learning tasks), and (2) learners receive guidance for the first learning task in a task class after which support slowly disappears in this task class.

Figure 1. A sequence of learning tasks, organized in easy-to-difficult task classes and with fading support in each task class



It is clearly impossible to use very difficult learning tasks right from the start of a curriculum or educational program because this would yield excessive cognitive load for the learners, with negative effects on learning, performance, and motivation (Sweller, van Merriënboer, & Paas, 1998; van Merriënboer, Kirschner, & Kester, 2003). The common solution is to let learners start their work on relatively easy learning tasks and progress towards more difficult tasks. In a whole-task approach, the coordination and integration of constituent skills is yet stressed from the very beginning, so that learners quickly develop a holistic vision of the whole task that is gradually embellished during the training. This is akin to the "global before local skills" principle in cognitive apprenticeship (Collins, Brown, & Newman, 1989, p. 485) or the "zoom lens metaphor" of Reigeluth's elaboration theory (1999). There are categories of learning tasks or task classes, each representing a version of the task with a particular difficulty (the dotted boxes in Figure 1). Learning tasks within a particular task class are equivalent in the sense that the tasks can be performed on the basis of the same body of generalized knowledge. A more difficult task class requires more knowledge or more embellished knowledge for effective performance than the preceding, easier task classes. In other words, each new task class contains learning tasks that are in the zone of proximal development of the learners (Vygotsky, 1934/1987). It is essential that the equivalent learning tasks within the same task class show a high variability, that is, differ from each other in terms of the saliency of defining characteristics, the context in which the task has to be performed, the familiarity of the task, or any other task dimensions that also vary in the real world (Paas & van

Merriënboer, 1994). Variability is a key factor for reaching the necessary level of generality and facilitating transfer of learning to daily life or future work settings.

Furthermore, when learners start to work on a new, more difficult task class, it is essential to give them guidance and support. This support diminishes in a process of “scaffolding” as learners acquire more expertise (see the filling of the circles in Figure 1). One powerful approach to scaffolding is known as the “completion strategy”. In this strategy, learners start to work on fully worked-out examples that confront them not only with a given problem state and a desired goal state, but also with an example solution. Questions and evaluation assignments stimulate the learners to reflect on the strong and weak points of the given solution. Studying worked-out examples focuses the learners’ attention on problem states and associated solution steps and so enables them to induce generalized solutions or schemata. Then, learners may proceed to work on completion tasks that present a given state, a goal state, and a partial solution that must be completed. There is still a sizeable support, because the given part of the solution provides direction to the problem solving process. Finally, learners receive conventional tasks without support – only then, they have to construct complete solutions. Several studies showed positive effects on learning for the completion strategy (Renkl & Atkinson, 2003; van Merriënboer & de Croock, 1992).

In a flexible curriculum, it should be possible to take differences between students into account. Some students are better able to acquire new complex skills or competencies and need therefore less practice and support than other students. In addition, elsewhere-acquired skills of new students should be taken into account. And complex skills or competencies are not coupled to separate courses or modules but developed throughout the curriculum or educational program, which makes it even more important to be able to select suitable learning tasks for students. In the 4C/ID-framework sketched above, this means that for each individual student, it should be possible to select the best task class to work on, and to select within this task class a learning task with the optimal level of support, at any given point in time. Electronic learning environments allow for such dynamic selection of learning tasks.

### **Dynamic Task Selection on the Basis of Mental Efficiency**

Models for dynamic task selection typically take learner’s performance as their input, defined in terms of the number of correctly answered test items, the number of errors, or the time on task. However, the 4C/ID-model stresses that other dimensions are at least equally important for the assessment of expertise. They include mental load, which originates from the interaction between task characteristics (e.g., task format, multimedia, task difficulty) and learner characteristics (e.g., age, prior knowledge, spatial ability) and so yields an a-priori estimate of cognitive load, and mental effort, which refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task (Paas & van Merriënboer, 1993, 1994b). Especially mental effort may yield important information that is not necessarily reflected in mental load and performance measures. For instance, it is quite feasible for two persons to attain the same performance levels with one person needing to work laboriously through a very effortful process to arrive at the correct answers, whereas the other person reaches the same answers with a minimum of effort. While both people demonstrate identical performance, ‘expertise’ may be argued to be higher for the person who performs the task with minimum effort than for the person who exerts substantial effort.

An appropriate assessment of expertise should thus at least include measures of mental effort and performance. Paas, Tuovinen, Tabbers and van Gerven (2003) discuss different measurement techniques for mental effort, including rating scales, secondary task methods, and psychophysiological measures. On the basis of a comprehensive review of about 30 studies, they conclude that “...the use of rating scales to measure mental effort remains popular, because they are easy to use; do not interfere with primary task performance; are inexpensive; can detect small variations in workload (i.e., sensitivity); are reliable, and provide decent convergent, construct, and discriminate validity” (p. 68). For the measurement of complex performance, several methods that assess and weigh different aspects of performance have been developed (see Hambleton, Jaeger, Plake, & Mills, 2000). However, most methods are very time-consuming. To make the assessment of complex performance more time-effective, Kalyuga and Sweller (in press) proposed a “rapid assessment test”, which asked students to indicate their first step toward solution of a complex task. High correlations (up to .92) were found between performance on “rapid assessment tests” and traditional performance tests that required complete solutions of corresponding tasks.

A final step in the assessment of expertise is the difficult task of combining a student’s mental effort and performance measures, because a meaningful interpretation of a certain level of invested effort can only be given in the context of its associated performance and vice versa. Paas and van Merriënboer (1993; see also Paas et al., 2003) developed a computational approach to combine measures of mental effort with measures of

associated performance to compare the mental efficiency associated with instructional conditions – under the assumption that learners’ behavior in a particular condition is more efficient if their performance is higher than might be expected on the basis of their invested mental effort or, equivalently, if their invested mental effort is lower than might be expected on the basis of their performance. Using this approach, high task performance associated with low effort is called high mental efficiency, whereas low task performance with high effort is called low mental efficiency. Unfortunately, this approach can only be used after all data of a group of students, working in different instructional conditions, have been gathered. Alternative methods are needed for the continuous assessment of expertise of individual learners. Such alternatives are currently under development in the context of adaptive eLearning.

## Adaptive E-Learning

Salden, Paas and van Merriënboer (in press) discuss the value of the 4C/ID-model for adaptive eLearning, with a focus on the dynamic selection of learning tasks. They describe adaptive eLearning as a straightforward two-step cycle: (1) assessment of a learner’s expertise, and (2) task selection. With regard to the ongoing assessment of expertise, they differentiated between a learner who needs to work laboriously to attain a certain performance level (low mental efficiency) and a learner who attains the same performance level with little mental effort (high mental efficiency). Only the second learner who solved the problem efficiently should be presented with a more difficult and/or less-supported learning task. With regard to task selection, given the learner’s mental efficiency one might select tasks (1) that provide less, equal, or more support to learners than the previous task(s); (2) that are less, equally, or more difficult than the previous task(s), and (3) that vary with regard to both support and difficulty.

### Selecting Learning Tasks with Different Levels of Support

In a study reported by van Merriënboer, Schuurman, de Croock, and Paas (2002), participants received a 3-hour introductory computer-programming course in the computer-based learning environment CASCO (Completion ASsignment COnstructor; van Merriënboer & Luursema, 1996). Participants received no support (i.e., conventional programming tasks; n = 8), support (i.e., completion tasks; n = 10), or adaptive support (n = 8). In the no-support and support conditions, each new learning task was selected from a database of tasks in such a way that the selected task offered the best opportunity to practice those programming concepts that were not yet mastered by the student. In the adaptive support condition, students selected completion tasks based on a subjective estimate of their mental efficiency: The tasks could range from fully worked-out examples to conventional tasks, that is, in their level of build-in support. All tasks that could be presented to the learners were of roughly the same difficulty level, and thus only differed with regard to the programming concepts that had to be practiced and, for the adaptive condition, the amount of given support. Learning tasks consisted of a problem statement and (1) explanations, concerning new programming concepts that were necessary for writing the program, (2) specific subtasks that could help to write the program, and (3) questions that were relevant for the task at hand. For completion tasks, a partial, to-be-completed program was presented in a full-fledged editor window; for conventional tasks, this editor window was empty. The CASCO interface is presented in Figure 2.

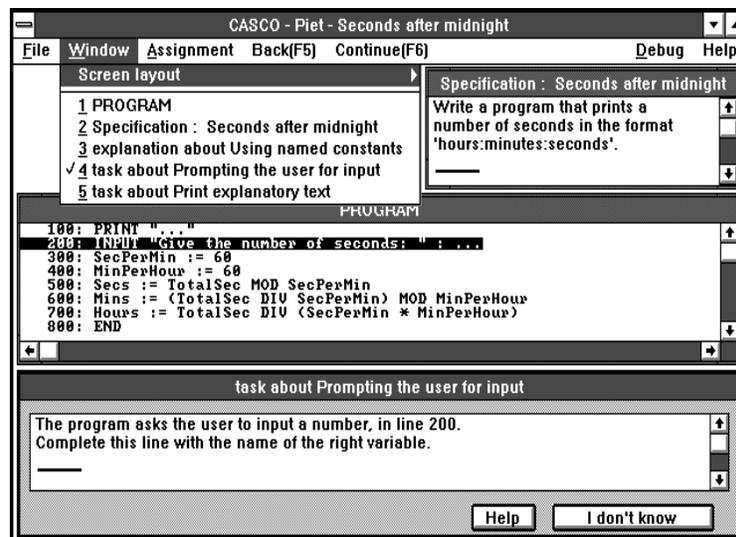


Figure 2. The CASCO Interface.

Practice data show that learners in the support group finished the highest number of learning tasks in the three-hour practice phase ( $M = 28.1$ ), compared to the no-support group ( $M = 8.3$ ) and the adaptive support group ( $M = 21.3$ ;  $F(2, 26) = 13.7$ ,  $MSE = 66.4$ ,  $p < .001$ ). In post-hoc tests, using Tukey's HSD, it was found that both the no-support and the support group ( $p < .001$ ) and the no-support and the adaptive support group ( $p < .01$ ) differed significantly. For a transfer test that was performed after the training, the proportion of correctly used programming concepts was .33 for the no-support group, .39 for the support group, and .55 for the adaptive support group. ANOVA indicated a significant difference between conditions,  $F(2, 26) = 3.6$ ,  $MSE = .03$ ,  $p < .05$ . As predicted, the adaptive support group outperformed the support and no-support groups. Concluding, adapting the level of support to the learners had beneficial effects on learning and transfer test performance.

### Selecting Learning Tasks with Different Levels of Difficulty

In the domain of Air Traffic Control (ATC), Camp, Paas, Rikers and van Merriënboer (2001) and Salden, Paas, Broers and van Merriënboer (2004) compared the effectiveness of a fixed easy-to-difficult sequence of learning tasks with dynamic task selection based on mental efficiency. In the mental efficiency condition, learners received ATC tasks at possible 10 levels of difficulty, starting at the lowest level. Depending on the assessment results, the next task was selected. For instance, a student who attains a performance score of 4 while his or her mental effort is 3 will be presented with a learning task that is one difficulty level higher than the previous task; another student who attains a performance score of 4 while his or her mental effort is only 1 will be presented with a learning task that is two difficulty levels higher than the previous task. In both studies, dynamic task selection yielded more efficient transfer test performance than the use of a fixed sequence of tasks. The mental efficiency condition was also more effective during training than the fixed condition: Participants needed fewer learning tasks to reach the highest difficulty level, reached a higher difficulty level, and made larger jumps to higher difficulty levels than students in the fixed condition.

In a just completed study, participants learned to use a Flight Management System (FMS) according to either (a) a fixed easy-to-difficult sequence of 16 learning tasks ( $n = 10$ ), (b) a system-controlled mental efficiency condition ( $n = 11$ ), and (c) a learner-controlled mental efficiency condition ( $n = 10$ ). Prior to training, the thirty-two learning tasks were categorized into eight difficulty levels (four tasks per level; note that only two of those four tasks were used in the fixed condition). In the system-controlled mental efficiency condition, performance and mental effort were measured and used to determine the difficulty of the next learning task according to a table that specified the increase/decrease in difficulty for each combination of mental effort and performance. For instance, if a participant had a mental effort score of 2 and a performance score of 5 (both measured on a 5-point scale), task difficulty was increased with three levels (+3); if a participant had a mental effort score of 5 and a performance score of 3, task difficulty was decreased with two levels (-2), and so forth. In the learner-controlled mental efficiency condition, participants were free to select the next task based on a subjective estimate of their mental efficiency. The tasks were performed in a realistic computer simulation of a Boeing 747 FMS developed by the National Aerospace Laboratory NLR (see Figure 3). Each task presented flight information of a certain route from airport A to airport B that learners had to program into the FMS simulation. A simulated flight had to be executed after entering all information. At certain points during the task, changes in the flight route were required and made it necessary for the trainees to adjust the original flight route.



Figure 3. The simulation of a Flight Management System (FMS).

Practice data show that learners in the mental efficiency conditions needed substantially less than the 16 learning tasks in the fixed condition to complete the training:  $M = 7.27$ ,  $SD = 1.19$  for the system-controlled condition ( $t(20) = -4.6$ ,  $p < .001$ ) and  $M = 6.50$ ,  $SD = 1.35$  for the learner-controlled condition ( $t(19) = -4.3$ ,  $p < .001$ ). In line with this finding, the mental efficiency conditions also needed less training time to reach the highest difficulty level than the fixed condition ( $F(2, 28) = 28.37$ ,  $MSE = 444.40$ ,  $p < .001$ ,  $\eta^2 = .67$ .  $M = 149.60$ ,  $SD = 22.77$  for the fixed condition,  $M = 117.35$ ,  $SD = 25.61$  for the system-controlled mental efficiency condition, and  $M = 78.69$ ,  $SD = 11.64$  for the learner-controlled condition). For a test with five transfer tasks after the training, an ANCOVA with number of learning tasks and time-on-task as covariates indicates that participants scored 2.89 ( $SD = .38$ ) in the fixed condition; 3.21 ( $SD = .20$ ) in the system-controlled mental efficiency condition, and 3.16 ( $SD = .22$ ) in the learner-controlled mental efficiency condition ( $M$ s are estimated marginal means). Whereas visual inspection indicates higher scores for the mental efficiency conditions, this difference does not reach statistical significance. However, the data clearly indicate that the mental efficiency conditions yield at least the same test performance with less practice tasks and in less time than a traditional fixed condition.

### Selecting Learning Tasks with Different Levels of Support and Difficulty

Kalyuga and Sweller (in press) conducted a study in which both the difficulty and the given support of the next task were adapted to the mental efficiency of the learner. They took a somewhat different approach to combining performance and mental effort measures than the previous studies. In the domain of algebra, a ‘rapid assessment test’ was used to measure performance and a 9-point rating scale was used to measure mental effort. Cognitive efficiency ( $E$ ) was defined as a combined measure for monitoring learners’ progress during instruction and real-time adaptation of instructional formats to changing levels of expertise. Cognitive efficiency is simply defined as  $E = P/R$ , where  $R$  is the mental effort rating and  $P$  is the performance measure on the same task. This indicator has similar general features as efficiency defined by Paas and van Merriënboer (1993), in that it is higher if similar levels of performance are reached with less effort or, alternatively, higher levels of performance are reached with the same mental effort. Students were presented tasks at different levels of difficulty, and for each level a critical level of cognitive efficiency ( $E_{cr}$ ) was arbitrarily defined as the maximum performance score (which was different per task level) divided by the maximum mental effort score (which was always 9). It should be noted that this technique makes it unnecessary to use a baseline group (previous studies used the “fixed” group to set this baseline). Cognitive efficiency is positive if  $E > E_{cr}$  and negative if  $E < E_{cr}$ . The rationale for this definition is that if someone invests maximum mental effort in a task but does not display the maximum level of performance, his or her expertise should be regarded as suboptimal. On the other hand, if someone performs at the maximum level with less than a maximum mental effort, his or

her expertise should be regarded as optimal.

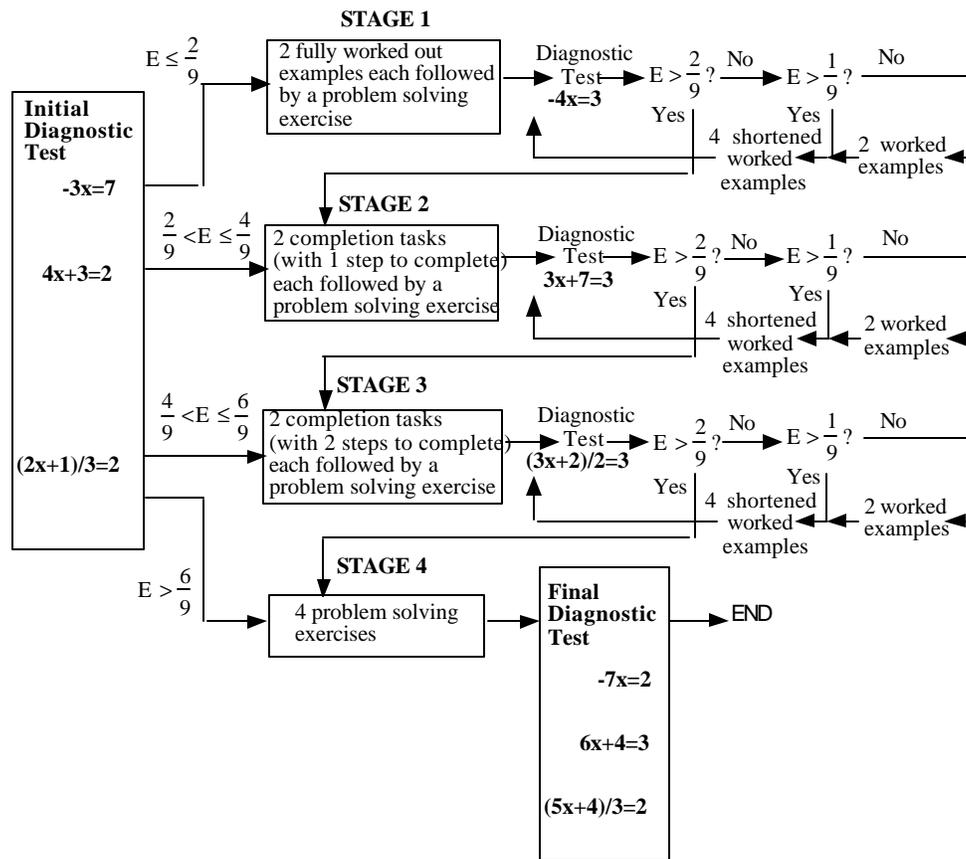


Figure 4. Selection algorithm governing the selection of learning tasks with different levels of difficulty (stages 1-4) and support (worked-out examples, completion tasks, and conventional tasks/problem solving exercises). Adapted from Kalyuga and Sweller (in press)

In the adaptive group, learners were presented algebra tasks at three different difficulty levels. If their cognitive efficiency was negative for tasks at the lowest level, they continued with the study of worked examples; if their cognitive efficiency was positive for tasks at the lowest level but negative for tasks at the second level, they continued with simple completion tasks; if their cognitive efficiency was positive for tasks at the lowest and second level but negative for tasks at the third level, they continued with difficult completion tasks, and, finally, if their cognitive efficiency was positive for tasks at all three levels, they continued with conventional problems. Similar adaptive methods were applied when students were working on the worked examples, completion tasks, or conventional problems (see Figure 4). Each student in the adaptive condition was paired to a student in the control condition, who served as a yoked control. Kalyuga and Sweller (in press) report higher gains in algebraic skills from pretest to posttest and higher gains in cognitive efficiency for the adaptive eLearning group than for the control group. Thus, in agreement with the other reported studies, adaptive eLearning was found to be superior to non-adaptive learning.

## Discussion and Conclusion

Modern instructional models stress the use of whole, meaningful learning tasks as the driving force for complex learning. However, learners are easily overwhelmed by the complexity of such tasks. It is thus critical to select each new learning task in such a way that it is best adapted to the individual needs of the learner. According to the 4C/ID model, adaptation mainly refers to (a) the—build-in—support that is provided to learners while they perform the task, and (b) the difficulty of the task (i.e., the task class it belongs to). As an additional constraint, the whole set of tasks that is provided to the learner must display a high level of

variability. In order to determine the optimal level of support and difficulty of a next learning task, an indication of the learner's performance is insufficient. After all, if two learners reach the same performance but one needs to put in a lot of effort (low mental efficiency) and the other does it almost effortlessly (high mental efficiency), the selected new task should be easier and/or contain more support for the first learner than for the second learner.

We discussed several empirical studies, which indicate that adapting the level of support, the difficulty of the learning task, or support as well as difficulty has beneficial effects on learning and transfer test performance. Thus, adaptive instruction is more effective than non-adaptive instruction. Three conclusions can be drawn from the presented studies. First, both the level of available support and the difficulty of the learning task are important dimensions to take into account for dynamic task selection. Second, performance alone is often an insufficient basis for task selection and should be complemented with, for instance, invested mental effort so that mental efficiency drives the task selection. Third, the 4C/ID-model proved to be not only useful to develop fixed training programs but also to develop adaptive forms of instruction.

While the presented results are promising, they also yield important questions for future research. A first question pertains to the complex relationship between difficulty and support. If a learner's mental efficiency is suboptimal, should we present a next task that is equally difficult as the previous one but with more support; should we present a next task that is less difficult than the previous one but with the same level of support; or should we vary both the available level of support and its difficulty? The 4C/ID-model suggests to vary only the support until the learner can perform the task without any support, according to relevant standards and criteria, and not until then to continue with more difficult learning tasks (i.e., progress to a next task class). However, strong empirical support for this claim is yet missing. Second, it is important to replicate our findings on dynamic task selection with lengthier tasks in real-life environments. Especially the measures of mental effort may be much more difficult to realize for such tasks and settings. Finally, an important issue for future research pertains to the level of control that learners should be given over task selection. The development of metacognitive skills and higher order skills is increasingly seen as an important goal of education, and this includes the ability to select yourself learning tasks that best help to reach educational and personal goals. The question is not if new learning tasks should be selected by the teacher (or another intelligent agent) or by the student, but how teachers can select learning tasks for students who are not yet able to do this, how they can help students to take more and more responsibility for selecting their own learning tasks, and how they can help students with this by giving advice and providing guidance. We will only be able to answer those questions if we understand the mechanisms of good learning task selection.

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