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Instructional Control of Cognitive Load in the Design of Complex Learning Environments

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Abstract

Instructional design theories focus more and more on authentic learning tasks that are based on complex real-life experiences as the driving force for learning. The general assumption of these theories is that providing learners with authentic ‘whole’ tasks helps them to integrate the knowledge, skills, and attitudes necessary for effective task performance, gives them the opportunity to learn to coordinate qualitatively different constituent skills that make up this performance, and eventually enables them to transfer what is learned to their daily life or work settings. However, these complex tasks pose such a high load on the learner’s cognitive system, that it may interfere with efficient learning if the instructional design is not properly aligned with the cognitive architecture. This chapter uses a cognitive load theory oriented perspective to describe the implications of focusing on complex tasks in instructional design for chosing effective instructional methods. First, the importance of inducing germane load for fostering transfer is outlined. Second, instructional methods that aim at balancing the intrinsic and germane load during complex learning are discussed. Finally, the implications of these methods for instructional design theories are clarified on the basis of three instructional design models that aim at complex learning.

1. Introduction

Recent instructional design theories (e.g., the case method, project-based education, problem-based learning, and competence-based education) tend to focus on authentic learning tasks that are based on real-life experiences as the driving force for complex learning (Merrill, 2002; van Merriënboer & Kirschner, 2001). According to these theories, authentic learning tasks have many different solutions, are ecologically valid, cannot be mastered in a single session, and pose a very high load on the learner's cognitive system. Consequently, complex learning has little to do with learning separate skills in isolation, but foremost it is dealing with learning to *coordinate* the separate skills that constitute real-life task performance. Thus, in complex learning the whole is clearly more than the sum of its parts, because it also includes the ability to coordinate the parts. In addition, in complex learning effective performance relies on the *integration* of skills, knowledge and attitudes – where, for instance, complex knowledge structures are underlying problem solving and reasoning skills and particular attitudes are critical to interpersonal skills or to performing safety procedures. Moreover, complex learning requires *differentiation* by recognizing qualitative differences among the task characteristics that influence the constituent skills that have to be applied. In Figure 1, an example is given of a simulated, authentic learning task for novice electricians in vocational education namely troubleshooting electrical circuits.

Insert Figure 1 about here

Some constituent skills are performed in a variable way across problem situations (e.g., troubleshooting skills such as orienting, diagnosing). Experts can effectively perform such *non-recurrent* skills because they have highly complex cognitive schemata available that help them to reason about the domain and to guide their problem solving behavior. Other constituent skills may be performed in a highly consistent way across problem situations (e.g., building or operating an electrical circuit). Experts can effectively perform such *recurrent skills* because their cognitive schemata contain rules that directly associate particular characteristics of the problem situation to particular actions. The classification between non-recurrent and recurrent aspects of complex performance is particularly important because the associated learning processes are fundamentally different from each other. For non-recurrent skills the main learning processes are related to schema construction and include induction or mindful abstraction from concrete experiences and elaboration of new information. For recurrent skills the main learning processes are related to schema automation, and include restricted encoding or proceduralization of new information in to-be-automated rules and compilation and strengthening of those rules.

This chapter is about the cognitive implications of focusing on authentic or complex tasks in education for the use of instructional methods. Because high cognitive load is a key characteristic of complex tasks, effective learning can only commence if the specific instructions within a complex task are properly aligned with cognitive architecture (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). The notion that the human cognitive architecture should be a major consideration when choosing or designing instructional methods for meaningful learning of complex cognitive tasks, is central to cognitive load theory (CLT; Paas, Renkl, & Sweller, 2003; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005). CLT assumes that if individuals are to learn effectively in a learning environment, the architecture of their cognitive system, the learning environment, and interactions between both must be understood, accommodated, and aligned.

According to CLT, well-chosen or well-designed instructional methods should decrease the load that is *not* necessary for learning (i.e., extraneous load, typically resulting from badly designed instruction; see Figure 2) and optimize the load that directly contributes to learning (i.e., germane load), within the limits of total available capacity in order to prevent cognitive overload. However, this chapter is about complex tasks which implicates that even after the removal of all sources of extraneous cognitive load, the intrinsic load resulting from dealing with the element interactivity in the tasks is still too high to allow for efficient learning. CLT, therefore, recommends instructional designers or teachers to use germane-load-inducing methods only in combination with relatively simple tasks, in which the simultaneous processing of all interactive information elements leaves some spare cognitive capacity. In this chapter, however, we oppose this approach by arguing that germane-load-inducing methods can be used with complex tasks. To accomplish this, intrinsic load and germane load must be balanced by limiting the element interactivity of learning tasks while using germane-load-inducing methods. First, we discuss research findings indicating that germane-load-inducing instructional methods used for practicing simple tasks are not effective for practicing complex tasks, at the cost of transfer of learning. Second, we explain how the intrinsic load of complex tasks can be managed to allow the germane load to increase. Third, the implications of this CLT oriented perspective on learning for instructional design theories are discussed on the basis of three instructional design models for complex learning. The chapter ends with a discussion of main conclusions and future research issues.

Insert Figure 2 about here

Task Complexity and Cognitive Load

Research indicates that many instructional methods that work well for simple tasks do not work well for complex tasks, and vice versa (for overviews, see Bainbridge, 1997; Wulf & Shea, 2002). This section will first discuss the differential effects of germane-load-inducing methods on learning simple and complex tasks, indicating that positive effects of these methods decrease with task complexity. Second, we will argue that for *transfer* of training to commence, it is essential to teach complex tasks with germane-load-inducing methods.

Germane-Cognitive-Load-Inducing Instructional Methods and Task Complexity

A first important germane-load-inducing method affecting learning is practice variability and, in particular, the way that different versions of a learning task are scheduled over practice trials. A common distinction is between low and high contextual interference. In a practice schedule with low contextual interference (i.e., blocked practice), one version of a task is repeatedly practiced before another version of the task is introduced. Under high contextual interference (i.e., random practice), all versions of the task are mixed and practiced in a random order. Contextual interference can be induced by varying the surface features of a task (e.g., context, representation; Quilici & Mayer, 1996), or the structural features of a task (e.g., underlying procedures). Varying the type of battery used in an electrical circuit, for example, would be varying a surface feature because this does not affect the laws of physics that apply to the circuit while varying the type of circuit (i.e., series or parallel) would be varying a structural feature because this does influences the laws of physics that apply to the circuit. For simple tasks, a robust finding is that high contextual interference results in less effective performance during practice (e.g., more time and/or more trials are necessary to reach a pre-specified level of performance), but higher performance during retention tests (for a review, see Magill & Hall, 1990). Possible explanations for the beneficial effects of high contextual interference are that the different versions of a task reside together in working memory and can be compared and contrasted to each other to yield more elaborate representations in memory (Shea & Zimny, 1983), and that high contextual interference conditions result in repeated forgetting of the action plan, resulting in reconstructive activities that eventually yield more accessible representations in memory (Lee & Magill, 1985). What the different explanations have in common is their assumption that random practice of different versions of a task induces *germane* learning processes that require more effort than does blocked practice, but yield cognitive representations that increase later transfer test performance.

The findings for contextual interference are less clear for complex tasks, which may be partly due to the fact that learners have difficulty to distinguish surface and structural features of such tasks (Ross & Kilbane, 1997). For complex tasks in sports, beneficial effects of high contextual interference are not found at all, or only found for high-expertise learners but not for low-expertise learners (Hebert, Landin, & Solmon, 1996). Using drawing tasks, Albaret and Thon (1999) explicitly manipulated task complexity (number of line segments to draw) and studied the effects of contextual interference. As expected, they found that the positive effects of random practice decreased with task complexity, and that for the most complex task blocked practice was even superior to random practice. These results convey the impression that complex tasks leave no processing capacity for the germane cognitive processes that help learners construct better cognitive representations.

A second germane-load-inducing method relevant to the design of practice is providing limited guidance and delayed feedback. For simple tasks, reducing the amount of guidance is typically beneficial to learning. For instance, physical guidance in learning motor skills (e.g., using a mechanical stop to indicate a target position, moving the performer’s limb) is more effective when it is used for a limited number of trials than when it is used for a high proportion of trials, and guidance that focuses a learner’s attention only on the external goal of a movement is more effective than guidance that focuses attention also on the specifics of the movement itself (Schmidt, 1991). Paas, Camp, and Rikers (2001) showed that providing limited guidance by loosely indicating the goal (i.e., the end point of the maze) is more effective in maze learning tasks than giving a precise description of the goal. Results indicate that for simple tasks, extensive guidance often has strong positive effects on performance during practice, but when it is withdrawn during tests learners who practiced with less or no guidance perform better than learners who practiced with extensive guidance. Similarly, giving feedback on some of the practice tasks or on varying aspects of performance results in more effective learning than giving feedback on all tasks or all aspects of performance. Moreover, slightly delayed feedback is more effective than concurrent or immediate feedback (Balzer, Doherty, & O’Connor, 1989).

The findings for the effects of guidance and feedback on complex tasks, however, show another picture. For complex movements in sports, extensive physical assistance proved to be superior to limited physical assistance (Wulf, Shea, & Whitacre, 1998). For striking tasks, Guadagnoli, Dornier, and Tandy (1996) convincingly demonstrated that relatively long feedback summaries (i.e., delayed feedback) were most effective for teaching simple tasks to low-expertise and high-expertise learners, and teaching complex tasks to high-expertise learners, but single-task feedback (i.e., immediate feedback) was most effective for teaching complex tasks to low-expertise learners (i.e., a situation with high intrinsic cognitive load). These results suggest that neither limited guidance and feedback, nor alternation for the aspects of the task that receive feedback, has positive effects on learning complex tasks. In contrast, it seems that the intrinsic load imposed by the complex tasks leaves no processing capacity allowing learners to develop early in the learning process their own internal monitoring and feedback mechanisms or cognitive representations of how different task aspects interact with each other.

The Transfer Paradox

The research on instructional design for simple and complex cognitive tasks shows that complex tasks leave no processing capacity for the germane cognitive processes that help learners construct better cognitive representations. In general, the results indicate that the positive effects of germane-load-inducing methods (i.e., random practice, limited guidance and delayed feedback) decrease as a function of task complexity. Therefore, it seems that instruction of complex cognitive tasks should not be based on the use of germane-load-inducing methods, but on using highly structured methods (i.e., blocked practice, step-by-step guidance and immediate feedback) that primarily facilitate performance by taking over part of the cognitive processing from the learner. We do, however, not support this conclusion. Highly structured methods may indeed have a positive effect on the acquisition curve and performance on retention tests, but *not* on problem solving and transfer of learning. Instead, we believe that if one aims at transfer of learning, and the ability to show performances that go beyond given learning objectives, it is necessary to use germane-load-inducing methods. This phenomenon, where the methods that work best for reaching specific objectives are not the methods that work best for reaching transfer of learning, has been described as the ‘transfer paradox’ (Van Merriënboer, De Croock, & Jelsma, 1997; see also Eaton & Cottrell, 1999). This phenomenon has important implications for the selection of instructional methods for complex tasks.

The germane-load-inducing methods that explicitly aim at transfer of learning should take two complementary dimensions of transfer into account. These dimensions are rooted in Selz’s Gestalt approach to transfer (cited in Mandler & Mandler, 1964) and Thorndike and

Woodworth's 'identical elements' approach to transfer (1901). They are closely related to the high road and the low road to transfer (Salomon & Perkins, 1989), innovation and efficiency in transfer (Schwartz, Bransford, & Sears, 2005), and schema-based and rule-based transfer (Van Merriënboer, 1997). The first approach stresses that transfer may be partly explained by general or abstract knowledge that may be *interpreted* in the transfer situation (i.e., other use of the same *general* knowledge); the second approach stresses that transfer may be partly explained by the *application* of knowledge elements that are shared between the practice and the transfer situation (i.e., the same use of the same *specific* knowledge). The germane-load-inducing methods balance both complementary dimensions, and facilitate the interpretive aspects of knowing for those aspects of a complex task that are different from problem to problem situation (e.g., troubleshooting an electrical circuit) as well as facilitate the applicative aspects of knowing for those aspects of a complex task that are highly similar from situation to situation (e.g., building or operating an electrical circuit; Van Merriënboer, 1997).

Whereas both transfer dimensions need to be carefully balanced, and adaptive experts score high on both dimensions (Gentner et al., 1997), it is important to note that instructional methods that explicitly aim for one or the other can also conflict with each other. The main problem is that starting with highly structured methods that give priority to the applicative aspects of knowing (e.g., building routines) seriously hampers the later development of interpretive aspects of knowing (e.g., building general schemas). These methods constrain the problem spaces within which learners work, and then make it more difficult for them to generate creative solutions or "think outside the box." An example is provided by a study of Schwartz, Martin, and Pfaffman (2005), in which children learned to manipulate pieces to help solve fraction problems. One group learned with pie pieces with different sizes, with a focus on routine building because the pieces are easily seen as fractions of a whole; the other group learned with tile pieces of equal sizes, with a focus on interpretation because the pieces should be interpreted as parts of a whole rather than just units. For subsequent problem solving with new materials (beans, bars etc.), it was found that the interpretation group was better able to use the novel materials, showed better progress, and eventually became more efficient than the routine-building group.

Concluding, highly structured methods such as blocked practice, step-by-step guidance, and immediate feedback may help to efficiently reach pre-specified objectives but yield low transfer of learning. In addition, they may block the later development of the second, interpretive dimension of transfer. Therefore, not these germane-load *reducing* methods, but their counterparts - random practice, limited guidance, delayed feedback - should be used to teach complex tasks. However, to avoid cognitive overload additional measures have to be taken. We argue that the intrinsic load of complex tasks and the germane load of instructional methods should be balanced during task performance. For a long time intrinsic load was considered unalterable by instruction, but recently the effects of different approaches to reduce intrinsic load on learning have been investigated (Ayres, 2006) and some techniques have been described that seem successful in reducing this load (Gerjets, Scheiter, & Catrambone, 2004; Pollock, Chandler, & Sweller, 2002).

Managing Intrinsic Load and Inducing Germane Load

According to CLT, the complexity of a task is largely determined by its degree of element interactivity. High-element interactivity requires the learner to process several elements and their relationships simultaneously in working memory in order to learn the task. Low-element interactivity allows the learner to serially process only a few elements at a time. In the next paragraphs we explain how intrinsic load can be managed so that germane load can be induced.

Managing Intrinsic Load

Instructional approaches to gradually increase the intrinsic load in a training are based on the sequencing of learning tasks from low to high element interactivity. Basically, this sequencing can be operationalized in part-whole or whole-part approaches (see Figure 3). In a part-whole approach the number of elements and interactions between elements may be initially reduced by simplifying the tasks, after which more and more elements and interactions are added. In a whole-part approach the number of elements and interactions between elements may be immediately presented in their full complexity, but the learner has to take more and more interacting elements into account when performing the tasks.

Insert Figure 3 about here

With regard to part-whole approaches, many studies indicate that learners benefit from learning tasks that are sequenced from simple, with relatively little interacting elements, to complex, with all interacting elements that are necessary for complete understanding. For instance, Mayer and Moreno (2003) discuss studies that show better transfer test performance when students first had to study which components make up a system, and only then how the system works. Kester, Kirschner, and Van Merriënboer (2004a; 2004b; 2006) studied the effects of presenting information necessary to solve a complex task. They found that not presenting all information at once leads to better transfer test performance. Pollock, Chandler, and Sweller (2002) and Clarke, Ayres, and Sweller (2005) considered mathematical learning tasks and found that, especially for low-expertise learners and high-element interactivity materials, first presenting isolated elements and only then the interacting elements yields higher transfer test performance than presenting all elements simultaneously from the start. Finally, Ayres (2006) also used mathematical learning tasks and found that especially low-expertise learners benefit from the initial reduction in element interactivity, whereas high-expertise learners benefit from high-element interactivity materials used right from the start.

Whole-part approaches present high-element interactivity materials in their full complexity right from the beginning, but use learning tasks that focus the learner’s attention on particular subsets of interacting elements. One way to emphasize varying interacting elements of a learning task is to constrain learners’ performance, either through forcing them to behave as an expert would do by requiring them to successfully complete a particular problem-solving phase before entering a next phase (Dufresne, Gerace, Thibodeau-Hardiman, & Mestre, 1992) or through the use of particular task formats such as worked examples and completion tasks.

Worked examples focus the learner’s attention on elements that represent correct solution steps only, so that they do not have to worry about potential solution steps that are not relevant for the task at hand. Completion tasks present a partial solution that must be completed by the learner. Like worked examples, they constrain the learner’s performance because not all potential solution steps need to be taken into consideration. Many studies indicate that low-expertise learners learn more from studying worked examples or from completing partial solutions than from independently performing the equivalent conventional tasks (for an overview, see Atkinson, Derry, Renkl, & Wortham, 2000). Furthermore, Kalyuga, Chandler, Tuovinen, and Sweller (2001) found that this effect reverses for high-expertise learners. Thus, to accommodate the learner’s increase in expertise during practice, task formats with low element interactivity (worked examples, completion tasks) should be gradually replaced by conventional tasks with high element interactivity. To ensure a smooth transition, one may start with worked examples, continue with completion tasks, and end with conventional tasks in an instructional strategy known as the ‘completion strategy’ (Van Merriënboer, 1990; see also Renkl & Atkinson, 2003).

Inducing Germane Load

Next to a low-to-high element interactivity sequencing strategy that lowers intrinsic load and thus frees up cognitive capacity, learning should be promoted by simultaneously implementing germane load inducing methods (for an example see Figure 4). As discussed earlier, random practice, limited guidance and delayed feedback are promising germane load inducing methods. Paas and Van Merriënboer (1994) investigated random practice in combination with worked examples and found that learners who received a training sequence of random worked examples invested less time and mental effort in practice and attained a better transfer performance than learners who received a sequence of blocked worked examples. Van Merriënboer, Schuurman, De Croock, and Paas (2002) obtained similar results showing that a training combining the ‘completion strategy’ with random practice yielded higher transfer test performance than a training combining it with blocked practice.

With regard to limited guidance and delayed feedback as methods to induce germane cognitive load, a study of Renkl (2002) indicated that using guidance, in the form of a minimalist description of the probabilistic rule that was used in a worked example provided, had beneficial effects on learning. In addition, Renkl and Atkinson (2003) studied the use of self-explanation prompts in combination with the 'completion strategy' in the domain of statistics (probability). During studying the worked examples they guided the learners by asking them which probability rule was applied in each solution step. They found a strong effect on transfer test performance for learners who received the self-explanation prompts compared to learners who did not receive these prompts. Robins and Mayer (1993) presented sets of worked examples in a training ordered by type and accompanied by feedback that described the problem types. They found superior transfer test performance for learners who received sets of worked examples together with delayed feedback. These studies all suggest that once the task complexity is reduced by lowering the element interactivity as a function of learner expertise, that is, by using a low-to-high element interactivity sequence or performance constraints, implementing germane load inducing methods has beneficial effects on transfer test performance.

Insert Figure 4 about here

As was shown in this chapter, instructional methods that aim at balancing intrinsic and germane cognitive load during complex learning have clear implications for instructional design and, in particular, the organisation of learning tasks in educational programs that are based on projects, real-life problems or cases, and other complex tasks. We first describe three example instructional design models that specifically aim at complex learning. We will indicate how these models are consistent with the presented methods that aim at balancing the intrinsic and germane cognitive load. First, a description is given of elaboration theory. This theory stresses the notion that working from simple to complex is a sine qua non for complex learning. Second, a description is given of goal based scenarios that focus on the importance of real-world application and transfer of learning. Finally, the four-component instructional design is discussed as an example of a theory trying to implement all basic principles of complex learning.

Implications for Instructional Design

The basic principle of Reigeluth's Elaboration Theory (1987, 1999; Reigeluth & Stein, 1983; Reigeluth, Merrill, Wilson, & Spiller, 1980; van Patten, Chao, & Reigeluth, 1986) is that instruction should be organized from the simplest representation of the learning task (i.e., the ‘epitome’, which contains the most fundamental and representative ideas at a concrete level), for example, a simple electrical circuit connected in series *or* parallel, to increasingly more complex and elaborated representations, for instance, a complex electrical circuit connected in series *and* parallel. Originally, the theory focused on the sequencing of instructional content in conceptual and theoretical domains. The broadest, most inclusive concepts are taught first, including the supporting content (i.e., relevant knowledge, skills and attitudes) related to them, and subsequently the ever narrower, detailed concepts are taught together with related supporting content. Later the theory also focused on sequencing interrelated sets of principles. Such a sequence first teaches the broadest, most inclusive and most general principles along with the supporting content, and then proceeds to teach ever narrower, less inclusive, more detailed and more precise principles and supporting content.

Elaboration theory clearly reflects the presented principles of complex learning. The elaborative approach to sequencing works from simple to complex wholes which closely resembles a whole-part approach to a low-to-high element interactivity sequencing strategy. The combination of organizing content (conceptual, theoretical) and supporting contents aims at the integration of knowledge, skills and attitudes which characterizes complex learning. The concept of “learning episodes” is used to denote instructional units that allow for review and synthesis without breaking up the idea of a meaningful whole and can be used to incorporate limited guidance and delayed feedback.

Goal based scenarios (Schank, 1993/1994; Schank, Fano, Bell, & Jona, 1993/1994) are the backbone of learning in Schank’s learning-by-doing paradigm (Schank, Berman &

MacPherson, 1999). These goal based scenarios represent “...a learning-by-doing simulation in which students pursue a goal by practicing target skills and using relevant content knowledge to help them achieve their goal” (Schank et al., 1999, p. 165). Like the learning episodes in elaboration theory, goal based scenarios provide an opportunity to integrate knowledge, skills, and attitudes in meaningful wholes which characterizes complex learning. Unlike elaboration theory, however, goal based scenarios pay far less attention to the sequencing of instruction. In contrast, there is a stronger focus on the performance of real-life tasks in authentic contexts in order to facilitate transfer of learning. This fits the Gestalt approach to transfer that more general goals (i.e., integrated objectives) should drive the learning process, because highly specific learning objectives invite learners to apply strategies that do not allow for transfer of learning (see also Machin, 2002, for the role of goals in reaching transfer of learning).

Van Merriënboer’s four-component instructional design model (4C/ID-model, 1997; Van Merriënboer, Clark, & De Croock, 2002; Van Merriënboer, Kirschner, & Kester, 2003) claims that learning environments for complex tasks can always be described in four components:

1. *Learning tasks*, which are preferably based on real-life tasks and fulfill the role of a backbone for the training program.
2. *Supportive information*, which is made available to learners because it helps them to perform the problem-solving and reasoning aspects of learning tasks. It mainly concerns information on how the domain is organized and how problems in the domain can be systematically approached by the learner.
3. *Procedural information*, which is presented to learners because it helps them to perform the routine aspects of learning tasks. It mainly concerns procedural steps that precisely specify under which conditions particular actions must be taken by the learner.
4. *Part-task practice*, which may provide learners with additional practice for routine aspects of the complex task that need to be developed to a very high level of automaticity.

Three basic prescriptions of the 4C/ID-model correspond with the main principles discussed in the previous sections. First, the model suggests to order learning tasks in so-called *task classes*, where earlier task classes have lower element interactivity than later task classes (i.e., a whole-part approach). Even the first task class contains whole and meaningful tasks (i.e., the most essential interacting elements) so that the learners may quickly develop a holistic vision of the whole task that is then gradually embellished in subsequent task classes. Second, when learners start to work on tasks in a new, more complex task class, it is essential to initially focus their attention on those elements that are most important for learning. This may be reached by first constraining and then more and more relaxing their performance, or by starting with worked examples, continuing with completion tasks, and ending with conventional tasks. Third and probably most important, the combination of ordering learning tasks in simple-to-complex task classes with scaffolding learners within a task class, enables the use of instructional methods that evoke a germane cognitive load. Thus, learning tasks should always, right from the beginning of the training program, show random practice, give limited guidance to learners, and provide them with delayed feedback on varying aspects of performance.

The three other components of the 4C/ID-model explicitly take the two transfer dimensions into account. Supportive information relates to the Gestalt approach that transfer is explained by general or abstract information that may be interpreted by a task performer to solve a new problem situation. Procedural information and part-task practice mainly relate to the ‘identical elements’ approach that transfer may be explained by the application of knowledge elements that are shared between the practice and the transfer situation.

Discussion

In this chapter we argued that the increasing focus of instructional design theories on the use of complex ‘real-life’ tasks has important implications for the use of instructional methods. Even after removal of all sources of extraneous load, these tasks are often so cognitively demanding that it is impossible to use transfer enhancing instructional methods right from the start of a training program. We used cognitive load theory to explain how to balance the intrinsic load imposed by a complex task and the germane load caused by instructional methods that aim for transfer. First, intrinsic load can be decreased early in learning by manipulating the element interactivity of the learning tasks. Then, learning tasks can be immediately combined with methods that induce germane cognitive load, such as random practice, limited guidance and delayed feedback. We showed that these instructional methods can easily be implemented in contemporary instructional design models for complex learning, such as the elaboration theory (Reigeluth, 1987; 1999), Schank's learning-by-doing paradigm (Schank, et al., 1999) and the 4C/ID model (Van Merriënboer, 1997).

Our analysis points out three important directions for future research. First, the assumed interaction between intrinsic-load reducing methods and germane-load-inducing methods has only been empirically confirmed for a limited number of concrete instructional methods. More research is needed to show that the interaction holds across a wide variety of methods. Second, more research is needed with highly complex real-life tasks performed in ecologically valid settings. Particular instructional methods such as variability might then have unexpected effects, for instance because it is difficult for learners to distinguish between the surface and structural features of such tasks. Finally, progress must be made with regard to the measurement of cognitive load. Especially instruments that allow researchers to disentangle changes in cognitive load into changes in intrinsic load on the one hand, and germane load on the other hand, would be very helpful to the in-depth analysis of research findings.

An important point to consider in the design of training of complex tasks is that the element interactivity or intrinsic load of a task depends on the expertise of the learner: The higher the expertise, the lower the intrinsic load. In other words, if an individual task performer develops more expertise in a task, the functional complexity of the task decreases. In a flexible and adaptive educational program, it should be possible to take differences between individual students into account when suitable learning tasks are selected. Some students have skills acquired elsewhere that should be taken into account, and some students are better able to acquire new skills and therefore need less practice than other students. In the 4C/ID-framework, this means that for each individual student it should be possible at any given point in time to select the best task class to work on, as well as the amount of performance constraints applied to the selected task. Consequently, a high-ability student may quickly proceed from task class to task class and mainly work on tasks with little performance constraints, while a low-ability student may need many more tasks to complete the program, progress slowly from task class to task class, and work mainly on tasks with sizeable performance constraints.

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Figure Captions

Figure 1. This example shows a malfunctioning electrical circuit (a). It contains two faults that appear when switch 1 is closed, that is, no current is flowing because the voltmeter and the ammeter are incorrectly connected (b) and after this is fixed two lamps explode because the voltage of the battery is too high for the lamps (c). The learner has to repair this circuit and in order to do that (s)he has to coordinate his/her troubleshooting skills (i.e., orient, diagnose, plan action) and circuit operating skills (i.e., execute plan), integrate his/her knowlegde about electrical circuits and skills to correctly perform the troubleshooting task and recognize the features of the electrical circuit that are relevant to reach a solution and those that are not. If these skills are properly executed this will result in a well-functioning electrical circuit (d).

Figure 2. This Figure contrasts a learning task with a high extraneous load because it requires a visual search between text and circuit (i.e., split attention; a) and a learning tasks with a lower extraneous load because it does not (b).

Figure 3. Two approaches to ordering complex tasks: Part-whole approach, which increases the number of interacting elements and whole-part approach, which emphasizes more and more interacting elements.

Figure 4. Starting point in this example of the two-stage approach to complex learning (i.e., troubleshooting an electrical circuit) is that all sources of extraneous load are removed (see Figure 2b), next intrinsic load is managed by lowering the element interactivity of the learning task (a) so that germane-load-inducing methods can be introduced (b).

Figure 1

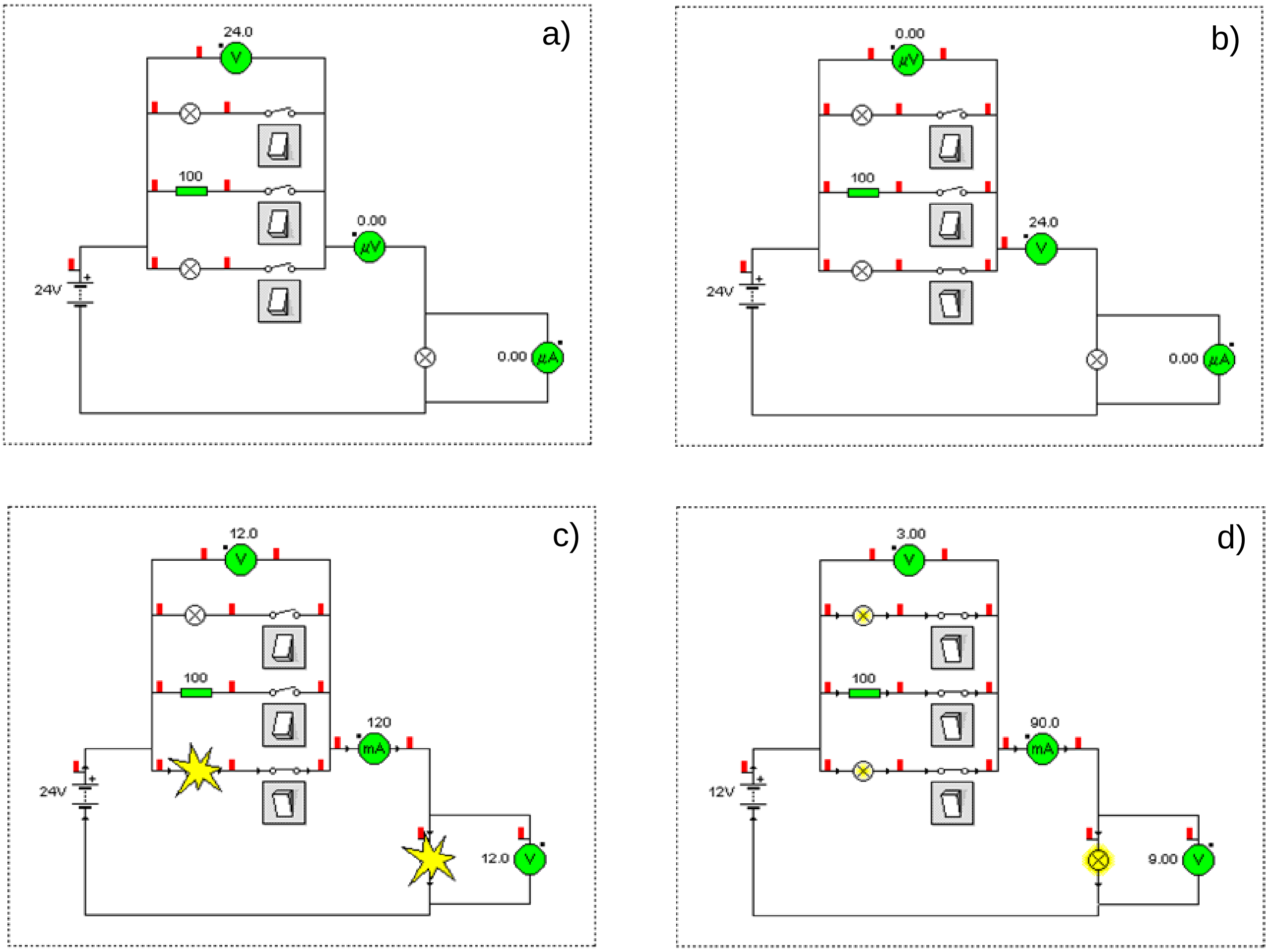
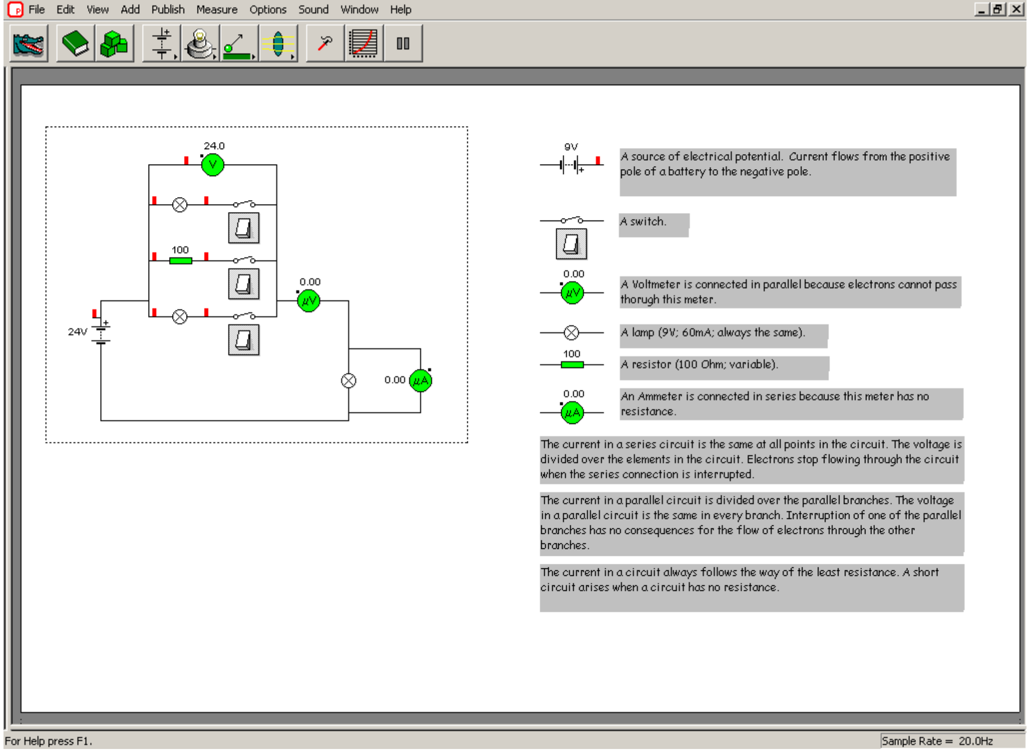

a)
24.0
V
100
0.00
µV
24V
0.00
µA
b)
0.00
µV
100
24.0
V
24V
0.00
µA
c)
12.0
V
100
120
mA
24V
12.0
V
d)
3.00
V
100
90.0
mA
12V
9.00
V

Figure 2



A source of electrical potential. Current flows from the positive pole of a battery to the negative pole.

A switch.

A Voltmeter is connected in parallel because electrons cannot pass thorugh this meter.

A lamp (9V; 60mA; always the same).

A resistor (100 Ohm; variable).

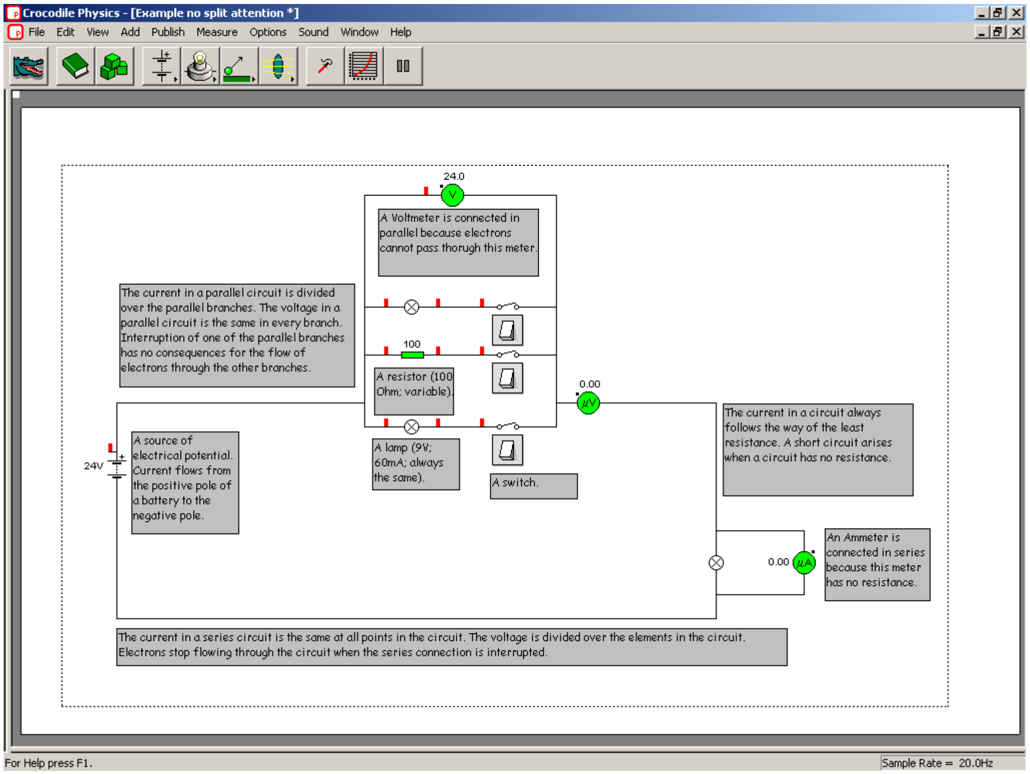
An Ammeter is connected in series because this meter has no resistance.

The current in a series circuit is the same at all points in the circuit. The voltage is divided over the elements in the circuit. Electrons stop flowing through the circuit when the series connection is interrupted.

The current in a parallel circuit is divided over the parallel branches. The voltage in a parallel circuit is the same in every branch. Interruption of one of the parallel branches has no consequences for the flow of electrons through the other branches.

The current in a circuit always follows the way of the least resistance. A short circuit arises when a circuit has no resistance.

a)



A Voltmeter is connected in parallel because electrons cannot pass thorugh this meter.

The current in a parallel circuit is divided over the parallel branches. The voltage in a parallel circuit is the same in every branch. Interruption of one of the parallel branches has no consequences for the flow of electrons through the other branches.

A resistor (100 Ohm; variable).

A source of electrical potential. Current flows from the positive pole of a battery to the negative pole.

A lamp (9V; 60mA; always the same).

A switch.

The current in a circuit always follows the way of the least resistance. A short circuit arises when a circuit has no resistance.

An Ammeter is connected in series because this meter has no resistance.

The current in a series circuit is the same at all points in the circuit. The voltage is divided over the elements in the circuit. Electrons stop flowing through the circuit when the series connection is interrupted.

b)

Figure 3

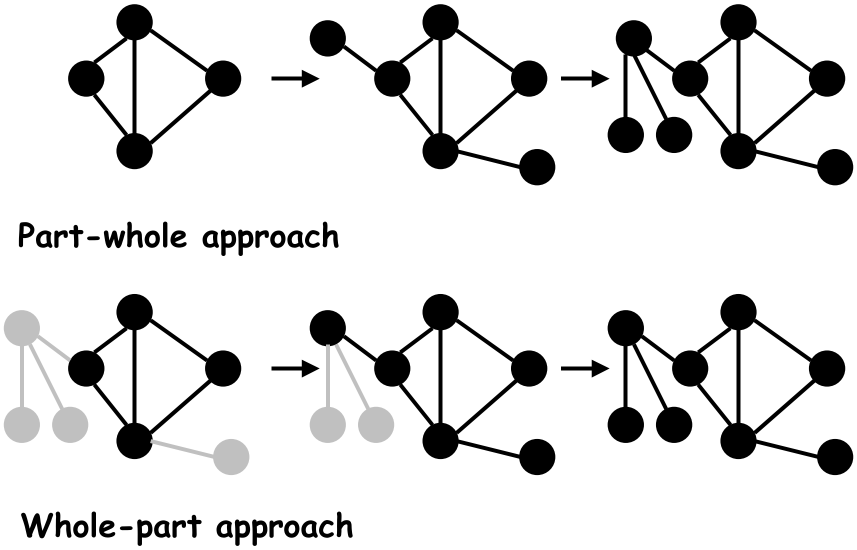
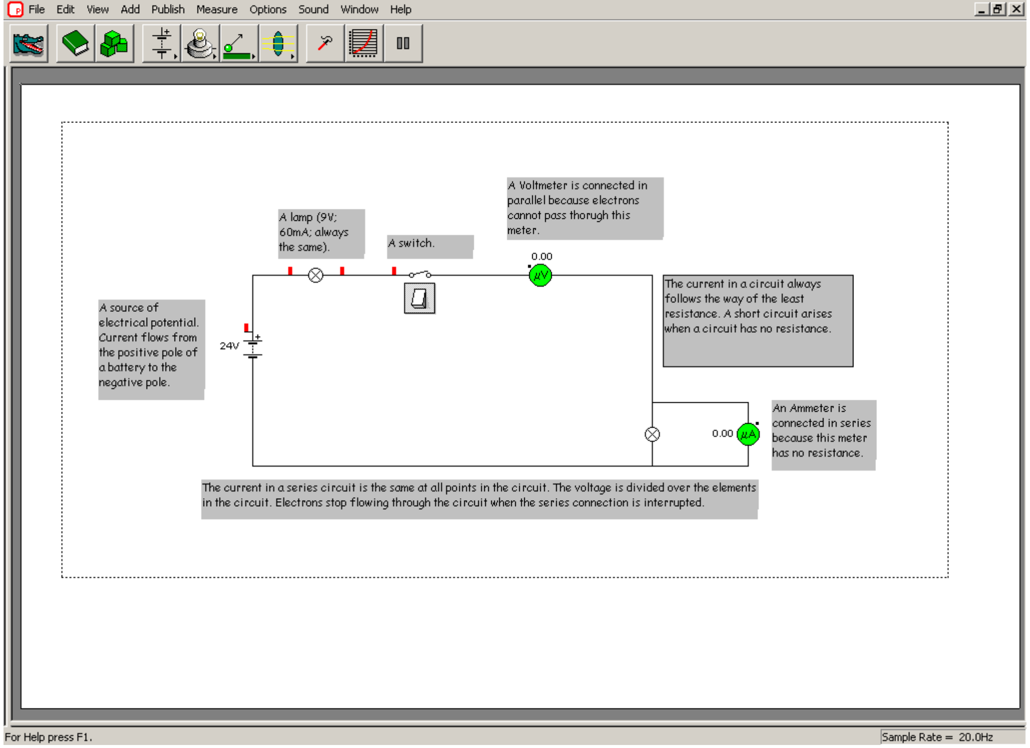


Figure 4



A source of electrical potential. Current flows from the positive pole of a battery to the negative pole.

A lamp (9V; 60mA; always the same).

A switch.

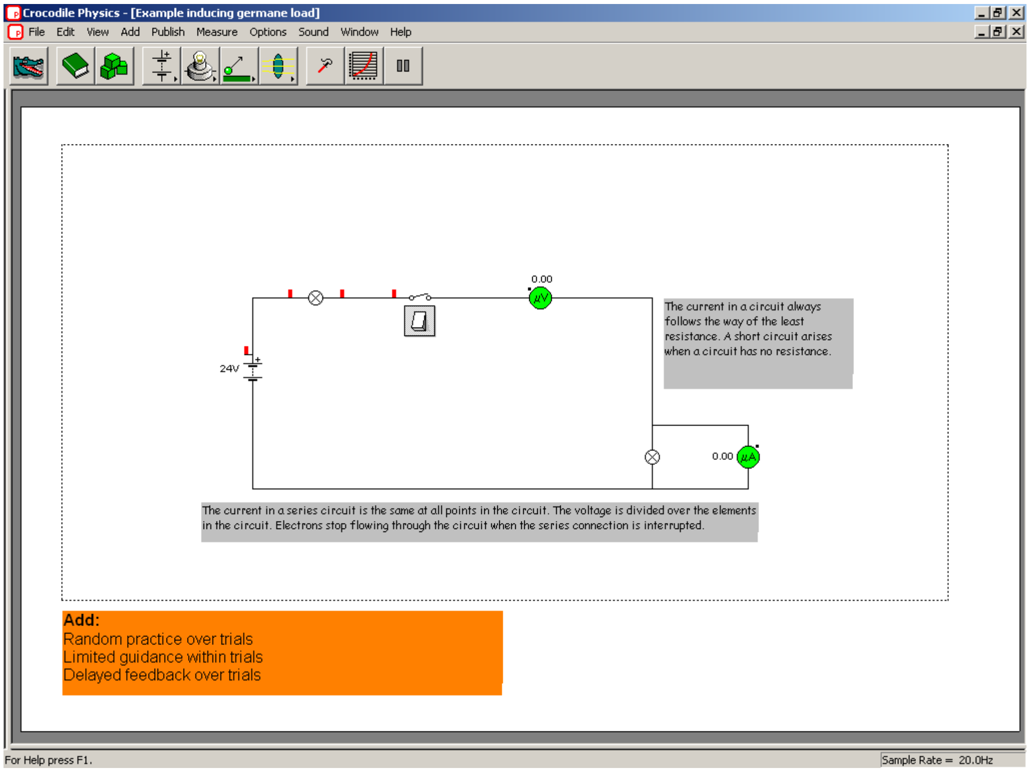
A Voltmeter is connected in parallel because electrons cannot pass thorugh this meter.

The current in a circuit always follows the way of the least resistance. A short circuit arises when a circuit has no resistance.

An Ammeter is connected in series because this meter has no resistance.

The current in a series circuit is the same at all points in the circuit. The voltage is divided over the elements in the circuit. Electrons stop flowing through the circuit when the series connection is interrupted.

a)



The current in a circuit always follows the way of the least resistance. A short circuit arises when a circuit has no resistance.

The current in a series circuit is the same at all points in the circuit. The voltage is divided over the elements in the circuit. Electrons stop flowing through the circuit when the series connection is interrupted.

Add:
Random practice over trials
Limited guidance within trials
Delayed feedback over trials

b)