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Fred Paas
University of Wollongong, fredp@uow.edu.au

Jeroen Van Merrienboer

Tamara Van Gog

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Designing Instruction for the Contemporary Learning Landscape

Fred Paas[1,2], Jeroen J. G. van Merriënboer[3], and Tamara van Gog[1]

[1]Erasmus University Rotterdam, the Netherlands

paas@fsw.eur.nl, vangog@fsw.eur.nl

[2]University of Wollongong, Australia

[3]Maastricht University, the Netherlands

j.vanmerrienboer@educ.unimaas.nl

Designing Instruction for the Contemporary Learning Landscape

The current learning landscape is constantly changing in terms of what is learned, the context in which learning takes place, and who is learning. From an instructional design perspective, this phenomenon creates a great challenge for researchers and designers of instruction to develop instruction that fits the new learning landscape. In this chapter we will first define the major concepts of instructional design and provide a historical overview of the field of instructional design. Then we will describe those changes in the learning landscape with regard to what ought to be learned, the learning context and the learners and their consequences for instructional design. We contend that learning tasks that are based on complex real-life experiences are considered as the driving force for learning in the contemporary learning landscape. Next, the main principles for the design of instruction for learning from these complex cognitive tasks are described. It is argued that instructional design needs to be responsive to the relatively great challenges such tasks pose to the cognitive capacity of the learner. Therefore, using the theoretical framework of cognitive load, it is argued that the characteristics of the structures that constitute human cognitive architecture need to be taken into account in the design of effective and efficient instruction. Design principles for learning tasks, sequences of learning tasks in fixed programs, and ways to create adaptive or personalized programs are discussed.

Instructional design: Definition and history

Instructional design is pre-eminently a multidisciplinary field. Many theories, from various disciplines (e.g., cognitive science, computer science, psychology, education, or neuroscience), yield valuable input for the further development of instructional design theory. In a recent article examining research publications and trends in instructional design, Ozcinar (2009) defined instructional design as:

> "The systematic development of instructional specifications, using learning and instructional theory derived from behavioral, cognitive and constructivist theories, in order to ensure the quality of instruction. It is the entire process of the analysis of learning needs and goals and the development of a delivery system to meet those needs, including development of instructional materials and activities, and testing and evaluating all instruction and learner activities" (p.559).

Instructional designers aim to construct or select instructional methods in the attempt to make learning effective, efficient, and appealing under specified circumstances. They typically do so on the basis of an analysis of, among other aspects, what ought to be learned and by whom, and in which context or under which conditions learning should take place. Researchers in the field of instructional design investigate the conditions under which particular methods yield desired effects and organize those methods in instructional design models or theories.

Ozcinar's (2009) definition of instructional design makes clear that several theoretical approaches have contributed to the design of instruction. As indicated in the following short historical sketch, based on McNeil (2008), the influence of those approaches on the field of instructional design has changed over time. Starting in the early 1900's and given a boost in the 1940's as a result of the military's enormous need for rapid training of new recruits for World War II, behaviorism was the predominant approach to instructional design. The behaviorist approach is based on the assumption that the internal states of the learner cannot be directly observed, instead learning is considered as a stimulus, response, and reinforcement process in which the response of a learner must be shaped by reinforcing it appropriately. The application of Skinner's (1981) research into operant conditioning (i.e., the use of consequences to modify the occurrence and form of behavior) and animal learning to human learning resulted in an elaboration of the theory of reinforcement, the so called Programmed Instruction Movement, which was characterized by the design of piecemeal instruction with immediate feedback (e.g., reward and punishment), drill and practice procedures, and self-paced programmed instruction.

The cognitive approach, which started to flourish in the 1960s, has its roots in cognitive psychology and information processing theory (proposed that like the computer, the human mind has a limited capacity for the amount and nature of the information it can process). A main characteristic distinguishing it from the behaviorist approach is its emphasis on the internal processes of learning with a focus on how the learner comes to know rather than respond in an instructional situation. A landmark in this period was the introduction of Instructional Systems Development by Glaser (1962), who first employed the term instructional system and articulated its components and properties. Another landmark was the introduction of task analysis to instructional design by Gagne (1965). Task analysis was used to determine what skills and knowledge are needed to do a job and then determining how those skills could best be learned. In the 1970s and 1980s the cognitive approach still dominated mainly through the work on instructional strategies of Bruner (1977), Merrill (1983), and Gagne (1985).

In the 1990s the constructivist approach to learning became popular. According to Jonassen (1991; see also O'Donnell, Volume 1),this approach is concerned with how we construct knowledge. The construction of knowledge is considered a function of the prior experiences, mental structures, and beliefs that one uses to interpret objects and events. Consequently, reality is more in the mind of the knower, that the knower constructs a reality, or at least interprets it, based upon his or her apperceptions. The two major strands of the constructivist perspective are the cognitive constructivism with Ausubel (1968), Bruner (1990), and Piaget (1972) as the most important theorists, and social constructivism with Vygotsky (1978) as the major theorist. Whereas social constructivism describes the mind as a distributed entity that extends beyond the bounds of the body into the social environment, cognitive constructivists describe the mind in terms of the individual, restricting its domain to the individual's head.

Most instructional design models that resulted from the theoretical approaches that dominated in the 20th century can be characterized as atomistic, part-task models. In order to deal with complexity, those models analyze a learning domain into smaller pieces and then teach the domain piece-by-piece. According to Van Merriënboer and Stoyanov (2008), the use of part-task models to design instruction has led to three basic problems in education. Firstly, *fragmentation*, indicating that students are often not able to combine the many pieces they have learned into coherent wholes. Secondly, *compartmentalization*, indicating that students have difficulties in integrating acquired knowledge, skills, and attitudes. Thirdly, *low transfer of learning*, indicating that learners are often not able to apply what they have learned to new problems and new situations.

As a reaction to the prevailing part-task models of learning and instructional design, in the 21st century there has been a growing interest in whole-task models focusing on authentic learning tasks that are based on complex real-life experiences as the driving force for learning (Merrill, 2002; Van Merriënboer & Kirschner, 2007). Whole-task models are considered to offer a solution to the three basic problems in education, because they analyze a learning domain as a coherent, interconnected whole and then teach it from very simple, yet meaningful wholes that are representative for the whole domain to increasingly more complex wholes. In addition, whole-task approaches to learning and instructional design seek to accommodate the demands imposed by the changing learning landscape, which will be described in a later section of this chapter.

Not surprisingly, the different theoretical approaches to instructional design have resulted in various substantially different instructional design models. However, an analysis of some of the major instructional design theories and models conducted by Merrill (2002; see also Merrill, Barclay, & Van Schaak, 2008) has shown that the associated instructional design models share some common fundamental underlying prescriptive principles, which are necessary for the design of effective and efficient instruction, and which are empirically verified (Merrill, 2007). Merrill identified the following five 'first principles of instruction':

Task-centered approach

- Learning is promoted when learners are engaged in a task-centered approach which includes demonstration and application of component skills.
- A task-centered approach is enhanced when learners undertake a progression of whole tasks.

Activation principle

- Learning is promoted when learners activate relevant cognitive structures by being directed to recall, describe or demonstrate relevant prior knowledge or experience.
- Activation is enhanced when learners recall or acquire a structure for organizing the new knowledge.

Demonstration principle

- Learning is promoted when learners observe a demonstration of the skills to be learned that is consistent with the type of content being taught.
- Demonstrations are enhanced when learners receive guidance that relates instances to generalities.
- Demonstrations are enhanced when learners observe media that is relevant to the content.

Application principle

- Learning is promoted when learners engage in application of their newly acquired knowledge or skill that is consistent with the type of content being taught.
- Application is effective only when learners receive intrinsic or corrective feedback.
- Application is enhanced when learners are coached and when this coaching is gradually withdrawn for each subsequent task.

Integration principle

- Learning is promoted when learners integrate their new knowledge into their everyday life by being directed to reflect-on, discuss, or defend their new knowledge or skill.
- Integration is enhanced when learners create, invent, or extrapolate personal ways to use their new knowledge or skill to situations in their world.
- Integration is enhanced when learners publicly demonstrate their new knowledge or skill.

The Changing Learning Landscape

In the following paragraphs we will describe the changing learning landscape in terms of what ought to be learned, the context in which learning takes place, and who is learning.

Changes in what ought to be learned

Because of the accelerating rate of change in society and technology, demands for instruction have changed. More than ever, people need to be equipped not only with knowledge of facts or procedures, but also with more general problem-solving and reasoning skills that allow them to deal with new, unfamiliar situations in their professional and everyday life. Thus, the aim of instruction is no longer primarily about learners having reached specific learning objectives at the end of the instructional phase, but about learners' ability to flexibly apply what has been learned in new problem situations after the instructional phase (i.e., *transfer*; Mayer & Wittrock, 1996) and their ability to maintain their future learning (i.e., *self-regulated* or *self-directe*d learning; Loyens, Magda, & Rikers, 2008).

Changes in the learning context

In addition to changes in what ought to be learned, there are also major changes in the contexts in which learning occurs nowadays. Changing contexts result, among other factors, from new technologies. In modern societies, people have opportunities to connect to other people and to vast information resources 24/7, through mobile phones, MP3 players, Personal Digital Assistants, laptop computers and other devices for ubiquitous computing, ambient intelligence, and augmented intelligence. These technologies have built-in affordances that allow for the realization of many instructional methods that sustain a wide range of different types of learning. As a consequence, time- and place-independent learning in technology-rich, informal and professional settings is becoming general practice. Moreover, like modern society as a whole, education is developing from a production economy to a service economy, where educational services are available on-demand and customized for the individual learner ('mass individualization') (Schellekens, Paas, & Van Merriënboer, 2003). These changes in context have important implications for our thinking about the delicate relationship between instruction and technology, or, methods and media.

Changes in learners

Not only are people able to learn more and more in out-of-school contexts because of changes in the learning context, they are also increasingly expected to do so. Because of rapid changes in information and technology, knowledge and skills are quickly becoming obsolete. Thus, there is an obvious need to regularly update knowledge and skills for individuals in all stages of their lives (‘lifelong learning’: Van Merriënboer, Kirschner, Paas, Sloep, & Caniëls, 2009). Because lifelong learning is not only situated in schools, but often in professional or daily life, learners increasingly participate in more than one learning network, and the composition of those networks continuously changes. A learning network is defined as a social network specifically designed to support lifelong learning (Van Merrienboer, Kirschner, Paas, Sloep, & Caniels, 2009). The typical composition of such job-related or personal social networks is heterogeneous, including learners with different cultural and professional backgrounds, prior knowledge, and learning goals. In addition, rather than one teacher there may be several people in the network taking on roles related to teaching, such as a tutor-role, an expert-role, a coaching-role, and so forth. Probably the most conspicuous development is that learning networks are often virtual. For instance, they may take the form of Web-based learning communities. Wenger (1998) discusses learning communities as one kind of “community of practice”, which is a social construct that places learning in the “…context of our lived experience of participation in the world” (p. 3). Web-based learning communities and communities of practice are sometimes seen as a new paradigm for learning in the 21st century. Interestingly enough, this development into the direction of communities goes hand in hand with a further development of individualized and personalized instruction. Although this may sound paradoxical, it is not illogical: the heterogeneity of learners for example in terms of age, prior knowledge and experience, or learning goals and learning styles have great implications for the effectiveness of instruction (Furnham, Volume 2). Therefore, one-size-fits-all instruction is not an optimal solution for such heterogeneous populations of learners, and personalized instruction that is adapted to the abilities and needs of the individual learner is required.

Consequences for Instructional Design

These changes in the learning landscape have major consequences for instructional design. Before addressing those consequences, however, it is important to note that the effectiveness of instruction is determined by the extent to which the characteristics of working memory and long-term memory are taken into account in the design of instruction (Paas, Renkl, & Sweller, 2003, 2004; Sweller, Volume 1; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005). Whereas working memory is responsible for short-term maintenance of information (around 18 seconds) and integration and coordination of the maintained information, long-term memory is responsible for long-term maintenance of information (from a few days to decades).

Cognitive schemata are the product of learning; they are structures in which knowledge is stored and organized in LTM. Learning takes places by associating new information elements with each other (schema construction) or with prior knowledge (schema elaboration) in WM. WM capacity, however, is limited to seven plus or minus two elements or chunks of information when holding information (Miller, 1956) and even fewer (ca. 4) when processing it (Cowan, 2001). This poses a bottleneck for learning when tasks contain a high number of interacting information elements. Because those elements have to be processed in working memory simultaneously for learning to take place, such tasks impose a high load on working memory. In cognitive load theory this is referred to as *intrinsic* cognitive load (Sweller et al., 1998). Cognitive load theory focuses on complex cognitive tasks, in which instructional control of cognitive load is critically important to meaningful learning. To realize this control, the theory uses current knowledge about the human cognitive architecture to generate instructional techniques.

Knowledge and expertise develop through the building of increasing numbers of ever more complex schemata in long term memory by combining elements consisting of lower level schemata into higher level schemata. A schema retrieved from long-term memory can be handled in working memory as a single information element. Therefore, the number of interacting elements and the intrinsic load imposed by a learning task decreases for learners who have prior knowledge of that task. Moreover, though high amounts of practice, some (sub)schemata can become automated and no longer require controlled, effortful processing, which further reduces the load on WM (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977).

Next to this intrinsic load imposed by the task, there is also load imposed by cognitive processes that are evoked by the way in which a learning task or a series of tasks is designed or delivered to learners. This load can result from processes that are ineffective for learning (i.e., imposing an *extraneous* cognitive load) or directly contribute to learning (i.e.,imposing a *germane* load; Sweller et al., 1998). For example, any instructional procedure that requires learners to engage in either a search for a problem solution or a search for referents in an explanation (i.e., when Part A of an explanation refers to Part B without clearly indicating where Part B is to be found) is likely to impose a heavy extraneous cognitive load because working memory resources must be used for activities that are irrelevant to schema acquisition and automation (Paas, Renkl, & Sweller, 2003). Germane load can be imposed by beneficial cognitive processes, such as elaborations, abstractions, comparisons, and inferences that are encouraged by the way in which the learning tasks are designed (e.g., Paas & Van Merrienboer, 1994). For instruction to be effective, intrinsic load should be optimized, extraneous load should be minimized, and germane-load should be optimized, so that available WM capacity is not exceeded and is used most effectively (Sweller et al., 1998).

Fostering transfer

Changes in what ought to be learned, more specifically, the need for the acquisition of flexible problem solving skills and self-regulated learning skills, have led to a shift away from traditional instructional design paradigms (Van Merrienboer, 1997; Van Merrienboer, Kester, & Paas, 2006). This shift can be defined along five dimensions: (a) from well structured towards ill-structured problems; (b) from domain-specific towards domain-general competencies; (c) from cognitive towards metacognitive processes (processes involved in learners' awareness of their own knowledge and their ability to understand, control, and manipulate their own cognitive processes); (d) from ‘expert-novice’ towards ‘expert-expert’ performance mappings, and (e) from specific learning objectives towards authentic reference situations.

Instructional design typically begins with defining learning outcomes, then identifies the cognitive processes and structures involved in achieving these outcomes, determines the relevant methods and techniques to activate these cognitive and personality dispositions, and finally measures the effects of the instructional arrangements according to particular criteria. Defining learning outcomes is related to analyzing possible reference situations for a particular educational program, which contains a set of ill-structured problems. This means confronting learners with authentic real-life situations and constructing a set of ill-structured learning tasks representing these situations. The question, however, is not only to involve learners in solving ill-structured problems but also to provide them with necessary and sufficient operational support, preferably matched to their individual needs and preferences (Van Merrienboer, Kirschner, & Kester, 2003). Learning to cope with ill-structured learning tasks requires not only domain-specific knowledge and skills but also domain-general competencies. Domain-general competencies are based on metacognitive strategies that operate on the cognitive structure and processes, which themselves are bound up with domain-specific knowledge and skills. Observing and comparing the performances of high profile professionals provides valuable information for the ways these experts behave in ill-structured problem situations, which can be used for modeling instruction in the most effective way.

The capability of solving problems is widely recognized as the most important competence that students should acquire to behave adequately in various professional contexts (Ge & Land, 2004; Jonassen, 2004; Merrill, 2002). Current theories of problem solving mostly reflect the results of research conducted on well-structured problems, while ill-structured problems are ill understood (Pretz, Naples, & Sternberg, 2003). However, more focus on ill-structured problems is necessary. Many authentic problems encountered in various fields are ill-structured, that is, are characterized by the availability of incomplete data or insufficient access to information; the existence of alternative and often conflicting approaches; the lack of a clear-cut problem-solving procedure; multiple possibly appropriate solutions

(Jonassen, 2004; Schön, 1996). Another distinguishing feature of ill-structured problem solving is the combination of multi-contextual influences and dynamics of uncertainty (Mirel, 2004). Often, the problem solver has to take different perspectives on a problem before finding one that gives insights into viable solution paths (Pretz et al., 2003). Research points out that different intellectual skills are needed for solving well-structured problems, which rely on applicative or recurrent skills that are highly domain-specific, and ill-structured problems, which rely not only on applicative but also on interpretive or non-recurrent skills that are less domain-specific (Cho & Jonassen, 2002; Hong, Jonassen, & McGee, 2003; Van Merriënboer, 1997). In this respect, the meaning of domain-specific and domain-general competencies is also changing because the combination of both is needed to solve ill-structured problems.

Domain-specific knowledge, skills, and attitudes are a substantial part of professional competence. But sometimes they are not sufficient for adequately responding to the challenges posed by ill-structured problem situations. Then, other types of competencies are required to manage the problem-solving process, in particular, the analysis of the problem situation, the generation of alternative solutions, the selection of the most appropriate solution for the given situation, and its implementation into practice. Pretz et al. (2003) describe these domain-general competencies as ‘metacognitive’ components of professional competence. This is indicated by the fact that these components emphasize the regulation, monitoring, and control of problem-solving activities to make the best use of technical, domain-specific knowledge and skills (Chambres, Izaute, & Marescaux, 2002; Metcalfe & Shimamura, 1996; Zimmerman & Campillo, 2003). Domain-general competencies may prevent the negative effects of ‘functional fixedness’ (Davidson, 2003; De Bono, 1990; Gick & Holyoak, 1983; Holyoak & Thagard, 1995; Keane, 1997; Weisberg &

Alba, 1981) and 'analysis-paralysis' (Von Wodtke, 1993), which are often present in ill-structured problem solving. Functional fixedness reflects the hindering effect of past experiences on problem solving, emphasizing the negative role of a problem-solving strategy that works well for certain tasks, but not for other tasks. When functionally fixed, people tend to look for existing solutions and easily jump to conclusions, completely ignoring the opportunity to identify better solutions. Analysis-paralysis is the tendency to spend unlimited time on analyzing the problem situation and generating ideas, with an inability to select among alternative solutions, draw conclusions, and plan the next steps in the problem-solving process.

Most research on learning from problem solving refers to the limited capacity of working memory as the most important cognitive factor determining learning performance (Hambrick & Engle, 2003; Paas et al., 2003, 2004; Van Merriënboer & Sweller, 2005). However, several cognitive theories emphasize the crucial role of long-term memory in learning from problem solving as well (Lubart & Mouchiroud, 2003; Robertson, 2001; Wenke & Frensch, 2003). Whereas long-term memory may be unlimited in terms of storing information elements, the retrieval of relevant information elements may cause problems in ill-structured problem-solving situations. Then, the information might actually be available, but not be accessible, which affects problem-solving performance of both novices and experts.

Most of the issues related to the role of long-term memory in ill-structured problem situations and the negative problem solving effects such as functional fixedness (i.e., cognitive bias that limits a person to using an object only in the way it is traditionally used) and negative transfer (i.e., detrimental effect of prior experience on the learning of a new task), can be explained by the 'paradox of knowledge structure.' This paradox states that the structure of knowledge both enables and restricts ill-structured problem solving. Knowledge organizes itself in knowledge structures (patterns, schemas), which are absolutely necessary for successful problem solving. They are easily recognizable, repeatable, give rise to expectancy, provide useful short-cuts to the solutions, and offer a platform for interpreting incoming information and communicating new solutions. Knowledge structures, however, may have a detrimental effect that hinder problem solving, especially in ill-structured situations. A knowledge structure can establish a dominance, which forces the problem solver to see and follow only one path and not be aware of other possibilities (Anderson, 1983; De Bono, 1990). People tend to quickly pick and apply a dominant problem-solving schema without investigating the problem situation for possible alternative solutions. Because of that, individuals are prone to select an inappropriate schema. Once a knowledge structure presents itself, the tendency is for it to get larger and more firmly established. This makes it very difficult to break off and jump into an alternative line. A person with insufficient knowledge structures might be unable to look at the information in a meaningful way, but a person with strong knowledge structures might not be able to look at the information in a new way.

Recent research on experts' problem solving performance in ill-structured situations emphasizes the crucial role of metacognitive knowledge and strategies for regulation, monitoring and control of problem solving activities, which could prevent the negative effects of the 'paradox of knowledge structure' (Jonassen, 2004; Pretz et al., 2003; Zimmerman & Campillo, 2003). Metacognitive processes operate on the internal representations of the problem solver, such as cognitive schemas, mental models, and plans. Metacognition emphasizes two essential functions: self-management and self-appraisal (Paris & Winograd, 1990; see also McCormick, Volume 1). Self-management refers to 'metacognition in action,' that is, operational support of problem solving in terms of analysis of the problem situation, idea generation, idea selection, and solution implementation. Self-appraisal refers to self-reflections on cognitive and affective processes in a problem-solving situation. Awareness about the existence of the ‘paradox of knowledge structure’ is metacognitive knowledge. The next step is successfully managing this phenomenon, that is, promoting the enabling part and suppressing the restricting part. Studies on expertise provide evidence that the ‘paradox of knowledge structure’ should be attributed to both novices and high profile professionals (Ericsson, 2003; Ericsson & Kintsch, 1995; Holyoak, 1991). High levels of domain knowledge can sometimes be an impediment to problem solving by limiting the search space to readily available ideas.

Research on expert-novice differences has been very fruitful to determine cognitive factors that play a role in the acquisition of expertise (Chase & Simon, 1973; Chi, Feltovich, & Glaser, 1981; De Groot & Gobet, 1996; Frensch & Sternberg, 1989). Comparing the performances of experts in different professional domains has equally proven valuable (see Ericsson, 2003; Ericsson & Charness, 1994; Ericsson, Charness, Feltovich, & Hoffmann, 2006). Holyoak (1991) identified issues in expert performance that cannot easily be explained by findings from classical novice-expert research: Experts do not always easily accomplish what novices accomplish with difficulties; expert search strategies are extremely varied and often opportunistic; expert performance does not show continuous improvement with practice; knowledge can sometimes be transferred across domains; the teaching of expert rules often does not lead to expertise; expertise depends on induction, retrieval, and instantiation of schematic knowledge structures rather than the acquisition and use of highly specific production rules, and skilled performance depends on the parallel integration of multiple sources of information rather than serial information processing. It has become clear that not only novices but also experts need specific support to improve their performance. Investigating what makes one expert better than another expert in ill-structured problem situations is a valuable research target in the field of learning and instruction. Such research may identify specific skills and underlying cognitive and metacognitive processes, such as factors related to ‘deliberate practice’ (Ericsson, 2003), which may have important consequences for instructional design.

The formulation of learning objectives has always been a critical part of the instructional design process. Traditional instructional design models analyze a learning domain in terms of distinct objectives, after which instructional methods are selected for reaching each of the separate objectives. This often results in atomistic, part-task models that yield instruction that is fragmented and piecemeal (Van Merriënboer, Clark, & de Croock, 2002), and learners' inability to combine the many pieces they have learned into coherent wholes, to integrate acquired knowledge, skills, and attitudes, and to apply what they have learned to new problems and new situations.

As mentioned in previous sections, transfer of learning is a major goal of contemporary education in order to meet the challenges posed by rapid societal and technological changes. Holistic or whole task instructional design models (e.g., Van Merriënboer & Kirschner, 2007) address these problems by analyzing a learning domain as a coherent, interconnected whole, which leads to a highly integrated set of objectives. Learning tasks are used that are based as much as possible on the real-life tasks that have to be performed after the learning phase. The use of ‘whole tasks’ facilitates the integration and coordination of knowledge, skills, and attitudes. That is, in contrast to the part-task approach, it is not left up to the learners to integrate and coordinate the parts later on when they have to perform the whole task after training (Van Merriënboer & Kester, 2008). Thus, a whole-task sequence for training is to be preferred and fosters transfer (see also Peck & Detweiler, 2000; Wightman & Lintern, 1985; Wightman & Sistrunk, 1987). It is important to note that using authentic whole tasks does not mean these tasks should be completely identical to real-life tasks. It is important to distinguish cognitive authenticity from physical authenticity, and cognitive authenticity is in general more important than physical authenticity. There can be good reasons for adopting a somewhat less physically authentic (simulated) learning environment (e.g., reducing material costs and costs of errors; reducing seductive details; to be able to take time for feedback and reflection during task performance, et cetera).

Real-life reference situations are used during assessments, to ask the learner to demonstrate that an integrated set of objectives has been reached. This not only puts learning objectives in a broader context and makes them meaningful but also requires learners to apply their knowledge, skills, and attitudes in an integrated manner, thus promoting transfer.

In designing instruction based on real-life tasks, several principles need to be taken into account in order to ensure that instruction is aligned with WM and LTM characteristics. These principles are also part of the four component instructional design model (4C/ID model, see Van Merriënboer, 1997; Van Merriënboer & Kirschner, 2007) that addresses the issue of how to teach complex cognitive skills.

First of all, to prevent the excessive cognitive load that is typically associated with authentic tasks, learners typically start working on learning tasks that represent relatively simple versions of the whole tasks that experts encounter in the field and progress towards learning tasks that represent more complex versions of the whole tasks as their expertise increases. For example, some of the task factors that determine how complex it is to perform a scientific literature search skill are the clearness of the concept definitions within the domain, the number of articles written about the topic of interest, and the number of search terms and Boolean operators needed to identify the topic of interest. Using these factors, the simplest task can be defined as a category of learning tasks (i.e., task class) in which the concepts are clearly defined, with only a few search terms, and which yields a limited amount of relevant articles. In contrast, the most complex task class can be defined as a category of learning tasks in which concept definitions within the domain are unclear and searches require many terms and Boolean operators in order to limit relevant articles. Additional task classes of an intermediate complexity level can be added in between by varying one or more of the task factors.

Learning tasks are grouped in so called task classes, in such a way that each task class consists of learning tasks at the same level of complexity. The task classes are sequenced to increase in complexity. In this way cognitive load is optimized because at any time in the training program learners receive learning tasks that are challenging to them but never too demanding on their cognitive capacities. The final task class represents all tasks, including the most complex ones that professionals encounter in the real world. For example, some of the task factors that determine how complex it is to perform the task of scientific literature search, which could be used to create less and more complex task versions are: (a) the clearness of the concept definitions within the domain (ranging from clear to unclear); (b) the amount of articles that are written about the topic of interest (ranging from small to large), and (c) the amount of search terms and Boolean operators needed (ranging from few search terms to many search terms that are interconnected with Boolean operators).

Given these factors, the assumptions for the first, simplest task class can be defined as follows: A category of learning tasks that confronts learners with situations in which the search is performed in a domain in which the concepts are clearly defined, with only few search terms and yielding a limited amount of relevant articles. The most complex task class is defined as a category of learning tasks that confronts learners with situations where concept definitions within the domain are unclear and in which searches have to be performed with many search terms interconnected by Boolean operators in order to limit the otherwise large amount of relevant articles. Additional task classes of an intermediate complexity level can be added in between by varying one or more of the task factors.

Secondly, within each task class, high levels of support or guidance should be provided on the first tasks, and should be gradually decreased. Task formats that provide high degrees of support and have been shown to foster learning for students who lack prior knowledge of tasks within that class are *worked examples* (i.e., a written, worked-out solution procedure is presented; for a review, see Atkinson, Derry, Renkl, & Wortham, 2000) or *modeling examples* (i.e., a solution procedure is demonstrated by a model; for a review, see Schunk, 1987), *completion problems* (i.e., partially worked-out examples in which the learner has to complete the steps that were not worked-out; e.g., Paas, 1992), *process-worksheets* or *process steps* (i.e., an overview of the general steps to be taken, but the learner has to work-out those steps; e.g., Hummel, Paas, & Koper, 2005; Van Gog, Paas, & Van Merriënboer, 2006). However, research has shown that such high-support formats like worked examples are only effective when they are well-designed, that is, prevent split-attention (i.e., when learners have to split their attention between various types of information within the same display to understand a task; for a review, see Ayres & Sweller, 2005) and presentation of redundant information (for a review, see Sweller, 2005). Also, they are only effective for novice learners who lack prior knowledge, and may lose their effectiveness or even have adverse effects on learning once learners have acquired some prior knowledge (see Kalyuga, Ayres, Chandler, & Sweller, 2003, for a discussion). Research has shown that taking into account the developing levels of knowledge of the learner, by starting out with a high degree of support or guidance and gradually decreasing that support, makes learning more effective and efficient. For example, a *completion or fading strategy* can be used, in which a transition is made from studying worked examples via completion problems with increasingly more blank steps for the learner to complete, to solving problems without any support (for a review, see Renkl & Atkinson, 2003). A factor to be considered in the design of problem-solving tasks for instruction, is that learners are usually given an explicit goal to reach, whereas research in a variety of domains has shown that providing people with a *non*-specific goal for problem solving leads to better learning outcomes (e.g., Ayres, 1993; Owen & Sweller, 1985; Paas, Camp, & Rikers, 2001; Sweller & Levine, 1982; Vollmeyer, Burns, & Holyoak, 1996).

It is possible that the tasks in the first task class (i.e., containing the least complex tasks that professionals may encounter in the real world) are too complex even with high levels of support and guidance. In this case, it becomes necessary to manage the intrinsic load imposed by the task, using a strategy that involves both whole-task and part-task sequencing (see also Pollock, Chandler, & Sweller, 2002; Van Merriënboer, Kester, & Paas, 2006) or that manipulates the relative emphasis of selected subcomponents, but leaves the whole task intact (i.e., emphasis manipulation approach; Gopher, Weil, & Siegel, 1989). Roessingh, Kappers, and Koenderink (2002) developed and tested a model to determine the optimal training time schedule for a combined training sequence with whole and part task practice. They concluded that if one part-task has to be included in the training, more than 50 % of the total training time has to be devoted to whole-task practice in order to maximize performance. So they suggested that even in cases where whole-task practice is not the only possible type of training, it still should take up the largest part of it.

Third, learning and especially transfer can be promoted by increasing the *contextual interference* between tasks within each task class. The contextual interference effect has been widely investigated in instruction of both motor skills (e.g., Magill & Hall, 1990; Shea & Morgan, 1979; Wulf & Shea, 2002) and cognitive skills (e.g., Carlson, Sullivan, & W. Schneider, 1989; De Croock, Van Merriënboer, & Paas, 1998; Helsdingen, Van Gog, & Van Merriënboer, in press; Jelsma & Pieters, 1989; Paas & Van Merriënboer, 1994; Schneider, Healy, & Bourne, 2002). This effect indicates that low contextual interference, as in a blocked sequence of different types of learning tasks (tasks of the same type are trained in blocks: e.g., AAA-BBB-CCC-DDD), often leads to better performance and lower cognitive load during learning than high contextual interference resulting from a random sequence of different types of learning tasks (different types of tasks are trained in a random order: e.g., A-C-D-B-B-C-A-D-A-B-D-C). This random sequence, however, leads to better retention and transfer after learning. Paas and De Croock (2004) have argued that the increase in cognitive load by contextual interference constitutes germane load, as it promotes meaningful learning by stimulating learners to compare the solutions to the different learning tasks and to abstract more general knowledge for solving a wide range of problems.

Another task-sequencing strategy that has been extensively investigated in cognitive psychology and is somewhat related to contextual interference is *spacing*.

The spacing effect refers to the consistent finding that in a given amount of study time, memory for repeated stimuli is mediated by the interval between the repetitions of the stimulus, that is, spaced stimulus presentations lead to better memory than massed presentations (for a review, see Dempster, 1988). Despite the robustness of both the contextual interference and the spacing effects in experimental research, these strategies are still not widely implemented in instruction programs (see Dempster, 1988, for a discussion of potential reasons concerning the spacing effect, many of which also seem to apply to contextual interference and still seem to apply today).

Fourth, supportive and procedural information should be provided 'just-in-time'. Supportive information supports problem solving and reasoning within a task class, by providing learners with for example causal, structural, or conceptual domain models, that help them acquire general, abstract schemata that apply to multiple tasks within that class (Van Merriënboer & Kirschner, 2007). Teachers typically call this information 'the theory', which is often presented in study books and lectures. Supportive information reflects both mental models and cognitive strategies. Models of how the world is organized may be described in a general sense and are typically illustrated by case studies. Cognitive strategies may be presented as systematic approaches to problem solving, describing the successive phases in a problem-solving process and the rules-of-thumb or heuristics that may be helpful to successfully complete each of the phases. Procedural information supports routine procedures and consists for example of specific descriptions of rules, scripts, or procedures (e.g., decision flow charts) necessary to perform a task ('how to' information; Van Merriënboer & Kirschner, 2007). However, if one would present all this additional information with the complex learning tasks, it would probably lead to cognitive overload. Therefore, 'just-in-time' information presentation is necessary, and according to the four component instructional design model (Van Merrienboer, 1997), supportive information is best presented before a task class because of its own inherent complexity, whereas procedural information is best presented during task performance. Surprisingly, however, findings by Kester, Kirschner, and Van Merriënboer (2006), are not entirely in line with this information presentation model. Their results indicated that the order of presentation did not really matter, as long as supportive and procedural information were not both presented at the same time (before or during task performance). Possibly, even though the theoretical assumptions for what is just-in-time presentation for supportive and procedural information seem sensible, it may really just be a matter of preventing cognitive overload by not presenting all information sources at the same time.

Fifth, feedback is one of the most important variables influencing the learning process. Feedback during instruction usually consists of external information about performance that can be used to reduce the gap between current and desired performance (cf. Ramaprasad, 1983). Giving appropriate feedback can not only contribute to learning by allowing learners to verify their answers, evaluate their progress, and determine the cause of errors (Johnson & Johnson, 1993), but can also motivate learners to remain involved in the learning tasks, provided that they perceive the feedback as helpful (Azevedo & Bernard, 1995; Chai, 2003; Hattie & Timperley, 2007; Hoska, 1993; Hyland, 2001; Keller, 1983; Mory, 2003; Ross & Morrison, 1993; Vollmeyer & Rheinberg, 2005). However, there are some important mediators of the effectiveness of feedback for learning: Content, frequency, and timing of feedback (Goodman & Wood, 2004; Kulhavy & Wager, 1993). Regarding content, feedback that not only allows learners to verify the correctness of their answers, but also provides information that will guide them towards obtaining a correct answer on future tasks seems to be the most effective for learning (Kulhavy & Stock, 1989). However, learners' prior knowledge is recognized as a factor of influence on feedback effectiveness (Hannafin, Hannafin, & Dalton, 1993).

Finally, learners may be prompted to process learning tasks more deeply, which is held to foster transfer via processes of reflection, elaboration, abstraction, and generalization. Many learners do not spontaneously engage in deep processing and need to be prompted to do so, for example with *self-explanation prompts* (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Renkl, 1997), such as "talk aloud and verbalize anything that comes to your mind" (according to the guidelines of Ericsson & Simon, 1993), or *critical thinking* prompts, such as the following proactive prompt used by Helsdingen (2008: p.97): "Are there any similarities between the following two cases? Which are they, and what is different between these cases?". Self-explaining has been mostly studied in combination with worked examples, however, there are some studies that have shown beneficial effects of self-explanation prompts on learning when combined with problem solving tasks (Aleven & Koedinger, 2002; De Bruin, Rikers, & Schmidt, 2007) or expository texts (Chi, De Leeuw, Chiu, & Lavancher, 1994). Moreover, self-explanation prompts can also be combined with a completion or fading strategy to enhance transfer even further (Atkinson, Renkl, & Merrill, 2003). Helsdingen (2008) studied the effects of critical thinking instruction (cf. Cohen, Freeman, & Wolf, 1996) consisting of a general introduction to the method prior to the learning phase and prompts during the learning phase, in relation to contextual interference. She found that blocked practice (i.e., practice with a series of similar learning tasks) combined with *proactive* critical thinking prompts resulted in transfer performance comparable to that obtained with random practice. The differential effectiveness of timing of prompts in different practice schedules is presumably due to cognitive load factors. Proactive prompts (i.e., given before a set of tasks) should be manageable in blocked practice, because the load imposed by a blocked schedule is lower. So, learners should be able to keep the prompts given before a set of tasks in mind and engage in more elaborate processing while working on those tasks. For a random schedule, it is exactly the other way around: providing prompts before a set of tasks might lead to cognitive overload, as the load imposed by a random schedule is already high.

In sum, there are many different instructional principles available for optimizing cognitive load and enhancing learning and transfer, and many of those principles can be successfully combined, but potential adverse effects on cognitive load resulting from certain combinations need to be considered.

Enabling personalized instruction

In the previous section we have described strategies for optimizing cognitive load, learning, and transfer, when designing 'fixed' or one-size-fits-all instruction. As mentioned before, changes in learners and in the learning context, require more personalized instructional trajectories adapted to the individual learner's abilities and needs. In the last decades, new technologies have 'technically' enabled the individualization of instruction. Nevertheless, up until now individualization in education has not been very successful because highly individualized learning trajectories can only be realized if the number of possible trajectories is very large. Thus, there is the need to develop a large amount of learning tasks and instructional materials beforehand in order to make individualization possible—and this threatens its cost-effectiveness. Only since the upsurge of Web technologies it has become possible to develop instruction for very large target groups. And thanks to the combination of technologies and large groups individualization is now not only technically feasible, but also becoming cost-effective. This process is known as ‘mass individualization’ or ‘mass customization’, and may be expected to yield an enormous increase in the flexibility of education (Schellekens et al., 2003). Research has shown that personalized, adaptive instruction in which the level of support and the level of complexity of learning tasks are adapted to the learner’s level of prior knowledge can be more effective and efficient than fixed training programs (see Camp, Paas, Rikers, & Van Merriënboer, 2001; Corbalan, Kester, & Van Merriënboer, 2006, 2008; Salden, Broers, Paas, & Van Merriënboer, 2004; Salden, Paas, & Van Merriënboer, 2006). Three types of models can be distinguished with regard to the design of adaptative instruction: system controlled, shared responsibility, and advisory (Van Merriënboer, Sluijsmans, Corbalan, Kalyuga, Paas, & Tattersall, 2006).

In *system-controlled* models, an instructional agent (trainer, e-learning application) selects the optimal learning task from all available tasks based on an assessment of the learner’s performance aspects on the previous task(s). An important question is how the dynamic adaptation of learning tasks can best be achieved. The algorithms that underlie task selection in such models can be based on assessment of different performance aspects (accuracy or time taken), cognitive load, or a combination of those (see e.g., Camp et al., 2001; Salden et al., 2004, 2006). As we have described earlier, the cognitive capacity needed to perform a task depends not only on task complexity but also on the level of schema construction and schema automation that an individual has attained (i.e., someone’s level of prior knowledge or expertise). This implies that individuals with more expertise are able to attain equal or higher levels of performance with less investment of mental effort (a measure of actually experienced cognitive load; Paas, Tuovinen, Tabbers, & Van Gerven, 2003).

Therefore, if performance is low, but mental effort is very high, a learner may need a task that is lower in complexity or provides more support. If performance is high, and effort is low, a learner may need a far more challenging task or one that does not provide any support. Algorithms for task selection that implement this strategy ensure that each next task is in optimal alignment with the individual learner's developing expertise. Even though there is no theoretical reason why such models (i.e., assessment and task selection algorithms) could not be implemented by trainers in regular settings, it will be very difficult to implement if instruction is not on a one-to-one basis. Therefore, this model is usually implemented in e-learning environments, using an application that automatically assesses performance, effort, or both; and uses this to select a next task based on some defined algorithm.

Kalyuga (2006, 2008; Kalyuga & Sweller, 2004, 2005) has extended the research on system-controlled adaptive instruction by studying different techniques for *rapid* assessment of prior knowledge or expertise. For example, Kalyuga and Sweller (2005) used a rapid assessment measure in the domain of algebra, which entailed asking learners to indicate their first step towards the solution as fast as possible. Another rapid assessment procedure used by Kalyuga (2008) relies on rapid verification rather than generation of solution steps: learners need to rapidly verify suggested steps at various stages of a problem solution procedure. This line of research seems very promising for system-controlled adaptive instruction, although it should be noted that the domains in which it has been studied thus far are highly structured, such as algebra, geometry, or kinematics. An interesting question is whether comparable techniques for rapid assessment could be found for more ill-structured tasks or problems.

In *shared responsibility* models an instructional agent registers the learner's performance and/or effort, and selects a suitable *subset* of learning tasks from all available tasks, after which the learner makes a final selection from this subset (Corbalan et al., 2006). These models can provide an improvement on system-controlled models, which do not provide students with freedom of choice over tasks, and with the opportunity to learn how to select learning tasks. Shared responsibility models provide some freedom of choice, which seems to have positive effects on learners' motivation (e.g., Corbalan et al., 2008; see also Graham & Weiner, Volume 1; Kaplan, Katz, Flum, Volume 2), but not too much, as too much freedom may lead to stress, high mental effort, and demotivation (Iyengar & Lepper, 2000; Schwartz, 2004). They also provide students with some control over their own learning process, without giving them full responsibility. Full responsibility (or fully self-regulated/self-directed learning; see the next section) may seem the ultimate way of realizing personalized instructional trajectories, but research has shown that this often leads to detrimental effect on learning when learners are not able to accurately evaluate their own performance or to select an appropriate next task in response to that assessment (Kostons, Van Gog, & Paas, 2010). Shared responsibility models can allow for *gradual* transfer of responsibility over assessment and task selection from the system to the learner.

In *advisory* models, either shared responsibility is implemented (i.e., an instructional agent selects a suitable subset of tasks) or learners have full responsibility (i.e., fully self-regulated/self-directed learning; see the next section), but in both cases the learner receives advise to support them in selecting a new learning task. Three types of advisory models may be distinguished: Procedural models, social models, and metacognitive models (Van Merriënboer et al., 2006).

Procedural advisory models basically provide learners with advice for task selection using the same rules or algorithms that could be applied to implement system control. These may include rules to compute efficiency on the basis of performance and invested time and/or effort, rules to decide on the desired level of support for a next learning task, and rules to decide when to continue to a next task class or difficulty level based on the performance and/or invested time and effort for conventional learning tasks (Kicken, Brand-Gruwel, & Van Merriënboer, 2008). Due to their algorithmic nature procedural advisory models are highly specific and will be difficult to transfer to other domains and learning settings.

Social advisory models apply self-organization principles to open an additional channel of advice for learners when sequencing learning tasks (Koper et al., 2005; Tattersall et al., 2005). The approach revolves around a continuous process of collecting, processing and presenting data on the paths taken by all different learners who use the learning tasks. A feedback loop is set up in which the progress of previous, successful learners is fed back to learners facing a similar sequencing choice (e.g., "other learners successfully reached the goal you are striving to attain by proceeding this way"). The aim is to allow learners to make informed choices concerning steps on their learning journey, based on actual rather than predicted learner behavior. In contrast to procedural models, social models apply a very general approach that is applicable over many learning domains and settings. But the feedback principles used are not very helpful for learners to improve their self-regulation skills.

To that end, *metacognitive* advisory models are more suited. These explicitly help learners to apply cognitive strategies for assessing their own performance, for matching these assessment results with the qualities of available learning tasks, for making an informed selection from those tasks, for planning their own work on those learning tasks, and so forth. This may help learners to develop cognitive strategies for regulating their own learning. As such, it may be hypothesized that a metacognitive advisory model is more effective than a procedural or social model for the development of self-regulation skills (see Zimmerman & Labuhn, Volume 1) and, in particular, task selection skills, but more empirical research is necessary to establish whether this is indeed the case.

Fostering self-regulated learning skills to sustain future and lifelong learning

Next to fostering transfer, a major aim of contemporary education is to foster self-regulated learning skills, because these play a major role in future self-directed learning (Loyens et al., 2008) in professional as well as in informal settings (i.e., lifelong learning). As was clear in the last section, this aim of helping learners acquire self-regulated learning skills is not effectively achieved by providing learners with full responsibility over what tasks to work on, in what order, and for how long. If self-regulated learning is to be as effective as fixed or adaptive instruction controlled by some instructional agent, learners need to have the ability to accurately judge their own learning and select an appropriate new learning task in response to that assessment (Kostons et al., 2010). Unfortunately, research has shown that many students are not very accurate in assessing their own performance and deciding which learning activities to pursue (either restudying or selecting novel information; Bjork, 1999; Kornell & Bjork, 2007). Instruction that aims to foster self-regulated learning might therefore need to incorporate training of self-assessment and task selection skills (Van Gog, Kostons, & Paas, 2010).

It is also often argued that stimulating students to reflect on their learning might make them more aware of their own learning processes and possible alternative strategies. The awareness of alternatives is considered a critical aspect of self-regulated learning, as it is prerequisite for changing a less than optimal study habit (Boekaerts, 1999; Boud, Keogh, & Walker, 1985; Ertmer & Newby, 1996). However, the beneficial effect of reflection on self-regulated learning can be expected to arise only if learners actually engage in reflection and when –again- their reflection is of good quality, meaning that they should be able to accurately diagnose their own process (what went well, what needs to be improved?) and come up with alternative strategies.

Research has shown that many learners are not likely to spontaneously engage in reflection and will require reflection prompts to trigger this process (Van den Boom, Paas, & Van Merriënboer, 2007; Van den Boom, Paas, Van Merriënboer, & Van Gog, 2004). However, even when prompted, high-quality reflection may be very difficult. When learners are prompted to reflect *during* the learning task, reflection becomes a kind of dual task that requires additional cognitive resources and therefore may interfere with learning from the task. Moreover, novices might not be able to engage in high-quality reflection, because –by definition- they lack knowledge of the task as well as knowledge of performance standards (i.e., what constitutes good/average/poor performance on a task; Dunning, Johnson, Erlinger, & Kruger, 2003). As a consequence, they will have difficulties determining what they need to improve, and determining what better alternatives for future courses of action would be. For learners with more knowledge of a task (advanced learners), this problem will be alleviated, because for them, the same task will impose a lower intrinsic load for them than for novices (see Sweller et al., 1998), and they are likely to have some more knowledge about performance criteria and standards based on their experience (Dunning et al., 2003). To make reflection prompts beneficial for novices, they might need to be followed by feedback (Butler & Winne, 1995) or reflective dialogues with a tutor (Chi, 1996; Van den Boom et al., 2007).

In the previous sections, learners' prior knowledge has repeatedly been mentioned as a learner characteristic that influences the effectiveness of instructional formats or sequences. This is a characteristic that is of course also important in lifelong learning, because of large variations in background and experience within groups of learners, and thus in levels of prior knowledge or expertise development. Another learner characteristic that is important for lifelong learning, although it has not received nearly as much attention in instructional design research, is the learner's age (see also Rogers, Stronge, & Fisk, 2005), as lifelong learning will evidently mean that more and more elderly people become involved in both formal and informal learning. A substantial body of research (for a review, see Reuben-Lorenz, 2002) has demonstrated that cognitive aging is accompanied by a reduction of working-memory capacity (e.g., Salthouse, Mitchell, Skovronek,& Babcock, 1989), slowed processing speed (e.g., Salthouse, 1996), difficulties inhibiting responses to irrelevant information (e.g., Hartman & Hasher, 1991), and deficits in integrative aspects of WM (e.g., Mayr, Kliegl, & Krampe, 1996). Given the important role that working memory capacity plays in learning, effects of aging on cognitive load and learning should be taken into account in instructional design.

In general, since instructional formats that deal with cognitive limitations in that they lead to an efficient use of the available WM capacity, for example by providing high degrees of support or guidance, it can be hypothesized that they will be especially effective for elderly learners (Paas, Van Gerven, & Tabbers, 2005; Van Gerven, Paas, Van Merriënboer, & Schmidt, 2000). Among others, Van Gerven, Paas, Van Merriënboer, and Schmidt (2002; see also Paas et al., 2001) tested this hypothesis by comparing learning by studying worked examples (high level of instructional support) with learning by solving conventional problems (no instructional support). As may have been clear from the discussion on (decreasing) instructional support above, according to cognitive load theory, novices who lack prior knowledge of a task learn more from instructional formats that provide a high degree of support, such as studying worked examples, than from solving the equivalent problems (Sweller et al., 1998). Their results indeed showed that, especially for older learners (above 60 years), the efficiency of studying worked examples is higher than the efficiency of solving conventional problems (i.e., less learning time and cognitive load leads to a comparable level of performance; for a discussion of instructional efficiency, see Paas & Van Merriënboer, 1993; Van Gog & Paas, 2008). Declines in working memory processes may not only be relevant for the choice of task formats though, but also for self-regulated learning, as this requires many of the control processes that may be affected by aging.

Current and future issues in designing instruction

Current instructional design is driven by contemporary education's focus on ill-structured realistic problems and the associated demands for flexible application of acquired knowledge and skills (i.e., transfer), and self-regulated learning. Holistic or whole task instructional design models are responsive to these demands by analyzing a learning domain as a coherent, interconnected whole, which leads to a highly integrated set of objectives, and facilitates the required integration and coordination of knowledge, skills, and attitudes. This chapter describes the four component instructional design model as an example of such models. This model is based on five principles that ensure that instruction is aligned with human cognitive architecture. Firstly, to prevent the excessive cognitive load that is typically associated with authentic tasks, learners start working on learning tasks that represent relatively simple versions of the whole tasks that experts encounter in the field and progress towards learning tasks that represent more complex versions of the whole tasks as their expertise increases. Secondly, within each task class, high levels of support or guidance are provided on the first tasks, and are gradually decreased. Thirdly, learning and especially transfer are promoted by increasing the contextual interference between tasks within each task class. Fourthly, supportive and procedural information is provided 'just-in-time'. Fifthly, feedback is used to reduce the gap between current and desired performance.

An important future issue in designing instruction is related to new technologies that have 'technically' enabled the individualization of instruction. Until now, individualization in education has not been very successful because highly individualized learning trajectories can only be realized if the number of possible trajectories is very large. Thus, there is the need to develop a large amount of learning tasks and instructional materials beforehand in order to make individualization possible. Only since the upsurge of Web technologies it has become possible to develop instruction for very large target groups. And thanks to the combination of technologies and large groups individualization, it is now not only technically feasible, but also becoming cost-effective. A distinction is made between system-controlled, shared-responsibility, and advisory models, in which an instructional agent, a learner, or both selects the optimal learning task from all available tasks based on an assessment of the learner's performance aspects on the previous task(s).

Conclusion

In this chapter we have provided a historical overview of the field of instructional design and discussed the characteristics of the contemporary learning landscape in terms of what ought to be learned, the learning context and the learners with regard to their consequences for instructional design. Next, the main principles for the design of instruction for complex cognitive tasks that pose relatively great challenges to the cognitive capacity of the learner were described. Using the theoretical framework of cognitive load, it was argued that the structures that constitute human cognitive architecture need to be taken into account in the design of effective and efficient instruction. Design principles for achieving transfer, enabling personalized instruction, and fostering self-regulated learning skills to sustain future and lifelong learning of complex cognitive tasks were discussed. Finally, current and future issues in designing instruction were discussed.

A challenge for evaluating the effectiveness of instruction designed according to the models and principles discussed here, lies in the fact that whether aims such as improving transfer to new tasks and situations, or improving the ability to regulate ones own future learning have been achieved only becomes apparent long after the instruction has ended. It is possible, however, to attain some indications of whether these goals have been achieved. For one, learners performance on authentic tasks that draw on transfer and self-regulation skills could be assessed repeatedly during instruction as well as immediately at the end of instruction and some time after that. Testing after instruction has ended is important; very often learners' performance improvement is measured only *during* instruction and although there is nothing wrong with this, one should not confuse improvements in performance during instruction with actual learning (Bjork, 1999). The research on the contextual interference effect discussed in this chapter shows for example that performance during the learning phase is not always a good indicator for learning: blocked practice may lead to performance improvement during the learning phase compared to random practice, although the latter is more effective on retention and transfer measures after the learning phase.

In this chapter, we have repeatedly discussed the influence of learner characteristics, but primarily from a cognitive perspective. Students' perceptions of instructional methods and learning environments can also affect the way in which they respond to instruction, and as a consequence, could affect their learning. For instance, Könings, Brand-Gruwel, and Van Merriënboer (2005) studied the perceptions of young Dutch students (13–16 years of age) who were confronted with an educational innovation, characterized by the use of meaningful learning tasks, more independent learning, and individualization. Whereas some students perceived this innovation as desirable and an impetus for their learning, others perceived it as undesirable and not helpful at all for promoting their learning.

In conclusion, we hope that this chapter will stimulate instructional designers and researchers to design instruction that is compatible with the characteristics of the contemporary learning landscape, thereby enabling people to learn effectively and efficiently from complex cognitive tasks.

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