Individual differences and cognitive load theory

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Introduction

The previous chapters discussed sources of cognitive load that are a result of the difficulty of the materials, the design of instruction, and the amount of mental effort invested by learners to process the new information. As outlined in these chapters, the major cause of cognitive load effects is the limited capacity of working memory. In this chapter, we will discuss how individual differences relate to the level of cognitive load that a particular learner experiences.

Individual differences in learner characteristics take many different forms, ranging from preferences for learning from different presentation formats (e.g., verbal, pictorial) or modalities (auditory, visual, haptic) and preferences for learning under different environmental conditions (e.g., lighting, noise level, or physical position) to cognitive styles (e.g., field dependency/independency), cognitive abilities (e.g., verbal, spatial ability), and intelligence (Carroll, 1993; Jonassen & Grabowski, 1993). The influence of individual differences on learning has been studied for several decades as aptitude-treatment interactions (ATI; Cronbach & Snow, 1977; Leutner, 1992; Lohman, 1986; Mayer, Stiehl, & Greeno, 1975; Plass, Chun, Mayer, & Leutner, 1998; Shute, 1992; Snow, 1989, 1994; Snow & Lohman, 1984, 1989). Aptitude-treatment interactions occur when different instructional treatment conditions result in differential learning outcomes depending on student aptitudes, in other words, when the effect of a given treatment is moderated by a given aptitude. Different aptitudes may influence learning in specific instructional environments, and the impact of a particular aptitude on a particular condition may only be observed for a particular type of learning outcome. For example, Plass et al. (1998) found that learners with visualizer vs. verbalizer learning preferences used multimedia links in a reading environment for second-language acquisition differently, resulting in different learning outcomes for text comprehension but not for vocabulary acquisition. The goal of this chapter is to focus on learner characteristics that are likely to affect the amount of available working memory and that, therefore, are expected to influence cognitive load during learning. It should be noted, however, that few studies exist that measured both individual differences and cognitive load.

Which types of individual differences might be expected to have a significant effect on cognitive load that is of practical relevance? For the purpose of this chapter, we use a typology of
individual differences that distinguishes between differences in information gathering, information processing, and regulation of processing (Table 1). Individual differences related to information gathering include learning styles, learning preferences, and personality types. This type of individual differences is characterized as value-neutral, i.e., as indicators of typical performance that are not linked to outcomes in a directional sense (Jonassen & Grabowski, 1993). For example, the visual v. verbal learning style indicates a person’s preference to learn with visual (i.e., pictorial) v. verbal learning material, but does not generally predict better performance for learners with one learning style versus the other.

Table 1. Categories of Individual Differences in Learning

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<tr>
<th>Information Gathering</th>
<th>Information Processing</th>
<th>Regulation of Processing</th>
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<td>Learning styles</td>
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The ATI hypothesis states that in order to be instructionally effective, learning environments need to match, learners’ individual differences. Although confirmed under specific circumstances (Homer, Plass, & Blake, 2006; Plass, Chun, Mayer, & Leutner, 1998), this hypothesis has to date not been empirically supported as a general principle for designing learning environments. One reason for this lack of empirical evidence may be the fact that few valid instruments exist to reliably measure individual differences variables, specifically in the field of learning styles and learning preferences (Leutner & Plass, 1998; Moreno & Plass, 2006).

Individual differences in information processing include cognitive controls, cognitive abilities, including intelligence and prior knowledge, which are viewed as value directional, i.e., as indicators of maximal performance and as predictors for learning success (Jonassen & Grabowski, 1993). Due to our focus on individual differences that can potentially affect cognitive load during learning, we will examine the role of prior knowledge (Kalyuga, 2005) and spatial abilities (Mayer & Sims, 1994; Plass, Chun, Mayer, & Leutner, 2003) as research has established a strong relationship between these constructs and working memory (Shah & Miyake, 1996).
Differences in regulation of processing include learners’ motivation and metacognition/self-regulation. Self-regulation was found, at least in a number of studies, to be a strong predictor for learning (Graesser, McNamara, & VanLehn, 2005; Leopold, DenElzen-Rump, & Leutner, in press; Pintrich & de Groot, 1990; White & Fredriksen, 2005; Zimmerman & Schunk, 2001) that significantly affects the level of cognitive load experienced by learners (Winne, 2001).

In this chapter, we first provide a more detailed discussion of the expertise reversal effect, i.e., the interaction of learners’ level of expertise and instructional design on learning outcome. Second, we extend the discussion to individual differences on spatial abilities and self-regulation. Third, we describe an adaptive approach that can be used to optimize instructional design in response to these individual differences. Finally, we outline questions and methodologies for future research on the relationship of individual learner characteristics and cognitive load.

Prior knowledge (Expertise Reversal Effect)

The previous chapter described a set of general instructional principles that support processes of schema acquisition and enable learning. One of these principles, the expertise principle, reflects the primary role of learner’s organized knowledge structures (schemas) in the learning processes. Research has identified prior knowledge as one of the most important individual difference factors influencing cognitive load during learning (Kalyuga, 2005; Mayer, 2001).

According to cognitive load theory, the magnitude of mental load in learning depends on the schemas that have been previously acquired by the learner. As explained in previous chapters, a learning element is a function of the level of learner expertise. What constitutes a learning element and which elements interact with each other depends on a learner’s schemas: a set of many interacting elements for one person may be a single element for another, more expert learner. Therefore, although experts in a particular domain do not possess larger working memory capacities, they experience a decreased working memory load because they have larger organized knowledge structures (or chunks of information) stored in long-term memory.

In some learning scenarios, however, expertise may actually trigger additional cognitive load because experts have to process information that, given their high level of expertise in the given domain, is unnecessary for them to assure successful learning. The expertise reversal effect
(see Kalyuga, Ayres, Chandler, & Sweller, 2003; Kalyuga, 2005, 2007) occurs when an instructional method that is effective for novices becomes ineffective for more knowledgeable learners (see also Lohman, 1986). Such a decline in the relative effectiveness of instruction with changes in learners’ levels of expertise can be explained within a cognitive load framework: When more experienced learners need to reconcile their available schemas with the conceptual models presented during instruction, working memory processing and storage load is likely to increase and cause an unnecessary extraneous cognitive load. Therefore, instruction that eliminates unnecessary material for a particular learner should be superior to instruction that includes such material.

Detailed instructional explanations, often essential for novices to understand the learning materials, may, with increasing levels of knowledge, become unnecessary. If detailed explanations are provided for these more experienced learners, processing this information may increase cognitive load and interfere with learning instead of assisting it. For example, many diagrams require additional explanations to be comprehended by novice learners. However, if a more advanced learner has sufficient knowledge to understand a diagram by itself, any additional verbal explanations of this diagram could be unnecessary. Yet, it would be difficult to ignore text that is physically integrated into the diagram or to ignore a narrated explanation accompanying the diagram. Processing the explanation, relating it to the diagram, and, most importantly, relating it to the knowledge structures the learner has already stored in long-term memory may result in significantly higher cognitive load than learning from the format that presents the diagram by itself (Kalyuga, 2005; 2006a; Sweller, 2005).

Techniques that integrate textual explanations into diagrams, replace visual text with auditory narration, and use worked examples to increase instructional guidance, were found to be effective means of reducing working memory overload for less knowledgeable learners (see Kalyuga et al., 2003, for an overview). However, with the development of learners’ knowledge in a domain, these techniques often result in negative rather than positive or neutral effects. Subjective measures of cognitive load supported the hypothesis that processing components of instruction that were unnecessary for more knowledgeable learners increased working memory load.
In most of the original studies on the split-attention effect in learning from diagrams and text, participants were novices that did not have a sufficient schematic knowledge base (Tarmizi & Sweller, 1988; Ward & Sweller, 1990; Sweller, Chandler, Tierney, & Cooper, 1990; Chandler & Sweller, 1991). However, even at those early stages of cognitive load research, it was noticed that differences between learners in domain-specific knowledge influenced the observed effects on learning outcome. For example, Mayer and Gallini (1990) demonstrated that physically integrated parts-and-steps explanatory illustrations were more effective in promoting scientific understanding (how brakes, pumps, and generators work) for low prior-knowledge learners than for high prior-knowledge learners. Although the results of this study did not show a complete reversal of cognitive load effects, it showed that the split-attention effect took place only for learners with low levels of expertise. Similarly, Mayer and Sims (1994) found that only novice students benefited from temporal coordination of verbal explanations with visual representations. There were no differences for high-experience learners who had already developed a sufficient long-term memory knowledge base.

Longitudinal research has demonstrated that the level of learner expertise was a critical factor that influenced the occurrence of the split-attention and redundancy effects (Kalyuga, Chandler, & Sweller, 1998). Direct integration of textual explanations into diagrams was beneficial for learners with very limited experience in the domain. Such materials were easier to process and resulted in a higher level of performance. However, in subsequent stages, as the learners' levels of expertise in the domain gradually increased, the pattern of results changed. The effectiveness of the integrated diagram-and-text condition decreased while the effectiveness of the diagram-alone condition increased. More experienced learners, who studied relatively new and more complex materials in the domain, reported relatively higher levels of mental load, which suggests that the text interfered with learning. The diagram-alone materials were easier to process and resulted in higher levels of performance on the subsequent tests. Similar patterns of results were obtained in other studies using different instructional formats and methods, such as dual-modality versus single-modality presentations of text and graphics, worked example instruction versus problem solving practice, and worked example instruction versus exploratory learning (Kalyuga, Chandler, & Sweller, 2000; 2001; Kalyuga, Chandler, Tuovinen, & Sweller, 2001; Tuovinen & Sweller, 1999). Additions to the original instructional text, designed to
increase text coherence, were found to only benefit low-knowledge readers; high-knowledge readers benefited from using the original text only (McNamara, Kintsch, Songer, & Kintsch, 1996). Other research tested cognitive-load predictions regarding individual differences in learning from multiple representations. Elementary students learned how to add and subtract integers with an interactive multimedia game that included visual and symbolic representations of the procedure, with or without verbal guidance. Verbal guidance helped to minimize cognitive load only for students with low prior knowledge, low computer experience, and a less reflective cognitive style (Moreno, 2002, 2005).

The above studies investigated instructional techniques for reducing extraneous cognitive load. As was mentioned in the previous chapter, when intrinsic or germane load exceed limits of working memory capacity for a given level of learner expertise, it could effectively become a form of extraneous load inhibiting learning processes. The expertise reversal effect was also observed with instructional methods used to manage intrinsic cognitive load. For example, to reduce the intrinsic load of some complex materials, an isolated-interactive elements instructional technique suggested by Pollock, Chandler, and Sweller (2002) recommends presenting first, separate units of information without showing the relations between them, and then presenting the original material showing all the interactions. However, this instructional method did not offer any benefits to learners who already possessed basic schemas in the domain. Reduction of intrinsic load is effective only for low-knowledge learners, but not for high-knowledge learners for whom the material does not have a high degree of element interactivity.

A similar expertise reversal with isolated-interactive elements effect has been demonstrated by Ayres (2005) in the domain of simple algebra transformations such as $5(3x-4) - 2(4x-7)$. A part-task, isolated-element strategy, where the constituent elements were isolated from each other (required only a single calculation to be made), benefited learning only for students with low prior knowledge. In contrast, students with a higher level of prior knowledge learned more from whole tasks where all elements were fully integrated (required four calculations to be completed per problem). A mixed strategy where students progressed from part-tasks to whole tasks, proved to be ineffective for both levels of prior knowledge.
In a study on visual complexity in learning from chemistry simulations, Lee, Plass, & Homer (2006) manipulated intrinsic cognitive load of the visual display by either presenting a simulation with three variables (temperature, pressure, volume of an ideal gas) on one screen, or separating the simulation into two parts ([1] temperature and volume; [2] pressure and volume of an ideal gas). Extraneous load was manipulated by optimizing the screen design using established cognitive load principles. They found an expertise reversal effect for comprehension and transfer, which manifested itself in that the measures of reducing extraneous load were effective for both low- and high-prior knowledge learners in the low intrinsic load conditions. In the high intrinsic load conditions, however, these load-reducing measures supported low-prior knowledge learners but hindered high-prior knowledge learners.

There have also been some preliminary indications of expertise-treatment interaction effects with instructional techniques designed to enhance germane cognitive load in learning. For example, Renkl (2005) demonstrated that an instructional technique that required learners to find and fix intentionally introduced errors in worked examples in order to increase germane cognitive load was beneficial for high-prior knowledge learners but not for low-prior knowledge learners.

Thus, some of the instructional design principles and techniques intended for expert learners are, as a result of the described findings, contrary to those recommended for novice learners. For example, it would be beneficial for expert learners to eliminate components of multimedia presentations that are unnecessary for them, even if the resulting format might only use a single presentation form of information (e.g., only visual diagram). Problem- and discovery-based learning environments with limited guidance could be effective for advance learners, but would typically not be recommended for novices. Similar reversal effects are expected to be found with other cognitive load reduction methods as learners become more advanced in a domain. An expertise reversal may be expected in situations where well-guided instructional presentations intended for novice learners are used with more advanced learners and, therefore, require an unnecessary additional expenditure of cognitive resources.

If the efficiency of instructional designs depends on levels of learner prior knowledge in a domain, with learners gaining optimal benefits from different formats at different levels of expertise, a major instructional implication of the expertise reversal effect is that instructional
techniques and procedures need to change as learners acquire more knowledge in a domain in order to minimize redundant activities at each level of expertise. According to the instructional design principles of fading (Renkl & Atkinson, 2003) and scaffolding (van Merrienboer, Kirschner & Kester, 2003), which are based on cognitive load theory, novice learners should be provided with considerable instructional support that could be gradually reduced as levels of learner expertise increase. Completion tasks (van Merriënboer, 1990), faded worked examples (Atkinson, Derry, Renkl & Wortham, 2000; Renkl, Atkinson, Maier, & Staley, 2002), or just varying the number and degree of details of guidelines or hints provided to students as they solve problems or explore learning environments could gradually change the levels of instructional support at intermediate and higher levels of learner expertise.

**Spatial Abilities**

Spatial abilities include three basic factors related to the processes of generating, retaining, and manipulating visual images: spatial relations, i.e., the ability to mentally rotate visual images; spatial orientation, i.e., the ability to imagine how visual images might look from a different perspective; and visualization, i.e., the ability to manipulate visual patterns and identify mental images (Carroll, 1993; Lohman, 1979). According to current working memory models, spatial abilities rely heavily on working memory resources, especially on its visuo-spatial sketchpad (VSSP) and executive control components (Baddeley, 1986; Miyake & Shah, 1999). Individual differences in spatial abilities are attributed to differences in spatial working memory, which is distinct from verbal working memory (Hegarty, Shah, & Miyake, 2000; Shah & Miyake, 1996). Research has also found that different spatial ability factors involve the VSSP and the executive control components of working memory to different degrees. For example, tests of spatial visualization appear to demand more involvement of executive control than tests of spatial relations, while the VSSP is important for all factors to maintain the visuo-spatial information in memory (Hegarty & Waller, 2005).

**Spatial Ability and Extraneous Load**

Most of the studies that related individual differences and cognitive load have investigated the effect of spatial abilities under different extraneous load conditions. For example, the temporal contiguity effect, which describes learning advantages for materials with
concurrent presentation of narration and animation over the successive presentation of narration and animation, was strong for students with high- but not for those with low-spatial abilities (Mayer & Sims, 1994). Coordinated presentation of visual and verbal explanations enhanced learning for high-spatial ability learners and also compensated for learners’ low level of prior knowledge (Mayer & Gallini, 1990; Mayer, Steinhoff, Bower, & Mars, 1995).

There is also evidence that levels of spatial abilities relate to extraneous load in a virtual learning environment. Exploring a virtual environment’s interface requires working memory resources; therefore, high-spatial ability students were better at exploring the interface than low-spatial abilities students. As a result, learners’ spatial abilities were highly correlated with levels of learning (Waller, 2000). Similar findings were obtained in research on audial navigation in voice-prompt systems. Untrained users were provided with four different navigation conditions: hierarchical, flexible, guided (all voice-controlled), and hierarchical (keypad-controlled) (Goldstein, Bretan, Sallnäs, & Björk, 1999). The authors suggest that because of their design, the hierarchical and flexible structures offer more flexibility, but require more cognitive engagement, whereas the guided condition reduced cognitive load, but provided fewer options. Although no differences in number of completed tasks, total completion time, or subjective attitudes were found across these conditions, participants who scored high on tests of spatial abilities completed their tasks most efficiently in the flexible structures than those users who obtained lower scores. Users with low spatial ability completed tasks more efficiently in the guided structures of navigation, suggesting that for these users, the guidance condition with lower cognitive load was more effective for the initial learning task, compared to high-spatial ability users, for whom the conditions with higher cognitive load (and more flexibility) were more effective (Goldstein et al., 1999).

Spatial abilities were found to differently affect different types of learning outcomes. The research by Mayer and Sims (1994), for example, found an effect of spatial abilities on transfer tasks, but not on tests of retention. In research on second-language acquisition, learners read a German text with or without the following types of annotations: textual-only, consisting of English translations of the selected German words; visual only, consisting of still images or video clips of the selected German words; or both text and visual annotations. These annotations were designed to aid learners’ selection of relevant information for understanding the meaning of
individual vocabulary items. Learning outcomes were measured using a vocabulary and a comprehension post-test. In the vocabulary post-test, high-spatial ability learners performed better than low-spatial ability learners when only visual annotations were available. Low spatial-ability learners, on the other hand, performed better than high-spatial ability learners when no annotations were available and when both visual and verbal annotations were available. This significant interaction effect of spatial abilities and treatment conditions for the vocabulary test was not found in the comprehension test (Plass, Chun, Mayer, & Leutner 2003). These results suggest that only high-spatial ability learners were able to focus on the main task of comprehending the text, while low-spatial ability learners spent more of their cognitive resources on the low-level processing and decoding of vocabulary words and less on the comprehension of the text. Learners’ spatial abilities, and the resulting different hypothesized levels of extraneous cognitive load, may have influenced learning strategies in processing the reading text, which were differently reflected in the two outcome measures.

Spatial Ability and Intrinsic Load

A small number of studies asked research questions that can be interpreted as to provide insights regarding the relation of spatial abilities and intrinsic cognitive load, even though none of them measured load directly. For example, Gyselinck and colleagues (2002) found that the beneficial effects of presenting illustrations with text disappeared when a concurrent tapping task was used to suppress visuo-spatial working memory. However, this pattern of results was present only in high, but not low-spatial ability subjects. Similarly, pictorial scaffolding in a geology multimedia simulation was more beneficial for high-spatial ability students than low-spatial ability students both on problem solving and transfer tests (Mayer, Mautone, & Prothero, 2002). In addition, high-spatial abilities students took significantly less time than low-spatial abilities students to process the learning materials. Authentic geology problems required high levels of spatial thinking, in which the pictorial-based scaffolding was particularly relevant and had a strong positive effect on high-spatial ability students. In contrast, purely verbal scaffolding did not have a similar effect (Mayer et al., 2002).

The instructional implications of these studies is that high spatial ability is typically related to better performance when instruction induces high levels of cognitive load, such as when it presents complex visuo-spatial materials. Whereas learners with lower spatial ability
may not be able to process such high load materials deeply, learners with higher spatial ability have the cognitive capacity to benefit from them. However, the majority of studies examining spatial ability effects did not explicitly measure cognitive load. With the exception of those studies where cognitive load was manipulated by design and predicted \textit{a priori} (e.g., Goldstein et al., 1999), the levels of cognitive load were inferred \textit{post hoc}, for example, from the analysis of study time and learning achievements. More systematic research needs to address the relationship of spatial abilities, cognitive load, and learning outcomes and directly measure cognitive load as well as cognitive abilities.

**Self-Regulation skills**

The concept of self-regulation describes the self-directed process of monitoring and regulating one’s learning. Self-regulation is a cyclical cognitive activity that involves forethought, performance or volitional control, and reflection (Zimmerman, 1998).

Evidence for the relationship of students’ self-regulation and their performance on academic tasks was found, for example, using the Motivated Strategies for Learning Questionnaire (MSLQ), where higher levels of reported self-regulation were associated with higher levels of academic performance (Pintrich & de Groot, 1990). Research has also shown that self-regulation strategies can be taught, and that such training can result in better learning outcomes when learning with instructional materials (see, e.g., Azevedo & Cromley, 2004, for hypermedia learning, and Leopold, DenElzen-Rump & Leutner, in press, and Leutner, Leopold & DenElzen-Rump, submitted, for learning from instructional texts). In this section, we will discuss research that can be interpreted as relating self-regulation to intrinsic load and to extraneous load, as well as research on the cognitive load impact of self-regulation scaffolds.

**Self-Regulation and Intrinsic Cognitive Load**

There is evidence that supports the notion that self-regulation is strongly related to overall cognitive load, and that high cognitive load can result in failure of self-regulation of effective performance in some learners (Baumeister, Heatherton, & Tice, 1994; Vohs & Heatherton, 2000). An important determinant of learners’ self-regulation is their level of prior knowledge, which, in turn, is a determinant of intrinsic cognitive load. Experts show more metacognitive awareness and have developed better self-regulation strategies than novices.
(Eteläpelto, 1993; Schönfeld, 1987; Shaft, 1995). Learners with different levels of prior knowledge regulate their own learning by employing different learning strategies (Hmelo, Nagarajan, & Day, 2000). Variations in learners’ knowledge structures seem also to be related to differences in individual learning strategies: the higher the prior domain-specific knowledge, the deeper the learning strategy that may be preferred by the learner (Beishuizen & Stoutjesdijk, 1999). Research on expert-novice differences in performance found also that learners’ self-regulation skills significantly influence working memory processes and the efficiency of managing cognitive resources (Moreno, 2002; Moreno & Durán, 2004). A study of children’s self-regulatory speech in mathematics activities, both individually in the classroom and in pairs in a laboratory setting, found that, in the individual classroom work, high achieving students had a statistically significantly larger frequency of regulatory speech than middle and low achieving students. In the lab setting, where children worked in pairs, these group differences disappeared, and the frequency of self-regulatory statements increased by a factor of up to five. Unlike the case of the classroom setting, where students seem to have experienced high load due to the difficulty of the assigned problems, the tasks given to students in the lab setting were matched to their level of prior knowledge (Biemiller, Shany, Inglis, & Meichenbaum, 1998). These results suggest that higher intrinsic load may lead to lower self-regulation activity as compared to lower intrinsic load conditions.

**Self-Regulation and Extraneous Cognitive Load**

Self-regulation activities themselves can also be viewed as generating extraneous cognitive load, as the monitoring, control, and reflection activities involved in self-regulation require the investment of additional mental effort. Self-regulation demands, therefore, may result – at least for unskilled self-regulated learners – in decreased performance (Cooper & Sweller, 1987; De Bruin, Schmidt, & Rikers, 2005; Kanfer & Ackerman, 1989) and failure to engage in subsequent self-regulation (Muraven, Tice, & Baumeister, 1998). Some of the reasons for these findings were highlighted in a study by Kanfer and Ackerman (1989) that involved learning in a complex skills acquisition task (air traffic control task). Participants in one group were initially instructed to do their best to complete the task, and they received specific goals only after several trials. A second group received specific goals from the beginning. Results showed that the group who initially did not receive specific goals reported higher self-regulatory activity and
outperformed the group that worked with specific goals from the beginning, suggesting that this method may have reduced extraneous cognitive load. Other studies found that positive learning outcomes depended on the types of goals given to the learners. In research on the acquisition of writing skills Zimmerman and Kitsantas (1999) demonstrated the benefits of setting goals that facilitate self-monitoring and self-regulation: Learners who were given process goals or outcome goals did not acquire writing skills as well as those who first received process goals and then shifted to outcome goals. This shifting of goals provided learners with a method to set hierarchical goals to guide their learning, a method which is suggested to lead to more independent and self-motivated learning (Bandura, 1997). Specific criteria for effective goals were identified in a study on goal setting and metacognition. This research found that study goals that allowed learners to derive adequate monitoring standards (e.g., specific behavioral objectives for each study session) were more effective in facilitating learning than goals that did not provide these standards (e.g., general learning goals or specific time-related goals; Morgan, 1985).

**Self-Regulation Scaffolds and Cognitive Load**

Research on the use of scaffolds to facilitate self-regulation in hypermedia learning found that the assistance of human tutors, externally facilitating the processes of regulating students’ learning, was more effective than providing students with no scaffolding or with lists of sub-goals to guide their learning (Azevedo, Cromley, & Seibert, 2004). It also showed that metacognitive scaffolds to support low self-regulated learners can be designed in a way that high self-regulated learners are not negatively impacted (Griffin, 2002). In Griffin’s study, scaffolds were included in an online writing course that allowed learners to reflect on the specific elements of the course that would be of value to them, allowed them to set specific learning goals for each task, and asked self-regulation questions related to the achievement of the learning goals. Results indicate that these scaffolds had little effect on low-level tasks but helped low self-regulators perform better in high-level tasks, suggesting that these scaffolds were more successful under high- than under low-load conditions. All learners receiving these scaffolds spent more time on task than those learners who did not receive them (Griffin, 2002).

Other research examined the influence of learners’ reported use of self-regulated learning strategies on learning performance in learner-controlled and program-controlled computer-based
learning environments (Eom & Reiser, 2000). The Self-Regulatory Skills Measurement Questionnaire (SRSMQ) was used to measure metacognitive, cognitive, self-management, and motivational strategies prior to the study. High and low self-regulators were randomly assigned to one of the two instructional conditions: learner-controlled and program-controlled. In the learner-controlled group, students were allowed to control the order of instructional events, whereas in the program-controlled group, the instructional sequence was predetermined. The results indicate that the performance differences between learners with high and low self-regulation skills were greater in the learner-controlled than in the program controlled condition. High self-regulators showed no significant differences in performance between conditions, however, low self-regulators scored higher in the program-controlled condition than in the learner-controlled condition. Low self-regulation skills might have contributed to the cognitive load experienced by learners in the learner-controlled condition similar to the increased cognitive load experienced by low-knowledge learners in low-guidance environments (such as exploratory or discovery-based learning). In a similar study, Yang (1993) obtained a marginally significant interaction effect between levels of self-regulation and types of instructional control. High self-regulators achieved higher post-test scores in the learner-controlled condition than in the program-controlled condition, while low self-regulators achieved higher scores in the program-controlled condition than in the learner-controlled one.

In summary, despite the general finding that learners with higher self-regulation perform better than learners with low self-regulation, the relationship of cognitive load and self-regulation is complex and depends on several different factors that relate to both the learner and the design of the materials. Learners with higher prior knowledge usually apply deeper and more effective self-regulation strategies that use the available working memory resources more efficiently than learners with low prior knowledge. There is evidence that under high cognitive load conditions, learners use less appropriate strategies for self-regulation than under low cognitive load conditions. The cognitive processes involved in self-regulation can add to the experienced cognitive load as a function of the effectiveness of an individual’s learning strategies. However, when goals and scaffolds are well designed, this extraneous cognitive load can be reduced and learning can be facilitated.
However, many of our conclusions about self-regulation and cognitive load are interpretations that can only be inferred since none of the research on self-regulation we reviewed included a direct measure of cognitive load. Further research should therefore more systematically explore the relationship of self-regulation, cognitive load, and learning outcomes by including appropriate measures of each construct.

**Optimizing cognitive load in adaptive learning environments**

Determining the most appropriate instructional design for each individual learner is a difficult task. The decision should provide sufficient verbal and/or visual information and guidance to allow each learner to comprehend the material, yet avoid unnecessary verbal or visual information that may create extraneous cognitive overload and hinder learning. A major instructional implication of the statistical interactions found between learner individual characteristics and learning is that instructional designs should be tailored to learners’ levels of knowledge, skills, and abilities (Leutner, 1992, 2004).

To achieve the required levels of flexibility, dynamic online instructional systems might include different interactive learning modes that allow different learners to access the same information represented in different formats (Plass et al., 1998). The same instructional material may also be presented in different ways to the same individual at different stages of learning as her or his level of experience in the domain increases. For example, only selected elements of the text, graphics, and links could be displayed on the screen, and auditory explanations could be turned on or off when required by an individual learner. In such learner-adapted instructional systems, the tailoring of instructions to an individual learner can be guided by continuously assessing the person’s learning performance based on either a sophisticated computational student model such as in intelligent tutoring systems (Anderson, Corbett, Fincham, Hoffman, & Pelletier, 1992), or using appropriate dynamic diagnostic assessment tools (Leutner, 2004). The first approach is limited to rather narrow instructional domains that need to be analyzed and described in-depth on the level of elementary production rules, and requires high levels of expertise in computational modeling. The second approach is more straightforward and based on repeated cycles of ‘test-adjust’ steps. However, even this second approach requires more diagnostically powerful and rapid assessment instruments than those used in traditional
educational assessment. A third approach, though pedagogically not as powerful and often not suitable for inexperienced learners, is to allow learners to make their own choices that adapt the environment to their needs.

Developing suitable embedded diagnostic tools is, therefore, a major prerequisite for adapting instruction to individual learner characteristics and optimizing cognitive load. Even experienced tutors often lack sufficient diagnostic skills for adapting their level of instructional guidance to the individual needs of their students (Chi, Siler, & Jeong, 2004). As a result, instead of adapting learning tasks to student characteristics, the same uniformly prescribed “subject matter logic” is often followed (Putnam, 1987). Online learning environments usually constrain computer-mediated communication, thus making an accurate diagnosis of individual student characteristics even more difficult (Nückles, Wittwer, & Renkl, in press). At the same time, these technologies offer new potentials for building adaptive learning environments based on embedded assessments of individual learners (Leutner & Plass, 1998).

For example, the empirical evidence for the expertise reversal effect described earlier indicates that instructional designs that are optimal for less knowledgeable learners might not be optimal for more advanced learners. In order to adapt online instructional methods to levels of learner expertise, accurate and rapid online measures of expertise are required. Because learners need to be assessed in real time during an online instructional session, traditional knowledge testing procedures may not be suitable for this purpose. Using a rapid schema-based approach to assess levels of learner expertise (Kalyuga, 2006b; Kalyuga & Sweller, 2004), recent cognitive load research demonstrated the feasibility of embedding assessment methods into online learning environments to optimize cognitive load. Two rapid diagnostic methods were investigated within this approach: the first-step method and the rapid verification method.

With the first-step method, learners are presented with a task for a limited time and required to indicate rapidly their first step towards solution of the task. Depending on a person’s specific level of expertise in a domain, the first step could represent different cognitive processes. A more experienced learner may rapidly indicate a very advanced stage of the solution (or even the final answer) skipping all the intermediate solution steps, because of high levels of acquisition and automation of corresponding processes. A relatively novice learner may be able to indicate only a very immediate small change in the problem state (or start applying
some random search processes). Therefore, different first-step responses would reflect different levels of expertise in a specific task area.

With the rapid verification diagnostic method, learners are presented with a series of possible (correct and incorrect) steps reflecting various stages of the solution procedure for a task, and are required to rapidly verify the suggested steps (for example, by immediately clicking on-screen buttons or pressing specific keys on the computer keyboard). In order to successfully verify more advanced steps of a solution procedure, a learner should be able to rapidly construct and integrate more intermediate steps mentally, which is an indicator of a more advanced level of expertise. Validation studies of both methods indicated high levels of correlations between performance on these tasks and traditional measures of knowledge that required complete solutions of corresponding tasks. Test times were also reduced significantly in comparison with traditional test times (by up to 5 times in some studies). Both rapid assessment methods were combined with a measure of mental load into an integrated indicator of the efficiency of performance that was used as an online measure of expertise in adaptive learning environments (Kalyuga, 2006a; Kalyuga & Sweller, 2005).

Conclusion

In this chapter we argued that individual differences in learners could affect cognitive load if they influenced working memory. We then focused on the relationship of cognitive load and prior knowledge, spatial abilities, and self-regulation. However, a strong limitation of our discussion is that, with the exception of prior knowledge, the relationship among the specific individual differences, cognitive load, and learning outcomes has not yet been studied with sufficient detail, and many of our conclusions had to be inferred from indirect measures of cognitive load.

Among the problems of many studies on individual differences is the way these differences are measured. The use of self-report instruments for measuring learner preferences or self-regulation seems to be a far less valid way to assess such differences than, for example, the direct observation of expressions of these differences either using log files of user behavior (Leutner & Plass, 1998) or using protocol analysis of user comments (Plass, Homer, & Kalyuga, 2006).
It should also be noted that much of the present research is based on undergraduate populations at highly selective universities, where prior knowledge, cognitive abilities, and metacognitive skills are typically high. Therefore, the participants in this research are not necessarily representative of the general population. Research needs to provide deeper insights into the effect of individual differences on working memory during learning, and include reliable and valid measures for both, learners’ individual differences and cognitive load during learning. Methods for measuring cognitive load are discussed in the following chapter.
INDIVIDUAL DIFFERENCES AND COGNITIVE LOAD

References


