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Metacognitive Load – Useful, or Extraneous Concept? Metacognitive and Self-Regulatory Demands in Computer-Based Learning

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ABSTRACT

Instructional design theories such as the *cognitive load theory* (CLT) or the *cognitive theory of multimedia learning* (CTML) explain learning difficulties in (computer-based) learning usually as a result of design deficiencies that hinder effective schema construction. However, learners often struggle even in well-designed learning environments. In this theoretical paper, I will argue that cognitive resources-oriented theories such as the cognitive load theory might profit from extending their predominantly cognitive focus to one that additionally considers metacognitive and self-regulation demands. Empirical results on learning from multiple external representations and research on tool use are integrated to illustrate that computer-based learning environments usually pose a variety of cognitive, metacognitive and self-regulatory demands on learners which require knowledge and skills that learners often lack. Specifically, empirical findings suggest that most learners are unable to regulate their learning automatically. I thus argue that these activities consume working-memory resources as do activities that are closely related to schema construction. My article concludes with suggestions on how the concept of metacognitive load can be incorporated into resource-oriented theories such as the CLT to explain a wider variety of phenomena.

Keywords

Cognitive load, Computer-based learning, Metacognition, Self-regulated learning, Working memory

Introduction

The environment(s) we live in are becoming ever more complex (Field, 2006). To meet the demands of contemporary and future learning environments and work places, the complexity of curricula, learning environments, and learning tasks has increased accordingly (van Merriënboer & Sluijsmans, 2009). In this context, complexity is not something we should try to avoid in general. Certain levels of complexity are actually necessary to stimulate and foster higher-order cognitive and metacognitive processes (Sawyer, 2006). However, there is a challenge as well: Increasingly complex and rapidly changing learning demands encounter the relatively stable and limited cognitive equipment of humans. Increasingly powerful computers and high-resolution computer screens make it possible to display ever more complex arrangements of texts, pictures, animations, and sounds simultaneously.

In an ideal world, learners would make flexible use of such complex arrangements and blend new information together with their background knowledge into increasingly rich mental models. Facing difficulties or impasses, learners would actively pose relevant questions, persistently hunt for answers, critically evaluate the quality of the answers retrieved, construct deep explanations of the subjective matter, apply the explanatory content to difficult problems, and consciously reflect on these cognitive activities (Graesser, McNamara, & VanLehn, 2005, p. 231). Empirical results, however, reveal several problems that learners usually encounter in rich learning environments. For example, they often have difficulty extracting and integrating information from complex displays (e.g., Ainsworth, 2006). Learners often have problems interacting effectively with the multifarious options that rich media environments usually offer (e.g., Clarebout & Elen, 2007). Related to the interaction problems, learners frequently have trouble effectively monitoring and regulating their learning activities (e.g., Azevedo, 2002). Such findings suggest that we need to balance the degree of complexity that is technically feasible with what is cognitively achievable and, therefore, educationally desirable.

A general question that arises is whether and how humans' capabilities can keep pace with these rapidly changing demands. In the context of computer-based learning environments (CBLEs), a related, but more specific set of questions arises, namely how effectively can learners utilize the various features that CBLEs s offer nowadays to acquire knowledge and skills in different domains (e.g., mathematics or biology)? What difficulties do learners typically encounter when interacting with CBLEs? How are such difficulties explained by contemporary psychological theories? What cannot be explained well and where should we, therefore, modify, extend or combine contemporary theories? And finally, how can CBL be made even more effective?

The overall goal of this article is to contribute to our understanding of factors that can account for the typical difficulties learners encounter in CBL. In the following I argue that, especially in individual learning in front of a computer screen (which is becoming and will remain an increasingly more common and important learning setting nowadays), successful learning depends primarily on learning environments that support not only learners' cognitive, but their metacognitive and self-regulation activities as well. Although there is growing interest in supporting all kinds of such activities, three factors are often overlooked. First, unless they are fully automatized, all these activities compete for limited mental resources. Second, as with cognitive demands that do not always benefit learning, some metacognitive and self-regulatory demands might not always be beneficial either. Third, learners will or cannot always take full advantage of the support offered. The latter will usually initially depend on different types and degrees of expertise on behalf of the learners. i.e., their domain-specific prior knowledge and cognitive, metacognitive, and self-regulatory skills. My central argument is that with their growing complexity, CBLEs pose cognitive as well as metacognitive and self-regulation demands on learners. I further argue that these demands may sometimes be beneficial, sometimes irrelevant (but neutral), but occasionally also harmful for learning. To support these arguments, I examine typical demands that CBLEs pose on learners and discuss the role of their expertise in coping with these demands. Against the background of empirical results from research on learning from multiple external representations (of the learning contents) and research on tool use (i.e., learners' use and conceptions of support measures in CBLEs) I finally propose incorporating the notion of metacognitive demands in resource-oriented theories such as such as the *cognitive load theory* (CLT; Chandler & Sweller, 1991; Sweller, 2003; Sweller, 2004) and the *cognitive theory of multimedia learning* (CTML; Mayer, 2005).

The remainder of the text is structured as follows. First, I sketch how CLT and CTML contribute to the explanation of many (but not all) difficulties in CBL. I then illustrate how external representations and support measures (often referred to as "tools") as the constituent elements of CBLEs pose different demands on learners and how learners' levels of expertise are related to this. Against this background, I argue that metacognitive theories, and especially theories of self-regulated learning (e.g., Winne, 1996) can provide valuable complementary explanations of difficulties in CBL. Finally, I demonstrate how resource-oriented theories such as CLT might profit from incorporating the notion of metacognitive load.

A cognitive-resources perspective on learners' difficulties in CBL

Instructional-design theories such as the cognitive load theory and/or the cognitive theory of multimedia learning explain suboptimal learning outcomes mainly as a consequence of less-than-ideal learning-environment designs; design deficiencies that absorb too much of learners' cognitive capacities (or resources), leaving too little capacity for making sense of the material and for learning activities. From the perspective of CLT and CTML, learning environments should therefore be constructed in ways compatible with the human cognitive architecture. According to these approaches, the limitations of human working memory in particular (Baddeley, 1992) should be considered when designing learning environments and learning tasks. As such, CLT and CTML can be called *cognitive-resource oriented theories*. In these resource-oriented theories (as I refer to them in the remainder of this article), working memory is the central hypothetical structure of the human cognitive system where incoming information from the sensory channels (mainly visual and auditory; Mayer 2005) is temporarily stored and processed.

In CLT, the critical learning mechanisms are schema acquisition and schema automation. It is assumed that novel information is processed in the light of existing schemata that allow the classification of objects and problems into categories and that provide the necessary information on how to deal with novel information (Sweller, 1994). In CTML, critical learning mechanisms refer to the selection of relevant (verbal and visual) incoming information, the organization of that novel information into meaningful structures and, most importantly, the integration of novel with existing information into coherent mental representations to be stored in long-term memory (LTM). CTML also assumes that information is stored in the form of schemata. Integration, therefore, refers to the construction of novel schemata and the modification of existing schemata. Integration can thus be equated with learning, given that the integration results in a lasting change in LTM. In CLT, an initial form of working-memory load can be attributed to the learning content's difficulty. Basically, this *intrinsic load* is related to the number of relevant concepts in a learning content that must be maintained and processed simultaneously in working memory (i.e., *element interactivity*) in order to understand the content. Intrinsic load varies with the learners' prior knowledge and experience in given and related domains (e.g., Kalyuga, 2011). Prior knowledge – in form of highly integrated and hierarchically structured schemata – allows learners to treat multiple related concepts as single chunks of information, thereby reducing processing demands and facilitating further schema acquisition. With further exposition to similar situations or problems where acquired schemata have been successfully applied (i.e. by practice), learners will ultimately be able to solve such problems effortlessly because the required knowledge and routines have been automated. In CLT and CTML it is further assumed that schema acquisition can only succeed when the working memory is not already overburdened by processing demands that do not contribute to learning. CLT refers to such unnecessary processing demands on the learning environment as *extraneous load* (Chandler & Sweller, 1991). CTML refers to such demands as *incidental processing* (Mayer 2005). In order to construct, refine, and automate schemata CLT and CTML assume that learners must engage in conscious cognitive processes (Paas et al., 2003). In the original CLT framework, such processes are assumed to induce a third form of (desirable) working-memory load referred to as *germane cognitive load* (Sweller, van Merriënboer & Paas, 1998). CTML refers to such demands that support schema-construction (i.e., selection, organization, and integration) as *essential processing*. However, even when a CBLE is designed to induce an appropriate amount of intrinsic load (relative to learners' prerequisites), a minor amount of extraneous load and fair amount of germane load, the environment's effectiveness will also strongly depend on the willingness of learners to engage in relevant cognitive processes. In acknowledging this active role of learners, the concept of *mental effort* was introduced. Mental effort is defined as the amount of cognitive capacity that a learner allocates to accommodate the demands imposed by the task (Paas et al., 2003).

Resource-oriented frameworks have greatly expanded our understanding of relevant factors that influence learning. For example, CLT research has identified crucial task characteristics such as task format, task complexity, time pressure, or the use of multimedia (Paas et al., 2003). However, these task characteristics also reveal the two potential shortcomings of resource-oriented theories elaborated below.

Potential shortcomings of resource-oriented theories

An initial potential shortcoming involves the coarse or broad terms of resource-oriented theories. CLT and CTML are framework theories. As such, these theories operate on a relatively high level of abstraction. Due to this high level of abstraction, these theories' descriptions are necessarily rather broad, often leaving ample room for (post-hoc) interpretation. On the other hand, these theories are also instructional design theories. As such, they aim to inform instructional designers, teachers, and educational decision makers. To be (even) more informative, such theories should probably provide explanations on a more specific level. For example, in CLT the types of activities that may induce germane load are not elaborated further, making it difficult to design activities that foster germane from a cognitive load perspective. In an evaluation of CLT, Schnotz and Kürschner (2007) define germane load as a kind of working memory load "due to cognitive activities that aim at intentional learning and that go beyond simple task performance" (p. 496). Among the cognitive activities that Schnotz and Kürschner (2007) assume to induce "germane load" are, for example, the conscious search for patterns in the learning material (i.e., mindful abstraction), the conscious application of learning strategies, the restructuring of a problem representation (in order to solve a task more easily), and metacognitive processes that monitor cognition and learning.

From my perspective, two things are important to keep in mind. First, there might be more activities or processes relevant to effective learning beyond those proposed by resource-oriented theories. Second, several such activities seem to require conscious effort (at least until fully automated) and can thus induce working memory load. Initial candidates for such learning-relevant activities are metacognitive and self-regulatory activities. However, instead of assuming that such activities would per se induce germane load, I prefer to argue that such activities can induce either germane load or extraneous load (or none at all) depending primarily on the learner's experience with that activity. For example, this assumption is supported by the well-known fact that the acquisition of a learning strategy initially usually decreases learning performance and outcomes (referred to as the "valley of tears") until that strategy can be applied automatically (i.e., without much conscious effort). According to this view, metacognitive and self-regulatory activities can be beneficial, ineffective, or even detrimental for schema construction. In this context we can ask whether there are any other unnecessary or even harmful demands on working memory that may have been overlooked or ignored by resource-oriented theories and if so, what the sources of these additional demands are.

In order to answer these questions, I propose to seek variables that resource-oriented theories do not usually focus on. First of all, resource-oriented theories are much more deeply concerned with cognitive demands that directly affect schema construction than with metacognitive and self-regulative demands and the potential roles that these processes might play in learning. Furthermore, resource-oriented theories assume well-integrated (domain-specific) schemata in long-term memory to guide metacognitive processes such as planning, monitoring, or evaluating rather automatically. Being automatic, these processes would not consume any working-memory resources (e.g., Sweller et al., 2011). However, how can we be certain that these processes consume no capacity? What, for example, about false beliefs or misconceptions about the purpose(s) of a CBLE or their various features? When such misconceptions (stored as schemata in long-term memory) guide the learning process, it is reasonable to assume that such misleading schemata would impose extraneous demands on learners' cognitive systems.

In addition, resource-oriented theories potentially (lead researchers and practitioners to) underestimate the complexity of the relationships between task characteristics, patterns of cognitive load, and learning outcomes. Can we expect high-quality learning outcomes to result from a specific "state-of-the-art" design rather deterministically? From the CLT perspective, the answer would probably be "yes." Given a specific instructional design, CLT would predict specific types of activities by the learners which should consequently result in specific patterns of cognitive load (Gerjets & Scheiter, 2003). However, Gerjets and Scheiter, for example, demonstrated that variables such as the goal configurations of teachers and learners, and learners' processing strategies can moderate the effects of instructional design on extraneous load. In their study, learners' beliefs and expectations influenced goals and intentions. Goals and intentions then strongly determined strategy choice and the mental effort invested (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). The resulting activities are assumed to correspond relatively straightforwardly to specific patterns of cognitive load, which then predict learning outcomes (Gerjets & Hesse, 2004). Such results suggest a more complex pattern of relationships among task, load, and outcomes. From a resource-oriented perspective, important learner activities or processes might also be overlooked as the following example will show.

In an evaluation study of a tried-and-tested PACT Geometry Cognitive Tutor (Aleven & Koedinger, 2000), students displayed significant improvement from pretest to posttest (leaving room for further improvement). The Cognitive Tutor program provided tailored, just-in-time support to the students during problem-solving. The students had ample experience with the CBLE and the learning domain. From a cognitive-load perspective, such a result would probably be interpreted as being the result of a successful combination of just enough intrinsic load (relative to students' level of prior knowledge), a moderate amount of extraneous (due to just-in-time support offered during problem-solving), and a reasonable amount of germane load (due to task design, the support offered, and the mental effort the learners invest). However, an in-depth log-file analysis revealed inefficient learning behavior. Learners waited too long to ask for help in case of errors, and they largely ignored a glossary that provided definitions and examples of the geometry principles. Moreover, when learners did ask for help, they immediately looked for the most specific level of help that virtually provided the solution to the task at hand. The authors attributed this inefficient help-seeking behavior to a lack of metacognitive knowledge and skills (e.g., being able to monitor one's progress) and proposed training these skills so that learners can make more effective use of available help. It's probably fair to say that in this particular study, neither cognitive load nor mental effort was assessed. However, even when learners might have reported little invested mental effort, without detailed information on their actual learning and help-seeking behavior, being aware that learners had not invested enough effort would probably not provide us with enough information for any instructional intervention.

As detailed later, theories of metacognition and self-regulation can provide us with alternative and complementary notions and models. In the next sections, empirical results of research on learning from multiple external representations and tools are reported to show that CBLEs can pose quite heavy metacognitive and self-regulation demands on learners in numerous ways.

Sources of metacognitive and self-regulatory demands in computer-based learning

To understand why resource-oriented theories cannot fully account for learners' difficulties in CBL, it is worth looking at the constituent elements of contemporary computer-based learning environments. A CBLE has to include different types of information resources (e.g., texts, illustrations, and help facilities). These resources can be functionally differentiated into resources *representing* the subject matter (e.g., principles of geometry) and resources *supporting* the subject matter's acquisition (i.e., *help facilities* or so-called *tools* such as a glossary). Both types of resources are often constructed of more than one (often multiple) external representations related to the same concept. For example, a geometry word problem might be accompanied by a diagram showing known and unknown angles as described in the word problem. Likewise, the definition of a geometry principle in a glossary might be illustrated by a corresponding diagram.

As such, multiple external representations and embedded tools can be regarded as the generic building blocks of computer-based learning environments, but also as two main sources of (potentially non-beneficial) metacognitive and self-regulatory demands. The demands increase with the number and qualities of relationships between these variously-constituent types of elements to each other as well as to the learning task. Closely related to this increase in complexity (comparable to the element interactivity within the learning content) are the demands on learners' self-regulation. For example, the tactical decisions concerning the allocation of attentional and cognitive processes become more demanding with each additional element (Lajoie, 1993).

Research on learning from multiple external representations (e.g., Ainsworth, 2006; van Someren, Reimann, Boshuizen, & de Jong, 1998) and research on tool use (e.g., Aleven, Stahl, Schworm, Fischer, & Wallace, 2003; Clarebout & Elen, 2008) provide us with many empirical examples of the typical difficulties learners experience in complex environments, and of more and less successful "coping" strategies. In the next two sections I illustrate results from these two lines of research which reveal that the difficulties in CBL can be differentiated as cognitive, metacognitive and self-regulatory difficulties.

Metacognitive and self-regulatory demands of external representations

Multiple external representations are thought to fulfill (at least) three different (but related) cognitive functions (Ainsworth, 2006). First, multiple representations can complement each other and thus provide a more complete picture of a difficult concept. For example, a verbal description of a mathematical function (e.g., $y = x^2 - 2$) can be accompanied by a line drawing depicting that function. Second, multiple representations can help to constrain each other's interpretations. For example, a table with data can be accompanied by a scatterplot. Inspecting the form of the points as detailed in the scatterplot can constrain how learners interpret the data from the table. Finally, and probably most importantly, multiple representations can be integrated (by the learners) to construct a more abstract internal representation of the material presented externally. For example, from a scatterplot and a table presented together, learners can infer a general rule about a functional relationship between the depicted data.

Research on learning from multiple external representations focuses mainly on how learners make sense of different symbol systems (e.g., text, numbers, and realistic pictures) and how external representations can be combined to contribute most to understanding and learning. Empirical results show that learners often have trouble learning from multiple external representations (e.g., Ainsworth, Bibby, & Wood, 2002). Learners tend to use different external representations in isolation and to use only a sub-sample of available representations, even when a learning task strongly suggests attending to all the representations available. Learners seem to find constructing referential connections between the concepts depicted by different external representations particularly difficult (Ainsworth, 2006).

In summary, students have difficulty (a) relating the contents of different external representations to one another and (b) understanding how different external representations can contribute to understanding and learning (i.e., understanding the representations' didactic functions). Difficulty relating contents of different representations reflects either cognitive or self-regulation problems. Having trouble understanding the didactic function of different (types of) external representations probably reflects metacognitive knowledge deficits more than cognitive deficits.

Metacognitive and self-regulatory demands of support measures (tools)

CBLEs can have a variety of overarching purposes, for example helping learners gain deeper understanding, acquire knowledge or develop skills quicker, or learn at one's own pace. As these overarching purposes require a number of more specific didactical strategies or tactics, a number of smaller, more specific help facilities are usually devised that are integrated in a package that we call a CBLE. From a functional perspective, therefore, we can consider CBLEs as collections of more or less related (or integrated) support measures (i.e., tools), each measure serving a specific purpose or function. It is thus worth taking a look at the functions that different tools should fulfill in the eyes of the instructional designers, how learners conceive the purpose of different tools, how learners actually use tools, and, finally, how the use of such tools might affect learning.

Tools in CBLEs are artifacts designed to support cognitive and metacognitive processes related to the actual learning task. An example of a cognitive tool is a pocket calculator embedded in a CBLE for algebra or geometry. An example of a metacognitive tool would be some sort of overview (e.g., a table) of accomplished and open tasks (to facilitate monitoring and planning). Tool use can thus be defined as student-system interactions (with help facilities in CBLEs) that aim to overcome or prevent problems during learning (Aleven & Koedinger, 2000).

Research on tool use has described typical ways in which learners use available tools and how different uses affect learning outcomes. A typical finding is that learners often ignore available tools even after they have proven to be useful (Clarebout & Elen, 2007). In addition, learners often use tools inadequately or at least not as intended by the instructional designers (e.g., Aleven et al., 2003; Clarebout & Elen, 2006). For example, in a log-file analysis on how school children in a geometry course used different tools of an intelligent tutoring system (a Cognitive Tutor Geometry), students did not use errors as a signal to request for help (Aleven and Koedinger, 2002). Moreover, when students did decide to request help, they often proceeded straight to the most solution-specific hints. This so-called bottom-out hint strategy indicates that at least some learners tend to use available help facilities in a non-learning-oriented manner (Aleven & Koedinger, 2002). Such gaming-the-system behavior is usually negatively associated with learning outcomes (Baker, Corbett, & Koedinger, 2004). On the other hand, for those learners who took their time to study the bottom-out hints, learning outcomes increased (Shih, Koedinger, & Scheines, 2008).

To summarize: learners tend to avoid using tools, they do not use them early enough or not at the right occasion. In addition, some learners tend to use tools too often or for the “wrong” purpose. Obviously, learners have difficulty while learning to map impasses to available help facilities. In other words, they have trouble deciding when to refer to which type of support. All these examples of typical ways of using tools in CBLE reflect metacognitive or self-regulation deficits more than cognitive deficits.

This overall negative picture might suggest that providing metacognitive and self-regulation support in CBLE is per se not very effective. In that case it would not be advisable for students to use such offers. There is, however, ample evidence that such support can be effective. For example, the frequency of monitoring activities has often been found to be a predictor of student learning (e.g., Winne, 2001; Winne & Hadwin, 1998). This could also be shown for studying complex topics using a hypermedia environment (Azevedo, 2005). For example, (Greene & Azevedo, 2007) could show that monitoring processes had a significant relation with the odds of having a more sophisticated mental model of a complex biological system (i.e., blood, heart, and circulatory system) at a knowledge posttest. Noticeably, the effect of monitoring processes on performance was above and beyond the effects of prior knowledge and age. Self-explanation is often considered as a metacognitive learning strategy (e.g., Aleven & Koedinger, 2002; Conati & VanLehn, 2000; see also Renkl, Berthold, Große, & Schwonke, 2013). Berthold and Renkl (2009) prompted self-explanations in learning probability theory in a CBLE (N = 170 high-school students; mean age approx. 16 years). They found that prompting self-explanation fostered conceptual understanding of the probability principles. Low-prior knowledge students, however, profited less from the intervention. The authors concluded that there are boundary conditions to be considered. Self-explanation prompts can lead to negative effects if the learners are confronted with learning materials that are very complex in relation to their prior knowledge (Berthold and Renkl, 2009). In a log-file analysis of a Cognitive Tutor study on learning geometry (Otieno, Schwonke, Renkl, Aleven, & Salden, 2011) learning outcomes had stronger relationships to self-explanation performance than to problem-solving performance during learning. Additionally, self-explanation performance was a stronger predictor for learning outcomes than prior knowledge. These results suggest that metacognitive support can enhance learning provided that some boundary conditions are considered.

Overall, research on learning from multiple external representations and tool use highlight the many difficulties that learners have using these external resources effectively. Most findings suggest that learners’ problems are more closely related to regulation of the learning process than to schema construction itself. We can therefore speak of the metacognitive and self-regulation demands that learning environments pose on learners. To localize or isolate factors that might affect these demands, we need to take a closer look at metacognitive knowledge prerequisites and their self-regulatory skills. However, as we know that these skills are closely related to learners’ domain-specific knowledge (i.e., their level of expertise in a domain) the inter-relationships between metacognition, self-regulated learning and level of expertise are the topic of the next section.

The role of learners' levels of expertise

Domain-specific knowledge (i.e., prior knowledge) is the best predictor of further learning (Ausubel, Novak, & Hanesian, 1978; Novak, 1990). Individuals' prior knowledge and learning trajectories (i.e., the speed of learning), however, vary substantially. Such inter-individual differences in prior knowledge and trajectories can alter the effectiveness of instructional measures (known as the *Expertise-Reversal-Effect*; Kalyuga, Ayres, Chandler, & Sweller, 2003) as well as the effectiveness of individual learning activities. For example, prior knowledge can affect (whether and) how effectively learners process external representations (e.g., Wood & Wood, 1999). It can also affect learners' need for help and how strategically they ask for help (e.g., Renkl, 2002). In a study on tool use in the domain of middle-school mathematics (Wood & Wood, 1999), low-prior knowledge learners used an intelligent tutoring system's tools more frequently than high-prior knowledge learners. Seeking help after an error was associated positively with learning outcomes in low-prior knowledge learners but not in those with high prior knowledge. On the other hand, errors during learning were negatively related to learning outcomes only in low-prior knowledge learners. The authors concluded that encouraging low-prior knowledge learners - especially those who refuse to ask for help spontaneously - to seek help more strategically (i.e., not necessarily more often) might be a promising approach to reduce confusion and enhance learning performance. Similarly, Baker et al. (2004) found that especially low-prior knowledge learners used tools in a non-learning oriented way, which was negatively related to learning outcomes.

Prior knowledge provides the context for the interpretation of new information and, as such, also provides the background for any metacognitive considerations on the learners' side (e.g., deciding on the need for help). Generally, metacognitive knowledge and regulation have been found to improve together with expertise within a particular domain. However, although domain-specific knowledge can facilitate the acquisition and use of metacognition, high levels of domain knowledge do not guarantee high levels of metacognition (Schraw, 1998).

Low prior knowledge can also impede metacognitive functioning (e.g., judging whether another hint would help to overcome an impasse; Schraw, 1998). Low-prior knowledge students have, for example, been found to use available information resources sub-optimally, which was attributed to metacognitive deficits (e.g., Baker et al., 2004). Low-prior knowledge learners are also more generally dependent on structure and scaffolding than are high-prior knowledge students (e.g., Kalyuga, 2007; Renkl, Stark, Gruber & Mandl, 1998). Therefore, low-prior knowledge learners might need metacognitive support more than high-prior knowledge learners. Often, however, low-prior knowledge learners do not benefit from metacognitive support. This finding can be explained by the fact that understanding and using a metacognitive strategy (in real time) is a cognitively-demanding activity. Therefore, especially low-prior knowledge learners can easily be overwhelmed, for example when advised to follow prescribed rules on when to use certain help facilities. The instructional challenge is to implement metacognitive support in a cognitively manageable way.

In summary, prior knowledge affects how much learners depend on information resources and how effectively they can make use of them. Prior knowledge can also affect how much learners profit from cognitive and metacognitive support. Against this background I hope to illustrate how metacognitive theories and self-regulation theories can contribute to our understanding of difficulties in CBL, and how these theories and resource-oriented theories might be integrated to provide a more complete picture of potentials and difficulties in CBL.

A self-regulated-learning perspective on difficulties in CBL

Self-regulated learning can be described as a behaviorally, metacognitively, and motivationally active participation in one's own learning (Zimmerman, 1986). Self-regulated learners employ cognitive strategies (e.g., elaboration) to attain learning goals. Choice of strategies, their application, and the quality of the outcomes of strategy application are embedded within and controlled by metacognitive activities such as planning, monitoring, and self-evaluating (Zimmerman, 1990).

Moreover, as with many CBLEs, learners can largely decide on their own whether, when and how to make use of available resources, one can argue that a self-regulated perspective (e.g., Schiefele & Pekrun, 1996; Boekaerts, 1999; Winne, 1996; Winne & Perry, 2000) becomes increasingly important in CBL. Even in highly structured environments (e.g., those that structure the sequence of learning tasks), room remains for variation in learners' choices and execution of cognitive and metacognitive activities. To make effective use of available external resources, learners need to adequately allocate and regulate their attentional and cognitive resources during learning. However, with each additional external resource, tactical decisions as to where and when to use one or the other resource become more demanding (Lajoie, 1993). Multiple sources of information can, therefore, easily overwhelm learners' self-regulatory capacities (Ainsworth et al., 2002).

From a metacognitive and self-regulatory perspective, learners should therefore be equipped with internal resources that allow them to cope with such additional metacognitive and self-regulatory demands. One such important internal resource is learners' knowledge about available external resources. Such knowledge can be conceptualized as a sub-type of metacognitive knowledge. As the knowledge about factors that affect cognitive activities, meta-cognitive knowledge (Flavell, 1979) refers to three broad categories: (a) person, (b) task, and (c) strategies. In Flavell's classic definition, the "task" category includes information about a proposed task available to someone, including knowledge about tangible resources necessary for task completion. As such, knowledge about external resources can be located in the task category. Consistent with this classification of knowledge about external resources, the four-stage model of SRL (e.g., Winne & Perry, 2000) differentiates between two broad knowledge categories: (a) knowledge about cognitive conditions (e.g., study tactics and strategies) and (b) knowledge about task conditions (e.g., instructional cues, time, and social context). In the four-stage model, knowledge about external resources is located in the "task conditions" category.

With respect to knowledge about external resources, yet another distinction must be made. Learners can have (or lack) declarative, procedural and conditional knowledge about external resources. Learners' declarative knowledge about external resources refers to knowledge about which resources are available in a certain context or environment. Learners' procedural knowledge about external resources refers to knowledge about how to use available resources. Conditional knowledge about external resources refers to knowledge about conditions for effective tool use (i.e., *when and why to use a specific tool*). Although extremely important, conditional knowledge is often overlooked. Learners are usually informed about which tools are available (declarative), and they are instructed (or they can read instructions) on how to use available tools (procedural). Often enough, however, learners are unaware of which situation is appropriate for using which type of tool (conditional) or when to refer to which (type of) external representation (e.g., a diagram).

In theories of metacognition (e.g., Efklides, 2008; Veenman, Van Hout-Wolters, & Afflerbach, 2006), conditional knowledge is basically defined as knowledge about "when" and "why to use a cognitive strategy. Such conditional knowledge is often regarded as an integral part of strategy knowledge (Paris, Cross, & Lipson, 1984) because to select and apply a strategy timely and adequately, it is essential to be able to relate strategies to specific relevant situations. It is worth noting that conditional knowledge in this sense is not the same as conditionalized knowledge in production system models such as the ACT- R theory (e.g., Anderson & Lebiere, 1998). Whereas (metacognitive) conditional knowledge is knowledge about relationships between (types of) situations and the to-be-applied knowledge or strategies, conditionalized knowledge is procedural knowledge with built-in, close connections to specific situations by internalized production rules (Renkl, Mandl, & Gruber, 1996). For purposes of simplicity, I will use the term "conditional knowledge" below when referring to metacognitive conditional knowledge.

Concerning the use of external sources, conditional knowledge could refer for example to knowledge about situations in which an online glossary should be consulted. Although most students nowadays might know how to use an online-glossary (i.e., browsing, finding, selecting and extracting information from the glossary), many may still lack knowledge about when to choose the glossary from among the many other available help facilities. The provision of conditional knowledge related to the use of help facilities should therefore enable learners to better associate outcomes of their monitoring of processing difficulties with control processes (i.e., the selection of appropriate tools), an assumption supported, for example, by an experiment of Schwonke et al. (2013). Learners provided with conditional knowledge about different help tools (e.g., a glossary, general and specific online-hints) in an intelligent tutoring environment used those tools more systematically and more strategically than learners without such support.

Noticeably, conditional knowledge about external sources does not necessarily develop just by being exposed to the resources–especially not when a CBLE is complex and the to-be-learned content is demanding. This assumption is supported by evidence that even learners with a lot of CBLE experience can display inadequate use of information sources. For example, Aleven and Koedinger (2000) found suboptimal help use in Cognitive Tutors even in learners

who had already spent more than 500 minutes in that learning environment. Therefore, it seems necessary to explicitly support students in developing conditional knowledge about information resources so that they can make better use of available resources.
Conditional knowledge, moreover, does not necessarily grow together with strategy knowledge (Schraw, 1998). For example, learners of mathematics can usually correctly apply mathematical procedures as long as they are told which procedure to apply; they know *how* to apply the procedure. However, those same learners may fail when they must decide on their own which of several different procedures to use. In other words, they often do not know *when* to use a procedure.

Learners differ both in their knowledge about external resources as well as in their conceptions about the roles or functions of these resources and their educational usefulness (Davis, 1989). These differences are related to more general inter-individual differences about the nature of knowledge, knowing, and learning (i.e., epistemological beliefs; e.g., Perry, 1970; Hofer & Pintrich, 2002). Such conceptions may be accurate, diffuse, wrong, or even absent. In addition, such conceptions may be congruent or incongruent to the instructional designers' intentions (Winne, 1982). Based on the CLT premise that knowledge and beliefs as represented in learners' long-term memory form the informational basis of the central executive component of working memory (e.g., Sweller et al., 2011), it is reasonable to assume that learners' potentially inaccurate knowledge and beliefs about such context variables can affect their cognitive, metacognitive, and self-regulatory activities. For example, Schwonke, Berthold, & Renkl (2009) analyzed effects of informing students about the didactic function of diagrams in worked-out examples on learning outcomes (in the domain of mathematics). The instruction enabled low-prior knowledge students to study the worked examples more efficiently. "Informed" low-prior knowledge students paid comparatively less attention to diagrams and equations but performed better in a post-test than "uninformed" low-prior knowledge students. On the other hand, the instruction prevented high-prior knowledge students from paying too little attention to the external representations. For the latter, paying greater attention to the representations was associated with better learning outcomes. Overall, these results stress the importance of learners' conceptions about didactic functions of external resources. More specifically, the results highlight potential relationships between learners' conceptions and important learning process variables (here, the distribution of learners' attention). In addition, the moderating effect of prior knowledge suggests that such conceptions can be related to learners' prerequisites.

Taken together, most CBLEs provide learners with a certain degree of freedom. To make effective use thereof, they have to rely on relevant self-regulatory skills and general metacognitive knowledge about CLBEs, the various features of a specific environment (e.g., conditional knowledge), and the didactic conceptions behind those features. A number of empirical results support the assumption that learners often lack these self-regulatory skills and relevant knowledge, or that they possess incorrect knowledge or conceptions that are inconsistent with the instructional designers' concepts. In light of inconsistent knowledge and skills on the part of learners, it seems reasonable to assume that CBLEs pose heavy metacognitive and self-regulatory demands on learners. In the next section, I therefore, propose considering ways to incorporate such demands into resource-oriented theories such as CTML and CLT. Exemplarily for CLT, I propose considering a type of metacognitive load (as Valcke already did in 2002 in his commentary to the special issue "Cognitive Load: Updating the theory?").

Extending the resource-oriented perspective

Against this background, it might not suffice for resource-oriented theories to concentrate on intrinsic and extraneous demands on schema construction, or to concentrate primarily on core cognitive processes such as selection, organization, and integration. Rather, resource-oriented theories (such as CLT and CTML) might profit from recognizing (a) that metacognitive and self-regulatory processes exist, (b) that these processes are essential for learning, and (c) that related activities can consume working memory capacity.

In his commentary to the special issue "Cognitive load: updating the theory?" Valcke (2002) proposed extending CLT by the *Metacognitive Load* concept. In his comment, he placed special emphasis on monitoring activities (e.g., monitoring the selection and organization of sensory information or monitoring the back-and-forth storage of information from long-term memory to short-term memory). Valcke further noted that metacognitive knowledge had not been explicitly considered in any of the state-of-the-art contributions to that particular issue. He attributed this lack to the intense focus on declarative and procedural knowledge. Valcke further proposed conceptualizing metacognitive load as a part of germane load. He argued that learners –besides the effort they invest in constructing and storing schemata–also expend effort monitoring these activities. He proposed the term *germane metacognitive load* to describe this type of load. However, Valcke's propositions have not been taken up by the CLT research community.

Nevertheless, I find the notion of working-memory load via metacognitive demands to be highly plausible and useful. We can assume that metacognitive load can be affected by the learning task, learning environment, and by learners' prior domain-specific knowledge as well as by their general metacognitive knowledge (e.g., knowledge about learning strategies). As such, metacognitive load can be considered a potential moderating variable to explain variation in learning outcomes as the result of a specific instructional design. I further assume that metacognitive load is directly related to learning activities and learners' interactions with the learning environment. As such, it can also be regarded as a potential mediating variable to explain effects of different instructional designs on learning outcomes.

In contrast to Valcke (2002), who conceptualized metacognitive load as a part of germane load, I rather propose conceptualizing metacognitive load as a form of working memory load that can add to either intrinsic (or germane) load or to extraneous load. In those cases where metacognitive and self-regulatory activities (such as planning, monitoring, and choosing or changing strategies and tactics) contribute to learning, these activities can be said to impose intrinsic (or germane) meta-cognitive load. In other cases in which working-memory load by metacognitive activities does not contribute to learning, I believe it should be called *extraneous metacognitive load* instead.

Whether learners' metacognitive efforts are intrinsic (i.e., beneficial) or extraneous (i.e., detrimental) might strongly depend on learner variables as well as context factors. For example, insufficient prior domain-specific knowledge can hinder effective monitoring. In addition, sub-optimally designed learning tasks and/or learning environments (e.g., split attention formats, redundant or irrelevant information) may require unnecessary monitoring and regulatory activities. We can further assume that different learning domains (e.g., mathematics, language learning) and, more specifically, different learning tasks (solving mathematics problems; vocabulary learning) not only differ in their degree of element interactivity (i.e., intrinsic load), but also in their metacognitive and self-regulatory demands. Such differences can refer to the quantity and quality of monitoring (e.g., setting of intermediate goals) and self-regulatory activities (e.g., tactics to be chosen). For example, from a cognitive load perspective, we would argue that learning a second language's grammar is harder than learning vocabulary because of greater element interactivity (in the presence of a degree of prior knowledge). From a metacognitive perspective, we could however argue that planning, monitoring, evaluating, and regulating activities will also differ in conjunction with these two learning tasks, and that each of these activities will probably be more demanding while mastering grammar than when learning vocabulary. One can, for instance, easily imagine that detecting an error or a misconception as well as fixing an error or overcoming a misconception is more demanding when learning grammar than when learning vocabulary. Thus we can assume that domain-specific prior knowledge and metacognitive knowledge prerequisites are directly related to an intrinsic meta-cognitive load.

Conclusion

Based on results from research on learning from multiple external representations and research on tool use, I have argued that there are metacognitive and self-regulation demands beyond the cognitive demands of CBL. These demands arise as a result of interaction with the external representations of the learning contents and learning task as well as interaction with a CBLE's tools. How much these additional metacognitive and self-regulation demands tax the learners' mental resources (especially their working memory) will largely depend on their level of metacognitive knowledge and skills. Therefore I propose considering a metacognitive type of load in resource-oriented theories such as CLT. This metacognitive load can be conceived as a type of working memory load by metacognitive or self-regulatory demands as a result of working on a learning task while interacting with a computer-based learning environment. Furthermore, metacognitive load can probably not be considered to always further learning. Rather, it may either be beneficial–when metacognitive and self-regulatory activities contribute to schema construction, ineffective–when the activities do not contribute to schema construction, or even detrimental–when the activities hinder schema construction. The quality of metacognitive demands will depend on a fit among at least three factors: (1) the learning task's design, (2) the design of the CBLE, (3) the learners' prerequisites (i.e., domain-specific knowledge, metacognitive knowledge and self-regulation skills). As a consequence, at least parts of the working-memory load that has so far been attributed to either intrinsic, germane, or extraneous demands on cognitive processes (i.e., selection, organization, and integration) by the learning content, learning task, or learning environment should probably instead be attributed to demands on meta-cognitive and self-regulation processes such as planning, monitoring, or regulating. In consequence, the incorporation of a metacognitive and self-regulation-induced type of load would allow resource-oriented theories to explain a wider variety of phenomena, help these theories to represent human information processing and learning more accurately, and, as a consequence, become even more valuable for present and future instructional designers.

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