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A Critical Reflection on Emerging Topics in Cognitive Load Research

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The use of information characteristics to design powerful learning environments has always been at the heart of cognitive load research. In order to promote understanding, the learners' resources should be allocated as much as possible to processes that contribute to schema acquisition. To rephrase this in the terminology used in cognitive load research: The learner's germane load should be optimized and their extraneous load should be minimized (Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005). This important principle is the backbone of many studies conducted ever since the introduction of cognitive load theory (CLT; Sweller, 1988).

This principle immediately provides us with two essential characteristics of a powerful learning environment. First of all, the design of the learning environment itself should be taken into account. How are the learning materials or problems presented to the learner? In what way does the learner interact with the environment? Are there elements in the environment that might be a source of extraneous cognitive load (e.g., split attention effect, redundancy effect)? Secondly, the background of the users should be taken into consideration. What do they already know? What is their motivation to use this learning environment? But also, and often forgotten, what is their age?

The papers in this special issue reflect the continuing endeavour of cognitive load researchers to optimize instructional design by considering the individual characteristics of the learner at all times. Below I will discuss the studies reported in this special issue on *Emerging Topics in Cognitive Load Research: Using Information and Learner Characteristics in the Design of Powerful Learning Environments*.

In order to examine the effectiveness of reducing task complexity (i.e., intrinsic cognitive load) Ayres (this issue) conducts two experiments in which high school students had to solve mathematical problems. His results showed that low (mathematical) ability students benefited more, in terms of error scores in the test phase, from an isolated or part-task strategy than high ability students, who benefited more from an integrated or whole-task strategy. This study is a nice example of the interaction of instructional method and ability level on performance. Kalyuga and colleagues were the first within a cognitive load framework to demonstrate that design solutions for novices do not necessarily transfer to higher ability levels and vice versa (Kalyuga, Ayres, Chandler, & Sweller, 1998).

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However, the interpretation of the results concerning the error scores in the acquisition phase, and associated subjective cognitive load, is less straightforward. Both low and high-ability students made less mistakes, $M = 0.86$ and $M = 1.17$, respectively, and experienced the lowest levels of cognitive load, respectively $M = 3.54$ and $M = 2.29$, in the part-task condition, which is not completely in line with the predicted expertise reversal effect. In order to account for this finding, the author suggests that the problems might have been too simple, especially for the high-ability students, and hence the levels of germane load might have been too low. This interpretation is also substantiated by the subjective cognitive load ratings of the students. The highest cognitive load was experienced by the low-ability students in the integrated condition and was only about 50% of the maximum load ($M = 4.55$). Unfortunately, the time to solve these problems in the acquisition and test phase was not registered. These data could have provided us with interesting clues about how to interpret the above-mentioned findings. In line with this, it would also have been interesting if the author had measured cognitive load during the test phase, for instance, to be able to explain why high-ability students in the acquisition phase showed such a sharp increase in error scores in the test phase while solving part-task problems.

Using a large group of ninth grade students, Olina, Reiser, Huang, Lim, and Park (this issue) investigated the influence of different problem formats, problem presentation sequence, and different ability levels, on an achievement and transfer test, and on subjective cognitive load ratings. As expected, the higher ability students outperformed the lower ability students on the criterion measures of achievement and transfer scores. However, the subjective cognitive load ratings during practice did not differ significantly between ability levels, and were rather low. The latter finding is especially surprising because on average the achievement and transfer test scores of both groups were relatively far removed from the maximum score. Moreover, the students showed relatively low achievement gains (about 11%) from pre-test to post-test. According to the authors this finding can be explained by the fact that these students already had relatively high levels of prior knowledge of punctuating sentences, as is corroborated by their pretest achievement scores. These learning gains indicate, therefore, that the experimental treatment had only a limited influence on their existing schemas of sentence punctuation. On the other hand, these findings (i.e., low achievement gains and low subjective load ratings), could also be interpreted as a lack of student motivation. Furthermore, as in the study of Ayres (this issue), it would have been interesting if the authors had collected subjective cognitive load measures during the transfer and achievement test. This would have enabled us to evaluate whether or not the experienced load during practice differed significantly from that during the test phases. Following the same line of reasoning, it would have been good if the researchers had registered the time both student groups needed to deal with these problems. It is not unlikely that higher ability students dealt with these problems more rapidly than lower ability students. Alternatively, if both groups would have received an equal amount of time to deal with these problems, a more distinct difference in performance between these students groups could have emerged. That is, time limitations could have accentuated differences in performance that are washed away when there are no strict time limitations. If this is true, it would shed a different light on the test scores and experienced cognitive load of the present study.

The study by Van Gerven, Paas, Van Merriënboer, and Schmidt (this issue) investigates the influence of instructional design on younger and older adults. As a matter of fact, it is one of the few studies within the framework of cognitive load theory that involves older adults. This special issue on learners' characteristics would not have been complete if the characteristic age would have been neglected. Moreover, research on ageing plays an increasingly more important role in a society with a proportional increase of the elderly. The authors hypothesized that bimodal processing of instructional material and increased training variability would lead to optimal learning conditions, especially for the older adults (Paas & Van Merriënboer, 1994; Renkl, Stark, Gruber, & Mandl, 1998; Van Gerven, Paas, Van Merriënboer, & Schmidt, 2000). The results on a secondary task (i.e., reaction time task) and a transfer task, however, did not show a disproportional advantage of the older as compared to the younger participants. Interestingly, although the younger participants outperformed the older participants on the transfer task (85% of problems were on average solved by the young participants, whereas the older participants solved on average 54%), a marked difference in subjective cognitive load was not found. The highest load experienced by the older participants was $M = 2.8$ (in the Unimodal, Blocked condition), which is about one third of the maximum score. The authors assume that this finding might be explained by a response bias of the elderly. Although a response bias might have played a role in their study, it is not clear what has led to this response bias; and why the younger participants did not show a response bias? An alternative explanation might be a difference in metacognitive processes, in particular monitoring effectiveness (i.e., the ability to discriminate between correct and incorrect answers, Koriat & Goldsmith, 1996) between younger and older participants. A more general problem investigating differences between younger and older participants concerns the often large within-group variation. That is, the older participants show a larger variation in, for example, education, age, physical health, intelligence, as compared to the rather homogenous younger group of psychology students. Although it is very difficult to circumvent this problem, this variation might have contributed, to some extent, to the present findings.

The study by Seufert and Brünken (this issue) investigated the effects of two types of support, surface feature level help (i.e., hyperlinks) and deep structure feature level help (i.e., detailed explanations), while learning about human metabolism. In particular, their study investigated the effects of both types of support alone or combined on learning performance and subjective cognitive load. In contrast to the authors' expectations, learning performance did not differ significantly between conditions. Furthermore, the students' performance was relatively low. The students' performance ranged between 51% and 57% of the maximum score. One explanation put forward by the authors is related to the complexity of the learning materials. As a result of this complexity, intrinsic cognitive load was increased to such an extent that hyperlinks could only be used superficially. This explanation is very plausible and substantiated by the students' subjective cognitive load that ranged between $M = 4.38$ (63%) and 5.63 (80%). Looking at the other side of the same coin, complexity of learning materials or intrinsic cognitive load is also determined by the students' prior knowledge. I concur with the authors that learning gains might not have reached significance because the participants, being psychology students, might not have benefited from both support types simply because they were not sufficiently involved in this task. This is not an unlikely explanation because 'traditionally' most psychology students are not very attached to problems within the domain of chemistry. A final issue that comes to mind reading this paper, and many other papers within the cognitive load framework, is related to the design of the learning materials (Rikers, Van Gerven, & Schmidt, 2004). In particular the way surface level help and deep structure help have been designed (see Seufert & Brünken, this issue, Figure 1).

Although the authors warn in their Introduction about the potential risk of distributing information by multiple representations (i.e., split attention effect, Chandler & Sweller, 1992), their design also forces the learner to integrate information from multiple sources. Especially, if the learners' prior knowledge is relatively low, this source of extraneous load could also have played a role in the outcomes of this study.

Kalyuga (this issue) describes an alternative method for diagnosing the acquisition of domain-specific knowledge, and an application of this method for optimizing cognitive load by tailoring instructions to the learners' ability. His alternative method (i.e., rapid verification tests) was compared to two other conditions: A combined adaptive condition (i.e., subjective cognitive load ratings and rapid verification tests), and a control non-adaptive condition. Findings showed that both adaptive conditions were superior to the non-adaptive control condition. However, there were no significant differences between both adaptive conditions. In other words, adding subjective cognitive load ratings to rapid verification tests did not lead to improved performance. The author attributes the latter finding to a lack of power of this study, and hence more research is necessary to disentangle this issue. However, it would have been interesting if an extra condition was added to the study: An adaptive condition solely based on subjective cognitive load ratings. This could have shed light on the question why adding subjective ratings in the combined condition was not completely successful. Therefore, it remains an empirical question whether the approach advocated by Kalyuga (this issue) proves to be of additional value as compared to previous adaptive methods (e.g., Camp, Paas, Rikers, & Van Merriënboer, 2001; Salden, Paas, Broers, & Van Merriënboer, 2004). Furthermore, it is important to note that many adaptive learning environments have been developed outside the framework of cognitive load theory. For instance, the Tutoring Research Group at the University of Memphis has developed AutoTutor, which simulates to a large extend a human tutor (e.g., Graesser, Wiemer-Hastings, Wiemer-Hastings, & Kreuz, 1999). Instead of explicitly evaluating the learner's understanding of the task at hand through subjective ratings or diagnostic tests, AutoTutor assesses the learners' understanding more implicitly through a natural dialog based on latent semantic analyses (Landauer & Dumais, 1997). That is, by evaluating the learners' answers to questions and the contributions of learners during the tutorial interactions, AutoTutor has proven to be very successful in assessing the learners' ability level, and to guide the learner to a deeper level of understanding.

Van Merriënboer, Kester, and Paas (this issue), address an important problem in cognitive load research: What to do if element interactivity (i.e., intrinsic cognitive load) of complex tasks is still too high for learning even after removal of all sources of extraneous load? Many previous studies within the cognitive load framework have almost exclusively focussed on reducing extraneous cognitive load or on inducing germane cognitive load, in order to improve the learners' understanding of the task at hand (Van Merriënboer & Sweller, 2005). These studies have demonstrated that the detrimental effects of extraneous cognitive load (e.g., redundancy effect, split attention effect, etc.) should be taken into account in instructional designs. Furthermore, these studies have shown us that germane cognitive load can be induced by practice variability, in particular random practice (i.e., all versions of a task are randomly mixed), or by providing feedback and guidance to the learner. What these studies do not tell us, is how to deal with the problem addressed above. In order to solve this problem, the authors propose a two-stage approach. The first stage consists of reducing intrinsic cognitive load by manipulating element interactivity of the learning tasks, which frees up cognitive resources. The second stage consists of allocating these resources to processes that induce germane cognitive load, which results in improved (transfer) performance. Although the solution provided by the authors is very straightforward (if the problem is too complex, make it simpler), it does not completely answer the question. That is, the authors could also have focussed on the learner's prior knowledge. Instead of reducing intrinsic load by manipulating the learning tasks, it would also have been possible to improve the learners' expertise level by teaching them, for instance, better strategies to tackle the task at hand (Van Gog, Ericsson, Rikers, & Paas, 2005). These newly acquired strategies might lead to a different perception of the problem by the learner (for instance through chunking of information), and consequently the intrinsic load will also be reduced without any adjustment of the original problem.

This concludes my review of these interesting studies bundled in this special issue. These studies do not only provide an overview of the current state of affairs within cognitive load theory, more importantly, they provide us with new and thought-provoking ideas about future research.

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