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Cognitive load and self-regulation: Attempts to build a bridge

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A R T I C L E I N F O

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A B S T R A C T

The editors of the Special Issue called for a more integrative approach to the study of cognitive load and self-regulation. The goal formulated for the Special Issue is ambitious. In my role as a constructive critic, I first summarized the findings in the 6 papers, identifying important questions and concerns that emerged while reading the papers. I also identified some general issues that need further clarification and elaboration: I argued that there is a strong need to reach consensus on the conceptualization and measurement of cognitive load and that new methodologies should be developed to capture cognitive load *in real time* and link it to strategy use.

1. Introduction

The editors of the special issue argued that due to the explosion of information it is absolutely essential that students learn to filter, select, and process incoming information and that teachers learn to design instruction in such a way that their students can acquire these self-regulation strategies. In other words, 2 complementary research traditions are involved in this important skill building processes, namely self-regulated learning and instructional design. These 2 research traditions have their own histories, theories, measuring instruments, and types of interventions.

The title of the special issue reveals that the editors called for a more integrative approach to the study of self-regulation and cognitive load. They argue that research in these two separate lines of research shows little overlap, even though studies often depart from the same or similar research questions. The goal formulated for the Special Issue is ambitious. The editors invited 6 research groups and asked them (1) to present innovative, empirical research that links the two domains of research and (2) to discuss how bringing together the 2 vast bodies of research can provide the foundation for research on contemporary issues in educational science. Has this ambitious goal been accomplished? In the next sections, I will first summarize the findings of the 6 papers, identifying important questions and concerns that emerged while reading the papers. Next, I will point to areas in need of investigation.

1.1. Summaries and critical issues related to the 6 articles

The focus of 3 of the manuscripts was on depth of processing, namely the papers by Schleinschok et al., Glogger-Frey et al., and Sidi et al. The former two studies wanted to improve depth of processing through improved metacognitive regulation. Both research groups argued that students often overestimate their level of understanding of a text and that this implies that they stop short of grasping its full meaning. Each research group proposed a specific cognitive strategy that could help students to improve their self-regulation strategies and they set up experiments to demonstrate that use of this strategy would result in more efficient monitoring and control. Sidi and her co-workers addressed a related question, namely: Can depth of processing be triggered by contextual cues?

Schleinschok, Eitel, and Scheiter (in this issue) predicted that instructing students to make a free-hand drawing of the content of a paragraph would be instrumental to (1) more accurate monitoring that allows students to make inferences that are directly relevant to understand the deep structure of the text and (2) to better cognitive control of the quality of what they encoded in their memory schemata. They set up 2 experiments with university students. In both experiments students were split up into a drawing group and a text-only group. All students had to read an expository text. After reading each of the 5 paragraphs they had to indicate

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how confident they were that they had encoded the paragraph well (JoI). The students in the drawing condition made a free-hand drawing after reading each paragraph. After reading the full text, they rated the quality of their encodings and indicated which paragraphs they wanted to re-study. Finally, they were requested to rate the degree of cognitive load (CL) that they had experienced. The research group postulated that drawing the content of a paragraph might be more effective than other learning strategies, such as summarizing and paraphrasing the text, because students will anticipate that they have to construct a coherent internal pictorial memory code, in addition to a verbal memory code. The researchers predicted and found that generating free-hand drawings *after* reading a paragraph leads to a more accurate metacognitive judgement of the quality of their learning (JoI) that better matched performance on the posttest. Students in the drawing condition were not only more aware of the quality of their understanding, they also preferred to re-study paragraphs for which they had the lowest JoI's, thus demonstrating that anticipation of the free-hand drawing task did not only guide and support their monitoring but it also informed them on the knowledge gaps they still had and needed to fill.

Experiment 2 was similar to experiment 1, but all students were allowed to restudy the paragraphs they had indicated for restudy. Contrary to expectations, students in both conditions selected paragraphs for re-study for which their JoL's were lower and they spent more time restudying them. In line with previous research, a high score on experienced CL was associated with lower scores on the different posttests (drawing task, verification task, and diagram labeling) in both experiments. However, this relation disappeared when JoLs were simultaneously entered into the regression model (this is not surprising given the high negative correlation (−0.69) between the two variables). The researchers concluded that JoL's rather than the experienced CL predicted post-test performance in the drawing condition. Even though I am not convinced that this research group captured CL in a valid way (see my discussion in the section on the meaning and measurement of CL), they demonstrated that requesting students to make a visual representation of the content of a paragraph *after* they finished reading it, is an active generative task that makes them aware that it is not sufficient to monitor at the surface level. Inspection of the internal pictorial code may act as a strong cue that more accurate monitoring is necessary to discover the deep structure of each paragraph.

Glogger-Frey, Gaus and Renkl (in this issue) set out to demonstrate that encouraging students to detect the rule or principle in multiple cases results in better understanding the deep structure of a text or problem. They designed a SRL environment and trained 8th grade students in a 20 min SRL training session to monitor for the critical features in a ratio problem. They compared the effect of the invention group with the performance of students who worked with guided examples. The two groups were compared on different process variables, such as their level of encoding, self-efficacy, awareness about knowledge gaps, and experienced CL, as well as their performance on a transfer task. The experiment was conducted in 2 regular school lessons. At the end of the first training sessions, the groups did not differ significantly on self-reports that assessed their self-efficacy and perceived knowledge gaps, but a main condition effect was noted on reported extraneous load measured with a 5 item scale. Extraneous load interacted with self-perceived performance in math and science (measured just before the training sessions), suggesting that only students who believed their math and science performance to be low had indicated that the extraneous load of the self-regulated activity was high (see my comments on capturing CL in the discussion section). The recall test conducted four days later revealed that there was no significant difference in the encoding of the surface features of the problems, but that students in the invention condition showed a deeper encoding of the problem's ratio structure. The students then worked on a second problem in their respective conditions, followed by a ten minutes lecture on ratios in physics, and by a near and far transfer task. It was predicted and found that the students who had worked in the invention condition would outperform students in the guided condition on the near and far transfer problems. Interestingly, both deep-structure encoding and extraneous load mediated the effect of the type of training sessions on transfer performance. And further exploratory analyses revealed that students in the invention condition had improved their in-depth processing during the *second* invention phase. By contrast, the explanations that the students in the guided practice conditions gave for the steps that an imaginary student took got worse during the second guided session. It is a pity that the researchers failed to measure students' self-efficacy, perception of extraneous load, awareness of knowledge gaps, and level of encoding in relation to the second practice sessions. This would have given us more insight into the advantages and disadvantages of having 2 training sessions. For example, would the students in the invention condition still report higher extraneous CL in the second invention session? Did insight into the structural relations occur already during the first SR training session in some student pairs and was it consolidated in the second training session in all student pairs? What was the exact role of the direct instruction that followed the second training sessions in consolidating this insight? Did it have the same effect in both conditions? These are but a few questions that await scientific investigation (see my discussion on multiple time points).

Sidi, Shpigelman, Zalmanov, and Ackerman (in this issue) informed the reader that the results of studies that compared students' performance in computerized learning environments with learning from texts in traditional environments are inconclusive. They clarified that the reported lower performance on screen as well as persistence of a paper preference in all age groups are not caused by technological disadvantages but are due to a qualitatively different reading process, characterized by many interruptions, attentional shifts, and multi-tasking. Overconfidence and less efficient work on screen contrast sharply with the reliable monitoring displayed while reading on paper. Sidi et al., hypothesized that screen environments encourage students to adopt a shallower processing style than paper environments, especially when they pick up cues that legitimize shallow processing. They wanted to know whether screen inferiority was due to the CL created by reading lengthy texts, or whether screen inferiority could also be demonstrated regardless of the reading burden. They set up 3 experiments to study the effect of different manipulations on response time, reported confidence after doing a task, calculated overconfidence, processing efficiency (correct solutions per hour), and success rate. They selected 6 challenging logic problems that could be stated briefly. In the first experiment, undergraduates were randomly allocated to the on screen and on paper group and worked either under time pressure (TP) or in a loose time frame (LTF). As predicted, TP resulted in screen inferiority reflected in lower processing efficiency and success rates, as well as poor calibration. Remarkably, when working in a LTF, these students showed more efficiency, higher success rates, and no differences in overconfidence, compared to the on paper group.

In the second experiment, the same problems were designed in a metacognitive transfer paradigm. Each of the 6 problem sets consisted of the following procedure: solving an initial problem, followed by a confidence rating, an explanation of the problem solution, solving a transfer problem, and a confidence rating. Students were told that they could work in a LTF but needed to monitor the time to complete the full problem set in time. The overall success rate of the initial problems was low, but improved in the