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Should self-regulated learning be integrated with cognitive load theory? A commentary

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ABSTRACT

Research on either cognitive load theory or self-regulated learning usually proceeds without reference to the other theory. In this commentary, we have commented on the editorial introduction and the six papers included in this Special Issue intended to indicate possible links between the two theories. To assist in this process, we have analysed some of the characteristics of both theories that either facilitate or impede the establishment of links. We conclude that while links are possible, the many differences between the theories present considerable barriers that will need to be overcome.

1. Introduction

Cognitive load theory has undergone continuous development over the last three decades. The driver of that development has had two major sources: the generation of new data based on randomised, controlled trials that have suggested additions and modifications to the theory, and the incorporation of external theoretical constructs that resonate with the theory. Both sources of theory development have been critically important to the success of the theory. The collection of papers that are the subject of this commentary fall under the second category with the suggestion that self-regulated learning and cognitive load theory should be integrated.

Whether an external theoretical construct can be usefully integrated with cognitive load theory depends on the extent to which the new construct accords with the core constructs of the theory. The initial core constructs were the relations between working memory and long-term memory with the critical construct being the change in working memory limits from severely constrained when dealing with novel information to largely unconstrained when dealing with knowledge stored in long-term memory. Subsequently, those relations between working and long-term memory have led to concepts associated with the transformation of the complexity of knowledge with changes in expertise (Chen, Kalyuga, & Sweller, in press) leading to the central concepts of element interactivity and intrinsic and extraneous cognitive load. More recently, the addition of concepts from evolutionary psychology (Sweller, 2015, 2016b) have transformed cognitive load theory in the last few years. Based on this evolutionary perspective, cognitive load theory deals with domain-specific information that we have not especially evolved to acquire, leading to biologically secondary skills. A biologically secondary skill is a skill that we can acquire but that we have not specifically evolved to acquire. Almost every topic that is taught in educational and training institutions consists of biologically secondary knowledge.

In contrast, generic-cognitive skills that, because of their importance, we have evolved to acquire, are biologically primary (Geary & Berch, 2016; Sweller, 2016a). Our ability to recognise faces or to solve previously unseen problems using generic-cognitive skills provide examples. As we will suggest below, self-regulated learning is probably a generic-cognitive, biologically primary skill. Because we have evolved to acquire generic-cognitive skills, they do not need to be explicitly taught since they are acquired automatically. In contrast, in order to reduce working memory load, we do need to explicitly teach the domain-specific skills that are the subject of cognitive load theory.

The cognitive architecture used by cognitive load theory is based

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on this evolutionary framework with, for example, that architecture applying to biologically secondary but not biologically primary skills (Sweller, Ayres, & Kalyuga, 2011). The architecture assumes: a very large long-term memory; evolved procedures for obtaining information from other people; evolved procedures for generating information via problem solving when information from other people is not available; a limited capacity, limited duration working memory when dealing with novel information; an unlimited duration, unlimited capacity working memory when dealing with familiar information stored in long-term memory designed to generate action appropriate to the environment.

In this commentary, the extent to which the work reviewed deals with issues that can be integrated within this framework will be analysed. We will begin with the editorial introduction.

2. Review of papers

This Special Issue of Learning and Instruction is devoted to the suggestion that cognitive load and self-regulated learning theories can and should be combined into a single theory. The Special Issue begins with an argument by the editors, De Bruin and van Merriënboer (this issue), supporting this suggestion. In particular, they suggest that cue monitoring is an important consideration for both self-regulated learning and for subjective ratings of cognitive load. They surely are correct with respect to cue monitoring. Nevertheless, there are other critical aspects and the different intentions and goals of the two theories seem to us to present insurmountable barriers to integration.

The first barrier concerns the goals of the two theories. Cognitive load theory has only one ultimate goal to which all other goals are subservient: the generation of novel instructional techniques. The ultimate success or failure of the theory rests entirely on the cognitive load effects that have been generated with, to this point, none of those effects depending on teaching learners cue monitoring. Of course, the fact that cue monitoring has not generated cognitive load effects does not mean it will not do so in the future.

Cue monitoring is important to self-regulated learning theory but the goals of the theory seem to lie elsewhere than the generation of instructional effects. As far as we are aware, over the quarter century that self-regulated learning theory has been discussed, few, novel, instructional effects based on randomised, controlled experiments have been demonstrated. As de Bruin and van Merriënboer indicate when discussing self-regulated learning: “Actual effects on learning outcomes are understudied but essential to validate the effect of interventions” (P. 19). With their different goals, it may be possible but very difficult to combine the two theories.

The second barrier to integration concerns the theoretical concepts used by the two theories. They are not only different, some are contradictory. Currently, cognitive load theory assumes that instruction is primarily concerned with domain-specific, biologically secondary information that we have not specifically evolved to acquire rather than the far more important, generic-cognitive, biologically primary information that we have evolved to acquire (Sweller, 2015, 2016a, 2016b; Geary & Berch, 2016). Self-regulation is probably a generic-cognitive, biologically primary skill that due to its importance to human functioning, cognitive load theory assumes is acquired automatically and so cannot be taught. Cue monitoring, which is central to self-regulated learning also may be biologically primary. If this conceptualisation is valid, the paucity of instructional effects associated with self-regulation will be permanent. Self-regulation can and should be studied as a generic-cognitive, biologically primary skill but it should not be confused with an instructional theory. (It needs to be emphasised that with extensive practice over many years, biologically primary skills can be improved as seen in elite athletes engaged in primary skills such as running. Whether previously acquired self-regulatory skills can and should be similarly improved after years of practice remains to be seen.)

The Raaijmakers, Baars, Schaap, Paas and van Gog (this issue) paper was co-authored by Fred Paas and so is reviewed here solely by John Sweller without input from Fred Paas. This paper compared the effect of positive or negative feedback on mental effort ratings. Since its introduction as an independent measure of cognitive load by Paas (1992), this measure has constituted by far the most commonly used index of load used in the field. It consists of a single item asking participants to indicate how much effort they devoted to the task in hand. Responses are most commonly made on a nine-point scale that rates effort from very, very low (or extremely low) to very, very high (or extremely high) effort.

The reasons for the popularity of this technique are not hard to find. Firstly, it is very easy to set up and administer requiring no more than a minute or so of participants' time. Secondly, and more importantly, it is far more sensitive to differences in cognitive load than any alternatives that have been devised. Thirdly, on the available evidence, it has a high degree of validity. Many experimental results using the technique have accorded closely with theoretical predictions of cognitive load theory. For these reasons, since its introduction, most studies using cognitive load theory as a theoretical framework have either used the Paas scale or a derivative to provide an independent measure of cognitive load.

Given the popularity of the Paas scale, studies of its characteristics are important. The current paper studied the effect of feedback concerning the accuracy of problem solving moves in attaining the problem goal on subjective impressions of mental effort. If a problem solver is told that his or her moves are appropriate in attaining the problem goal does this information alter subjective ratings of mental effort compared to being told that the moves are inappropriate? The results indicated that being told that moves are inappropriate increased subjective ratings of effort compared to being told that moves are appropriate. The fact that actual mental effort is not the only factor determining mental effort ratings but that feedback concerning the content task performance also can affect the ratings is an important finding.

As the authors suggest, these results indicate that subjective measures of cognitive load should be administered prior to learners receiving feedback on their task performance since the nature of that feedback can itself alter subjective impressions of cognitive load. While the reasons for this result currently are unclear, users of the scale need to be aware of this important effect which should be readily avoidable under most conditions by appropriately timing the presentation of the scale.

The paper by van Loon, Destan, Spiess, De Bruin, and Roebers (this issue) compared a group of 5/6 year old children to a group of 7/8 year olds to investigate developmental differences in the use of cues and self-protection in self-evaluations of performance. Self-evaluations of performance are essential for effective self-regulation and subsequent performance (e.g., Dunlosky & Rawson, 2012). It was assumed that young children's self-evaluations are often overconfident, because they may not yet be able to take valid cues, such as perceived task difficulty and invested mental effort, into account. It is not clear at what age children become able to take item difficulty cues into account, and to what extent this cue use explains age differences and accuracy of self-evaluations. Interestingly, Van Loon and colleagues found no developmental increase in reliance on item difficulty as a cue for performance self-evaluation, which means that even the youngest children (5/6 years) made adaptive use of item difficulty for their confidence judgments.

This finding is important in the context of cognitive load theory, in which learners' perceptions of task difficulty are typically used as estimators of the load imposed by a learning task on working memory. The research conducted in the past three decades has shown that learners can introspect on their cognitive processes with no difficulty in assigning numerical values to the perceived task difficulty or invested mental effort (for an overview see, Paas, Tuovinen, Tabbers, & Van Gerven, 2003) without any formal instruction. The finding of Van Loon and colleagues that even young children are able to base self-evaluations on valid task difficulty cues suggests that self-evaluation is a generic-cognitive skill that human beings have evolved to acquire, and so can be classified as biologically primary (Paas & Sweller, 2012). The fact that previous research by Koriat and colleagues (Koriat & Ackerman, 2010; Koriat, Ackermann, Lockl, & Schneider, 2009) did not find that children younger than 8 years of age could base self-evaluations on cues derived from the difficulty of the task can be explained by the type of learning task that was used. Whereas the latter studies used textual learning tasks, Van Loon and colleagues used an image learning task. The image learning task consisted of images of real objects (e.g., dog, eyes, moon, sun) which had to be learned together with the associated Kanji symbols. The textual learning tasks used by Koriat, Ackerman, Lockl, and Schneider (2009) and Koriat and Ackerman (2010) consisted of word-pairs and general knowledge to be learned, respectively. In contrast to the textual learning tasks, which can be characterised as biologically secondary skills, it is clear that at least part of the image learning task can be characterised as a biologically primary skill. This difference might explain the differences found in children's ability to use item-difficulty cues for self-evaluation. It would be interesting for future research to see whether even younger children are able to use task difficulty without any formal instruction as a cue for self-evaluation in tasks that rely more on biologically primary skills, such as associating images of real objects with each other.

Finally, it needs to be noted that none of the tasks used in any of these studies would qualify as complex in terms of the number of interactive elements, which is the measure used by cognitive load theorists for task complexity. So, one could argue that cognitive load theory was not designed to explain the results of these studies, and we want to emphasize that the above speculation needs to be considered in this light.

The Schleinschok, Eitel, and Scheiter (this issue) paper describes two experiments in which the researchers investigated whether monitoring accuracy and self-regulation can be improved when learning from expository text is followed by a generative free-hand drawing task. Although the researchers found some evidence for a positive effect of drawing on learners' monitoring accuracy in Experiment 1, in both experiments no effects of the drawing assignment on learning outcomes were found.

With regard to cognitive load theory, the researchers were interested in the effects of the drawing task on cognitive load. Initially, in the theoretical introduction, the authors argued that on the one hand the drawing assignment could impose a germane load on learners, because it requires learners to elaborate on the text contents and involves more sensory modalities as the text needs to be translated into a visuo-spatial format. On the other hand, if the learning content already imposes a high intrinsic load, the extra load imposed by the drawing assignment could lead to cognitive overload with negative effects on monitoring accuracy, self-regulation and learning outcomes. Surprisingly, when formulating their hypotheses, the authors decided to combine these arguments into a new assumption that the drawing activity would have negative effects on learning performance, because it requires resources that could otherwise be used for actual learning. This assumption means that at this point the drawing activity is no longer seen as imposing germane load, or cognitive overload, but more as imposing an extraneous cognitive load.

Another point in this study that is relevant in the context of cognitive load theory is the authors' conclusion that it seems as if prospective judgments of learning are more predictive of actual performance than retrospective judgments regarding one's past learning experience (i.e., the cognitive load ratings). It needs to be noted that the judgments of learning were measured by asking participants how confident they were that they would answer questions about the text correctly. Cognitive load was measured by asking participants to indicate how easy or difficult it was to learn something about the phenomenon. It is clear that the question used for the judgment of learning was specifically designed to estimate future test performance, whereas the question used for cognitive load measurement was designed to give an estimate about the experienced cognitive load during learning. Although there might be a relation between perceptions of difficulty of learning a task and later performance, it is clear that this relationship is less direct than the relation between a judgment of learning and later performance. In rating the cognitive load, a learner only looks back, whereas in a judgment of learning the learner will have to look back and forward. To make a more valid comparison between cognitive load ratings and judgments of learning, future research could use a question for cognitive load that asks the learner to indicate how easy or difficult it will be to answer questions about the learning task correctly.

The Glogger-Frey, Gaus and Renkl (this issue) paper provides data critical to the *invention activities/productive failure* issue. In one of the remarkably few experimental studies of this topic that properly controls variables (Hsu, Kalyuga, & Sweller, 2015; Sweller, Kirschner, & Clark, 2007), Glogger-Frey et al. found that invention activities were superior to studying a worked example on transfer problems. In their Discussion, they briefly touch on the expertise reversal effect as a possible explanation of their results. We would like to suggest it provides a complete explanation.

The worked example effect occurs when studying worked examples is superior to solving the equivalent problems. The effect usually is obtained when learners are struggling to understand novel, high element interactivity information. In other words, they are novices dealing with complex, new information and so require worked examples to guide them through the problem-solving process. Once element interactivity is reduced by increases in expertise (Chen et al., in press), studying worked examples becomes ineffective or can even have negative consequences. Providing guidance for low element interactivity information is highly likely to be less effective than having learners generate information themselves (Chen, Kalyuga, & Sweller, 2015, 2016a, 2016b). These interactions lead directly to the Glogger-Frey et al. results.

Previous work (Glogger-Frey, Fleischer, Grueny, Kappich, & Renkl, 2015) by this research group found worked examples to be superior to inventing activities. The current work is similar to the previous work except that additional practice activities were provided. Based on the expertise reversal effect, we might expect that additional practice with its attendant increases in expertise and decreases in element interactivity would eliminate the need for worked examples resulting in generation activities being increasingly effective. Precisely that result was obtained by Glogger-Frey, Gaus and Renkl providing some very important data.

As indicated above, proper control of variables has largely been missing in action in this area and so the Glogger-Frey, Gaus and Renkl paper is one of the few to demonstrate an invention activities effect using a valid experimental design. The sole reason for running a randomized, controlled trial is to establish causality. With only one variable altered at a time, any differences between conditions can be assumed to be caused by that variable. If multiple

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variables are altered simultaneously, we have no way of knowing which variable caused any differences.

We would like to urge researchers in this area to consider using a simple worked example followed by problem solving versus problem solving followed by worked example design. Such a design provides a clear test of the invention activities hypothesis associated with easily controlled variables: everything remains constant except the order of presentation of the tasks. Using such a procedure usually indicates a worked example – problem solving sequence is superior to the reverse sequence (Hsu et al., 2015; Leppink, Paas, Van Gog, Van der Vleuten, & Van Merrienboer, 2014). We would expect such results except when element interactivity is too low to generate a worked example effect.

In their paper, Sidi, Shpigelman, Zalmanov and Ackerman (this issue) describe three experiments in which they asked participants to solve problems either on paper or on screen to investigate whether the medium provides contextual cues that affect metacognitive processes and problem-solving performance. This study revives the famous debate of the 1990s between Dick Clark (1994) and Robert Kozma (1994) about the influence of media on learning.

From the point of view of cognitive load theory, it is interesting that this study uses Gavriel Salomon's (1984) ideas about the differential investment of mental effort as a function of perceptions and attributions. Salomon was the first to show that the a priori perceptions of children of television as easy and print as difficult impacted the amount of mental effort they invested during learning of the same content through the different media. Children invested more effort in and achieved higher learning outcomes after learning from materials in printed format than from the same materials presented on a television. Similarly, Sidi and colleagues hypothesized that computerized environments lead people to adapt shallower processing than paper environments under manipulations that legitimate compromise, regardless of the reading burden or the cognitive load generated by time pressure. The findings of the experiments suggest that problem solving performance on screen can even be better than on paper under a low load (no time pressure) condition. However, under a high cognitive load (time pressure) condition or with low perceived importance of the task, the success rate on screen was reduced but not on paper. The results indicate that working on screen is highly sensitive to a high cognitive load imposed by time pressure and task characteristics that signal legitimacy for shallow processing, and this affects both metacognitive and cognitive processes. On paper, the default mode of work seems to be characterized by in-depth processing, even in the presence of such task characteristics as high cognitive load and low perceived importance of the task.

The paper by Maranges, Schmeichel, and Baumeister (this issue) is interesting and potentially influential. We agree with the basic theoretical orientation which assumes that self-regulation is biologically limited. While not stated explicitly, this view is implicit throughout the paper, e.g. “Research has revealed that self-regulation is functionally limited: After using it on one task, people perform more poorly on subsequent tasks that also require self-control (P. 4).” This statement is in accord with the suggestion that self-regulation is a biologically primary skill. It is an important assumption. Furthermore, it may apply far more widely than just to self-regulation. All tasks that require the use of working memory may have a similar effect. The more working memory is used without rest, the less effective it may become. In effect, working memory resources may be depleted whether they are used for self-regulation or for other tasks. Indeed, the well-known massed versus spaced effect that occurs when information that is spaced over time, tends to be learned better than the same information that is massed without spacing. We seem to have evolved to lose available working memory resources after use and regain them after rest.

As indicated by the results described in this paper, the differential effects of susceptibility to pain or emotion as a consequence of resource depletion as opposed to additional cognitive activity are important. It is interesting that if working memory resources are devoted to a cognitive task they will not be available to process negative physical or emotional feelings. In other words, cognitive load can reduce physical or emotional feelings. In contrast, if working memory resources are unavailable due to depletion rather than due to current use, negative physical or emotional feelings will increase rather than decrease. These contrasting findings are not intuitively obvious thus increasing their importance.

While we have no doubts concerning the importance of these findings, we doubt cognitive load theory can explain the results. It was not designed for this purpose. While the theory can readily explain the effects of emotion or pain on working memory and so learning or problem solving performance (Fraser, Ayres, & Sweller, 2015; Fraser et al., 2014; Smith & Ayres, 2016), it was not designed to explain the effects of cognition on perceptions of emotion or pain. Of course, when dealing with instructional matters, we are likely to have more interest in the effect of emotion or pain on working memory and achievement test performance than the effect of working memory on feelings of emotion or pain. The primary aim of the theory and the primary dependent variables used have been associated with knowledge or problem solving test performance. As a consequence, we feel cognitive load theory is silent and cannot throw a great deal of light on these interesting results.

3. Conclusions

The purpose of this Special Issue has been to attempt to integrate cognitive load theory and self-regulated learning, two areas that have largely proceeded without reference to each other. That objective is important. Nevertheless, there are difficulties inherent in this aim. As indicated above, current versions of cognitive load theory place an emphasis on biologically secondary knowledge and domain-specific skills as opposed to biologically primary knowledge and generic-cognitive skills. Primary knowledge and generic-cognitive skills can be used to facilitate secondary knowledge and domain-specific skills but are rarely the object of instruction because they are acquired automatically due to evolutionary pressures. Self-regulated learning is likely to be a biologically primary skill and so unteachable but the distinction between biologically primary and secondary knowledge is rarely, if ever considered by self-regulated learning theorists. That disjunct between the two areas is likely to render attempts to combine them difficult both for theoretical reasons and because the procedures used also tend to be different.

From a theoretical perspective, if self-regulated learning is a biologically primary skill, attempts to demonstrate successful teaching of the skill should be difficult using properly controlled experiments with far transfer as a dependent variable. Far transfer is required to ensure that differential test performance is due to differential acquisition of self-regulatory knowledge rather than differential domain-specific content. If teaching someone to self-regulate does not improve general self-regulation that transfers to unrelated tasks, it may be legitimate to ask what the benefits are of teaching self-regulation. Successful far transfer demonstrations are few and far between thus providing support for the suggestion that self-regulated learning is a biologically primary skill. We simply do not have a large body of literature demonstrating the successful teaching of transfer-inducing, self-regulated learning.

There also are methodological differences that need to be overcome between many of the studies used within a cognitive

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load theory framework and a self-regulated learning framework. For example, in contrast to the current papers, the procedures used by many empirical papers using a self-regulated learning framework do not include a content knowledge test of any kind. Because content knowledge is central to cognitive load theory, it is almost universally included in empirical work using cognitive load theory as a base. As indicated previously, the ultimate aim of cognitive load theory is to facilitate content knowledge. Any attempts to unite the theoretical divide also will need to unite this empirical divide.

Notwithstanding the above caveats, the work reported in this Special Issue is interesting and important. We can see the common emphasis on cue-monitoring in both self-regulated learning research and measures of cognitive load as suggested by de Bruin and van Merriënboer. While cue-monitoring is probably a generic cognitive, biologically primary skill, there should be advantages to investigating the commonalities between the two theories with respect to this construct. We look forward to future work investigating relations between these two areas.

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