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REVIEW ARTICLE

Self-management as a Bridge Between Cognitive Load and Self-regulated Learning: the Illustrative Case of Seductive Details

Alexander Eitel[1] · Tino Endres[2] · Alexander Renkl[2]

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Abstract
The main goals of this paper are to exemplify and further elaborate on the theoretical connections between cognitive load and self-regulated learning. In an effort to achieve this, we integrate the concepts of self-control and self-management within the effort monitoring and regulation (EMR) framework laid out by de Bruin et al. (Educational Psychology Review this issue). More specifically, we argue that (1) cognitive load results from how the instruction is *processed* and not just from how it is designed (cf. self-management effect). (2) How instruction is processed by students (also) depends on their skill and will to self-control. For instance, high self-control may reflect compensatory processing of poorer instructional designs so that these designs may not lead to higher extraneous cognitive load. As soon as students' willingness to self-control declines (e.g., with increasing study durations or previous demanding tasks), there is a closer link between (poorer) instructional designs and (higher) extraneous cognitive load in self-regulated learning tasks. Combining (1) and (2), we consider cognitive load to be influenced by self-control; (self-)control, in turn, is one central process of the monitoring-control cycle that characterizes self-regulated learning. We support these theoretical arguments by referring to empirical research in the domain of learning with multiple representations—with a particular focus on learning with and without seductive details during extended study episodes. We conclude with suggestions for further research.

Keywords Self-regulated learning · Cognitive load · Self-control · Self-management effect · Seductive details effect · Redundancy effect

Alexander Eitel
alexander.eitel@psychol.uni–giessen.de

[1] Department of Educational Psychology, University of Giessen, 35394 Giessen, Germany

[2] University of Freiburg, Freiburg im Breisgau, Germany

Introduction

The present article refers to a part of the research agenda that the EARLI emerging field group "monitoring and regulation of effort" laid out to build a theoretical bridge between self-regulated learning and cognitive load (cf. de Bruin et al. this issue)—a very useful and almost overdue endeavor. Within the present article, we will refer to the "effort monitoring and regulation" (EMR) framework postulated by the emerging field group (de Bruin et al. this issue). In particular, we address one of the main research questions that derive from it: "How do we optimize cognitive load during self-regulated learning tasks?" To answer this question, it is sensible to consider students' ability and willingness to self-control their behavior by self-managing their cognitive load. Accordingly, in the present article, we will refer to and integrate a model of self-control (Inzlicht and Schmeichel 2012) with the EMR framework. To make our arguments as concrete as possible, we will elaborate on the case of learning with seductive details over an extended study duration (Bender et al. submitted). In the following, we will start with a brief introduction of cognitive load and the self-management effect and then integrate these concepts with theories on self-regulated learning and self-control.

Cognitive Load and Instructional Design

The concept of the cognitive load was and is especially influential in the context of the "traditional" instructional design idea. This means that a teacher or instructional designer creates, modifies, and assembles instructional materials in a way that students learn in an efficient way and thus have enhanced learning outcomes. Cognitive load theory (Sweller et al. 1998, 2019) can support teachers in their efforts to optimize the design of instructional materials so that students' learning outcomes are potentially optimized. Arguably two of the most important aspects to consider based on cognitive load theory are (1) to choose a level of complexity (i.e., element interactivity of the contents; Sweller et al. 1998, 2019) that is not too high and in accordance with students' prior knowledge levels and (2) to structure, sequence, and arrange instructional materials in a way that unnecessary demands on the cognitive system are avoided. The former aspect refers to the intrinsic cognitive load that should be kept on a manageable degree (not too high). The latter aspect refers to the extraneous cognitive load that should be kept to a minimum (e.g., Sweller et al. 2011). Taken together, both types of load constitute the overall cognitive load (e.g., Kalyuga 2011; Kalyuga and Sweller 2014); they are additive, meaning that the higher the extraneous cognitive load, the less room for intrinsic cognitive load within the cognitive system. Therefore, a high extraneous cognitive load should be avoided especially when an instructional topic or task is complex and, therefore, induces high intrinsic cognitive load. In general, a big difference in intrinsic minus extraneous cognitive load is preferable. This is actually considered the germane cognitive load in recent conceptualizations of cognitive load theory (Sweller et al. 2019), meaning the load induced by relevant learning processes directed to a schema or mental model construction and modification.

As instructional tasks in schools and universities are often quite complex (e.g., understanding subatomic processes or structural equation modeling), optimizing the design to reduce extraneous cognitive load is typically recommended. These recommendations align with much of the empirical research showing that a designer can reduce students' extraneous cognitive load, and therefore foster learning outcomes, for instance by refraining from presenting information that is irrelevant and/or redundant for achieving the instructional goal (redundancy effect, e.g., Mayer and Moreno 2003; Rey 2012; Kalyuga and Sweller 2014) or by presenting information that needs to be integrated (e.g., verbal descriptions and their corresponding diagram elements) in close spatial and temporal contiguity so that splitting of attention is avoided or at least reduced (contiguity effect; see Ginns 2006; Schroeder and Cenkci 2018, for meta-analyses).

The aforementioned instructional recommendations are typically addressed to teachers or instructors—they optimize the materials so that students' information processing and cognitive load are consequently optimized (load that results from the task or environmental demands; Paas et al. 1994). However, this strong view of instructional design—the design determines students' information processing and cognitive load—may be too narrow and one sided. In the following, we broaden this view, basing our argumentation on previous research considering cognitive load as, at least in part, self-determined or "self-managed" by the student (Mirza et al. 2020). The latter view is also in line with the view of a self-regulated learner whose will and skill affect learning (and cognitive load) over and above the material decisions made by the teacher or instructional designer (e.g., Bjork et al. 2013; Gerjets and Scheiter 2003).

Self-management of Cognitive Load

Already in the classical conception of cognitive load theory (Sweller et al. 1998), the instructional designer did actually not exclusively decide upon students' cognitive load. Rather, an *intrinsic* cognitive load has always been a function of both, content complexity and students' prior knowledge levels (see also research in the context of the expertise-reversal effect; Kalyuga and Renkl 2010). The self-management effect within cognitive load theory goes one step further, suggesting that also *extraneous* cognitive load is not a mere function of the provided design, but also a function of how it is modified and dealt with by students (Mirza et al. 2020). The basic idea behind self-management is that cognitive load results from how the instruction is *processed* and not just from how it is designed. It is the suboptimal processing of an instruction, and not the suboptimal instructional design per se, that increases cognitive load and hampers performance (see also arguments by Gerjets and Scheiter 2003). A suboptimal design does not have to be processed in a suboptimal way by students. Under certain circumstances, students may optimally process suboptimal instruction.

A first necessary circumstance for such self-management to occur is that students invest sufficient effort to compensate for poorer instructional design that might otherwise increase extraneous cognitive load. Another circumstance is that students are taught on how to improve a suboptimal design by themselves. In typical experiments in the context of the self-management effect (e.g., Gordon et al. 2016; Roodenrys et al. 2012; Sithole et al. 2017), students show better learning outcomes and reduced extraneous cognitive load when they were instructed on how to physically integrate text pieces into diagrams (e.g., by drag-and-drop). In doing so, students reduced split attention; they improved the instructional design in terms of cognitive load by themselves, which was in turn beneficial to performance. More generally speaking, they did not process the suboptimal instructional design in a suboptimal fashion (after improving it); therefore, their extraneous cognitive load was not increased. One may conclude that their load was (partially) self-managed instead of being (exclusively) instructor managed.

An open question in this line of research is, however, to what degree self-managing one's cognitive load goes back *only* to a reduction in one's extraneous cognitive load. So far, research on self-management of cognitive load focuses on improving cognitive load by reducing the extraneous cognitive load (see Mirza et al. 2020, for a recent overview). Theoretically, one may argue that being guided on how to integrate text and diagrams by oneself (to reduce split attention) directly contributes to the construction of integrated mental models (e.g., Mayer 2014; Schnotz 2014) and thus should increase the "productive" mental effort, also known as the germane cognitive load. Results from Cierniak et al. (2009) indicate that a reduction of split attention (manipulated between subjects) led to a better comprehension of complex facts through an increase of germane cognitive load besides a decrease in extraneous cognitive load. Such results indicate that the idea of improving cognitive load by self-managing should not be restricted to reducing the extraneous but also to increasing the germane cognitive load. Nevertheless, following the recent conception of cognitive load theory (Sweller et al. 2019), these two types are closely tied to each other anyway.

The most recent idea in the context of self-management is that students do not even need to physically optimize the design to improve their cognitive load by themselves (Eitel et al. 2020). This idea was inspired by empirical findings and previous theoretical work in the field (Gerjets and Scheiter 2003). Studies showed that it was sufficient to inform students about the roles that the different representations within the instructional materials play (e.g., constructing function or mere decorative function) so that students processed the instruction in an optimized fashion, which led to reduced extraneous cognitive load and better performance (cf. Eitel et al. 2019; Schwonke et al. 2009). More specifically, in the study of Eitel et al. (2019), students learned with seductive details (i.e., interesting but irrelevant details; cf. Garner et al. 1989) and were either informed about their irrelevance for the learning goals or not. Eitel et al. found that, compared with a control condition without seductive details, students experienced higher extraneous cognitive load and showed worse performance only when they learned with seductive details and were *uninformed* about their irrelevance. When being informed about their irrelevance, neither an increase in extraneous cognitive load nor a decrease in performance occurred due to the seductive details. The redundancy effect was thus moderated by students being (un-)informed about redundant or irrelevant information (see also Eitel et al. 2020). This effect was also replicated in a recent study by Bender et al. (submitted). One can conclude from these studies that students in the informed condition decided not to (deeply) process irrelevant information even though it was present in the instruction. Students thus self-managed their cognitive load by self-controlling their cognitive processing.

In a similar vein, results from studies by Schwonke et al. (2009) and by Gerjets et al. (2000) come to the conclusion that the link between instructional design and cognitive load or performance is moderated by students' processing strategies. For instance, Schwonke et al. (2009) showed that the benefits of designing instruction using multiple representations depend on the way students process the representations. More specifically, students' performance levels in the study of Schwonke et al. depended on whether they processed the diagrams as translational aids to integrate information from text and equations or not. This fits the overall pattern of results that multiple representations are not always helpful to learning but only when students process them in an integrated fashion (see also Eitel 2016). Depending on their knowledge, beliefs, or learning goals, students may decide to process multiple representations in an integrated fashion or not. These decisions moderate the effectiveness of an instructional design comprising multiple representations. Hence, our conception of self-management of cognitive load (when learning with multiple representations) aligns with the concept of a self-regulated learner who decides on his or her own about when and which information to process (cf. Bjork et al. 2013; Boekaerts 2017). We will elaborate on the relations between the self-management of cognitive load, self-control, and self-regulated learning in the following. As a conclusion for this paragraph, we consider cognitive load to be not just a direct result of the instructional design; but rather, it depends on how students deal with the design.

Self-management of Cognitive Load and Self-regulated Learning

In our opinion, the concept of self-management of cognitive load is a good example of a theoretical bridge between cognitive load and self-regulated learning. Self-management of cognitive load lies somewhere in the middle between the perspective of the instructor versus the student being completely in charge of cognitive load and learning success. It thus integrates ideas from both instructional design and self-regulated learning research. On the one hand, self-management interacts with the instructor's design to explain cognitive load outcomes. On the other hand, self-management of cognitive load is part of the self-regulation of learning; it can be conceptualized as a control process within the metamemory framework (Nelson and Narens 1990) that builds the backbone of the EMR framework (De Bruin et al. this issue).

More specifically, the EMR framework aptly locates cognitive load in the middle between the object level, where cognitive processing of instructions takes place, and the meta-level, where the thoughts about one's cognitive processing are represented (see Fig. 1). Specifically, the meta-level represents both one's study goals and the perceived progression that was already made towards achieving one's study goals. The latter requires continuous monitoring; cues for such monitoring usually come from the object level (e.g., the perceived difficulty of connecting ideas from subsequent sentences when reading through a text). Based on these cues, decisions about which control processes to initiate are made at the meta-level (e.g., do I need to re-read sentences or not?). Thus, self-regulated learning is usually considered to involve a monitoring-control cycle leading towards the desired learning goal (see also in other models by, e.g., Pintrich 2000; Zimmerman 2000). According to the EMR framework (de Bruin et al. this issue), processing on the object level provides cues *both* for cognitive load and for the meta-level (monitoring). The meta-level, in turn, controls both the object level and the cognitive load that results the specific processing of instruction.

We postulate that, within the EMR framework, self-management is reflected in the control mechanism from the meta-level to the object level; the latter then affects cognitive load (see the two bold green arrows in Fig. 1). Due to self-management, an increase in extraneous cognitive load is avoided due to students' optimized processing of suboptimal instructions. More specifically, because students are informed about how to deal with suboptimal instruction (information represented on meta-level), control processes are initiated that make the learning task (on object level) actually easier than when such information would not have been presented. Self-management thus reduces cognitive load, along with the perception of it, that is reflected in the cognitive load rating (although we acknowledge that cognitive load and the perception of cognitive load can be fundamentally different; see Scheiter et al. 2020, for a thorough discussion).

To further elaborate on the highlighted relations within the EMR framework, we recur to the study by Eitel et al. (2019), where students self-managed their cognitive load differently when they had been informed about the irrelevance of seductive details or not. When being informed that seductive details are irrelevant and thus rather distract from reaching the learning goal (= reasoning on meta-level), students could control their cognitive processing (= object level) by ignoring the irrelevant information in the form of seductive details (see bent green

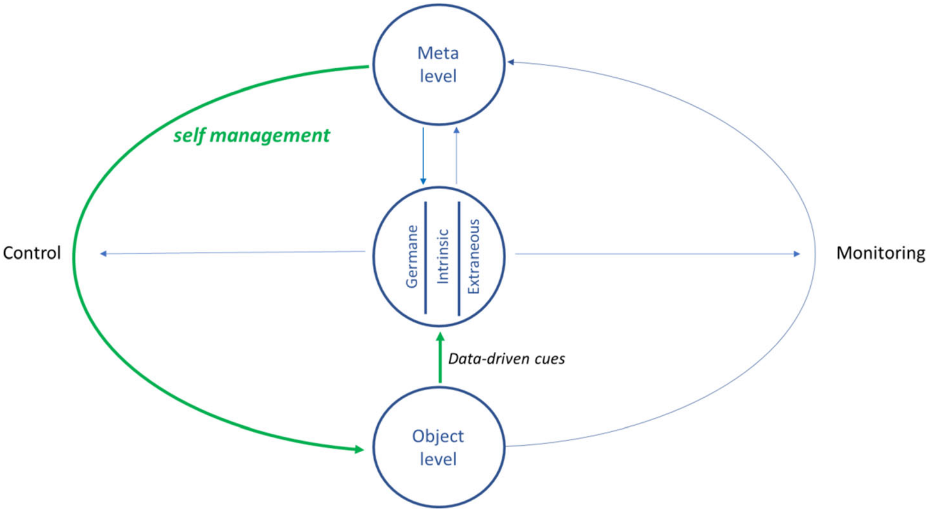

Fig. 1 The EMR framework with proposed inclusion of self-management of cognitive load (graphic adapted from de Bruin et al. this issue)

arrow in Fig. 1). Hence, students were not much distracted by the details, their cognitive processing remained focused on the learning goal to a similar degree as in the case of missing seductive details; thus, the data-driven cues (e.g., how hard it feels to connect relevant ideas) that inform cognitive load (see short green arrow in green in Fig. 1) were the same without and with seductive details (when informed) so that, in consequence, there was no increase in extraneous cognitive load. Students self-managed their cognitive load by controlling their cognitive processing. To provide another example, when students had been taught how to improve a split-attention design on their own in previous research (cf. Roodenrys et al. 2012), students controlled their cognitive processing, and thus managed their cognitive load, by first physically modifying the design on their own (see bent green arrow in Fig. 1), that then led to improved processing on the object level, and in turn, to reduced extraneous cognitive load (see short green arrow in green in Fig. 1).

Taken together, we argue that self-management of cognitive load is a control process during self-regulated learning, as indicated in the EMR framework. Under certain circumstances (e.g., being informed about the irrelevance of irrelevant information), students can effectively self-manage their cognitive load by engaging in compensatory cognitive processing (e.g., actively ignoring irrelevant information). However, by definition, self-management as a *control* process during self-regulated learning requires *self-control*. Exerting self-control is hard work and can become more difficult with increased study duration. This will be in the focus of the next section.

Self-management of Cognitive Load and Self-control

The previous sections mainly elaborated on whether and when students are *able* to self-manage their cognitive load. For instance, when students are informed about seductive details being irrelevant, they make an effort ignoring them, thereby optimizing their cognitive processing and cognitive load. However, this might not always be true. Students need to be both able *and willing* to carry out effortful control processes such as ignoring irrelevant but interesting details (cf. Corno and Kanfer 1993; McCombs and Marzano 1990). The degree to which students carry out such processes is contingent upon their current motivation, which typically results from the product of success expectancy, task value, and anticipated motivational costs (Feldon et al. 2019; Jiang et al. 2018). The higher the motivation, the more willing students are to carry out effortful control processes as an act of self-control (a volitional process). Self-control, more generally, refers to the capacity for bringing one's behavior in line with one's personal goals, ideals, or values. Self-control is often initiated when discrepancies between the desired goal states and current states are detected (e.g., Carver and Scheier 2001). Thereby, self-control is considered to be the deliberate and effortful subset of self-regulation (Baumeister et al. 2007). Mapped to the self-regulated learning situation, it is what keeps students persist during studying and avoid temptations, even though the temptations might seem quite attractive at the moment. However, engaging in self-control is hard work; it involves deliberation, attention, and vigilance. Therefore, humans cannot exert self-control over unlimited periods of time (Lindner et al. 2017; Muraven and Baumeister 2000). We thus argue that the duration of study is an important predictor of student's willingness to self-manage their cognitive load by (self-)controlling their cognitive processing.

More specifically, the process model of depletion (Inzlicht and Schmeichel 2012) postulates that after engaging in much self-control, people become less motivated to engage in further self-control; instead, people become more motivated to engage in things that are more personally rewarding, interesting, and enjoyable. They thus experience a shift in motivational orientation ("I do not want to control myself now"). This shift is accompanied by a shift in attentional focus; attention is directed away from cues signaling the need to exert control and increasingly towards cues signaling gratification ("I see rewards"). People then may fail to notice when control is actually required. Mapped to the situation of self-regulated learning, one may conclude that in the beginning minutes of instruction, students are willing to self-control themselves, meaning that they engage in compensatory cognitive processing when facing a suboptimal instructional design (cf. Eitel et al. 2019). For instance, they actively integrate information in a split-attention format or they actively ignore irrelevant information even though it is interesting (as in the case of seductive details), thereby focusing on what is relevant to achieve the learning goal. In terms of the EMR framework, adequate control of learning is initiated on the meta-level, including the self-management of cognitive load. Thus, a suboptimal design may not lead to increased extraneous cognitive load in the beginning of the instruction (see Fig. 2).

With increasing study duration, however, students may start to experience shifts in motivation and attention. They may be less willing to engage in effortful compensatory processing when facing a suboptimal instructional design. As possible consequences, students may engage in daydreaming, cyberslacking, pausing, or quit studying early to search for more gratifying things somewhere else. Alternatively, students may search for and attend to gratifying information within the instruction. The latter could be expected to be especially true when seductive details are added to instructions as they are, by definition, interesting and entertaining details that are added to instructions even though they are irrelevant to achieving the learning goals (cf. Alexander 2019; Garner et al. 1989). Accordingly, one may expect that with increasing study duration, students have more problems actively ignoring the details, but rather search for and attend to them as gratifying information. As seductive details are, at the same time, irrelevant, they might hamper learning and increase the extraneous cognitive load when they receive increased attention towards the end of an extended study episode (see Fig. 3). In terms of the EMR framework, there is increasing exhaustion on the meta-level to be expected with increasing study duration, which is why students may fail to notice or

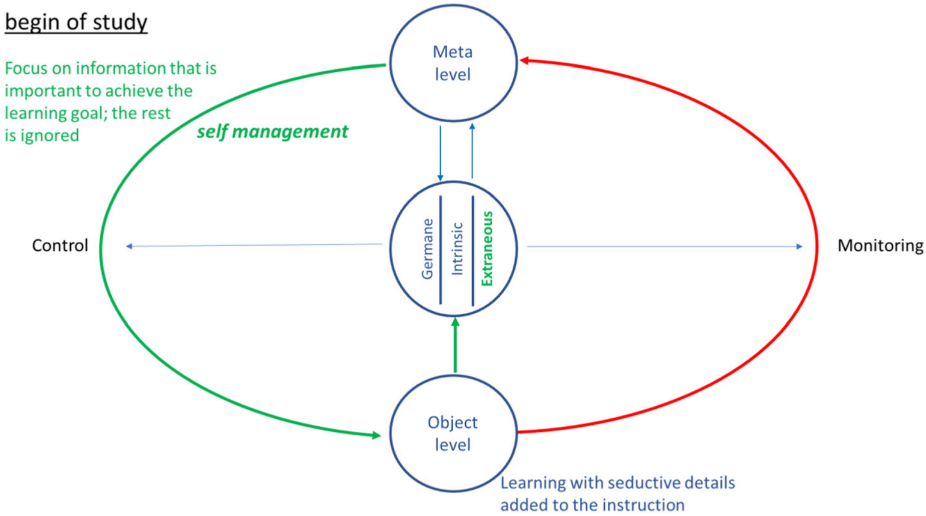

Fig. 2 The EMR framework with the proposed inclusion of self-management during the first minutes of studying

concentrate when control is actually required (Inzlicht and Schmeichel 2012). In consequence, cognitive load is increased and learning outcomes suffer. We tested these hypotheses in an empirical study that we outline in the following paragraph.

Illustrative Empirical Study: Seductive Details in Instructions and Self-control

Specifically, here we put forward and test the hypotheses derived from the EMR framework (de Bruin et al. this issue) and process model of depletion (Inzlicht and Schmeichel 2012) in

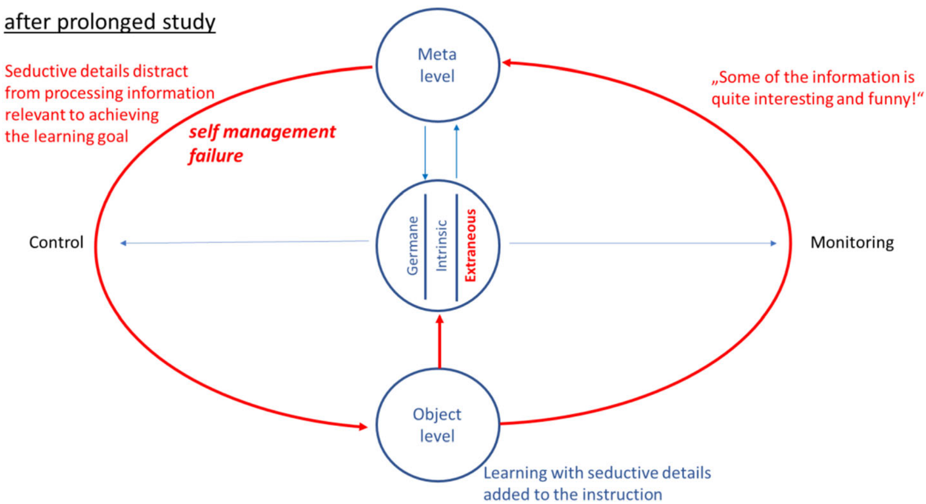

Fig. 3 The EMR framework with the proposed inclusion of self-management (failure) after many minutes of studying

the previous paragraph; namely that good instructional design, one that optimizes cognitive load in a classical sense, is more important the weaker the students' ability and willingness to self-control. Students' willingness to self-manage cognitive load (as an act of self-control) is typically weaker when they had to sustain attention for a longer time during studying and not so much in the beginning. Hence, a suboptimal instructional design should (1) increase extraneous cognitive load and (2) reduce learning outcomes especially after prolonged studying, where the willingness to self-control by the self-managing cognitive load is reduced (cf. Figs. 2 and 3).

We tested these hypotheses in a recent experiment (Bender et al. submitted), in which students ($N = 193$) learned either without seductive details or with seductive details about atomic models in chemistry, and received knowledge tests afterwards. This sample size allowed detecting the expected effects of medium size (Cohen's $f = 0.25$) with a high power statistical power (0.88). The study materials were spread across five chapters. Study times were learner paced for all five chapters. There were knowledge tests for each one of the five chapters. Seductive details always comprised both text and graphic; they were (remotely) connected to the instructional topic, interesting, and irrelevant for the instructional goals (e.g., a detail referred to Homer Simpson being a supporter of the Albuquerque Isotopes). All students, regardless of whether they received seductive details or not, learned from chapter 1 to chapter 5 (= last chapter). Students indicated their cognitive load directly after learning each one of the five chapters (questionnaire items adapted from Klepsch et al. 2017).

The main results are depicted in Fig. 4. Learning with vs. without seductive details interacted with the chapter of instruction (first vs. final) for both extraneous cognitive load and learning outcomes as the dependent variable (both $p_s < .05$). More specifically, post hoc contrasts revealed that seductive details did neither affect cognitive load nor learning outcomes for the first chapter (both $p_s > .20$); by contrast, and as expected, the details increased extraneous cognitive load and decreased learning outcomes for the final chapter (both $p_s < .05$). Results are thus in line with the hypotheses. A suboptimal instructional design, one that included seductive details, increased extraneous cognitive load and decreased learning outcomes (only) after prolonged studying. This effect was mediated by a reduction in positive affect. Interestingly, the details had no effect on the first chapter (even though statistical power was high). One may thus conclude that students were, in principle, able to self-manage their cognitive load here—which they also did in the beginning. However, students did not successfully self-manage their cognitive load during learning in the final chapter anymore,

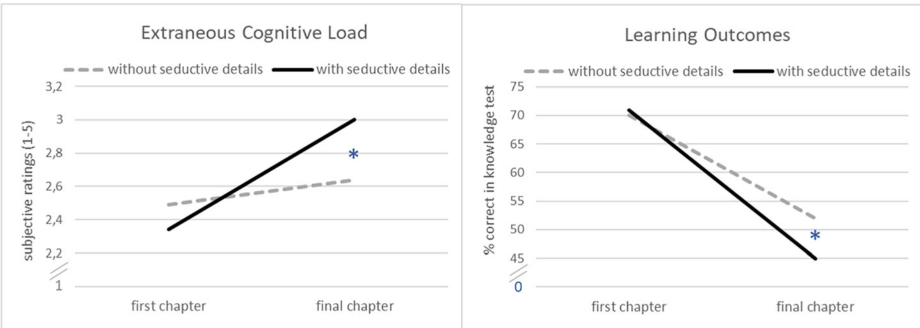

Fig. 4 Results for students' ratings of extraneous cognitive load (left panel) and performance in the knowledge tests (right panel) depending on experimental condition (without vs. with seductive details) and study chapter (first vs. final)

which may indicate that their willingness to self-control was insufficient. In terms of the process model of depletion (Inzlicht and Schmeichel 2012), students searched for and attended more to gratifying information, in this case, the seductive details, when studying the final chapter. Accordingly, seductive details distracted from learning in the final chapter, thereby increasing extraneous cognitive load and decreasing learning outcomes (cf. Fig. 4). The degree to which potential differences in chapter difficulty affected this interaction needs to be subject to further research.

To sum up, integrating the idea of self-control depletion (Inzlicht and Schmeichel 2012) within the EMR framework (de Bruin et al. this issue) allowed us to derive accurate hypotheses about what happens when students learn with a (sub-)optimal instructional design for an extended time. As the latter is rather the rule than the exception in self-regulated learning tasks, we consider this result and reasoning a good example to concretize how cognitive load and self-regulated learning are conceptually and empirically related. Also, we hope that it made clear which concepts could be considered to fill in the missing conceptual links between cognitive load and self-regulated learning (e.g., self-management; self-control depletion).

It is important to note that we do *not* conclude from these results that optimizing an instructional design in terms of cognitive load is *only* important towards the end of a longer instruction. This hypothesis would be inconsistent with findings from meta-analytical reviews—for instance, one about the contiguity effect that did not find stronger contiguity effects with longer than with shorter duration of instruction (Schroeder and Cenkci 2018). Rather, we argue that students' abilities and their present willingness to exert self-control affect the effects of an (optimized) instructional design. The lower the self-control the stronger the instructional design effects are to be expected. We thus expect this moderation by self-control to generalize across instructional design principles even though some caveats need to be considered (see next section). Besides having studied for a longer time already, students' willingness to engage in self-control also depends on whether there have been other demanding tasks prior to the learning task (cf. sequential task paradigm; Baumeister et al. 1998). Even though the classical ego depletion effect found with this paradigm has gotten under attack empirically (e.g., Hagger et al. 2016), the basic idea of losing (part of) one's willingness to self-control after having to self-control for some time seems valid (e.g., Inzlicht and Friese 2019). The idea of losing one's willingness to self-control after previous tasks requiring self-control is important to consider in light of many experiments in educational psychology applying prior knowledge and ability tests (e.g., working memory; intelligence) prior to having students learn with the instructional materials. Students' ability and willingness to self-control might already be substantially reduced when starting to learn with the materials so that, quite paradoxically, this might explain why strong effects of instructional design manipulations (either in line with cognitive load theory or not) emerged even with short durations of presenting the instructional materials.

Besides the continuous effort that needs to be put in the present learning task, the magnitude of required self-control during learning also depends on the relative attractiveness of behavior alternatives. This is referred to as opportunity costs (Kurzban et al. 2013) or as motivational costs in recent efforts to bridge motivation and cognitive load (Feldon et al. 2019). More specifically, it may be hard to persist during studying when friends are present or when the smartphone is in reach, and when there are additionally no sanctions for either talking to friends or cyberslacking on the smartphone (e.g., because one is at home: high opportunity or motivational costs). Opportunity or motivational costs for studying are lower when students are in class with a teacher present. Most behaviors other than studying are likely to be sanctioned by the teacher. The alternative behaviors may thus not seem so attractive. Studying in class requires fewer self-control than studying at home. Hence, one may conclude that an optimized instructional design may be especially important when learning at home, where the opportunity costs are high (i.e., a typical self-regulated learning situation). As conclusion, regardless of how they are affected both the ability and willingness to self-control interact with the instructional design to impact on cognitive load and performance.

Answer to Research Question and Ideas for Further Research

We started this manuscript with a research question related to the EMR framework, and we now want to (partially) answer it by summarizing our main argumentation. The question was "how do we optimize cognitive load during self-regulated learning tasks?" To answer this question, one first needs to clarify "who is *we*"? Referring to the self-management effect, *we* means both the teacher or instructional designers and the students themselves. When students have the skill and will to deal with suboptimal instructions by themselves, the instructional design does not need to be optimized by the teacher. To what degree an instructional design that is optimized according to load-reducing techniques could even backfire when students know how to deal and expect "suboptimal" designs (similar to the expertise-reversal effect; e.g., Richter et al. 2018) should be subjected to further research?

Nonetheless, a partial answer to the aforementioned research question is that cognitive load should be "optimized," whenever needed; that is, when students either do not know or are not willing to engage in compensatory processing of a suboptimal design by themselves. Whether students engage in compensatory or optimal processing of (suboptimal) instructions is a matter of their ability and willingness to self-control. First of all, students are likely to differ in their willingness to invest mental effort into learning as an act of self-control, even though such differences are hardly considered in the context of cognitive load theory this far (see also Scheiter et al. 2020, for recent criticism). Such differences, however, are important to be considered as potential moderators of instructional design effects. For instance, one may argue that whether self-pacing of instruction is more beneficial than system pacing (segmenting effect; Rey et al. 2019) depends on the degree to which students are willing to invest cognitive effort. Accordingly, results from a study by Kühl et al. (2014) showed that only students with a high dispositional need for cognition but not students with a low need for cognition profited from self-pacing the instruction. Probably only the students with high a need for cognition invested sufficient mental effort to profit from self-pacing when given the opportunity.

Second of all, even if students start studying with high ability and willingness to self-control, the latter can become depleted after extended study times, preceding demanding tasks or high opportunity or motivational costs. More specifically, depletion may result from having to process long instructional materials (e.g., Bender et al. submitted) or from having to complete time-consuming study assignments such as journal writing (see Nückles et al. 2020). Both tasks bear the risk of students giving up due to declines in motivation and self-control. We thus argue that especially in such study situations, it is important to optimize the instructional design, for example, by applying load-reducing techniques such as integrating text and diagram information, excluding irrelevant information, or providing worked examples. We welcome further research that seeks to evaluate these claims on an empirical basis—preferably across a broad range of instructional design effects found in the context of cognitive load theory (e.g., redundancy, contiguity, modality).

Existing research already indicates that these claims may likewise apply to the personalization and the segmenting effect (Endres et al. 2020; Kühl et al. 2014). In an experiment by Endres et al. (2020), participants saw a video about the basics of photography either in a personalized and conversational style (including an avatar called Lisa who wants to take nice pictures to show around, etc.) or in a neutral style. Results revealed that the personalized and conversational style increased situational interest (compared with the neutral style) that in turn reduced ECL and fostered learning outcomes—the latter only in the final part of a three-part instructional video. It seems the personalized style made it easier for students to sustain attention through the whole video. Students might have saved more self-control resources for later with the personalized video. The benefits became evident in the final phase of studying. Conversely, one may argue that students were able to compensate for the less-engaging neutral video in the first two but not in the final part of the instructional video anymore.

Notably, existing research already indicates that applying this hypothesis to other instructional design effects is not without limitations. There is recent evidence that the present hypothesis does not apply to all sorts of operationalization of the redundancy effect. Rop et al. (2018a) found that students started to ignore irrelevant information with increasing task experience. Negative effects of a suboptimal instructional design (that includes irrelevant information) were thus sometimes diminished (Rop et al. 2018b) and not amplified as found here, with increasing study duration. The main difference is that seductive details, which are not just irrelevant but also interesting, were used in the illustrative study here, whereas rather neutral irrelevant information was used in Rop et al. (2018a) or in the Rop et al. (2018b) study. Hence, the beneficial cognitive strategy of ignoring the irrelevant contents required fewer self-control in these studies than in the study by Bender et al. (submitted) that was outlined here. Accordingly, not the detrimental effects of increasing self-control depletion but the beneficial effects of strategy acquisition dominated, and therefore, the redundancy effect was not stronger but weaker with increasing trials and study duration.

As the latter example suggests, to fully understand and accurately predict learning behavior and outcomes, always a combination of cognitive and motivational-volitional factors need to be considered. Here we specifically referred to self-control (depletion) as motivational facet moderating the effects of instructional design on cognitive load and learning outcomes. We thus recommend to account for the effects of self-control and motivation in future cognitive load research. Notably, the most recent conception of the cognitive theory of multimedia learning (Mayer 2014), along with extensions of this theory such as the cognitive-affective theory of learning with media (CATLM; Moreno and Mayer 2007) or the cognitive-affective-social theory of learning with media (CASTLM; Schneider et al. 2018) explicitly include the concepts of motivation and metacognition. Even though not always modeled explicitly, these theories postulate that the degree to which effort is invested in cognitive processing of instructions depends on the (current) motivation and results from metacognitive monitoring. So, we hope that also the concept of self-control (as part of self-regulated learning) will find its way into cognitive models on instruction processing more strongly in the future.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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