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INTERVENTION STUDY

The Interplay of Cognitive Load, Learners' Resources and Self-regulation

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Abstract

Self-regulated learning depends on task difficulty and on learners' resources and cognitive load, as described by an inverted U-shaped relationship in Seufert's (2018) model: for easy tasks, resources are high and load is low, so there is no need to regulate, whereas for difficult tasks, load is too high and resources are too low to regulate. Only at moderate task difficulty do learners regulate, as resources and load are in equilibrium. The purpose of this study is to validate this model, i.e., the inverted U-shaped relationship between task difficulty and self-regulatory activities, as well as learner resources and cognitive load as mediators. In the within-subject study, 67 participants reported their cognitive and metacognitive strategy use for four exams of varying difficulty. For each exam task difficulty, cognitive load, and available resources (such as prior knowledge, interest, etc.) were assessed. Multilevel analysis revealed an inverted U-shaped relationship between task difficulty and the use of cognitive strategies. For metacognitive strategies, only a linear relationship was found. Increasing cognitive load mediated these relationship patterns. For learner resources we found a competitive mediation, indicating that further mediators could be relevant. In future investigations a broader range of task difficulty should be examined.

Keywords Self-regulated learning · Task difficulty · Learners' resources · Cognitive load

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Building Bridges between Self-Regulated Learning and Cognitive Load Theory

In recent years, some attempts have been made to build bridges between two of the most important theoretical frameworks in the field of education, i.e., models of self-regulated learning (SRL) and cognitive load theory (CLT; Sweller et al., 1998). While SRL and the respective models deal with self-generated thoughts, feelings, and actions, which are systematically oriented toward attainment of students' own goals (Zimmermann, 2002), CLT has a focus on cognitive processes while learning and how instruction can be designed to optimize learners' limited cognitive resources. One bridge-building approach is the Effort Monitoring and Regulation Framework (EMR; de Bruin et al., 2020), which aims to explain how mental effort influences self-regulatory processes such as monitoring. De Bruin et al. (2020) emphasize the importance of linking cognitive load and self-regulated learning perspectives to understand how to optimize self-regulation. The link between the two concepts is bidirectional: Self-regulation requires cognitive resources and thus causes cognitive load. But depending on the load demands of a task, learners can adjust their self-regulatory activities, and thus cognitive load can cause or affect self-regulation. This complex interplay is explained in Seufert's (2018, 2020) model of self-regulation as a function of resources and perceived cognitive load. Depending on task difficulty, load and learners' resources vary and influence the actual use of self-regulatory activities: Easy tasks, such as learning simple lists of familiar words, are experienced as less demanding and may not activate intensive self-regulatory activities. It is a low-stress task for which learners have sufficient resources. Learners may show strong self-regulation in medium difficult tasks, for which they still have resources but the task is not too loading. For even higher task difficulty, resources might be scarce and demands are too high, so learners may decide not to invest in self-regulation because the task itself is already too demanding.

Overall, these examples illustrate that learners' self-regulation depends on different aspects, either inherent to the task or due to their own characteristics. The interplay of the learners' resources and the cognitive load experienced through tasks of varying difficulty seems to influence whether and to what extent learners self-regulate. This is the main assumption of Seufert's (2018) model. If the model is valid, it could provide a starting point for research into the interplay between self-regulation and cognitive load. It could also provide a framework for teachers and learners to support the specific factors, i.e. balancing task affordances with learner resources and cognitive load, to promote self-regulation. Based on these overarching objectives, this paper aims to validate the model and empirically test its basic assumptions. Therefore, this research aims to investigate the influence of perceived task difficulty on the use of self-regulatory activities. Due to the often observed inter- and intra-individual differences in learning behavior (Jonassen & Grabowski, 2012), the role of cognitive load caused by the learning task and the importance of learners' available resources in this context will also be investigated.

Self-Regulation as a Function of Resources and Perceived Cognitive Load

The main purpose of Seufert's (2018, 2020) model of self-regulation as a function of resources and perceived cognitive load is to provide a research framework for studies of the interplay between SRL and CLT. However, it makes strong assumptions about the relationship between its main parameters, which need to be supported by empirical evidence.

Before presenting the main parameters and assumptions of the model, it is necessary to understand what Seufert (2018, 2020) actually understands by self-regulation in her model. Based on different models of self-regulation (Schmitz & Wiese, 2006; Zimmerman, 1990), which emphasize the dynamic and cyclical process of self-regulation, learners perform self-regulatory activities before, during and after learning. Learning strategies are crucial in this whole process, and they can be either cognitive, metacognitive or resource-based. While cognitive strategies refer to conscious plans for processing the information of the given task, metacognitive strategies aim to optimize the learning process itself. Resource-based strategies are used to support the learning process by utilizing or managing external sources, like help or time (Boekaerts, 2011). In a perfectly self-regulated learning process, learners use metacognitive strategies to set their goals, plan their learning activities, and choose cognitive strategies that match the affordances of the task before learning. During learning, these strategies are applied and learners metacognitively monitor whether strategies and goals are still aligned. If not, they regulate, i.e., they adjust their strategies or goals and use different strategies, regulate their effort, or give up. Even after learning, self-regulation is necessary to reflect on all the processes before and after learning that relate to processing the task and managing the learning process. Based on reflection, learners can draw conclusions for future learning situations (Zimmerman, 1990). In summary, based on the description in Seufert (2018) self-regulatory activities include cognitive and metacognitive strategies before, during, and after learning. As in this model resource-based strategies are not focused specifically we also restrain from analyzing learners' resource-based strategy activities. Seufert's model of *self-regulation as a function of resources and perceived cognitive load* (2018, 2020; see Fig. 1) describes various parameters that influence the intensity of these self-regulatory activities.

The crucial parameter of Seufert's model (2018, 2020) is the *difficulty of the task*, which due to the author includes the original learning task and, in addition, the self-regulation possibilities during the handling of this task. A typical example would be a student preparing for an exam. He or she has to memorize and understand the content itself, but at the same time has to organize the learning process, i.e. make plans, monitor progress, and regulate in case of difficulties. The difficulty of the content may be strongly related to the complexity of managing the learning process Moreover, Seufert (2020) emphasized that task difficulty may arise not only from objective affordances but also from learners' decisions to engage more or less with the task as needed, for example, because they like it or dislike it, are particularly interested in it or not.

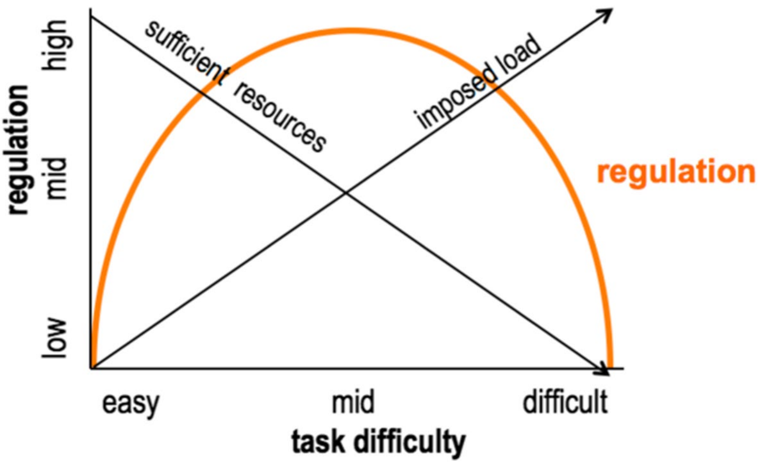

Fig. 1 Self-regulation as a function of resources and perceived Cognitive Load (Seufert, 2018)

Closely related to task difficulty, two relevant and counteracting forces mediate whether learners actually engage in self-regulatory activities.

First, *cognitive load* increases as task difficulty increases. Thereby, all three types of load, intrinsic, extraneous and germane load are linked to task difficulty. While intrinsic affordances in terms of task complexity are inherent to the task and can hence be seen as part of task difficulty, cognitive load may also arise from extraneous affordances of the task which are not related to the task objectives like search processes, or due to germane resources invested (Sweller et al., 1998). If the overall imposed load of the task is too high, self-regulatory activities may cease.

Second, as task difficulty increases, *learners' resources* for successfully completing the task decrease. Or one could argue the other way round that the task is perceived as difficult because of a lack of resources. These resources include cognitive abilities, most importantly prior knowledge (Dochy, 1994) or working memory capacity (Cowan, 2014) as well as skills or capacities for successful self-regulation, such as motivation or metacognitive skills (Zimmerman, 2008). With insufficient resources, learners are no longer able to self-regulate.

Taking all these parameters together, Seufert's (2018, 2020) model shows an inverted U-shaped curve for self-regulatory activities as a function of task difficulty, with the two opposing mediators load and resources. On one end of the spectrum, learners may not need to regulate when the task is very easy because the available resources are sufficient, resulting in a perceived low load. Conversely, at the other end, they may struggle to regulate when tasks are too difficult, as resources become insufficient and load is perceived to be very high (e.g., Moos, 2013). Optimal self-regulation occurs with tasks of moderate difficulty, where resources and load are balanced, allowing learners to use their resources effectively. The imposed load serves as a catalyst for the initiation of self-regulation, while still being manageable enough to not hinder the process.

In the following, the main assumptions of the model are explained and justified: (1) task difficulty influences self-regulatory activities, (2) cognitive load increases with task difficulty and mediates the effect on self-regulatory activities, (3) learner resources decrease with task difficulty and mediate the effect on self-regulatory activities. Finally, (4) the relationship between the two possible mediators, resources and load, is discussed.

Task Difficulty Influences Self-Regulatory Activities

With regard to Seufert's (2018, 2020) model, it is important to emphasize that the task not only includes the actual learning task at hand, but also the regulation of the learning process while dealing with the task. With regard to perceived task difficulty, empirical studies show that learning tasks that are moderately challenging and thus of medium difficulty promote the use of self-regulatory strategies (Middleton & Midgley, 2002; Turner & Meyer, 2004). In contrast, when the challenge is too high or too low, learning tends to be less self-regulated (Turner & Meyer, 2004). Seufert's (2018, 2020) model makes the same assumption, but it still needs to be empirically tested.

Cognitive Load Increases with Task-Difficulty and Mediates the Effect on Self-Regulatory Activities

The assumption that cognitive load increases with task difficulty and mediates the effect on self-regulatory activities involves three distinct aspects. First, that the task itself and second, that the regulation of the learning process imposes cognitive load and that the load increases with the difficulty or complexity of both. The third aspect is that the load aspect of task difficulty at both levels mediates the intensity of self-regulatory activities.

That cognitive load increases with the difficulty of the task itself is an inherent assumption of CLT (Sweller et al., 1998) and therefore perceived task difficulty is often used as an indicator of mental effort and cognitive load (Paas et al., 2005). The number of interrelated elements indicates the intrinsic load of the task, and as the complexity of the elements increases, so does the interactivity of the elements. In addition, tasks can also be more difficult if learners have to deal with extraneous processes such as searching or navigating, which is indicated by extraneous load. And learners can invest mental effort which is germane to the task but nevertheless requiring cognitive capacity.

Studies show that regulating the learning process is often experienced as demanding and stressful because it requires cognitive capacities in addition to the actual learning task (Efklides, 2011; Lajoie, 1993; Schwonke, 2015). Therefore, in all phases of the cyclical model of self-regulated learning, learners are confronted with cognitive and metacognitive demands that increase cognitive load. While the intrinsic cognitive load caused by the regulatory task is mostly dependent on the complexity of the actual learning task, extraneous cognitive load is induced when the demands are not sufficiently integrated into the learning task (Seufert, 2018). This could be the case, for example, when external learning goals are not made explicit, thus hindering planning and goal setting. Self-regulatory processes can also be productive for learning and can therefore be considered germane. However, this is only possible if sufficient resources are available to facilitate comprehension, schema construction and automation, and learning success (De Bruin & van Merriënboer, 2017; Sweller & Paas, 2017). In particular, metacognitive strategies require many capacities (De Bruin & van Merriënboer, 2017). As the cognitive load theory only focuses on cognitive factors, an extension of the germane cognitive load to include the concept of metacognitive load has already been proposed (Valcke, 2002). It is assumed that the germane cognitive load results from the construction of knowledge schemata, whereas the metacognitive load results from the monitoring of the learning process and the control of schema construction and storage (Schwonke, 2015; Valcke, 2002). In summary, the total demands imposed by the learning task and self-regulatory processes may exceed the capacity of working memory (Schwonke, 2015).

The question of whether task load has the potential to mediate learning behavior, i.e., self-regulatory activities, can be answered with the EMR framework (de Bruin et al., 2020), which is based on Koriat's (1997) cue utilization framework. Learners use various cues, such as perceived task difficulty or effort, to evaluate their learning process and to adjust their learning behavior. Learners primarily respond to perceived difficulties or discrepancies in the learning process with increased regulation of learning behavior. For example, reading speed is reduced for complex texts (Baker & Brown, 1984) and more learning time is invested in more difficult tasks (Van Loon et al., 2017). In addition, learners use deep strategies especially when faced with difficulties or inconsistencies during the learning process (D'Mello & Graesser, 2012). Difficulties in creating graphics for textual content or explaining what they have learned in their own words can also indicate a lack of understanding, leading to increased strategy use (De Bruin & van Merriënboer, 2017; Schleinschok et al., 2017).

According to the Cue Utilization Framework (Koriat, 1997), task difficulty is an intrinsic cue that can inform the learning process either directly or indirectly through mnemonic cues. Mnemonic cues represent "phenomenal experiences" (Koriat, 1997, p. 351) during information processing, such as perceived cognitive load. Accordingly, learners may use task difficulty to assess the perceived cognitive load imposed by the task and adjust their learning behavior, including self-regulated learning (Van Loon et al., 2017). Therefore, this study examines cognitive load as a mediating variable for the relationship between difficulty and self-regulatory activities.

Although, as mentioned above, learners respond to difficulty with increased strategy use, there is evidence that highly complex tasks leave less working memory capacity for self-regulatory processes, and cognitive overload is possible (Kanfer & Ackerman, 1989; Moos & Azevedo, 2008). Van Gog et al. (2011) showed that when working on complex tasks, monitoring the learning process increases cognitive load and leads to impaired learning performance, whereas this is not observed for simpler tasks. Thus, when task load is high, the additional demands of self-regulatory processes may exceed the capacity of working memory, which may explain why less self-regulatory learning occurs (Schwonke, 2015; Van Gog et al., 2011).

Learners' Resources Decrease with Task-Difficulty and Mediates the Effect on Self-Regulatory Activities

With regard to the third assumption of Seufert's (2018, 2020) model, which needs to be empirically supported, it is first necessary to discuss which potential resources learners can have for self-regulation and how they are related to task difficulty.

Regarding learner characteristics relevant for self-regulation, studies show that the ability to engage in self-regulated learning increases with age, from childhood to adulthood (Boekaerts, 1999; Dolmans & Schmidt, 1994; Paris & Paris, 2001; Whitebread et al., 2007). Other personal factors that are more specific to learning are outlined in the Individual Prerequisites for Successful Learning model (INVO model, Hasselhorn & Gold, 2013) or in comparable models like the good information processor model (Pressley et al., 1989). They distinguish between cognitive and motivational-volitional prerequisites. Cognitive prerequisites include prior knowledge, strategy use and metacognitive knowledge as well as working memory and attentional focus (Hasselhorn & Gold, 2013). As motivational prerequisites particularly intrinsic motivation is described as crucial as well as goal orientation, interest, self-efficacy and learners' self-concept (Hasselhorn & Gold, 2013). These resources are briefly presented in the following section with a strong focus on prior knowledge as one of the most critical factors in learning.

Prior knowledge, as one of the key parameters for learning success, is also important with respect to self-regulated learning (Schwonke, 2015). Prior knowledge can facilitate selective attention, lead to faster activation of concepts in working memory, and increase interest and motivation (Hasselhorn & Gold, 2013). Prior knowledge also provides free working memory capacity that can be invested in self-regulatory processes (DeStefano & LeFevre, 2007; Schwonke, 2015). As was shown for hypertext tasks, learners with higher levels of prior knowledge plan and monitor their learning process more than learners without prior knowledge (Moos & Azevedo, 2008). Taub et al. (2014) also highlight the greater use of metacognitive learning strategies by individuals with higher levels of prior knowledge, while no differences are observed in cognitive strategy use as a function of expertise. For individuals without prior knowledge, the use of metacognitive strategies in particular exceeds the limited capacity of working memory, so that free resources are invested only in knowledge acquisition to avoid overload (Kanfer & Ackerman, 1989; Moos & Azevedo, 2008; Taub et al., 2014). As prior knowledge increases, and thus in terms of Seufert's (2018, 2020; Fig. 1) model on the left, sufficient capacities are available both for processing the learning task and for planning, monitoring, and regulating the learning process (Van Gog et al., 2005). Therefore, cognitive load theory can also be used to explain why self-regulated learning is more effective for individuals with higher levels of prior knowledge (Azevedo et al., 2008; Van Gog et al., 2005). However, for individuals with very high prior knowledge, it can be assumed that learners no longer need additional self-regulatory processes for successful goal attainment. This argument may also apply to all other resource variables.

In addition to prior knowledge, the INVO model (Hasselhorn & Gold, 2013) states that *strategy use and metacognitive knowledge* are essential for self-regulatory activities, as many studies have shown (Bannert et al., 2015; Boekaerts, 1999; Butler

& Winne, 1995). As learners gain experience in using strategies, they will be able to tackle more difficult tasks and apply learning strategies successfully (Dresel et al., 2015; Stebner et al., 2022).

Working memory capacity and attentional focus are also factors that are strongly related to task difficulty as they improve task performance (Ilkowska & Engle, 2010). Dealing with the task and being self-regulatory while doing so at the same time requires working memory capacity and the ability to suppress irrelevant aspects. With sufficient capacity and focus learners are able to handle both task levels.

Motivational components are also important for self-regulated learning. The will to persistently engage in a learning task is associated with greater strategy use (Wolters, 2003). In particular, *intrinsically motivated* individuals learn in a more self-regulated manner in contrast to learners that are extrinsically motivated. For intrinsically motivated learners learning is rewarding in itself, because it is interesting, while extrinsically motivated learners seek reward from others or try to avoid punishment (Deci & Ryan, 1985; Standage et al., 2005).

Furthermore, *motivational goal orientation* is central, with different orientations being distinguished (Pintrich, 2000). Individuals with a learning goal orientation pursue the goal of improving their skills and knowledge (Butler & Winne, 1995; Spinath et al., 2002; Wolters et al., 1996). Whereas learners with an approach-performance goal orientation strive to prove their abilities, learners with an avoidance-performance goal orientation try to conceal deficient abilities (Ames, 1992; Elliot & Harackiewicz, 1996). In the final goal orientation, work avoidance, learners try to avoid a lot of work, so they prefer tasks that require less effort (Meece & Holt, 1993; Spinath et al., 2002). Empirical studies show that individuals with a learning goal orientation are more self-regulated learners and therefore have better academic performance (Abar & Loken, 2010; Boekaerts et al., 2006; Kolić-Vehovec et al., 2008). While an approach-performance goal orientation may also be beneficial for self-regulated learning, an avoidance-performance goal orientation, as well as a tendency to avoid work, is associated with lower use of learning strategies (Abar & Loken, 2010; Elliot & Harackiewicz, 1996).

High *interest* is also associated with more frequent use of self-regulatory strategies (Horvath et al., 2006; Schiefele, 1991). In this context, interest can be considered a facet of motivation and describes the preference to engage with certain topics (Hidi, 2000).

Another factor to be considered is expected *self-efficacy*. This term describes "the belief in one's own ability to plan and perform the necessary (required) actions in such a way that future situations can be mastered" (Bandura, 1995, p. 2). Specifically, individuals with higher self-efficacy expectations engage in more self-regulated learning by setting challenging goals, using learning strategies, and demonstrating high effort and persistence in task completion (Butler & Winne, 1995; Duijnhouwer et al., 2012; Richardson et al., 2012; Schunk, 2008).

Also closely related to self-efficacy expectancies is the *learner's self-concept*, with this study focusing on academic self-concept. Academic self-concept varies across school subjects and describes learners' perceptions of their own academic abilities (Hasselhorn & Gold, 2013; Pintrich & Garcia, 1994; Schunk, 1991).

Studies show that individuals with a positive self-concept use more self-regulatory strategies (Burnett & Proctor, 2002; Ommundsen et al., 2005). They are also more motivated and attribute learning success to their own abilities and efforts, thus feeling in control of their learning process (Ommundsen et al., 2005).

In order to validate the model of Seufert (2018) all the different prerequisites are incorporated in one overall factor of resources.

Relations between Cognitive Load and Learners' Resources

Seufert's (2018, 2020) model implies that the two opposing forces of resources and load are negatively related. Available resources can reduce the cognitive load of a task and thus prevent impairments in learning performance. Thus, cognitive load seems to depend on different characteristics of learners, such as ability, interest, or prior knowledge (Brünken et al., 2003).

Individuals with a high level of prior knowledge usually estimate tasks more easily due to existing knowledge structures in long-term memory and show a lower cognitive load from the learning task (Van Gog et al., 2005). Therefore, individuals with higher prior knowledge also have more working memory capacity available for parallel self-regulatory processes (Große & Renkl, 2006; Moreno, 2006). Furthermore, research shows that as learning strategies are used more frequently, their application becomes increasingly automatic and less cognitively taxing (Schwonke, 2015). In addition, Steele-Johnson et al. (2000) demonstrated that individuals with a learning goal orientation are better able to cope with cognitively taxing learning situations and also have higher self-efficacy expectations. Individuals with a performance goal orientation believe more strongly in their ability to perform tasks that are less cognitively demanding. Thus, while individuals with a learning goal orientation prefer cognitively taxing learning environments to increase their knowledge, learners with a performance goal orientation prefer less taxing situations to demonstrate their abilities (Steele-Johnson et al., 2000).

However, as task difficulty increases, fewer resources are available and the compensatory effect with respect to cognitive load decreases. For example, confidence in successfully completing a task and belief in one's own abilities decrease, resulting in lower motivation (Schunk, 1991). In addition, learners show less interest (Horvath et al., 2006) and prior knowledge might be insufficient when facing higher difficulty (Kalyuga, 2007; Van Gog et al., 2005). Thus, it can be assumed that individuals with sufficient resources are less burdened by additional self-regulatory processes and are more likely to use these (Seufert, 2018). However, these resources decrease with increasing task difficulty.

Regarding the model of Seufert (2018, 2020), it is only stated that both forces are relevant to explain the intensity of self-regulatory activities and that they are negatively related. It is not explicitly argued that self-regulation varies because of the interaction of both factors. Thus, this paper focuses on the relations between task-difficulty and self-regulation mediated by load and separately by resources as a mediator. For the sake of completeness, the negative relationship between load and resources is will be substantiated.

Present Study

Since the aim of this study is to validate the model of self-regulation as a function of resources and perceived cognitive load (Seufert, 2018, 2020; see Fig. 1), the different parameters of the model are evaluated and analyzed in terms of their expected relationships.

The basic idea of this study is to examine these parameters with regard to four successive exams of varying difficulty and to survey students for each exam regarding their perceived task difficulty, their resources and load, and their respective self-regulatory activities. Thus, the task at hand encompasses both the exam and the preparation for the exam, but the perceived task difficulty is primarily determined by the subject and perceived complexity (i.e. intrinsic cognitive load) in relation to the specific exam. The learner's resources and the perceived load (i.e. extraneous and germane load), on the other hand, primarily come into play in the preparation for the exams.

In order to ensure high task relevance and a wide range of task difficulty, we chose exams in English, Mathematics, German, and a profile subject with presumably varying difficulty from rather easy to rather difficult. Nevertheless, students rated the difficulty of each task, as perceived task difficulty is crucial in the model to be tested. Overall, the study is a within-subject study with four measurement points and additional questionnaires before the first exam to assess descriptive data and task-related resources. As learner resources, prior knowledge, strategy knowledge, interest, motivational goal orientation, academic self-concept, and self-efficacy expectancy were assessed with reference to the INVO-model (Hasselhorn & Gold, 2013). Regarding cognitive load, we assessed intrinsic, extraneous, and germane load.

With this setup, we aimed to validate Seufert's (2018, 2020) model and its main assumptions. The research question is whether the intensity of self-regulatory activities depends on perceived task difficulty and whether this influence is mediated by learners' resources and cognitive load. This interplay of parameters will be analyzed with respect to the use of cognitive strategies (RQ1) and metacognitive strategies (RQ2).

As modeled by Seufert (2018, 2020), we hypothesize that the use of cognitive strategies (H1a) is influenced by perceived task difficulty with a significant negative quadratic effect. We further expect that the effect of task difficulty on cognitive strategy use will be mediated by learner resources (H1b) and cognitive load (H1c).

For the use of metacognitive strategies (H2), we also expect that it will be affected by perceived task difficulty with a significant negative quadratic effect (H2a). We further expect that the effect of task difficulty on metacognitive strategy use will be mediated by learner resources (H2b) and cognitive load (H2c).

Method

Participants

The 67 participants in the study (53.7% female) were students in grade 11 at a local vocational school. The decision to use this sample was based on the assumption that students of this age and school type have already developed learning strategies with sufficient variance (Paris & Newman, 1990). They were around 17 years old ($M_{age}=16.72$; $SD_{age}=0.83$) and had one of the following profiles: technology and physics (13.4%), economics (46.3%), welfare, education and psychology (20.9%) and public health (19.4%). Students gave their written informed consent in accordance with the Declaration of Helsinki and with the ethical committee of the authors' institution.

Design and Procedure

We implemented a within-subject design providing different school subjects with different perceived task difficulty (German, English, Mathematics, profile subject), assessing students' cognitive load and available resources, and their use of self-regulatory activities in terms of strategy use in their respective exam preparation. In order to ensure a sufficiently large variance in exam difficulty, the selection of exam subjects was based on an expert assessment by the deputy headmaster. According to this, German—as the mother tongue of most pupils—was assessed as the easiest exam, followed by English as a foreign language. Mathematics was rated as the most difficult. The difficulty of the profile subject is assumed to vary according to the students' chosen focus. The four exams took place over a period of seven calendar days, with a break of two to three days between each two exams. The sequence of exams was the same for all participants, with English, followed by Mathematics, German and the profile subject.

About a week before the first exam, participants completed a pretest. The pretest comprised, an online questionnaire that lasted about 30 min and was completed in the school's computer labs. Following an introduction with an explanation of the study process participants gave their informed consent for participating in the study. The online survey aimed to collect demographic data, assess the perceived difficulty of subjects, the expected difficulty of the upcoming exams, interest levels, and record the students' previous grades in each respective subject. Next, the students completed the questionnaires to assess their previous use of learning strategies, learning and achievement motivation in each subject, and their academic self-concept. Additionally, the online-questionnaire gathered data on the students' self-efficacy expectations regarding the different exams.

In the school hours directly after each exam, the students received a paper–pencil questionnaire focused on the preceding exam and its preparation. Each questionnaire took approximately 15 min to complete and started with items related to exam preparation in general. The students then answered the items for assessing the learning strategies and a differentiated measurement of cognitive load experienced during the respective exam.

Instruments

Perceived task difficulty

The perceived difficulty of the four exams and exam preparation in English, Mathematics, German, and the profile subject was recorded in the pretest as the central independent variable in this study. We used two items ("How do you rate the difficulty of the respective subject in general?", "How do you rate the difficulty of the upcoming exam in the respective subject?") with a seven-point Likert scale ranging from 1 = very easy to 7 = very difficult. In addition, the perceived complexity of the tasks following the respective examinations was included for this independent variable in order to also take into account the demands of regulating one's own learning process. For this purpose, the two items for intrinsic cognitive load were integrated (e.g., "The exam was very complex"; "For this exam, many things needed to be kept in mind simultaneously"). For the further statistical analyses, an overall scale for perceived difficulty for each subject was calculated based on the 4 items with an internal consistency of $\alpha = 0.64$.

Learners' resources

According to Seufert's model (2018, 2020), the relationship to cognitive load and task difficulty applies to all these resources in the same way. For this reason, no differentiated assumptions were made about the individual resources, but they were summarized in an omnibus measure. Finally, due to pragmatic considerations and the context of the repeated measures design in an authentic school setting, no further resources were included.

To measure available resources as another mediator variable, the study used an overall scale consisting of various resources in the learning context, namely goal orientation, previous strategy use, prior knowledge, interest, self-concept, and self-efficacy. These were recorded subject-specifically in the online pre-test.

Goal orientation Motivational goal orientation was assessed using the Scales to Assess Motivation to Learn and Achieve (SELLMO; Spinath et al., 2002). Since only orientation to learning goals and, to some extent, approach-performance goals have so far been shown to be conducive to the use of learning strategies, only these two scales were measured: Learning goals with six items ($\alpha = 0.79$, e.g., "In Math/ English/ German/ In the profile subject, I am concerned with understanding complicated content.") and approach-achievement goals with four items ($\alpha = 0.73$, e.g., "In Math/ English/ German/ In the profile subject, I am concerned with showing that I am good at something."). Items were recorded using a five-point Likert scale (1 = not at all true, 5 = true exactly) separately for each subject.

Previous strategy use Prior experience in strategy use as another resource was recorded in the pre-test as the frequency of previous strategy use, using the Learning Strategies in Study Questionnaire (LIST; Wild & Schiefele, 1994; described earlier). For this study, 11 items were used to assess previous use of cognitive learning strategies with subscales for repetition, organization and elaboration ($\alpha = 0.64$; e.g., "I make short summaries of the most important content to help me think"). For the metacognitive learning strategies scale, nine items for planning, monitoring and regulation were used ($\alpha = 0.47$; e.g., "Before learning an area of material, I consider how to proceed most effectively"). The items were selected according to their suitability for the specific context of exam preparation. Since the items cover a wide range of cognitive, respective metacognitive strategies, the low internal consistency is not surprising.

All items were answered on a five-point response scale from 1 = very seldom to 5 = very frequently.

Prior knowledge As prior knowledge, the grade in the past exam in the respective subject was asked on a six-point response scale from 1 = very good to 6 = insufficient (range of responses across all subjects: past grade: $Min = 1$, $Max = 6$). For the aggregated resource score, it was recoded so that higher scores mean higher prior knowledge.

Interest Learners' interest was queried using the item "How interesting do you find the following subjects?" which students answered on a seven-point Likert scale ranging from 1 = not interesting at all to 7 = very interesting.

Self-concept To determine the perception of one's own academic abilities in the respective subjects as another resource, the Scales for the Assessment of Academic Self-Concept (SESSKO; Schöne et al., 2002) were used. The questionnaire contains 22 items that are used to assess academic ability, differentiating four reference norms: In comparison to classmates ("social," six items, $\alpha = 0.95$, e.g., "I can do less than my classmates in (subject) … more than my classmates."), in comparison to the demands of the school context ("criterial," five items, $\alpha = 0.94$, e.g., "When I look at what we have to be able to do in (subject), I find that I can do little … a lot."), compared to earlier time points ("individual," six items, $\alpha = 0.93$, e.g., "I cope with the tasks in (subject) worse than before … better than before.") and without considering a reference norm ("absolute," five items, $\alpha = 0.95$, e.g., "I find learning new things in (subject) difficult … easy."). Students responded to the items specifically for each subject using a five-point Likert scale.

Self-efficacy In addition, the General Self-Efficacy Expectancy scale (Schwarzer & Jerusalem, 1999) was used to assess students' self-efficacy expectancy, and thus their confidence and trust in being able to handle a difficult situation, with 10 items. An exemplary item reads, "I face difficulties calmly because I can always trust my abilities." Participants answered these items for each subject on a four-point Likert scale ranging from 1 = not true to 4 = true exactly ($\alpha = 0.93$).

For further statistical analyses, an aggregated resource scale was used with an internal consistency of $\alpha = 0.86$, calculated from the mean of the six resources scales described above. As the resources were based on different scales, they were first converted into percentages and then an overall scale for the resources was formed from the mean.

Strategy use To assess strategy use during exam preparation as the dependent variable, the items relating to cognitive and metacognitive strategy of the Learning Strategies in Study (LIST; Wild & Schiefele, 1994) questionnaire were administered after each exam analogous to the previous strategy use, described above. The items were adapted to refer to the preparation of the previous exam. For cognitive learning strategies scale, with subscales for repetition, organization and elaboration (e.g., "I made short summaries of the most important content to help me think") internal consistency was $\alpha = 0.85$. For the metacognitive learning strategies scale, with subscales for planning, monitoring and regulation (e.g., "Before learning an area of material, I considered how to proceed most effectively.") internal consistency was $\alpha = 0.85$.

Cognitive Load

The Questionnaire for the Subjective Measurement of Cognitive Load by Klepsch et al. (2017) was given after each exam to assess cognitive load experienced during exam preparation. The questionnaire contains three items for extraneous cognitive load ($\alpha = 0.74$; e.g., “The presentation of the learning material was unfavorable to really learn something”) and two items for germane cognitive load ($\alpha = 0.68$; e.g., “I have made an effort not only to memorize individual things, but also to understand the overall context”). The two items for intrinsic cognitive load ($\alpha = 0.61$) were used for perceived task difficulty, as described above. In addition, the questionnaire includes two general items about the effort invested in the learning task. All items were answered by participants on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). For the statistical analyses, an overall scale with an internal consistency of $\alpha = 0.62$ was formed for cognitive load, consisting of the mean of the items on extraneous and germane cognitive load as well as on invested effort.

Data preparation and analysis

To prepare and analyze the data, we used SPSS Statistics version 25. To test for differences in task difficulty, cognitive and metacognitive strategies between school subjects, we conducted repeated measures ANOVAs. To avoid the accumulation of alpha errors, the bonferroni-corrected p-values for the ANOVA post hoc tests in the manipulation check were calculated and reported at a significance level of $p < 0.05$. As our study design implied a nested data structure including learners (level 2) and their self-reports and outcomes (level 1: perceived task difficulty, cognitive load, relevant resources, use of learning strategies with respect to each of the four exams), as the assumptions for parametric testing were met, we tested whether hierarchical modeling was suitable for testing our hypothesis. Upon inspection of Q-Q-plots, normality of level 2 residuals was assumed. Homoscedasticity was also assumed based on inspection of scatterplots for level 2 residuals and predicted values. Finally, based on the ICC criteria (> 0.05), hierarchical modeling was appropriate and thus we calculated hierarchical regression models (Heck et al., 2013; Nezlek et al., 2006). To account for initial differences of the respective learners' variables, we used random intercept fixed-slope models. Based on our approach of using a homogeneous sample in a comparatively standardized exam context, we assumed that the differences on the dependent variables were quite similar across learners. Thus, no random slopes were tested. To allow reasonable interpretations as well as to compare the relative influence of the different predictors, all variables were z-transformed.

Based on our hypothesis, we used suitable paths models and applied Sobel tests to test our hypothesis (see Appendix). Based on the theoretical model assumptions, a quadratic effect appeared plausible in addition to linear effects, so these were also included in the statistical analyses.

Results

Manipulation and assumption check

We assumed that different school subjects led to differing perceived task-difficulties. Based on the reported perceived task difficulty, differences in task-difficulty were determined (($F(2.71, 178.73) = 8.65$, $MSE = 1.09$, $p < 0.001$, $\eta^2 = 0.12$). By post-hoc testing, we revealed a higher perceived task difficulty in Math compared to English ($MD = 0.69$, $SE = 0.19$, $p = 0.004$, $d = 0.60$), a higher difficulty of the profile subject compared to English ($MD = 0.78$, $SE = 0.16$, $p < 0.001$, $d = 0.77$) and a higher difficulty of the profile subject compared to German (see Table 1 for respective means).

To test the assumed interplay of the two forces, load and resources, described in the model of Seufert (2018, 2020), the mean correlation between learners' resources and cognitive load over all subjects was calculated. Overall, with $r = 0.22$ ($p = 0.037$) the assumed negative correlation was not supported by the present findings. In detail, we found a heterogenous pattern for the subjects ($r_{\text{English}} = -0.22$, $p = 0.068$; $r_{\text{German}} = 0.24$, $p = 0.050$; $r_{\text{Mathematics}} = -0.04$, $p = 0.771$; $r_{\text{Profile}} = 0.24$, $p = 0.048$).

Descriptives

We revealed significant differences between subjects, concerning the use of cognitive and metacognitive learning strategies during the respective exam preparation (see Table 2).

Post-hoc testing revealed a more frequent use of cognitive learning strategies during preparation for the Mathematics exam compared to the English exam ($MD = 0.29$, $SE = 0.10$, $p = 0.04$, $d = 0.38$). In addition, metacognitive strategies were used more frequently in preparing for the exam in the profile subject than for the

Table 1 Means and standard deviations (in brackets) for independent, dependent and mediator variables for different subject exams

	English	German	Mathematics	Profile
Task difficulty (1 – 7)	3.53 (1.16)	3.85 (0.91)	4.22 (1.16)	4.31 (0.83)
Strategy use (1 – 5)				
Cognitive	2.82 (0.76)	2.86 (0.87)	3.11 (0.76)	3.34 (0.73)
Metacognitive	3.17 (0.85)	3.00 (0.90)	3.27 (0.86)	3.31 (0.81)
Cognitive load (1 – 7)	4.60 (0.88)	4.95 (1.00)	5.04 (1.05)	5.05 (1.03)
Resources (%)	67.55 (12.64)	65.15 (9.32)	68.18 (12.88)	69.95 (10.80)

Scale ranges are provided in brackets next to variables

German exam ($MD = 0.32$, $SE = 0.08$, $p = 0.001$, $d = 0.36$). With regard to cognitive load, the repeated-measures ANOVA revealed significant differences between school subjects ($F(3, 198) = 4.32$, $MSE = 0.70$, $p = 0.006$, $\eta^2 = 0.06$). The post-hoc test implied a significantly higher load with respect to the Mathematics ($MD = 0.44$, $SE = 0.14$, $p = 0.020$, $d = 0.47$) and profile subject ($MD = 0.45$, $SE = 0.17$, $p = 0.049$, $d = 0.47$) exams compared to the English exam. Based on the repeated-measures ANOVA, we found no significant differences between subjects in available resources ($F(3, 198) = 2.46$, $MSE = 115.31$, $p = 0.064$).

Effects of Perceived Task Difficulty on Cognitive Strategies (H1)

We tested our hypotheses based on random intercept fixed slope models (for details see method section: data preparation and analysis).

Our first hypothesis focused on the effects of perceived task difficulty on cognitive strategies. In line with our expectations (H1a), which postulated a significant effect of perceived task difficulty on cognitive strategy use, we found significant linear and quadratic total effect (linear $\gamma 0(\beta 1) = 0.22$, $SE = 0.05$, $p < 0.001$; quadratic: $\gamma 0(\beta 2) = -0.07$, $SE = 0.03$, $p = 0.020$; see Table 3 in the appendix). For an overview see Fig. 2. This finding reflects that although cognitive strategy use increased with increasing perceived task difficulty, cognitive strategy use in exam preparation decreased at higher levels of perceived task difficulty.

We hypothesized a mediating effect of available resources (H1b). In line with our hypothesis, we revealed a significant indirect linear effect of perceived task difficulty on cognitive strategy use, mediated by available resources ($a \times b = -0.18$, $z = —4.90$, $SE = 0.04$, $p < 0.001$; see Table 3). With increasing perceived task difficulty, fewer resources were available, which resulted in lower cognitive strategy use. The opposing signs of direct and indirect paths (see Fig. 2) indicate a competitive mediation (Zhao et al., 2010). Thus, the positive direct effect of difficulty on cognitive strategy use competes with the negative indirect effect that difficulty exerts through decreased resources. Moreover, no significant mediation was found for the quadratic effect ($a \times b = -0.02$, $z = —1.88$, $SE = 0.01$, $p = 0.060$).

As hypothesized, we found cognitive load to be a significant mediator (H1c): For the linear effect, based on the Sobel test, we identified cognitive load as a partial mediation ($a \times b = 0.10$, $z = 3.27$, $SE = 0.03$, $p = 0.001$; see Table 3 in the appendix). This effect implies that with increasing perceived task difficulty cognitive load also increases, which leads to a more frequent cognitive strategy use. Moreover,

Table 2 Results of the two repeated-measures ANOVAs displaying the cognitive and metacognitive learning strategies during exam preparation

	*df**	*F*	*MSE*	*p*	partial η^2
Cognitive strategies	2.72, 179.81	13.63	0.32	< 0.001***	0.17
Metacognitive strategies	2.58, 170.21	3.68	0.42	0.018	0.05

*Greenhouse Geisser corrected degrees of freedom

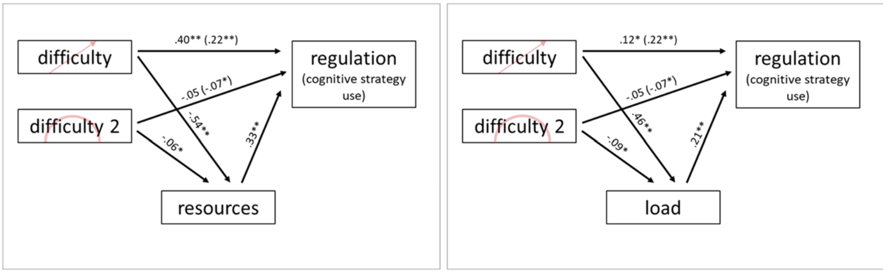

Fig. 2 Path models for cognitive strategy use with resources as mediator (on the left) and cognitive load as mediator (on the right); total effects in brackets

consistent with our hypothesis (H1c), the quadratic relationship was fully mediated by cognitive load ($a \times b$ = -0.02, z =—2.28, SE = 0.01, p = 0.023).

Effects of Perceived Task Difficulty on Meta-Cognitive Strategies (H2)

In our second hypothesis, we focused on the effect of perceived task difficulty on the use of meta-cognitive strategies. For an overview of the results see Fig. 3. With regard to metacognitive strategy use, we revealed the expected linear total effect (H2a) of perceived task difficulty on learning strategy use (linear: γ0(β1) = 0.16, SE = 0.05, p = 0.001). With increasing perceived task difficulty, the use of meta-cognitive strategies increased. However, we found no significant quadratic total effect (quadratic: γ0(β2) =—0.06, SE = 0.03, p = 0.063; see Table 4 in the appendix). Due to the lack of a total quadratic effect, we therefore focused more on the total linear effect as well as the indirect effects.

As hypothesized, we found an indirect linear effect of perceived task difficulty on metacognitive strategy use mediated by resources ($a \times b$ = -0.12, z = -3.61, SE = 0.03, $p < 0.001$). Similar to cognitive strategy use, the pattern of direct and indirect effects revealed a competitive mediation effect. Thus, while increasing difficulty directly relates to increased metacognitive strategy use, it exerts a negative indirect effect by

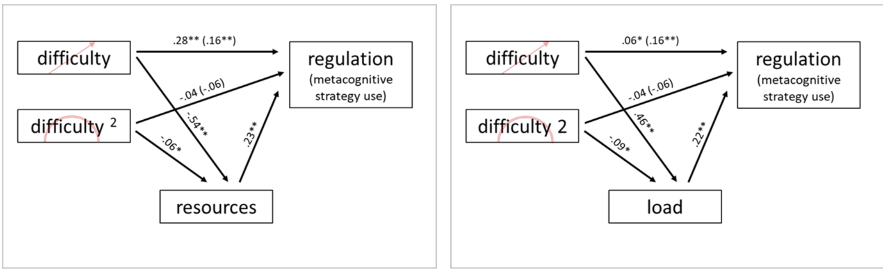

Fig. 3 Path models for metacognitive strategy use with resources as mediator (on the left) and cognitive load as mediator (on the right); total effects in brackets

decreasing available resources. No significant, indirect quadratic effect could be supported by the data ($a \times b = -0.01$, $z = -1.77$, $SE = 0.01$, $p = 0.076$).

Analyzing the mediation effect of cognitive load (H2c) using a Sobel test, an indirect quadratic relationship was revealed for perceived task difficulty on metacognitive strategy use ($a \times b = -0.02$, $z = -2.32$, $SE = 0.01$, $p = 0.020$). In addition, a partial mediation of the linear relationship by cognitive load was found ($a \times b = 0.10$, $z = 3.41$, $SE = 0.03$, $p < 0.001$).

Discussion

The aim of our study was to analyze the assumptions of the model *of Self-regulation as a function of resources and perceived Cognitive Load* by Seufert (2018, 2020) and thus the interplay of task difficulty and self-regulatory activities mediated by resources and load. In order to challenge the model of Seufert (2018, 2020) empirically, it was necessary to operationalize different levels of difficulty. We assumed that the exams in English, German, Mathematics, and profile subject would be of increasing difficulty. As our manipulation check confirmed, learners in fact rated the difficulty of these exams in this increasing order. Self-regulatory activities, i.e. the use of different learning strategies, also varied significantly across the four different exams, again in the same increasing order. This indicates a linear increase in both difficulty and self-regulatory activities. Perceived cognitive load also followed this pattern. In contrast, learners' resources showed a different pattern and tended to remain stable over the four exams. In the following sections the two research questions regarding the interplay of task difficulty, load and resources with cognitive (RQ1) and metacognitive strategy use (RQ2) and the respective hypotheses are discussed.

Effects on Cognitive Strategy Use (RQ1)

Regarding the effects on cognitive strategy use, we observed, consistent with our first hypothesis (H1a), both a linear and a quadratic relationship of perceived task difficulty and cognitive strategy use. According to this, students organized, elaborated, and repeated learning material more often during exam preparation when the task difficulty was moderate, whereas they used cognitive learning strategies less often when the task difficulty was easy or difficult; however, the linear relationship was stronger than the quadratic one. This effect may be attributed to the constrained variance in exam difficulty and the categorization of exams as no more than moderately difficult. Consequently, based on the data collected, it is not possible to fully empirically explore the extent to which difficult exams are related to the theoretically hypothesized decline.

Regarding the ratings of cognitive load, a similar pattern could be observed. Accordingly, it is possible that the cognitive load was not so high with regard to each test, so that, in contrast to previous research (Efklides, 2011; Kanfer & Ackerman, 1989; Lajoie, 1993; Moos & Azevedo, 2008; Schwonke, 2015), further working memory capacity was still available for the application of self-regulatory strategies. In summary, and in line with other research findings, students responded to perceived difficulty in particular with more frequent use of cognitive strategies to increase their learning success (Baker & Brown, 1984; D'Mello & Graesser, 2012; Van Loon et al., 2017). However, a decrease in strategy use with increasing difficulty was not evident, as both difficulty and cognitive load were, on average, rated as moderate at best.

Regarding the mediation paths we found no mediation by resources with regard to the quadratic relationship between perceived task difficulty and the application of cognitive learning strategies, but a significant indirect linear effect (H1b). Accordingly, as task difficulty increased, available resources, such as interest or self-efficacy expectancy, decreased, resulting in lower cognitive strategy use during exam preparation. This observation supports previous research findings that higher task difficulty is associated with a decrease in resources (Horvath et al., 2006; Kalyuga, 2007; Schunk, 1991; Van Gog et al., 2005). In addition, consistent with other research findings, self-regulatory strategies were used more frequently during exam preparation as resources increased, such as higher levels of prior knowledge (DeStefano & LeFevre, 2007; Schwonke, 2015) and interest (Horvath et al., 2006; Schiefele, 1991), stronger learning goal or performance goal orientation (Abar & Loken, 2010), or higher self-efficacy expectancies (Butler & Winne, 1995; Duijnhouwer et al., 2012). At the same time, a significant positive direct effect of task difficulty on the use of cognitive strategies remained, revealing a pattern of competitive mediation (Zhao et al., 2010). This indicates task difficulty is likely to exert an additional positive effect on cognitive strategy use through one or several other mediators. One possible candidate could be the domain characteristic and their typical learning materials. In math or natural science for example other strategies could be instrumental to deal with abstract materials like formulas, tables or diagrams than in more text-related domains like language or history.

Cognitive load turned out to be a mediator between task difficulty and cognitive strategy use as expected. The inverse U-shaped relationship between task difficulty and cognitive strategy use was fully explained (H1c). Supporting the assumptions of Seuferts model (2018), learners' cognitive load initially increased with increasing task difficulty, and according to the quadratic relationship, cognitive load decreased again with higher task difficulty. Hence, cognitive load is directly linked to task difficulty with its task-immanent demands and the additional self-regulatory demands and cognitive load is an important predictor for self-regulatory activities. This is even more interesting as both aspects, extraneous and germane aspects of load have been incorporated. Which of these load types act in which way nevertheless needs further, differentiated investigations.

Effects on Metacognitive Strategy Use (RQ2)

Regarding the effects on metacognitive strategy use, a positive linear effect of perceived difficulty on the use of metacognitive learning strategies was plausible whereas the quadratic relationship was not supported (H2a). As task difficulty increased, students more frequently planned, monitored, and regulated their learning process during exam preparation. This finding was in contrast to the assumption that metacognitive strategies in particular are used less frequently when task difficulty is too high, as planning, monitoring, and regulating the learning process requires a particularly large amount of cognitive capacity (De Bruin & van Merriënboer, 2017). Thus, the present findings were not in line with previous research findings that learners are most self-regulated when faced with moderate challenges (Atkinson, 1957; Middleton & Midgley, 2002; Turner & Meyer, 2004). As discussed earlier, this finding may be due to the fact that there were variance limitations with respect to task difficulty and cognitive load.

Regarding the assumed mediation by the available resources, we found a negative indirect linear effect of perceived difficulty on the use of metacognitive learning strategies, only (H2b). The higher the task difficulty, the fewer resources were available, resulting in less use of metacognitive learning strategies in exam preparation. Based on our findings, learners had decreasing available resources with increasing task difficulty. Hence high task difficulty went along with less planning, monitoring, and regulating the learning process during exam preparation. Similar to cognitive strategies, the remaining positive direct effect indicated a competitive mediation pattern. Therefore, the effect of task difficulty on metacognitive strategy use may be further explained by complementary mediators. As mentioned earlier, domain characteristics could be taken into account.

We found an indirect quadratic effect and a full mediation by cognitive load of the linear effect of task difficulty on metacognitive strategy use (H2c). Students reported the highest cognitive load at moderate task difficulty, where cognitive load was associated with more frequent metacognitive strategy use. The linear relationship between cognitive load and metacognitive strategy use was not in line with the findings of previous research literature that when cognitive load is too high, there are no longer sufficient resources for additional self-regulatory processes (e.g. Eitel et al., 2020). Given that even the exams with the highest difficulty were only rated moderately in load, learners appear to have sufficient resources to cope with the load, even for the most difficult exams analyzed in this study.

Theoretical and Empirical Implications

The integrated model of Seufert (2018) could be partially supported by the results. Key correlations were reflected in the results. It was found that as task difficulty increased, cognitive load increased while resources decreased. Due to the lack of interaction between cognitive load and resources, it was not shown, as expected, that individuals with moderate task difficulty increased self-regulated learning, as cognitive load and resources were balanced in this case. That load and resources are not negatively related as expected might be explained by the combination of extraneous and germane load into one overall load indicator as both types could have reverse relations with resources. While for extraneous load one would assume a negative relation to resources, this might be the other way round for germane load. Learners can invest more mental effort when they have more resources. This might have been the case in this study. Future research should re-test this model with differentiated measures of load and separate analyses for germane and extraneous processing. The same is the case for the analysis of learners' resources. Based on the model an overall, combined indicator with many different resources have been built and analyzed. However, a differentiated analysis of how different resources affect strategy use specifically would be valuable. Moreover, a stronger focus on cognitive resources and a higher variance in difficulty could be theoretically and empirically interesting.

Methodological implications, strengths and limitations

Based on the interpretation of the results and the theoretical implications, limitations as well as strengths of the study can be identified.

The first positive aspect of this study is that a high degree of everyday relevance was achieved by asking students to prepare for upcoming exams as usual and to report on their preparation, cognitive load, and resources. Thus, participants were not asked to acquire subject matter in an artificially created learning situation. In addition, established questionnaires were used to assess learning strategies, cognitive load, and available resources. Another strength is that all hypotheses were tested separately for cognitive and metacognitive learning strategies, whereas previous studies often addressed self-regulatory processes in general terms. Furthermore, this study included other relevant variables such as motivational goal orientation, academic self-concept, or self-efficacy expectancies, which are of central importance in the learning context. The within-subject design also has advantages. For example, because the same person is interviewed repeatedly, fewer experimental participants are needed. Furthermore, the design allows for perfect parallelization of all person-specific confounding variables (Charness et al., 2012). Finally, the computation of multilevel models can be evaluated positively, as dependencies between repeated interviews of the same person are taken into account (Heck et al., 2013).

Despite these strengths, the study has methodological limitations. First, the sample was small, so that weaker or medium effects may have gone undetected due to low statistical power. While the general rule of thumb for multi-level models is that 20–30 units at level 2 are sufficient, the literature indicates that a significantly higher number (80 or more) at level 2 is required for multi-level mediation in order for the model to converge reliably (Li & Beretvas, 2013).

In addition, the sample was homogeneous and not very representative, as only students in the 11th grade of a technical secondary school were surveyed. This makes it difficult to extrapolate the results to other age groups or school types and thus to generalize. Moreover, the limited number of measurement points, specifically the four times we measured in relation to the written exams per subject, might have posed a significant issue in accurately capturing the extended period of exam preparation. This scarcity in data points could undermine the reliability of multilevel model calculations and raise doubts about the accuracy of the parameter estimates. Hence, in forthcoming studies, the utilization of methodologies like experience sampling could potentially provide deeper insights and yield more dependable data for parameter estimation purposes. Finally, due to the small sample size, complex models could not be established (Li & Beretvas, 2013). However, more complete models that address resources and cognitive load simultaneously as mediators are indispensable to fully uncover the complex relationships indicated by Seufert (2018, 2020). Additionally, exploring more complex analyses, such as incorporating random slope models, could provide valuable insights into potential individual variations in the relationships and interplay of self-regulation, cognitive load, and task difficulty. Another important issue that might be addressed in future studies is the integration of learning outcome measures as an additional criterion. Based on models of self-regulation, actual performance is reflected after learning and will therefore inform future learning situations and engagement in self-regulatory activities (e.g. Zimmerman, 2002). In the present study, this influence could only have been measured after the assessment of the exam, i.e. during the holidays, which was not practical. From a theoretical point of view, we only focused on self-regulatory activities as this is the dependent measure in Seufert's (2018) model, but the picture would still be more complete with complementary data. It could be assessed how current self-regulatory activities are related to actual learning performance and whether learners' planning for the next phase of exam preparation is affected. Weaknesses in the operationalization of this study are also evident. For example, the independent variable focused more on the difficulty of the learning task to be completed, whereas the difficulty of simultaneously using self-regulation strategies was only indirectly taken into account via the retrospective recording of intrinsic cognitive load.

In addition, the use of self-report questionnaires for retrospective assessment of self-regulated learning and cognitive load can be viewed critically. In this regard, the quality of self-report questionnaires must be questioned, as individuals often exhibit introspection deficits, cannot adequately recall their strategy use, and thus make inaccurate statements about their learning behavior (Greene & Azevedo, 2010). Direct situational measures of strategies or multi-method approaches are mostly stronger related to learning outcome measures (Artelt, 2000; Dörrenbächer-Ulrich et al., 2021; Rovers et al., 2019). In addition, the assessments of strategy utilisation could have been affected by the performance experiences in the exams. Furthermore, self-report measures of self-regulatory strategy use are based on the assumption that self-regulated learning is static and can be recorded separately from the current learning process (Greene & Azevedo, 2010). Thus, the cyclical process of self-regulated learning could not be captured in this study. This raises the question of the extent to which the difficulty ratings of the exams also changed during the learning process, and the extent to which self-regulated learning behaviors changed as a result. In addition, changes in cognitive load during the learning process could not be taken into account because a self-report questionnaire was used for retrospective recording (Schmeck, et al., 2015). These weaknesses could be counteracted by diary studies, for example. However, these represent an ethically questionable burden for students in the phase of highly relevant final examinations. For this reason, we consider the applied approach of retrospective recording to be the most appropriate for this authentic setting, despite the weaknesses mentioned.

Finally, the measurement of learners' resources comprised a highly aggregated score of different constructs. This was in line with Seufert's (2018, 2020) model, in which the assumptions about the relationship between learners' resources and task difficulty apply equally to all types of resources. However, this assumption can itself be questioned, although this was not the focus of the present study. In addition, further resources or measurement methods could have been considered. Cognitive resources like prior knowledge, measured by valid tests instead of prior grades, or working memory capacity could have been taken into account and could have strengthened the relation to cognitive load. With regard to the INVO model, learners' achievement emotions could be a relevant parameter as they influence learning motivation, strategy use, and academic performance (Mega et al., 2014; Pekrun et al., 2002). Because of these limitations, the practical implications that can be derived from the study are limited, and therefore further research is needed.

Practical Implications and Future Perspectives

Self-regulated learning is an important area of research due to its profound educational implications in shaping individuals' lifelong learning journey (Dignath & Büttner, 2008). In our study, we focused on the context of learning in a Vocational College. In this context our findings imply that task difficulty, cognitive load, and resources are relevant factors to consider in relation to self-regulated learning.

Therefore, it seems to be important for students that they are challenged with different task difficulties, including challenging ones, in order to stimulate self-regulation processes in a systematic way. However, based on previous literature, this goes along with the inherent risk of an overload of working memory, which is why fewer learning strategies are used (Efklides, 2011; Kanfer & Ackerman, 1989; Lajoie, 1993; Moos & Azevedo, 2008; Schwonke, 2015). Future research should continue to address this issue. When challenging learners, resources like a positive self-concept, high self-efficacy expectations, a strong interest and motivation seem to be crucial as they mediated at least the linear effects on cognitive and metacognitive strategy use. Interest could be raised by creating a reference to everyday life even for abstract learning content (Hasselhorn & Gold, 2013). Self-efficacy and confidence could be fostered by positively reinforcing small successes with praise (Drössler et al., 2007). In addition, to improve academic self-concept, strengths should be highlighted and weaknesses should be addressed with tips and suggestions for improvement (Hasselhorn & Gold, 2013). These instructional approaches could be used to foster self-regulated learning while being challenged by difficult tasks.

In order to adequately capture self-regulated learning, contemporary and process-oriented methods should be used in future studies. For example, the thinking aloud method (Bannert & Mengelkamp, 2008) or the evaluation of traces of cognitive processing during the learning process are suitable for this purpose, e.g., notes, markings, or diagrams drawn (Winne & Perry, 2000). Alternatively, learning diaries can be used to continuously record the learning process over time (Nückles et al., 2020; Zimmerman, 2008). In this way, it would be possible to record the cyclical phases of self-regulated learning. In addition, further subscales of resource-related strategies should be considered in the future, as well as a more general focus on the individual subscales of all learning strategies.

With regard to a renewed review of Seufert's (2018) integrated model for predicting self-regulated learning, future research should focus more on cognitive resources, as these are presumably associated with learners' cognitive load. Despite the model's general assumptions on resources and load it would nevertheless be interesting to test the model for effects of different resources and for different aspects of cognitive load.

Conclusion

The aim of the present study was to empirically challenge Seufert's model (Seufert, 2018). The assumed interplay that self-regulatory strategies are increasingly used with increasing task difficulty, which was mediated by increasing cognitive load, could be empirically supported. For cognitive strategies even the u-shaped relation could be found which indicates that for too difficult tasks learners cease to use those strategies. With increasing task difficulty, learners exhibit fewer personal factors relevant to successful learning, such as a positive self-concept or high self-efficacy expectations. As a result, the positive influence of difficulty on the use of self-regulatory strategies may be compromised. Therefore, the task of teachers in promoting self-regulated learning is to confront learners with challenging tasks and at the same time to strengthen relevant facilitating factors or individual prerequisites for successful learning while managing cognitive load.

In future studies, the correlations observed in this research should also be examined with regard to interindividual differences in a classroom in order to achieve the best possible promotion of self-regulated learning for all students. This could be one promising way to help learners discover the world independently and to actively construct knowledge and gain learning competencies.

Appendix

Table 3 Multilevel analysis on the influence of task difficulty, resources and cognitive load on the use of cognitive learning strategies (b-, c- and c'-paths)

Parameter	Null model	Model 1a	Model 1b	Model 1c
Fixed effects				
Intercept	0.01 (0.10)	0.07 (0.10)	0.05 (0.09)	0.05 (0.09)
Level-1				
Task difficulty		0.22** (0.05)	0.40** (0.05)	0.12* (0.06)
Task difficulty^2		-0.07* (0.03)	-0.05 (0.03)	-0.05 (0.03)
Resources			33** (0.06)	
CL				0.21** (0.06)
Random effects	-0.34*	-0.05	-0.35*	-0.15
$\sigma^2 u(\beta 0)$	43** (0.12)	0.43** (0.10)	0.34** (0.08)	0.38** (0.09)
$\sigma^2 \epsilon$	0.57** (0.75)	0.49** (0.06)	0.44** (0.05)	0.48** (0.06)
Model fit				
AIC	698.07	684.89	658.69	676.89
BIC	708.83	695.62	691.58	687.62
-2*Log Likelihood	692.07	678.89	652.69	670.89

CL = cognitive load. $*p<0.05$, $**p<0.01$

Table 4 Multilevel analysis on the influence of task difficulty, resources and cognitive load on the use of metacognitive learning strategies (b-, c- and c'-paths)

Parameter	Null model	Model 2a	Model 2b	Model 2c
Fixed effects				
Intercept	-0.00 (0.10)	0.05 (0.10)	0.04 (0.09)	0.03 (0.09)
Level-1				
Task difficulty		0.16** (0.05)	0.28** (0.06)	0.06 (0.06)
Task difficulty^2		-0.06 (0.03)	-0.04 (0.03)	-0.04 (0.03)
Resources			0.23** (0.06)	
CL				0.22** (0.06)
Random effects	-34*	-0.05	-0.15	-0.35*
$\sigma^2 u(\beta 0)$	0.51** (0.11)	0.50** (0.10)	0.43** (0.09)	0.43** (0.09)
$\sigma^2 \epsilon$	0.49** (0.05)	0.46** (0.05)	0.45** (0.05)	0.45** (0.05)
Model fit				
AIC	692.88	689.07	677.39	680.86
BIC	703.64	699.81	688.12	691.58
-2*Log Likelihood	686.88	683.07	671.39	674.86

CL = cognitive load. $*p<0.05$, $**p<0.01$

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Declarations

Conflict of Interest The authors state that they conducted the research without having any commercial or financial relationships that could be interpreted as a potential conflict of interest.

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