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Article

The Moderating Role of Interest in the Relationship between Perceived Task Difficulty and Invested Mental Effort

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Abstract: Including motivational variables such as interest in the cognitive load framework is an ongoing process. Of particular interest is the question of how motivational variables influence the investment of mental effort. In this study, we investigated how topic interest affects the investment of mental effort in simple tasks. A total of 1543 students' judgments regarding invested mental effort, perceived task difficulty, and topic interest for 32 tasks of a chemistry test were analyzed at the task level based on item response theory parameters. Additionally, objective task difficulty was calculated. The Rasch parameters were used for correlation and moderated regression analyses. The results indicated that when perceived task difficulty was low, students invested more mental effort in solving tasks of low topic interest compared to tasks of high topic interest. With increasing perceived task difficulty, the amount of invested mental effort rose for tasks of low as well as high topic interest. However, the difference between tasks of low and high topic interest in the amount of invested mental effort decreased as perceived task difficulty increased and even vanished when perceived task difficulty roughly corresponded to students' performance capability. These results are in line with flow theory and the expectancy-value-cost model of motivation. When solving tasks that match their performance capability, students can experience a flow situation. However, when solving rather easy tasks of low interest, students can experience motivational costs in terms of additional effort, such as an increased need for motivational self-regulation. The results of this study provide a basis for systematically investigating and better understanding the relationship between interest, task difficulty, invested mental effort, flow experience, and emotional costs.

Keywords: cognitive load; invested mental effort; perceived task difficulty; topic interest; objective task difficulty; emotional costs; motivational self-regulation; chemistry test

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1. Introduction

Cognitive load theory has long focused primarily on the cognitive aspects of learning. In recent years, however, several attempts have been made to include affective aspects, that is, motivational and emotional processes [1–4]. The present study contributes to the growing literature including motivational processes in the cognitive load framework by investigating whether topic interest has an impact on the investment of mental effort. We used a large data set (N = 1543) collected based on a multi-matrix design to evaluate a chemistry test at the end of lower secondary school. In addition to the chemistry tasks to be solved, the test featured additional questionnaire items regarding cognitive load and topic interest for each of the tasks [5]. All our follow-up analyses were performed on the level of tasks, with the units of analysis being the tasks and their characteristics (as opposed to participants and their characteristics). The analyses were based on ideas from cognitive load theory [6,7], flow theory [8], and expectancy-value-cost theory [9], suggesting that topic interest moderates the regression of invested mental effort on perceived task difficulty.

In the following, we will first present a short introduction to cognitive load theory before briefly introducing the core ideas of flow theory and the expectancy-value-cost model of motivation. Finally, we will discuss recent approaches to extend cognitive load theory to include motivational processes.

1.1. Cognitive Load Theory

Cognitive load theory [6,7,10–13] is based on the assumption that working memory, unlike long-term memory, has a limited capacity. Furthermore, information must be actively processed in working memory to be successfully stored in long-term memory. However, processing information in working memory causes cognitive load. Depending on whether this load contributes to learning or not, cognitive load theory distinguishes between intrinsic and germane cognitive load on the one hand and extraneous cognitive load on the other [12–19]. Intrinsic load directly contributes to learning and depends on the complexity of the learning content, that is, the number of interacting elements that are to be processed simultaneously in working memory (element interactivity). Germane cognitive load directly contributes to learning as well and depends on the specific way the elements are processed in terms of generative learning to construct a coherent mental representation of the learning content. Extraneous cognitive load, however, is based on cognitive processing that does not directly contribute to learning and can be caused, for example, by poor instructional design. There is ongoing discussion about whether germane cognitive load actually represents a type of load that is independent of intrinsic cognitive load [18]. Although a number of multidimensional cognitive load instruments seem to be able to measure germane cognitive load over and above intrinsic and extraneous cognitive load [15,20,21], a recent study found no correlation between germane cognitive load and immediate and delayed learning outcomes [22]. In said study, only intrinsic cognitive load was found to be negatively related to performance, which indicates that cognitive load is a two-dimensional concept. Working memory resources rather than germane cognitive load proved to be a relevant factor for learning success in situations with high intrinsic load. The authors of the study thus suggested investigating the extent to which affective factors are relevant to the availability of working memory resources.

The types of cognitive load add up to the total cognitive load imposed on working memory (additivity hypothesis [23]); when the total cognitive load exceeds the limited capacity of working memory, learning performance is reduced. Cognitive load theory therefore provides guidance on how extraneous cognitive load can be reduced so that sufficient capacity for germane cognitive load is available for a given intrinsic cognitive load. Cognitive load theory was originally developed to describe learning processes. However, the theory can be applied to all other processes involving working memory and the cognitive processing of information. One example is students' processing of the tasks of a subject matter test, such as a test on chemistry knowledge and skills.

Using questionnaire items, overall cognitive load can be measured in terms of perceived task difficulty and invested mental effort [14,16,24–27]. Perceived task difficulty depends on the complexity of the task and the availability of prior knowledge for processing the task, whereas invested mental effort denotes the cognitive capacity allocated to cope with the resulting demands. When tasks are not too difficult, perceived task difficulty and invested mental effort are positively correlated. That is, when task difficulty increases, invested mental effort increases as well (up to the point when a learner or problem solver gives up because a task is perceived as too difficult to be mastered [28,29]).

1.2. Flow Theory

Flow theory describes flow as a state in which a person's inherent abilities and the perceived challenge of an activity are in equilibrium [8,30]. In this case, the challenge posed by the activity is greater than the challenge posed by everyday activities but still appears manageable. The flow state creates harmony within the self so that attention is completely focused on the activity; there is simply no cognitive capacity left to focus on other things. All attention is focused on the requirements of the activity and on what needs to be completed next. There is no room for doubt, uncertainty, and extraneous thoughts. The sense of time is also lost in this flow state. Flow experiences often occur in well-structured areas, such as skiing in powder snow, motorcycling on a mountain pass road, or computer programming. Such activities require clear goals and offer relatively short-term and unambiguous feedback, so skills and challenges can be easily controlled and varied. From a motivational point of view, flow experiences are usually actively sought out because the state itself is perceived as desirable. To maintain flow, the complexity of the activity must increase consistently so that new challenges are found and new skills can be developed (dynamic of flow). When skills and perceived challenges are not in balance, anxiety (high challenge, low skills) or relaxation/boredom (low challenge, high skills) can occur. In both cases, less than the full amount of cognitive capacity is devoted to the ongoing activity.

In terms of cognitive load theory, flow describes a situation in which the investment of mental effort is exclusively determined by the perceived difficulty of the task. That is, other motivational processes beyond flow play a subordinate role in the investment of mental effort in such a task. However, if the skills and challenges associated with a task are out of balance—leading, for example, to the experience of anxiety or boredom—other motivational processes come into play [8,31]. These include motivational self-regulation to cope, for instance, with reduced expectancy (in the case of anxiety), reduced value (in the case of boredom), and increased costs (in the case of both anxiety and boredom).

1.3. The Expectancy-Value-Cost Model of Motivation

According to the expectancy-value-cost model of motivation [9], motivation is composed of three components: expectancy ("Can I complete the task?"), value ("Do I want to complete the task?"), and cost ("What are the costs associated with completing the task and am I prepared to bear them?"). While expectation and value are positively related to each other, both are negatively related to cost [31–33].

All three components can be further differentiated. For example, interest is considered one of three sub-components of value (alongside achievement value and utility value) [34]. Interest represents the willingness to engage with a certain content or topic. How pronounced and stable this willingness is depends on how strong the interest already is in terms of repeated engagement and acquired knowledge. At higher levels of developed interest, the individual looks for opportunities to re-engage with the topic of their interest [34]. In a review article, Hidi [35] points out that research often distinguishes between situational interest and individual interest. Increased value, knowledge, and positive feelings characterize individual interest. Individual interest is described as a stable factor that develops over time. In contrast, situational interest arises spontaneously through interaction with the environment. Topic interest is described as another relevant interest construct for research and can be generated by both existing individual interest in a topic and spontaneously aroused situational interest in the topic. Regardless of whether topic interest can be traced back to individual interest or situational interest, it is described as relevant to affects and, thus, to persistence in learning and learning outcomes [35].

Regarding costs, negative perception seems to be a crucial aspect [31]. For example, although students described effort as a motivating factor for the class for which they were most motivated, excessive effort was a reason for disliking the class for which they were least motivated. However, too little effort was also cited as a de-motivating factor for their least motivated class. According to Flake et al. [31], and in line with flow theory, the two de-motivating factors for the least motivated classes are the perception of excessive effort ("This course is too demanding") and the perception of too little effort ("This course is too boring"). Both signal an imbalance between skills and challenges, leading to emotional costs such as anxiety or boredom. In general, emotional costs correlate negatively with long-term topic interest, and costs have been shown to be a relevant predictor of performance, procrastination, and avoidance intentions in mathematics at the secondary school level [32], among others. A recent study showed that the expectancy-value-cost model explains achievement better than an expectancy-value model in some cases; the study emphasizes that the situational context must be taken into account when investigating motivation [33].

Cognitive load, particularly extraneous cognitive load, can be considered a source of motivational cost [1] that is relevant to learners' motivation to solve similar tasks in the future and their expectation of success in solving such tasks. In their study, Feldon et al. investigated how the amount of (extraneous) cognitive load during instruction influenced participants' post-instruction self-efficacy [36]. Their findings suggest that self-efficacy is not only influenced by students' achievement in previous tasks [37] but also by the cognitive load imposed on them by the previous tasks, regardless of whether they achieved them [38].

1.4. Motivational Factors in the Cognitive Load Framework

When Paas [39] proposed the mental effort rating scale, he considered motivation a relevant factor for mental effort investment but assumed that the participants in his study were sufficiently and equally motivated so that motivational effects were negligible. Among others, concerns about high dropout rates in online learning courses led to a more serious consideration of motivation within the cognitive load framework. Paas et al. argued that "the motivation to achieve well" [40] (p. 26) is necessary, specifically for learning scenarios outside a laboratory and with a longer duration. Therefore, they recommended capturing learners' motivation in addition to invested mental effort and performance. They further stated that "[a]s long as a task is not too easy and not too difficult, ratings of task difficulty may correlate highly with ratings of invested mental effort. Most importantly, it is clear that mental effort is a voluntary mobilization process of resources, which depends on the task demands in relation to the amount of resources the learner is willing or able to allocate" [40] (p. 32).

Following these first thoughts, the Cognitive and Affective Theory of Learning with Media (CATLM; [4,41,42]) extended existing cognitive theories of learning with media by adding the explicit assumption that motivational factors influence learning by affecting cognitive engagement (a similar model was presented even earlier [43]). Mayer [44,45] also complemented his Cognitive Theory of Multimedia Learning by adding assumptions about motivational processes: motivation is described in terms of "the learner's willingness to exert effort to engage in appropriate cognitive processing during learning" [45] (p. 70), with interest as one of the driving forces of the learner's motivation (in addition to affect, beliefs, and feelings of social connection).

In addition to motivation, another approach to increasing learners' engagement is to focus on emotional factors in the design of learning tasks (emotional design). Some relevant studies varied the learning materials (for example, by introducing warm colors), which was effective in improving learning [46–48]. Other studies added elements to the learning materials (seductive details such as pointing out the usefulness of ATP (adenosine triphosphate) in different areas, such as sports in a biology lesson on ATP); however, this was generally not effective in improving learning [49,50].

In the literature, motivational and emotional factors are discussed as mediators or moderators in predicting students' cognitive engagement and learning [2]. On the one hand, motivation (or emotion) can mediate the effect of a specific instructional design factor (e.g., using warm colors) on invested mental effort and learning outcomes. On the other hand, motivation (or emotion) can moderate, for instance, the influence of perceived task difficulty on invested mental effort (as investigated in the present study). If, as an example of moderation, low motivation leads to the need to invest more mental effort than expected, this need would represent a source of additional cognitive load [3]. This can also be assumed concerning emotional effects. Thus, whereas Feldon and colleagues [1,36,38] investigated motivation as an *outcome* of cognitive load, in the present study we investigated (low) motivation as a *source* of (additional) cognitive load.

1.5. Research Question and Hypothesis

The present study investigates the following research question: does interest moderate the relationship between perceived task difficulty and invested mental effort? For any particular student who is working on a test at school, only a small number of test items or tasks will exactly match their skills; the majority of tasks will either be too easy or too difficult. According to flow theory, working on a task that matches a student's skills will cause a state of flow. In this state of flow, the entire cognitive capacity of the student is devoted to processing the task. However, facing a task that is perceived as too easy compared to the student's skills will cause relaxation or even boredom or disengagement. Nevertheless, assuming that a student taking a test at school is compliant and wants to perform well, they will not disengage and will persist in processing the task at hand (instead of deciding to stop), which might even create a feeling of anger. Persistence when feeling boredom and anger requires mental effort in terms of motivational self-regulation, in addition to the mental effort required for completing the task. However, this need to invest additional mental effort to cope with the emotional costs of boredom and anger should not be challenging because sufficient cognitive capacity is available given the ease of purely processing the task. In this situation, interest comes into play. If a student is highly interested in the topic of the task, this topic interest (i.e., the wish to engage with the content) will prevent them from feeling bored (and, perhaps, even angered) even though the task is not challenging. Consequently, compared to the uninterested student, the interested student will not need to invest additional mental effort into motivational self-regulation to cope with emotional costs. In other words, high topic interest, unlike low topic interest, will compensate for coping with emotional cost when processing tasks of low perceived difficulty.

Accordingly, we formulated the following hypothesis for our study: Topic interest moderates the effect of perceived task difficulty on invested mental effort, such that simple tasks that are perceived as interesting are associated with less invested mental effort than simple tasks that are not perceived as interesting. In line with flow theory, we assume that skills and challenges are not in balance for easy tasks. For interesting easy tasks, only a small amount of mental effort must be invested. In contrast, for uninteresting easy tasks, a comparatively high level of mental effort must be invested to cope with the additional emotional costs that are associated with processing the task.

2. Materials and Methods

2.1. The Original Study

The objective of the original study was to develop a test to assess students' chemistry content knowledge and their abilities to make chemistry-related decisions at the end of lower secondary school. Based on this assessment, the study aimed to determine the influence of affective factors, such as interest in the task and motivation when working on the task, on task difficulty. The participants were 1543 students (51.7% male, M_{age} = 15.2, SD = 0.87) in their final year of German lower secondary schools in 2015 [5]. Chemistry teachers and school headmasters decided to participate in the study with their classes, but every student and their parents had the chance to refuse participation without consequences. Although institutional review board approval is not necessary at German schools, the study design complied with the recommendations of the German Research Foundation for Good Scientific Practice. The data were collected in 2015 in German schools during regular chemistry lessons near the end of lower secondary school. Paper–pencil materials and a multi-matrix design were used to administer the 32 tasks of the test. According to this multi-matrix design, each student worked on two of the 32 chemistry tasks, resulting in approximately 96 students per task. Each task consisted of four items. Half of the tasks were developed to measure the competence area of content knowledge and the other half to measure the competence area of decision-making. The tasks were developed based on the educational standards for the subject of chemistry in lower secondary schools in Germany [51]. The tasks only required prior knowledge, which should have been acquired on the basis of the educational standards in chemistry lessons. The information required to answer the task was presented to the students in the respective task stem. The items about dealing with specialist knowledge required the students to select, organize, or integrate information from the task stem. Before running the study, the psychometric quality of the test items was evaluated in a pre-study. Among others, a distractor analysis was carried out, and all distractors with a response frequency under 5% were replaced with suitable distractors.

Students' answers to each item were coded as correct (1) or incorrect (0). ConQuest was used for item response theory (IRT) analysis. The analysis was conducted on a person-centered basis to obtain IRT parameters at the item level. A two-dimensional Rasch model (Dimension 1: content knowledge; Dimension 2: decision-making) showed a good statistical fit to the data (item reliability = 0.96, $0.85 \leq MNSQ \leq 1.17$). The task difficulty parameter ($-2.59 \leq$ item difficulty content knowledge ≤ 1.40; $-1.85 \leq$ item difficulty decision-making ≤ 2.67) was determined as the mean of the item difficulty parameters for each task ($M_{conten\ knowledge} = -0.63$; $M_{decision\text{-}making} = 0.83$). The instruments used to measure students' skills in the two areas of competence exhibited good statistical characteristics ($0.21 \leq$ item discrimination ≤ 0.80). Only one item from the content knowledge competence area had a discriminatory power below the recommended characteristic value ranges [52]. However, this could result from the fact that a high level of difficulty was measured for this item (item difficulty = 3.418); therefore, it was included in the calculations for further analyses.

Upon completion of each task, students were requested to provide subjective ratings regarding cognitive load and affective variables such as topic interest (because the other affective variables from the original study were not used for the present study, they are not presented in detail here). Cognitive load measures were collected by asking students about perceived task difficulty [53,54] (seven-point rating scale from "very easy" to "very difficult") and invested mental effort [39] (seven-point rating scale from "very low" to "very high"). The two-dimensional Rasch model for the rating scale assessing cognitive load (Dimension 1: perceived task difficulty; Dimension 2: invested mental effort) demonstrated satisfactory fit (item reliability = 0.93, $0.72 \leq MNSQ \leq 1.35$). Topic interest (3 items; item example: "I found the task on smoking interesting") [55–57] was measured using a five-point rating scale from "completely agree" to "completely disagree". The Rasch model for the rating scale assessing topic interest also demonstrated acceptable fit (item reliability = 0.97, $0.60 \leq MNSQ \leq 1.91$). Based on these analyses, the data set contained task-related values for objective task difficulty, perceived task difficulty, invested mental effort, and topic interest.

2.2. Data for the Present Study

For the present study, we used the Rasch parameters from the original study at the task level. Hence, our data set consisted of 32 tasks with Rasch parameters of objective task difficulty, perceived task difficulty, invested mental effort, and topic interest for each task.

Objective task difficulty was aggregated from students' right or wrong responses to the items forming one task of the chemistry test. The mean value of the Rasch parameters of the four associated items was calculated for each task. Tasks that were answered correctly by very few students were considered difficult tasks and associated with positive Rasch values for objective task difficulty.

Perceived task difficulty was the Rasch parameter of students' ratings regarding the perceived difficulty of the specific task. Tasks with positive Rasch values for perceived task difficulty were tasks that were perceived to be difficult (ratings of 6 or 7), whereas tasks with negative Rasch values for perceived task difficulty were perceived to be easy (ratings of 1 or 2).

Invested mental effort was the Rasch parameter of students' ratings regarding the mental effort invested in the specific task. Tasks with positive Rasch values for invested mental effort were tasks in which students invested considerable effort (ratings of 6 or 7), whereas tasks with negative Rasch values for invested mental effort were tasks in which students invested little mental effort (ratings of 1 or 2).

Topic interest was the Rasch parameter of students' ratings regarding topic interest for the specific task. Again, positive Rasch values (ratings of 4 or 5) signaled high topic interest in the task, and negative values reflected low topic interest in the task (ratings of 1 or 2).

All ratings were collected after the students had completed the tasks. Accordingly, it is not possible to say whether interest corresponded to spontaneous interest (situational interest) that arose in the test situation or whether the students already had a stable, long-term interest (individual interest) in the topics, which had developed through repeated engagement. Both alone—and their combination—are conceivable. In both cases, topic interest can be expected to be positively related to student outcomes [35].

Importantly, the Rasch model has the property of specific objectivity [58]. That is, if the model holds for a set of data, the task or item parameters are generally independent of the specific sample of participants, and the person parameters (in which we were not interested) are generally independent of the specific sample of tasks or items. In other words, the Rasch parameters of our 32 chemistry tasks represented genuine properties of the tasks: the objective difficulty of a given task (based on students' task performance), the level of difficulty that students generally perceived for said task, the amount of effort that students generally reported having invested in the task, and the level of topic interest that students generally reported for the task. Thus, the calculation of the Rasch parameters for cognitive load ratings was task-specific and did not exhibit the problem of aggregated cognitive load ratings across multiple tasks described by Leppink and van Merriënboer [59].

2.3. Data Analysis

The Rasch parameters of the 32 tasks of the chemistry test were imported to SPSS (version 28). The tasks were the units of observation, and the Rasch parameters were the variables. To investigate the relationships between the variables, we computed linear correlations (Pearson's r). The SPSS PROCESS tool (version 4.2; [60]) was used to analyze the influence of interest on the relationship between invested mental effort and perceived task difficulty (PROCESS Model #1). In the results section, we report F-ratios, R^2, and changes in R^2 for the model. Additionally, we report t-ratios, regression coefficients (B), and standard errors (SE) for the model parameters as well as the results based on Johnson–Neyman output. For all analyses, 95% bias-corrected and accelerated confidence intervals, based on 10,000 bootstrap samples for correlations and 50,000 bootstrap samples for the PROCESS parameters (95% CI), are reported in parentheses [61].

3. Results

3.1. Correlations

In the first step, linear correlations were computed to examine the relationships between the variables of interest (objective task difficulty, perceived task difficulty, invested mental effort, and topic interest; Table 1). As expected, invested mental effort and perceived task difficulty were highly correlated ($r = 0.78$, $p < 0.001$, 95% CI [0.56, 0.91]). Both invested mental effort and perceived task difficulty was correlated with objective task difficulty. Perceived task difficulty and objective task difficulty were almost perfectly related ($r = 0.91$, $p < 0.001$, 95% CI [0.85, 0.96]). In contrast, the correlation between invested mental effort and objective task difficulty was remarkably lower ($r = 0.69$, $p < 0.001$, 95% CI [0.45, 0.86]). The mental effort that students invested in solving a task therefore did not depend exclusively on the objective difficulty of the task.

Further correlation analyses indicated that only perceived task difficulty was positively correlated with topic interest, while the correlation between topic interest and invested mental effort was not significant. Thus, higher topic interest did not entail higher invested mental effort.

Table 1. Pearson correlations.

	Objective Task Difficulty	Perceived Task Difficulty	Invested Mental Effort	Topic Interest
Objective Task Difficulty				
Perceived Task Difficulty	0.91 (<0.001) [0.85, 0.96]			
Invested Mental Effort	0.69 (<0.001) [0.45, 0.87]	0.78 (<0.001) [0.56, 0.91]		
Topic Interest	0.41 (0.019) [0.10, 0.65]	0.54 (0.002) [0.29, 0.73]	0.24 (0.182) [−0.16, 0.58]	

Note. Pearson's *r*, (*p*), [95% BCa CI, based on 10,000 bootstrap samples], $N_{\text{tasks}} = 32$.

3.2. Analyzing the Impact of Interest

To investigate whether topic interest moderated the relationship between perceived task difficulty and invested mental effort, we used the SPSS Tool PROCESS to specify a linear regression model with perceived task difficulty and interest and their interaction as predictors and invested mental effort as the criterion (Figure 1).

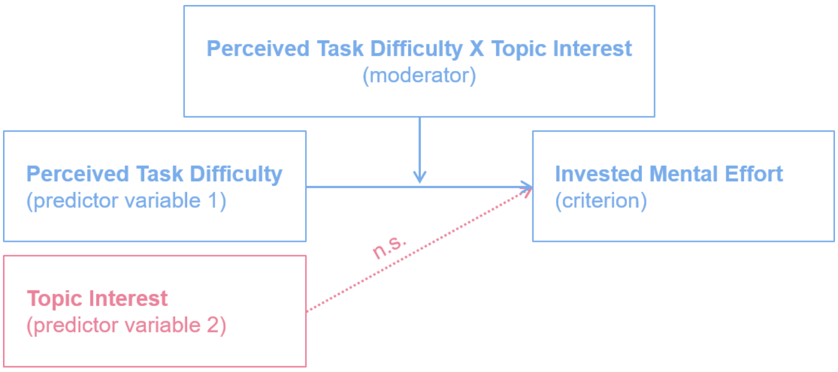

Figure 1. Statistical model.

The results showed that perceived task difficulty was a significant predictor ($B = 0.43$, 95% CI [0.26, 0.57], $SE = 0.07$, $t(26) = 5.84$, $p < 0.001$), whereas topic interest was not ($B = -0.06$, 95% CI [−0.14, 0.04], $SE = 0.05$, $t(26) = -1.14$, $p = 0.263$). However, the interaction term (perceived task difficulty X interest) turned out to be a significant predictor ($B = 0.26$, 95% CI [0.03, 0.62], $SE = 0.12$, $t(26) = 2.23$, $p = 0.034$). Overall, the model accounted for 71% of the variance of invested mental effort, with the interaction term explaining 5% of the variance beyond the main-effects terms. The interaction indicated that when topic interest was low (1 *SD* beneath the mean), there was a significant but low positive relationship between perceived task difficulty and invested mental effort ($B = 0.38$, 95% CI [0.20, 0.56], $SE = 0.09$, $t(26) = 4.39$, $p < 0.001$). When topic interest was at the mean, the relationship between perceived task difficulty and invested mental effort was stronger ($B = 0.51$, 95% CI [0.37, 0.65], $SE = 0.07$, $t(26) = 7.53$, $p < 0.001$). When topic interest was high (1 *SD* above the mean), the relationship between perceived task difficulty and invested mental effort was strongest ($B = 0.63$, 95% CI [0.45, 0.82], $SE = 0.09$, $t(26) = 7.13$, $p < 0.001$). As expected, these results suggest that topic interest moderated the regression of invested mental effort on perceived task difficulty.

To visualize the moderated regression, we split the 32 tasks at the median of topic interest into interesting and uninteresting tasks. In a scatter plot (Figure 2a), the regression of invested mental effort on perceived task difficulty is displayed separately for uninteresting (blue) and interesting (red) tasks. For tasks that were perceived to be rather easy, there is a gap between interesting and uninteresting tasks, with the latter requiring considerably more mental effort than interesting tasks. However, this difference in invested mental effort between interesting and uninteresting tasks vanishes as perceived task difficulty increases. Given that uninteresting tasks beyond the point of intersection of the two regression lines are missing, it remains unclear whether the effect is inverse for tasks perceived as more difficult.

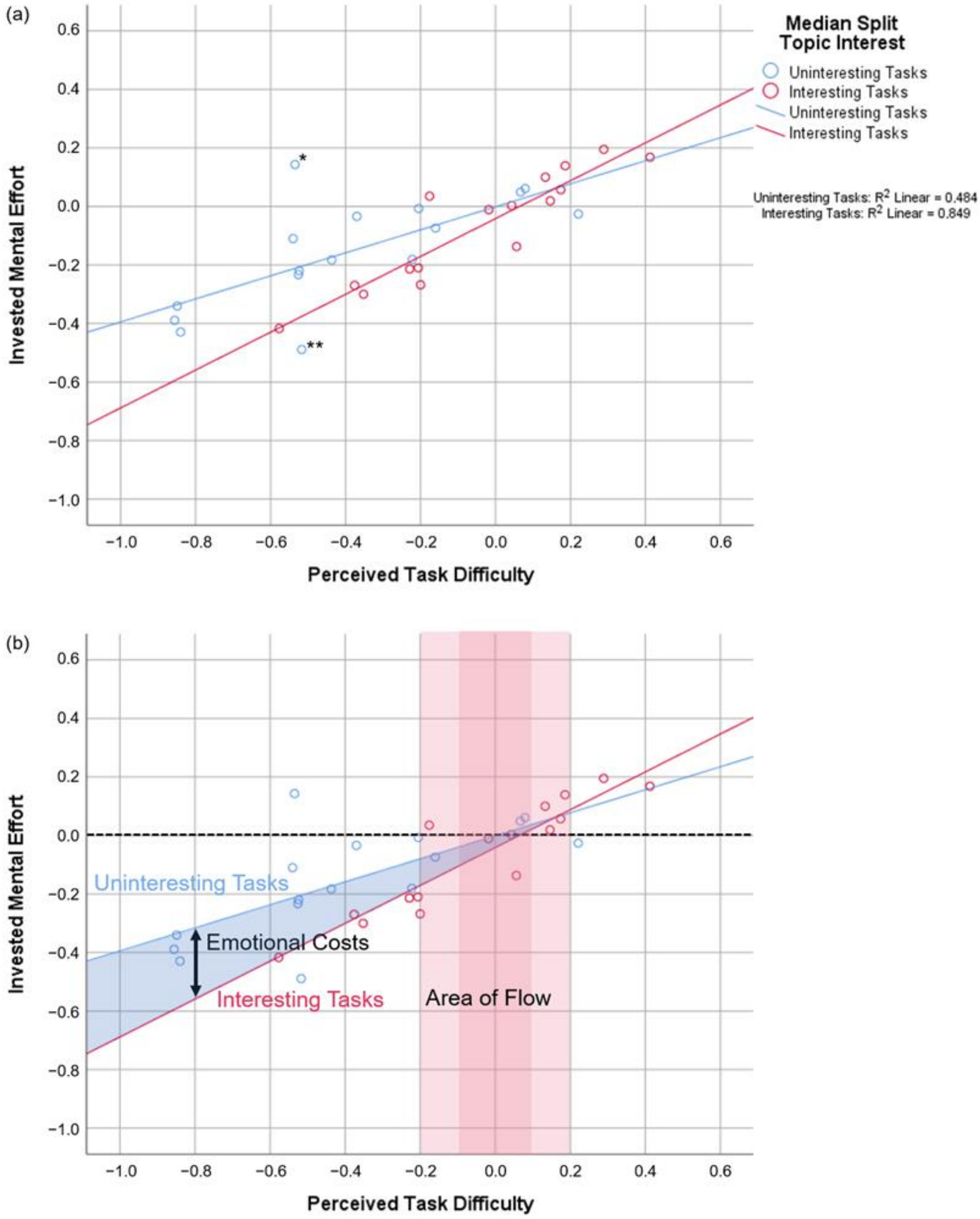

Figure 2. Interaction effect. (**a**) Scatterplot visualizing the moderated regression of invested mental effort on perceived task difficulty for interesting and uninteresting tasks; (**b**) Emotional costs.

Note. Invested mental effort and perceived task difficulty for the 32 tasks are represented as Rasch parameters on Logit scales.

Note. The blue area describes emotional costs (investment of additional mental effort). The red area describes a state of flow where perceived task difficulty roughly corresponds to students' performance capability.

There seem to be two outliers in Figure 2a regarding the regression line for the uninteresting tasks (blue line, the point marked (**) at −0.54, 0.14 and the point marked (*) at −0.52, −0.49). However, when these two points are excluded from the analysis, the interaction of perceived difficulty and interest remains significant (B = 0.16, 95% CI [0.01, 0.57]).

4. Discussion

The present study used an existing data set evaluating a chemistry test at the end of German lower secondary school. The test consisted of 32 tasks. In our analyses, the tasks were used as the units of observation, and the Rasch parameters of the tasks were the variables. The Rasch parameters relied on data from 1543 students who solved the chemistry test based on a multi-matrix design (objective task difficulty). Furthermore, students rated each task for perceived difficulty, invested mental effort, and topic interest. The Rasch parameters of our 32 chemistry tasks represented genuine properties of the tasks. All Rasch parameters were task-specific and, therefore, did not exhibit the problem of aggregated cognitive load ratings across multiple tasks [59].

The correlation analyses supported the expectation of van Gog and Paas [27] that invested mental effort and perceived task difficulty measure a similar construct (cognitive load) but not the same thing (r = 0.78). Perceived task difficulty correlated nearly perfectly with objective task difficulty (r = 0.91), in line with the findings of Ayres [53]. The smaller correlation (r = 0.69) between invested mental effort and objective task difficulty indicated that invested mental effort did not exclusively depend on cognitive aspects but also on motivational ones [40]. Unexpectedly, invested mental effort was not directly related to topic interest. Accordingly, there was no direct link between interest in a task and the effort invested in that task.

Nonetheless, a moderated regression analysis indicated that topic interest moderated the linear regression of invested mental effort on perceived task difficulty. Figure 2b helps to conceptualize this moderated regression: the tasks in the red area of the figure were perceived by participants with average ability as not too easy and not too difficult, as indicated by a Rasch parameter of 0.0 +/− 0.2 for perceived task difficulty. According to flow theory [8,30], these tasks represent an equilibrium of perceived skills and challenges, resulting in an experience of flow. The lower left part of the figure shows tasks that were perceived to be easy, as indicated by negative Rasch parameters < −0.2. These tasks lie outside the equilibrium of skills and challenges, probably resulting in an experience of boredom.

However, the decrease in invested mental effort as perceived task difficulty decreases differs for interesting and uninteresting tasks: interesting easy tasks are associated with a lower investment of mental effort than uninteresting easy tasks. Concerning interesting tasks, we assume that the students would like to interact with these tasks because they were interested in the tasks' topic and did not mind that these tasks were not perceived to be challenging. Consequently, they would not feel bored, and there would be no (or very low) emotional costs with which to cope. This result is in line with findings from interest research, which support the hypothesis that interest leads to spontaneous attention to interesting aspects, which are thus processed more quickly [35].

Conversely, uninteresting easy tasks were linked to a higher investment of mental effort. Students were not interested in interacting with these tasks (although they were required to do so), and they did not perceive them as a challenge. Therefore, we assume that they would feel bored and the emotional costs to cope with would be high. This is in line with the findings of Flake et al. [31], who found that a lack of challenge (which caused boredom, i.e., emotional costs) was a reason why students perceived a course as not motivating. We hypothesize that the additional amount of mental effort is caused by the need for motivational self-regulation, such as convincing and continuously reminding oneself not to become distracted and to continue working even though the task is boring. Accordingly, the additional effort invested in uninteresting easy tasks can be considered an emotional cost given that students have to self-regulate their emotions.

As perceived task difficulty increases, the difference in mental effort investment between interesting and uninteresting tasks decreases (center of Figure 2b). The reduction in additional mental effort (i.e., emotional costs) with increasing perceived task difficulty supports the idea that flow situations, where skills and challenges are balanced, have no emotional costs and, therefore, do not require motivational self-regulation. This idea is supported by the fact that the point of intersection of the two regression lines is close to the middle of the two scales. At this point, invested mental effort is not influenced by topic interest but exclusively relies on perceived task difficulty.

Overall, the findings are in line with the hypothesis that easy tasks that are interesting are associated with lower cognitive load (i.e., invested mental effort) than easy tasks that are not interesting. Still, because there are no uninteresting tasks in Figure 2b beyond the point of intersection, the given sample of tasks does not allow us to discuss situations where students are over-challenged by very difficult tasks, resulting in negative emotions such as anxiety (as predicted by flow theory).

Furthermore, the results generally substantiate Grund et al.'s [62] suggestion to differentiate the allocation of effort by cause: effort by complexity, effort by need frustration, and effort by allocation. In this sense, the mental effort invested in easy tasks is initially determined by effort by complexity. For uninteresting tasks, additional effort (effort by need frustration) must be integrated, resulting in a higher total effort for these tasks.

Limitations and Further Research

Analyzing existing data comes with some limitations. First, all analyses were performed with tasks as the unit of observation (task level), not students (student level). This allowed us to make general statements about tasks, including that easy, uninteresting tasks are associated with a higher level of invested mental effort than easy, interesting tasks. However, our analyses at the task level did not allow us to draw conclusions about individual psychological processes. Future studies analyzing data at the student level are thus needed. Second, our results are limited to tasks of a chemistry test at the end of German lower secondary school. They should therefore be replicated by intervention studies in other domains (following, for example, a 2×2 design, varying topic interest and task difficulty as factors, and measuring invested mental effort as the dependent variable and perceived task difficulty as a mediator). Third, measuring emotional costs and motivational self-regulation would be necessary given that we interpreted our results with respect to these two variables without corresponding measures in our data set. Fourth, in our data, topic interest was measured after students had processed the tasks, which limited our findings. Future studies should measure topic interest before the students process the tasks and differentiate between stable individual interest and spontaneously aroused situational interest. Fifth, the data set lacks tasks that are uninteresting and difficult. Both interesting and uninteresting difficult tasks would be necessary to test whether interest is a relevant factor for the investment of mental effort even in situations in which the demands of the tasks are higher than students' abilities (which would probably lead to emotional costs such as anxiety). To understand individual differences in dealing with tasks for which challenges and skills are not balanced, analyses at the student level are necessary.

Our analyses used perceived task difficulty as an indication of the balance between ability and challenge. Even though perceived task difficulty correlated almost perfectly with objective task difficulty ($r = 0.91$), the two values are not identical. One possible reason could be that although the order of the Rasch parameters of task difficulty on the logit scale can be assumed to be valid for all individuals, the distance between an individual's ability parameter and the mean of the item difficulty parameters on the logit scale varies. In our data set, perceived task difficulty was always lower than objective task difficulty: on the regression line for objective task difficulty and perceived task difficulty, the value for perceived task difficulty was -0.18 when the objective task difficulty was 0.00 on the logit scale. Further research is thus needed to determine whether perceived task difficulty is more important to a flow experience than objective task difficulty and what role the difference between the two plays.

Our assumption that the higher invested mental effort for easy, uninteresting tasks is caused by motivational self-regulation is an interpretation of our results based on theoretical considerations and previous research. However, this interpretation could not be tested empirically in our study because the necessary data were not available in the data set. Consequently, further research should consider how other constructs (prior knowledge, objective task difficulty, self-efficacy) influence the individual investment of mental effort. In interpreting the data, we assumed that there was a balance between ability and challenge for certain tasks. At the task level, the data set makes statements about the balance between average perceived task difficulty and average invested mental effort. At the individual level, this does not necessarily always equate to a student's ability and challenge.

Finally, our results raise the question of whether the additional cognitive load caused by the extra mental effort needed when working on uninteresting easy tasks should be considered extraneous cognitive load. This view is supported by the fact that this additional load appears unnecessary, unlike for interesting easy tasks. Alternatively, the additional load may be necessary to show persistence and solve these uninteresting easy tasks successfully. Following this line of reasoning, the additional load would be better described as a germane cognitive load or as a pertinent factor for activating relevant working memory resources [22]. Corresponding measuring instruments (i.e., multidimensional cognitive load measures and working memory resources) would be required to settle this question.

5. Conclusions

The present study contributes to research seeking to integrate motivation into cognitive load theory. Specifically, we investigated whether there is an interaction between perceived task difficulty and interest that affects invested mental effort. To do so, we used an existing data set from a chemistry test. All analyses were performed at the task level using task-specific Rasch parameters, which were calculated from students' responses. The results showed that the mental effort invested in uninteresting easy tasks was greater than for interesting easy tasks. At first glance, our finding that interest can compensate for investing additional mental effort to cope with emotional costs when processing unchallenging test items or tasks may be counter-intuitive to cognitive load researchers. This is because other researchers attempted to increase invested mental effort by arousing students' interest. However, the two ideas need not contradict each other. Our analysis only describes the area in which skills are greater than challenges (left side of Figure 2b); for the area where challenges are greater than skills (right side of Figure 2b), the idea that interest could increase students' willingness to invest mental effort would be consistent with our findings.

Overall, our results shed light on the role of motivational variables in the context of cognitive load theory. Our results have both theoretical and practical implications. On the theoretical side, our results indicate that the relationship between motivation and cognitive load is not simply uni-directional but bidirectional. Whereas Feldon and colleagues [1,36,38] showed that motivation can be an outcome of cognitive load, our results show that motivation (in this case: low motivation) can be a source of cognitive load (in this case: a source of additional cognitive load when processing easy tasks). This theoretical insight opens up new research questions, such as questions concerning possible chained effects of low motivation as a predictor of higher cognitive load (in terms of increased mental effort), which in turn might have differential effects on students' motivation. On the practical side, our results indicate that teachers would be well advised to focus on raising students' interest, especially when students are expected to process tasks or problems that are very easy for them. In addition to the need to replicate the results and test our interpretation that higher mental effort is caused by motivational self-regulation, a central question is whether additional mental effort represents an emotional cost and how this is related to extraneous and germane cognitive load and the experience of flow.

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