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Instructing students on effective sequences of examples and problems: Does self-regulated learning improve from knowing what works and why?

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Abstract

Nowadays, students often practice problem-solving skills in online learning environments with the help of examples and problems. This requires them to self-regulate their learning. It is questionable how novices self-regulate their learning from examples and problems and whether they need support. The present study investigated the open questions (1) to what extent students' (novices) task selections align with instructional design principles and (2) whether informing them about these principles would improve their task selections, learning outcomes, and motivation. Higher education students ($N = 150$) learned a problem-solving procedure by fixed sequences of examples and problems (FS-condition), or by self-regulated learning (SRL). The SRL participants selected tasks from a database, varying in format, complexity, and cover story, either with (ISRL-condition) or without (SRL-condition) watching a video detailing the instructional design principles. Students' task-selection patterns in both SRL conditions largely corresponded to the principles, although tasks were built up in complexity more often in the ISRL-condition than in the SRL-condition. Moreover, there was still room for improvement in students' task selections after solving practice problems. The video instruction helped students to better apply certain principles, but did not enhance learning and motivation. Finally, there were no test performance or motivational differences among conditions. Although these findings might suggest it is relatively 'safe' to allow students to independently start learning new problems-solving tasks using examples and problems, caution is warranted: It is unclear whether these findings generalize to other student populations, as the students participating in this study have had some experience with similar tasks or learning with examples. Moreover, as there was still room for improvement in students' task selections, follow-up research should investigate how we can further improve self-regulated learning from examples and practice problems.

KEYWORDS
example-based learning, higher education, motivation, problem-solving, self-regulated learning, task selection

1 | INTRODUCTION

Problem-solving is an important part of curricula at many schools and colleges, for example in courses involving physics, technology, engineering, or mathematics (Van Gog et al., 2020). Many of the problem-solving tasks that students encounter in these courses are algorithmic, meaning that students have to learn to perform a procedure that takes them from a described initial situation to a described goal situation (Newell & Simon, 1972). Solving these tasks requires conceptual and procedural knowledge of what actions to perform, why, and how to perform them. Research on instructional design has resulted in several principles for optimizing the acquisition of problem-solving skills for novices (i.e., students with little if any prior knowledge of the task at hand). These principles are concerned with how to ensure that novices work on problem-solving tasks that provide an optimal level of instructional support and complexity given their current level of knowledge (4C/ID Model; Van Merriënboer, 1997; Van Merriënboer & Kirschner, 2013). For an overview of all the principles, see Table 1.

1.1 | Instructional design principles to support acquisition of problem-solving skills

The example-based-learning-principle postulates that replacing all or a substantial number of practice problems with worked examples (i.e., a written step-by-step explanation of how to solve a problem; e.g., Van Gog et al., 2011) or video modelling examples (i.e., a person demonstrating and/or explaining a problem-solving procedure on video; e.g., Kant et al., 2017) helps novices to learn more (i.e., is more effective) with less time and effort investment (i.e., is more efficient) than solving practice problems without any instructional support (e.g., Sweller et al., 2011; Van Gog et al., 2019). Moreover, recent findings show that studying examples also increases students' self-efficacy during learning compared to only solving practice problems (e.g., Van Harsel et al., 2019, 2020; Coppens et al., 2019). When alternating examples and problems, research has shown that novices should start with an example (instead of practice problem-solving), as this is more efficient for learning than starting with problem-solving only (e.g., Van Harsel et al., 2019, 2020; Van Gog et al., 2011). We refer to this as the example-first-principle.

These principles should be considered in relation to task complexity. Students should ideally be working on tasks that are at an optimal level of complexity given their current level of expertise (4C/ID Model; Van Merriënboer, 1997; Van Merriënboer & Kirschner, 2013). The lowest-level-first-principle postulates that novices should start with a task at the lowest level of complexity. From there, the level of complexity should gradually increase as their knowledge increases: the simple-to-complex-principle (cf. 4C/ID model). According to the 4C/ID model, students should receive a high level of instructional support (like an example) at the start of each new complexity level: The start-each-level-with-example-principle.

Following these principles should thus make novices' learning process more effective and efficient, and make them feel more self-efficacious. However, these principles have been derived mainly from research with fixed (or adaptive) sequences of examples and problems (at different complexity levels), where the learning environment software or the experimenter determined whether, when, and for how long a learner should study examples or solve practice problems.

TABLE 1 Effective, efficient, and motivating principles derived from instructional design research on learning new problem-solving skills

Principle	Explanation	References
Example-based-learning-principle	Replacing all or a substantial number of practice problems with examples helps novices to learn more (i.e., is more effective) with less time and effort investment (i.e., is more efficient) than solving practice problems without any instructional support.	e.g., Sweller et al. (2011), Van Gog et al. (2019)
	This is also more motivating in terms of self-efficacy and perceived competence.	Authors et al., (2019, 2020)
Example-study-first-principle	Novices should start the learning phase with an example instead of a practice problem, as this was found to be more efficient than starting with problem-solving only, and also more motivating.	e.g., Van Gog et al. (2011) Authors et al., (2020)
Lowest-level-first-principle	Novices should start with a task at the lowest level of complexity	Van Merriënboer (1997), Van Merriënboer and Kirschner (2013)
Simple-to-complex-principle	Novices should gradually increase the level of task complexity as their knowledge increases	Van Merriënboer (1997), Van Merriënboer and Kirschner (2013)
Start-each-level-with-example-principle	Novices should receive a high level of instructional support (like an example) at the start of each new complexity level	Van Merriënboer (1997), Van Merriënboer and Kirschner (2013)

Nowadays, students often learn new problem-solving tasks via online learning environments, in which examples and practice problems (at different complexity levels) are made available (e.g., Roll et al., 2011). These online environments usually require students to self-regulate their learning (e.g., when doing homework or studying for a test). Self-regulated learning requires students to plan, execute, monitor, evaluate, and control their learning (e.g., Nelson & Narens, 1990; Winne & Hadwin, 1998; Zimmerman, 1990). In the context of learning new problem-solving tasks, self-regulated learning requires students to decide which task they want to perform, monitor their progress while performing the task (and possibly adjust their strategies while working on the task), judge their performance after the task is completed, and to use this judgement as input for deciding what subsequent task to work on (i.e., decide what learning task fits their learning needs best, e.g., Van Gog et al., 2020; De Bruin & Van Gog, 2012).

It is as yet unclear (a) to what extent novices' task selections during self-regulated learning of examples and problems align with the instructional design principles that have found to be effective, efficient, and motivating for acquiring new problem-solving skills, and (b) whether informing students about such principles would improve their task selections, motivation, and learning outcomes. This study addresses those questions.

1.2 | Self-regulated learning of problem-solving tasks with examples and problems

Self-regulated learning of problem-solving tasks is notoriously difficult for novices, because they need to be able to accurately assess their understanding or performance on the just completed task and subsequently select a new task with the right level of complexity and support (Van Gog et al., 2020; De Bruin & Van Gog, 2012). Research has shown that novices often experience difficulties in accurately assessing their performance (e.g., Dunning et al., 2004; Koriat & Bjork, 2005) and mostly overestimate (though sometimes underestimate) their own performance (e.g., Hacker & Bol, 2019; Kostons et al., 2010, 2012). Consequently, tasks might be selected that are too complex or too simple, or do not provide the necessary instructional support (e.g., Dunlosky & Rawson, 2012). Moreover, novices do not always seem to be aware which task aspects influence how much they learn (e.g., Kostons et al., 2010; Nugteren et al., 2018), and therefore tend to select tasks based on irrelevant (e.g., cover stories) instead of relevant task aspects (i.e., complexity and support; e.g., Corbalan et al., 2008).

Based on these findings, one might expect that novices experience difficulties when self-regulating their learning from examples and problems. Indeed, a recent study conducted by Foster et al. (2018) found that novices make suboptimal choices when they are in control of selecting tasks to work on. In their study, university students had to learn how to solve probability problems and were repeatedly given the choice of whether to study a worked example or to practice solving a (completion) problem. Results showed that on average, students opted more often for (completion) problems than examples and rarely started the learning phase with example study. These choices are at odds with the example-based-learning-principle and the example-first-principle, as studying examples, especially at the start of the learning phase, is more efficient (and effective), and motivating for learning than (starting with) problem-solving only (e.g., Van Harsel et al., 2020; Van Gog et al., 2011).

In contrast, Van Harsel et al. (submitted) found other results. Higher education students learned how to solve a math problem by selecting six learning tasks from a database that consisted of 45 learning tasks that differed in format (worked examples, video modelling examples, and practice problems), complexity (three levels), and cover story. Results showed that most of the learners' choices matched with the instructional design principles: the vast majority of students selected many examples during the learning phase, as they started the learning phase with an example at the lowest complexity level and often started a new complexity level with example study as well. However, the complexity of tasks was built up less well by only half of the sample: Particularly those who performed poorly on the posttest kept selecting examples or practice problems at the lowest complexity level. It is, however, an open question whether self-regulated learning would be as effective as fixed sequences of tasks based on those principles, as research has shown that fixed learning paths are often more effective for novices' learning than self-chosen learning paths (see e.g., Azevedo et al., 2008; Lawless & Brown, 1997; Niemiec et al., 1996). Moreover, as there still might be room for improvement in novices' task selections (based on their test performance scores), they might benefit from instructional support to help them self-regulate their learning, for instance by explicitly informing learners prior to self-regulated learning about the principles derived from instructional design research.

1.3 | Strategy instruction to support self-regulated learning of problem-solving tasks

Explicitly informing students about learning strategies has been found to be successful for increasing learners' metacognitive beliefs and/or knowledge (e.g., Endres et al., 2021; Lineweaver et al., 2019; McCabe, 2011; Yan et al., 2016) and their use of these strategies (e.g., Biwer et al., 2020). Ariel and Karpicke (2017) even found that explicitly informing students about learning strategies also improved their learning outcomes They asked university graduates to learn Lithuanian-English word-pairs. Students could decide for themselves whether to restudy word-pairs, whether to retrieve already learnt word-pairs from memory (i.e., retrieval practice, a proven effective study strategy for word-pair learning; Rowland, 2014), or to stop learning. The experimental condition received a short written instruction with information about the effectiveness and mnemonic benefits of repeated retrieval practice and how to use it, while the control condition did not receive this information. Results showed that students in the experimental condition used the repeated retrieval practice strategy more often than those in the control condition, and subsequently outperformed the control group on an immediate cued-recall test. Students in the experimental condition even (spontaneously) used retrieval practice to learn novel materials a week later more often than the control condition.

A possible explanation for why informing students about effective learning strategies can improve the use of such strategies and learning (cf. Ariel & Karpicke, 2017) could be that this information helps learners become (more) aware of the value of a strategy and increases their metacognitive knowledge (i.e., knowledge about why and which strategies are [not] beneficial for learning). In turn, this could increase the likelihood that an individual will search for, modify, and apply that strategy (e.g., Tullis et al., 2013; Yan et al., 2014).

These findings are promising, given that this approach of informing students about effective strategies would be relatively easy to use across a variety of learning materials and contexts. However, it is an open question whether this approach would also be effective for improving self-regulated learning of problem-solving skills with examples and problems.

1.4 | The present study

As the results of Authors (submitted) are rather surprising in light of other related research showing that novices, especially at the start of the learning phase, make suboptimal choices when they are in control of selecting tasks to work on (e.g., Foster et al., 2018), the first research question of this study reads: *Does the finding that students' choices during self-regulated learning align quite well with the instructional design principles for optimizing the acquisition of new problem-solving skills for novices* (cf. *Authors, submitted) replicate?* To shed further light on the quality of students' task selections, the present study also explored what tasks learners select after solving a practice problem, which was not possible in Authors (submitted) as practice problem performance data were unavailable.

The second research question of this study reads: *Is self-regulated learning as effective, efficient, and motivating as a fixed task sequence based on the principles derived from instructional design research?* We consider this an open question. It is possible that self-regulated learning would have motivational benefits over a fixed task sequence, given that related research suggests that allowing students to have (some) freedom of choice during learning might improve motivational variables such as interest or task involvement (e.g., Corbalan et al., 2008). However, it is questionable whether this also applies to motivational variables such as self-efficacy and perceived competence. At the same time, self-regulated learning might be less conducive to learning outcomes than a predetermined sequence, as novices often lack the necessary knowledge to make effective educational decisions (e.g., Merrill, 2002) and focus on irrelevant instead of relevant task aspects (e.g., Corbalan et al., 2008). Indeed, self-regulated learning has been found to impair learning outcomes relative to teacher- or computer-controlled fixed or personalized instruction (see e.g., Azevedo et al., 2008; Lawless & Brown, 1997; Niemiec et al., 1996).

Thirdly, given that there still was room for improvement in learners' task selections and test performance scores in the study of Authors (submitted), the third research question of this study was: *Does explicitly informing learners about instructional design principles enhance their self-regulated learning of examples and problems (at different complexity levels), performance, and motivation compared to self-regulated learning without such information?* Assuming that students in the 'informed self-regulated learning condition' actually adopt these principles after receiving explicit instruction (cf., studies on other learning strategies: Ariel & Karpicke, 2017; Biwer et al., 2020), one could expect their choices to be better aligned with the principles than students' choices in the self-regulated learning condition and therefore show higher test performance (i.e., on conceptual questions, isomorphic tasks, and procedural transfer tasks), attained with lower effort investment and time-on-task in the learning and posttest phase. As for the comparison between the informed self-regulated learning and fixed sequences condition, we consider this an open question. If informing students about effective principles for learning from examples and problems would help students select better tasks, they might show similar performance as the fixed sequences condition. Effects on self-efficacy and perceived competence are explored.

2 | METHOD

2.1 | Participants and design

Participants were 241 students from a Dutch university of applied sciences ($M_{age} = 18.84$, $SD = 1.76$; 232 male), enrolled in the first year of an electrical and electronic mechanical engineering program. Participants had to learn how to approximate the definite integral of a function using the trapezoidal rule. They were randomly allocated to one of three conditions, namely the (1) informed self-regulated learning condition (ISRL; $n = 109$), (2) self-regulated learning condition (SRL; $n = 60$), and fixed sequences condition (FS; $n = 72$). More participants were assigned to the ISRL-condition to increase the chances of having a sufficiently large subset of students who would follow the advice and to be able to explore differences between students who did and did not follow the advice. The experiment consisted of three phases: (1) pretest, (2) learning phase, and (3) posttest. Participants who did not finish the isomorphic (and transfer) items on the posttest on time were excluded from further analysis ($n = 42$). Moreover, we also excluded 49 participants with too much prior knowledge (indicated by a score of 5 or more out of 9 on the prior knowledge test), because we were specifically interested in the selection behaviour of novice learners. Therefore, the final sample consisted of 150 participants ($M_{age} = 18.68$, $SD = 1.57$; 143 male) divided over the ISRL-condition ($n = 66$), SRL-condition ($n = 32$), and FS-condition ($n = 52$). Students could earn study credits for participation. All participants gave informed consent in the learning environment.

Descriptive statistics of demographic variables are presented in Table 2. There were no differences among conditions regarding age ($H(2) = 0.53$, $p = 0.768$). As one of the assumptions of the Chi-squared test was not met, we could not analyze whether groups

TABLE 2 Descriptive statistics of demographic variables

	Fixed sequences condition (n = 52)	Informed self-regulated learning condition (n = 66)	Self-regulated learning condition (n = 32)
Gender			
Male	49 (94.2%)	63 (95.5%)	31 (96.9%)
Female	3 (5.8%)	3 (4.5%)	1 (3.1%)
Preliminary education			
Senior general secondary education	29 (55.8%)	40 (60.6%)	19 (59.4%)
Pre-university education	5 (9.6%)	11 (16.7%)	4 (12.5%)
Vocational education	11 (21.2%)	12 (18.2%)	7 (21.8%)
University of applied sciences	7 (13.4%)	3 (4.5%)	2 (6.3%)

TABLE 3 Correlation coefficients (r) from Pearson correlation analysis (Gender) and Spearman correlation analysis. (Preliminary education) between main outcome variables and gender and preliminary education

	Gender		Preliminary education	
	r	p	r	p
Learning phase				
Mental effort	0.050	0.543	−0.017	0.837
Posttest				
Conceptual Questions	−0.099	0.230	0.151	0.065
Isomorphic Tasks	0.115	0.162	0.091	0.269
Procedural Transfer Task	0.114	0.166	0.143	0.081
Self-efficacy	−0.082	0.317	**0.168**	**0.040**
Perceived Competence	−0.103	0.209	0.107	0.192

Note: Significant p-values are bolded.

differed on the ordinal variables (gender, highest preliminary education level). Therefore, we computed correlations to determine whether there was a relation among the ordinal variables and the main outcome variables. There were no significant correlations (see Table 3), except for a positive correlation between highest level of preliminary education (i.e., university of applied sciences) and self-efficacy measured after the learning phase ($r = -0.182$, $p = 0.026$). However, as the three conditions did not differ in self-efficacy measured after the learning phase, it is unlikely that a potential difference in distribution of preliminary education levels among conditions would have affected the results.

2.2 | Materials

All materials were based on the materials developed by Van Harsel et al. (2019, 2020) and Authors (submitted), and presented in a web-based learning environment.

2.2.1 | Pretest

The pretest consisted of five conceptual knowledge questions that measured participants' understanding of the trapezoidal rule ($\alpha = -0.73$). These questions consisted of a multiple-choice part with four answer options and an explanation part where participants had to explain their answer (see Appendix A for an example of a pretest question). Note that a possible reason for the poor reliability of the pretest is that students had (very) low prior knowledge but a 25% chance to guess the right answer.

2.2.2 | Instructional video

The instructional video that was used to inform students in the ISRL-condition on effective instructional design principles started with a brief explanation of the procedure of the experiment. Students were informed that they were going to select learning tasks themselves and would receive help on how to select the most effective and efficient learning task, based on well-established findings from scientific research. Then, a total of four 'rules' were presented: (a) 'At the start of the learning phase, choose a task at the lowest complexity level', (b) 'When you mastered a complexity level, choose a task one complexity level higher', (c) 'Start each new complexity level with example study and alternate with practice problems when you want to check whether you understand how to solve the problem' (d) 'Start the learning phase with a video modelling example and continue with written examples when more example study is necessary'. We added the fourth rule as there are some indications that a video modelling example is preferred at the start and worked examples later in the training phase (e.g., Authors, submitted; Hoogerheide et al., 2014). This might be explained by the fact that in video modelling examples, information is demonstrated step-by-step and the combination of dynamic visual information and the model's verbal explanations take the learner by the hand. In worked examples, information is also demonstrated step-by-step, however, shown all at once. This allows for efficiently looking up difficult problem-solving steps and therefore might be preferred later in the learning phase. Each rule was accompanied with the necessary background information about why this rule would help students learn more and when/how to apply it (see Appendix B). The instructional video lasted 223 s.

2.2.3 | Task database

Together with three mathematics teachers from the university of applied sciences where the study was conducted, a task database consisting of 45 learning tasks was developed (see Figure 1). The tasks required participants to approximate a specific region under the graph of a function using the trapezoidal rule. The trapezoidal rule is an integration method that can be used to approximate the area under a curve by dividing that area into trapezoids or 'strips' (rather than using rectangles). By adding up the surface of the 'strips', one can approach the total area under that curve. The tasks varied in complexity level, task format, and cover story.

Complexity level

The learning tasks were developed at three levels of complexity. Tasks at *complexity level 1* required participants to use the trapezoidal rule to approximate the region under the graph of a polynomial function of degree 2 (i.e., quadratic function). Moreover, functions were constructed in such a way that participants had to calculate more than two intervals and calculate with fractions and positive numbers only. Tasks at *complexity level 2* were more difficult, since they asked participants to calculate with negative numbers as well. Tasks at the highest complexity level (i.e., *complexity level 3*) additionally asked participants to use the trapezoidal rule to approximate the region under the graph of a polynomial function of degree 3 (i.e., cubic function).

Format

The learning tasks were developed in three different formats: video modelling examples, worked examples, and (conventional) practice problems. Video modelling examples consisted of a screen recording of a female model's computer screen, where she demonstrated (with PowerPoint slides and handwritten notes) and explained step-by-step how to solve a problem using the trapezoidal rule. The model started with an introduction on the trapezoidal rule, followed by an explanation of the problem state and an explanation of how to use the information that was presented on the screen to solve the problem (i.e., the graph of a function, the left border and right border of the area, the number of intervals, and the formula of the trapezoidal rule). Subsequently, she showed and explained how to solve the problem by calculating four steps: (1) 'compute the step size of each subinterval', (2) 'calculate the x-values', (3) 'calculate the function values for all x-values', and (4) 'enter the function values into the formula and calculate the area', and ended the video by providing the final answer.

Worked examples were presented on one page and consisted of a written step-by-step explanation of the solution procedure. Worked examples also started with a short description of the problem state and some additional information that was needed to solve the problem (i.e., the graph of a function, the left border and right border of the area, the number of intervals, and the formula of the trapezoidal rule). Subsequently, written explanations (and correct answers) were given for each of four steps on how to solve the problem.

Practice problems also started with a short description of the problem state and the additional information that was needed to solve the problem. However, it was not explained how to use the information that was given to solve the problem. Participants received the following assignment: 'Approach the area under the graph using the information that is given. Write down all your intermediate steps and calculations'. Screenshots of the three task formats are presented in Appendix C.

Cover story

Finally, tasks varied in cover story. For example, participants could solve a problem that asked them to approximate how many litres of beer were tapped within a certain amount of time (i.e., drinking beer) or approximate how often the circular platform of a carousel rotates

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Level 1			Level 2			Level 3		
Video modeling examples	Worked examples	Practice problems	Video modeling examples	Worked examples	Practice problems	Video modeling examples	Worked examples	Practice problems
Drinking beer	Drinking beer	Drinking beer	Running	Running	Running	Carousel	Carousel	Carousel
Energy measurement	Energy measurement	Energy measurement	Drinking water	Drinking water	Drinking water	Rowing	Rowing	Rowing
Fitness	Fitness	Fitness	Washing machine	Washing machine	Washing machine	Perfume	Perfume	Perfume
Fuel consumption	Fuel consumption	Fuel consumption	Soapsuds	Soapsuds	Soapsuds	Coffee consumption	Coffee consumption	Coffee consumption
Traffic	Traffic	Traffic	Plasterer	Plasterer	Plasterer	Chocolate party	Chocolate party	Chocolate party

FIGURE 1 Screenshot of the task database

in a given period of time (i.e., carousel). The cover stories were similar for each task format that was provided within a complexity level (e.g., drinking beer could be selected as video modelling example, worked example, and practice problem), yet the numbers used differed per task format.

2.2.4 | Task sequences and task selection

During the learning phase, participants in the two SRL conditions could select six tasks from the task database (see Figure 1; each task could be selected only once). They were instructed that the posttest would include tasks at all three complexity levels. Participants in the FS-condition received six tasks from the task database in the following order: (1) video modelling example at complexity level 1, (2) worked example at complexity level 1, (3) practice problem at complexity level 1, (4) worked example at complexity level 2, (5) practice problem at complexity level 2, and (6) worked example at complexity level 3. The cover stories of these tasks were randomly chosen.

2.2.5 | Posttest

The *posttest* consisted of five tasks. The first three tasks concerned a level 1, 2, and 3 task; these were isomorphic to the learning phase tasks ($\alpha = 0.81$). The fourth task was a procedural transfer task that required participants to use the Simpson rule to approximate the definite integral under a graph. Simpson's rule is also a numerical integration method, however, uses quadratic polynomials (instead of the straight-line segments) to approximate the region under a graph. The final task consisted of five questions that aimed to measure participants' understanding of the trapezoidal rule ($\alpha = 0.48$), and these were isomorphic to the pretest questions. Examples of test tasks are shown in Appendix A.

2.2.6 | Mental effort

Mental effort was measured using a 9-point rating scale (Paas, 1992), asking participants to rate how much mental effort they invested in studying an example or solving a practice problem. Answer options ranged from (1) 'very, very low mental effort' to (9) 'very, very high mental effort'. Mental effort was rated after each learning and posttest task, with the exception of the five conceptual posttest questions (where it was rated only once after the final item).

2.2.7 | Self-efficacy

Self-efficacy was measured by asking participants for their confidence in that they could approximating the definite integral of a graph using the trapezoidal rule. Answer options ranged from (1) 'very, very unconfident' to (9) 'very, very confident' (Van Harsel et al., 2019; adapted from Hoogerheide et al., 2016).

2.2.8 | Perceived competence

Perceived competence was measured using an adapted version of the *Perceived Competence Scale for Learning* (Van Harsel et al., 2019, 2020; based on Williams & Deci, 1996), consisting of three items (instead of the 4 items), such as 'I feel confident in my ability to learn how to approximate the definite integral of a graph using the trapezoidal rule'. Participants had to rate on a scale of (1) 'not at all true' to (7) 'very true' to what degree the items applied to them ($\alpha = 0.95$).

2.3 | Procedure

Fourteen single sessions (with 9 to 24 participants per session) that lasted 102 min on average were run in a computer classroom at participants' university of applied sciences. Before each session, a headset, pen, and scrap paper were placed on the tables. After participants arrived, the experimenter first explained the aim and procedure of the experiment. Then, participants were told that they could work at their own pace (with a maximum of 135 minutes), and that they had to write down as much as possible and to write an 'X' if they really did not know what to answer. Students could use a calculator (different from Authors, submitted).

After the instructions, participants entered the online learning environment. Each task and questionnaire were presented on a separate page. Participants were unable to go to the next page before completing the current task/questionnaire and were unable to go back to any previously completed pages. Time-on-task was logged.

Participants were first provided with a short demographic questionnaire (e.g., age, gender, highest preliminary education level), the pretest, and self-efficacy and perceived competence questionnaires. Next, the learning environment provided written instructions about the learning phase. For the SRL conditions, these instructions explained that six tasks had to be selected from the task database and how to select a task to work on. Participants in the ISRL-condition additionally were told that they had to watch an instructional video that explained how to select tasks to learn most effectively and efficiently. In the FS-condition, participants were told that they had to study or solve the tasks that were provided to them. In all conditions, participants had to rate their mental effort and self-efficacy after each task in the learning phase. After the learning phase, participants had to turn their scrap paper upside down and were provided with a new scrap paper. Then, participants completed the self-efficacy and perceived competence questionnaires and the posttest. After the posttest, participants handed in their materials and left the classroom. For an overview of the procedure, see Figure 2.

2.4 | Data analysis

To answer our first research question, we used the same approach as Authors (submitted). We first analyzed what tasks participants selected in the SRL conditions and coded the task format

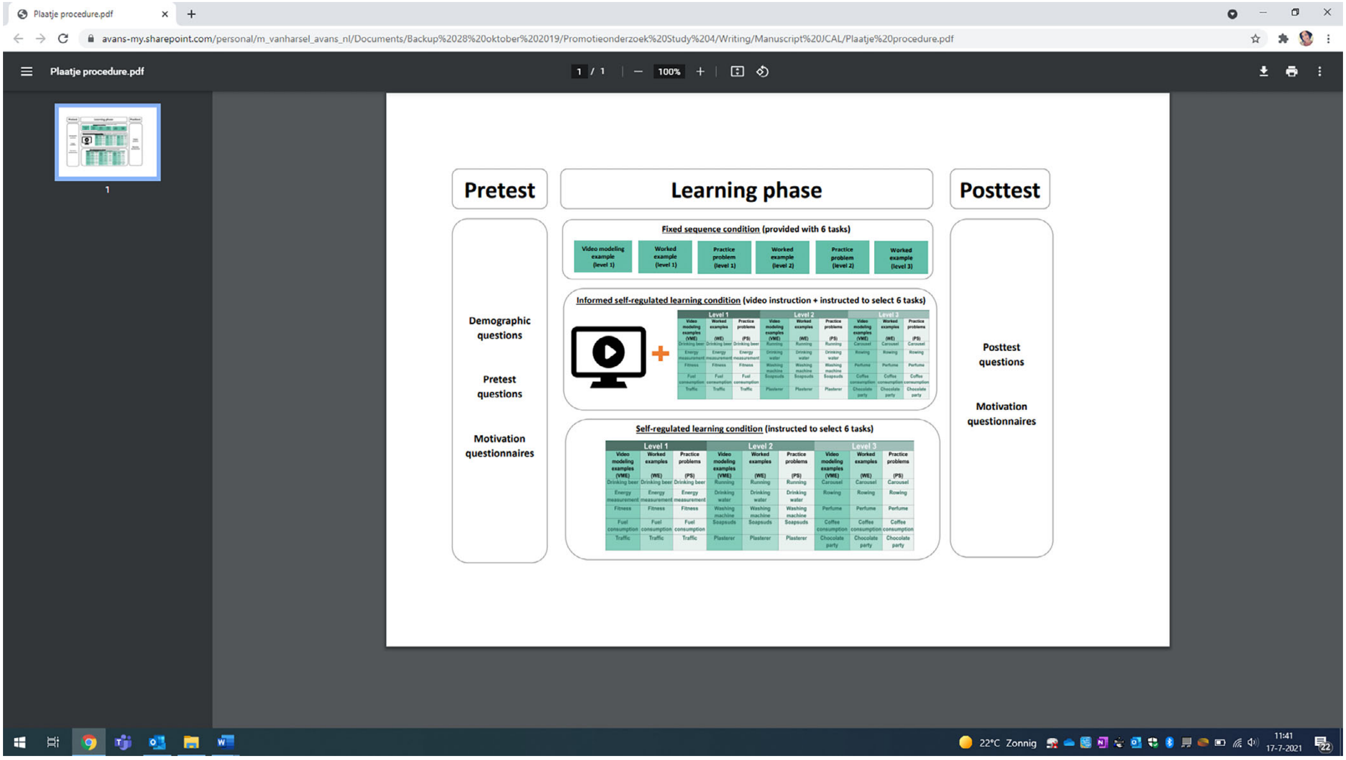

FIGURE 2 Overview of the procedure

(video modelling example, worked example, practice problem) and complexity level (1, 2, or 3) of the selected learning tasks, and converted the scores into percentages. We then coded to what degree participants' task-selection behaviour matched with the evidence-based instructional design principles (i.e., example-based-learning, example-first, simple-to-complex, lowest-level-first, and start-each-level-with-example-principle). For each principle, participants could earn 1 point in total. Following the example-first-principle and lowest-level-first-principle was awarded with 1 point and 0 points were assigned when the principle was not followed. For the example-based-learning-principle, simple-to-complex-principle, and start-each-level-with-example-principle, 1 point was granted when the principle was followed entirely, 0.5 points when the principle was followed partially, and 0 points when the principle was not followed at all (same scoring protocol as used in Authors, submitted). For each participant, a total score was computed that represented how well all principles were followed (maximum: 5 points).

Then, we scored participants' performance on the practice problems. A maximum of 8 points could be earned for each practice problem, with 2 points for calculating each step correctly: (1) the step size of each subinterval, (2) all x-values, (3) the function values for all x-values, and (4) using the correct formula for the area under the graph and providing the correct answer. In step two, three, and four, 2 points were given when all solution steps were correct, 1 point was given if half or more of the steps were correct, and 0 points when less than half of the steps were correct. To explore how well students' task-selection behaviour matched with their performance on the practice problems, we scored whether students selected a new task (i.e., video modelling example, worked example, or practice problem) on a higher complexity level when a practice problem was graded with 6 or more out of 8 points (75% or more correct). We also scored whether students selected a new task (i.e., video modelling example, worked example, or practice problem) on a similar (or lower) complexity level when a practice problem was graded with less than 6 out of 8 points (less than 75% correct).

To answer our second and third research question, we also used the same approach as Authors (submitted). We first scored performance on the conceptual pretest and posttest items. On the conceptual pretest questions and conceptual posttest questions, participants could earn a maximum of 9 points. One point could be earned for the first open-ended question (correct answer: 1 point; incorrect answer: 0 points) and 2 points for the other open-ended questions. Participants were only rewarded with the maximum of 2 points when they got the answer right and provided correct explanations. Only 1 point was awarded when the answer was correct but the explanation was incorrect or missing and 0 points were given when the answer and explanation were incorrect. With regard to performance on the posttest, the isomorphic posttest items (i.e., three tasks, max. score = 24 points) and procedural transfer item (i.e., 1 task, max. score = 8 points) were scored similarly to the learning tasks. Averages of mental effort invested in the learning tasks and posttest tasks were calculated, as well as the averages of participants' self-efficacy and perceived competence ratings before, during (only self-efficacy), and after the learning phase.

3 | RESULTS

Descriptive statistics were used to evaluate the first research questions on how students behaved in the SRL conditions, how well their behaviour matched with evidence-based principles from instructional design research, and whether students made the right choices in the learning phase according to their performance on the practice problems. Percentages are only mentioned in the text if they cannot be found in the tables.

Non-parametric tests were used to answer the second and third research question because the main variables were not normally distributed (i.e., the kurtosis and/or skewness values, divided by their *SE*, were below -1.96 or above $+1.96$; cf. Field, 2009). The effects of Test Moment (Pretest and Posttest) were tested with Wilcoxon signed-rank tests. Differences between the SRL conditions in following the instructional design principles were tested with Mann–Whitney U tests. Differences between the ISRL-Condition, SRL-Condition, and FS-Condition regarding cognitive (i.e., performance on the conceptual tests, isomorphic test, procedural transfer test, as well as mental effort and time-on-task in learning and posttest phases) and motivational aspects of learning (i.e., self-efficacy and perceived competence) were tested with Kruskal–Wallis tests. For post-hoc tests, we used Mann–Whitney U tests, with a Bonferroni corrected significance level of $p < 0.017$ (i.e., 0.05/3) for the Wilcoxon signed-rank tests and a Bonferroni-corrected alpha level of $p < 0.017$ (i.e., 0.05/3) for the Kruskal–Wallis tests. For the post-hoc tests, the effect size of Pearson's correlation (r) is reported (i.e., $Z/\sqrt{N}$), with values of 0.10, 0.30, and 0.50 representing a small, medium, and large effect size, respectively (Cohen, 1988).

Before non-parametric analyses were conducted, we checked for pre-existing differences among the three conditions. Kruskal–Wallis tests showed no significant differences among conditions on pretest performance $H(2) = 2.60$, $p = 0.273$, nor on self-efficacy $H(2) = 0.73$, $p = 0.696$, or perceived competence $H(2) = 1.70$, $p = 0.919$. We also checked whether participants in the ISRL-Condition actually watched the instructional video detailing the instructional design principles. Results showed that 57.6% of the participants watched the entire video (i.e., $n = 38$), 21.2% watched between half and three quarter of the video ($n = 14$), and 21.2% watched less than half of the video instruction ($n = 14$). Additionally, we explored whether there were differences between these three subgroups in terms of following the instructional design principles and cognitive and motivational aspects of learning (see Appendix D).

3.1 | To what extent do novices' task-selection patterns match with the findings from example-based learning research?

We first checked the percentages of selected examples and problems (see Tables 4 and 5) and complexity levels (Table 6), and analyzed how well students' choices matched with the instructional design principles (Table 7) in the ISRL and SRL-Condition. Almost all participants in both conditions started the learning phase with an example instead of a practice problem. On the second learning task, the percentage of selected examples rapidly decreased whereas the percentage of practice problems increased in both conditions. In de ISRL-Condition, problem-solving was preferred over example study on the second and third learning task, however, example study became most popular again on the fourth and fifth learning task. In the SRL-Condition, example study remained most popular up to and including the fifth learning task. Only on the last learning task, practice problems were preferred over example study in both conditions. With regard to our first research question, findings of the SRL-condition seems to be in line with the findings of Authors (submitted).

Moreover, participants in the SRL-Condition preferred video modelling examples (37.4%) over worked examples (27.0%), however, formats were almost equally preferred in the ISRL-Condition (video modelling examples: 29.6%; worked examples: 28.8%). In both conditions, participants clearly preferred a video modelling example as the first learning task compared to a worked example (or a practice problem). These percentages dropped considerably on the second learning task, as worked examples became more popular. Nevertheless, the popularity of the video modelling examples rose again on the third and fourth learning task (especially in the SRL-Condition); however, these percentages dropped again on the last two learning tasks. The selection of worked examples remained fairly stable in the ISRL-Condition from the second learning task onwards, with an outlier on the fifth learning task. In the SRL-Condition, the selection of worked examples dropped after the second learning task, yet increased again on the last two learning tasks. Considering our first research question, findings of the SRL-condition again replicate the results of Authors (submitted).

TABLE 4 Percentages of selected examples and practice problems in the informed self-regulated learning condition ($n = 66$) and self-regulated learning condition ($n = 32$)

	Informed self-regulated learning condition		Self-regulated learning condition	
	Example	Practice problem	Example	Practice problem
Learning task 1	95.5%	4.5%	100%	0%
Learning task 2	43.9%	56.1%	56.3%	43.7%
Learning task 3	46.2%	53.8%	59.4%	40.6%
Learning task 4	57.6%	42.4%	58.1%	41.9%
Learning task 5	66.7%	33.3%	71.0%	29.0%
Learning task 6	40.6%	59.4%	41.9%	58.1%

TABLE 5 Percentages of selected video modelling examples, worked examples, and practice problems in the informed self-regulated learning condition ($n = 66$) and self-regulated learning condition ($n = 32$)

	Informed self-regulated learning condition			Self-regulated learning condition		
	Video modelling example	Worked example	Practice problem	Video modelling example	Worked example	Practice problem
Learning task 1	84.8%	10.6%	4.6%	81.3%	18.7%	0.0%
Learning task 2	9.1%	34.8%	56.1%	18.8%	37.5%	43.7%
Learning task 3	20.0%	26.2%	53.8%	43.8%	15.6%	40.6%
Learning task 4	34.8%	22.7%	42.4%	41.9%	16.1%	41.9%
Learning task 5	18.2%	48.5%	33.3%	29.0%	42.0%	29.0%
Learning task 6	10.9%	29.7%	59.4%	9.7%	32.3%	58.1%

TABLE 6 Percentages of selected complexity levels (Level 1, 2, and 3) in the informed self-regulated learning condition ($n = 66$) and self-regulated learning condition ($n = 32$)

	Informed self-regulated learning condition			Self-regulated learning condition		
	Complexity level 1	Complexity level 2	Complexity level 3	Complexity level 1	Complexity level 2	Complexity level 3
Learning task 1	97.0%	0.0%	3.0%	87.5%	6.3%	6.2%
Learning task 2	89.4%	4.5%	6.1%	75.0%	18.8%	6.2%
Learning task 3	47.7%	46.2%	6.1%	40.6%	40.6%	18.8%
Learning task 4	18.2%	60.6%	21.2%	22.6%	45.2%	32.2%
Learning task 5	15.2%	30.3%	54.5%	16.2%	29.0%	54.8%
Learning task 6	14.1%	15.6%	70.3%	16.1%	19.4%	64.5%

Findings also showed that the level of complexity was gradually built up in both conditions. The lowest complexity level was selected most on the first two learning tasks, the second complexity level was selected most on the third and fourth learning task, and the most difficult complexity level was selected most on the last two learning tasks. With regard to our first research question, the results of the SRL-condition are again in line with the findings of Authors (submitted).

Analyzing how well students' choices matched with the instructional design principles revealed that participants' choices in both the ISRL and SRL condition matched very well with these principles (see Table 7),[1] replicating the findings of Authors (submitted) considering the SRL condition. Moreover, results revealed that in both SRL conditions, many participants followed (almost all of) the principles entirely (as their total score was between 4.5 and 5 out of a maximum of 5 points; ISRL: 57.6%, SRL: 46.0%) or partially (as their total score was between 3 and 4.5 out of a maximum of 5 points; ISRL: 37.9%, SRL: 50.1%). As a result, there were no significant differences between the ISRL-Condition and the SRL-Condition on the 'total score' ($U = 930$, $p = 0.294$, $r = 0.106$), nor in the degree to which both conditions followed the example-based-learning-principle ($U = 1022.5$, $p = 0.570$, $r = 0.057$), example-study-first-principle ($U = 1104$, $p = 0.223$, $r = 0.123$), lowest-level-first-principle ($U = 956$, $p = 0.068$, $r = 0.184$), or start-each-level-with-example-principle ($U = 1170$, $p = 0.209$, $r = 0.127$). There was, however, a significant difference between conditions in following the simple-to-complex-principle ($U = 838.5$, $p = 0.042$, $r = 0.205$), which was followed entirely by 77.3% of the participants in the ISRL-Condition and only by 53.1% of the participants in the SRL-Condition.

3.2 | To what extent do novices make effective task selections after a practice problem-solving attempt?

To shed further light on the quality of students' task selections, we categorized the type of decisions students made after problem-solving practice, taking into account whether they performed well on the practice problem (75%–100% correct; 'standard achieved') or not (less than 75% correct, 'standard not achieved'). The results are presented in Table 8. The ISRL-Condition made many more task selections after a practice problem than the SRL-Condition (i.e., 125 vs. 48, respectively). Both conditions made more effective task-decisions (i.e., moving up a complexity level after achieving the standard, or not moving up a complexity level after failing to achieve the standard) than ineffective task-decisions (all other choices, classified as 'other task-selection decisions'). However, there was definitely room for improvement in both conditions, as approximately 40% of the task selections were likely classified as ineffective for learning.

TABLE 7 Percentages of example-based learning principles applied in the informed self-regulated learning condition ($n = 66$) and self-regulated learning condition ($n = 32$)

	Informed self-regulated learning condition			Self-regulated learning condition		
	Principle followed entirely	Principle followed partially	Principle followed not at all	Principle followed entirely	Principle followed partially	Principle followed not at all
Example-based-learning-principle	93.9%	4.6%	1.5%	90.6%	9.4%	0.0%
Example-first-principle	95.5%	X	4.5%	100.0%	X	0.0%
Lowest level-first-principle	97.0%	X	3.0%	87.5%	X	12.5%
Simple-to-complex-principle	77.3%	6.0%	16.7%	53.1%	28.1%	18.8%
Start-each-level-with-example-principle	77.3%	18.2%	4.5%	87.5%	12.5%	0.0%

Note: X, not a scoring option for this principle.

3.3 | Do the fixed sequence, informed self-regulated learning, and self-regulated learning condition differ on cognitive and motivational aspects of learning?

Then, we analyzed whether the three conditions differed on cognitive and motivational aspects of learning (see Table 9). Note that we explored whether the results would change if we excluded those participants in the ISRL-Condition who did not watch the entire video detailing the instructional design guidelines. It was decided to keep these students in the sample, because removing them would not change the findings.

3.3.1 | Cognitive aspects of learning

Performance on test tasks

Analyses revealed that conceptual knowledge increased from pretest to posttest ($Z = 5.86$, $p < 0.001$, $r = 0.478$). Post-hoc analyses showed significant increases in the FS-Condition ($Z = 3.94$, $p < 0.001$, $r = 0.547$) and ISRL-Condition ($Z = 1.97$, $p = 0.001$, $r = 0.482$), but not in the SRL-Condition ($Z = 5.86$, $p = 0.049$, $r = 0.348$). There were, however, no differences among conditions regarding students' performance on the conceptual knowledge posttest, ($H(2) = 0.21$, $p = 0.900$), the isomorphic posttest tasks ($H(2) = 1.34$, $p = 0.511$), or the procedural transfer task ($H(2) = 0.97$, $p = 0.616$).

Mental effort

There was no significant difference among conditions on the (average) self-reported mental effort invested in the learning tasks, ($H(2) = 3.16$, $p = 0.206$), nor on the average invested mental effort in the conceptual knowledge posttest questions ($H(2) = 3.23$, $p = 0.199$), isomorphic posttest tasks ($H(2) = 5.87$, $p = 0.053$), or procedural transfer task ($H(2) = 0.50$, $p = 0.780$).

Time-on-task

There was also no significant difference among conditions on average time-on-task invested in the learning tasks, ($H(2) = 4.22$, $p = 0.121$), conceptual knowledge questions ($H(2) = 0.08$, $p = 0.961$), or

TABLE 8 Percentages of task-selection decisions after practice problem solving in the informed self-regulated learning condition ($n = 66$) and self-regulated learning condition ($n = 32$)

	Informed self-regulated learning condition 125 task-selection decisions after practice problem solving	Self-regulated learning condition 48 task-selection decisions after practice problem solving
Effective task-selection decisions		
Standard achieved, video modelling example on higher complexity level	16.8%	18.7%
Standard achieved, worked example on higher complexity level	18.4%	12.5%
Standard achieved, practice problem on higher complexity level	7.2%	2.1%
Standard not achieved, video modelling example on similar or lower complexity level	4.0%	14.6%
Standard not achieved, worked example on similar or lower complexity level	8.0%	6.3%
Standard not achieved, practice problem on similar or lower complexity level	5.6%	8.3%
Ineffective task-selection decisions		
Other task-selection decisions[a]	40.0%	37.5%

Note: Standard achieved = performance 75% or higher.
[a]Other task-selection decisions concern ineffective decisions, such as selecting a task at a higher complexity level when the standard was not achieved (performance lower than 75%) or selecting a task at a similar or lower complexity level when the standard was achieved.

TABLE 9 Mean (M), standard deviation (SD), and median (med) of conceptual questions (range 0 to 9), isomorphic tasks (range 0 to 24), procedural transfer task (range 0 to 8), mental effort (range 1 to 9), self-efficacy (range 1 to 9), and perceived competence (range 1 to 7) for the informed self-regulated learning condition (n = 66), self-regulated learning condition (n = 32), and fixed sequences condition (n = 52)

	Informed self-regulated learning condition			Self-regulated learning condition			Fixed sequences condition		
	M	SD	Med	M	SD	Med	M	SD	Med
Pretest									
Conceptual questions	2.50	1.13	3.00	2.66	1.23	3.00	2.25	1.25	2.00
Self-efficacy	3.09	1.65	3.00	2.91	1.97	2.00	3.04	1.86	3.00
Perceived competence	2.62	1.50	2.33	2.49	1.40	2.17	2.65	1.47	2.17
Learning phase									
Self-efficacy	6.71	1.00	6.83	6.14	1.16	6.08	6.42	1.45	6.67
Mental effort	3.20	0.99	3.33	3.71	1.04	3.50	3.45	1.50	3.33
Time-on-task	8.28	2.43	8.50	7.38	2.32	8.00	7.50	2.17	7.25
Posttest									
Conceptual questions	3.73	2.23	3.00	3.63	2.49	3.50	3.77	2.21	4.00
Isomorphic tasks	14.62	7.84	16.50	13.41	7.05	14.50	13.38	7.67	15.50
Procedural transfer task	3.29	3.48	2.00	2.41	3.12	0.00	2.77	2.95	2.00
Mental effort conceptual questions	3.70	1.62	3.00	4.09	1.73	4.00	3.46	1.78	3.00
Mental effort isomorphic tasks	3.66	1.87	3.33	4.60	2.01	4.33	3.66	2.03	3.00
Mental effort procedural transfer task	4.59	2.78	3.00	4.81	2.82	4.00	4.35	2.52	3.00
Time-on-task conceptual questions	4.92	2.15	5.00	4.88	2.88	5.00	5.15	2.99	5.00
Time-on-task isomorphic tasks	8.82	3.29	8.33	10.17	3.15	10.00	10.51	3.61	9.67
Time-on-task procedural transfer task	4.64	2.99	5.00	5.59	4.11	6.00	6.56	4.23	6.00
Self-efficacy	7.27	1.22	7.00	6.72	1.11	6.50	7.06	1.65	7.00
Perceived competence	5.86	0.89	6.00	5.52	0.77	5.33	5.62	1.23	6.00

procedural transfer task ($H(2) = 5.92$, $p = 0.052$). Conditions differed in the average time-on-task invested in the isomorphic posttest tasks, $H(2) = 7.86$, $p = 0.020$. Follow-up analyses revealed that the ISRL-Condition invested less time in the isomorphic posttest tasks compared to the FS-Condition ($U = 1247.5$, $p = 0.011$, $r = 0.234$). No differences were found between the ISRL-Condition and SRL-Condition ($U = 1326$, $p = 0.041$, $r = 0.207$), nor between the SRL-Condition and FS-Condition ($U = 812.5$, $p = 0.857$, $r = 0.020$).

3.3.2 | Motivational aspects of learning

Self-efficacy

We found a main effect of Test Moment on students' self-efficacy from before to after the learning phase (at a sample level), ($Z = 10.45$, $p < 0.001$, $r = 0.853$), indicating that the self-efficacy medians significantly increased over time in the ISRL-Condition ($Z = 7.09$, $p < 0.001$, $r = 0.873$), SRL-Condition ($Z = 4.73$, $p < 0.001$, $r = 0.836$), and FS-Condition ($Z = 6.09$, $p < 0.001$, $r = 0.845$). Self-efficacy after the learning phase did not differ among conditions ($H(2) = 4.67$, $p = 0.097$). We did, however, find a significant difference among conditions regarding average self-efficacy ratings *during* the learning phase ($H(2) = 7.86$, $p = 0.020$). Post-hoc analyses revealed that average self-efficacy ratings were higher in the ISRL-Condition than the SRL-Condition ($U = 702.5$, $p = 0.007$, $r = 0.271$). No significant differences were found between the ISRL-Condition and FS-Condition ($U = 1881.5$, $p = 0.369$, $r = 0.083$), nor between the SRL-Condition and FS-Condition ($U = 680.5$, $p = 0.162$, $r = 0.129$).

Perceived competence

Analyzing whether perceived competence increased from pretest to posttest revealed a main effect of Test Moment ($Z = 10.54$, $p < 0.001$, $r = 0.861$). Perceived competence significantly increased in the ISRL ($Z = 7.07$, $p < 0.001$, $r = 0.870$), SRL ($Z = 4.94$, $p < 0.001$, $r = 0.874$), and FS-Condition ($Z = 6.11$, $p < 0.001$, $r = 0.847$). No differences were found among conditions, however, with regard to perceived competence rated after the learning phase, $H(2) = 5.34$, $p = 0.069$.

4 | DISCUSSION

This study investigated higher education students' self-regulated learning of problem-solving tasks in an online learning environment. We investigated whether the findings of Authors (submitted) that students regulate their learning from examples and practice problems quite well (i.e., in alignment with what we know to be effective task sequences from instructional design research) would replicate (Research Question 1), whether self-regulated learning of examples and problems would be as effective as fixed sequences of examples and problems (Research Question 2), and whether informing learners prior to self-regulated learning about the principles for effective task sequences derived from instructional design research would enhance their task selections, and thereby learning and motivation compared to self-regulated learning without such information and studying fixed sequences of tasks (Research Question 3).

Regarding the first research question, our results replicated the findings of Authors (submitted), as task selections of students in the self-regulated learning condition (and informed self-regulated learning condition) largely aligned with the instructional design principles. Almost all students followed the example-first-principle and lowest-level-first-principle by starting the learning phase with an example (predominantly a video modelling example) at the lowest complexity level. Also, the majority of students started each new complexity level with example study (and therefore selected more examples than problems) and built up the level of complexity of the learning tasks reasonably well, adhering to the start-each-level-with-example-study, example-based-learning, and simple-to-complex-principle. When exploring in more detail what task selections learners make after having solved a practice problem, we found that students made more effective (e.g., selecting a task at a higher complexity level when sufficiently high performance was achieved) than ineffective task selections (e.g., selecting a task at a higher complexity level when sufficiently high performance was not yet achieved), however, there seemed to be room for improvement.

As for the second research question, we found that self-regulated learning as effective, efficient, and motivating as a fixed task sequence based on the principles derived from instructional design research, since there were no performance or motivation differences between the self-regulated learning and fixed sequences condition. This is somewhat surprising in light of previous findings that fixed learning paths are often more effective for novices' learning than self-regulated learning (see e.g., Azevedo et al., 2008; Lawless & Brown, 1997; Niemiec et al., 1996). That self-regulated learning did not have additional motivational benefits might also seem surprising, as previous research suggests that providing learners with control over task selection can increase their motivation in terms of interest and involvement (e.g., Corbalan et al., 2008). However, self-regulated learning might not foster students' motivation in terms of perceptions of their own abilities (e.g., self-efficacy and perceived competence), possibly because this is much more related to learning outcomes (e.g., Collins, 1982), where we also found no effect.

With regard to the third research question, we found that explicitly informing learners about instructional design principles did enhance their self-regulated learning of examples and problems (at different complexity levels). That is, no significant differences were found between the two self-regulated learning conditions in how their task selections matched with the instructional design principles, except that students in the informed self-regulated learning condition followed the simple-to-complex-principle more often than students in the self-regulated learning condition did spontaneously. However, this facilitative effect did not enhance the informed self-regulated learning condition's learning or motivation compared to the self-regulated learning condition. There were two exceptions: relative to the self-regulated learning condition, the informed self-regulated learning condition showed more confidence in their own abilities during the learning phase (but this effect was not found after the learning phase) and invested less time in the posttest tasks isomorphic to the tasks in the learning phase. Finally, we did not find any differences on cognitive and motivational aspects of learning between the informed self-regulated learning condition and fixed sequences condition.

These findings raise an important question: Why did we (and Authors, submitted) find that students were already quite good at regulating their learning of examples and problems, while other studies found that having control over what information to study or what tasks to work on is not (entirely) effective for novices' self-regulated learning (e.g., Foster et al., 2018), and often less effective than learning from computer pre-structured or personalized sequences of tasks (e.g., Azevedo et al., 2008; Lawless & Brown, 1997; Niemiec et al., 1996)? A possible explanation is that our sample may have had substantial prior experience with learning from examples (cf. Authors, submitted). Although we cannot corroborate this idea with data, our students were likely quite experienced with example-based learning, because their electrical and electronic mechanical engineering programs rely heavily on mathematics. Example-based learning indeed is a very common strategy for learning mathematical problem-solving skills (Hoogerheide & Roelle, 2020). If students were accustomed to studying examples when learning new math problem-solving skills, this would explain why examples were selected more early and often. By contrast, Foster et al. (2018) tested a mixed student population (from the university's participant pool) that possibly had less experience with mathematics in their curricula and therefore with example-based learning. If true, this could explain why students in that study chose example study less early and often.

An alternative explanation is that the design of our task database helped students to rely more heavily on example study and lowest complexity level first, because it was displayed as an organized table left to right, starting with a video modelling example and lowest level task on the left side. Research has shown that in left-to-right languages, users often exhibit a viewing pattern that favours the left (and towards the top) of (web) pages or images (e.g., Afsari et al., 2016; Djamasbi et al., 2011). This 'viewing strategy' might have influenced students' task selections in such a way that it would lead one to generally select an example and low level task first and then a practice problem. This was different from the study of Foster et al. (2018), where each item in the SRL-condition was preceded by an description on screen that explained what a problem-solving and worked-example format looked like. Participants clicked on a button marked 'PS' or 'WE' to select the format for the subsequent assignment. In principle, future research could control for this by randomizing or counterbalancing the position of the task types and complexity levels in the task database. However, from an educational practice perspective, this would not be recommendable as it would disrupt learners' intuitive understanding of the task database layout (e.g., the buildup in complexity and support levels) which is information they need to be able to make their decisions.

Another important question is: Why did our intervention only show a minimal effect on students' task selections and why did it not enhance their learning and motivation? One possible explanation could be that approximately 40% of the students in the informed self-regulation condition did not watch the entire instructional video. However, additional exploratory analyses revealed no significant performance or motivational differences among conditions when those who did not watch the entire video were excluded (see Appendix D). A more likely explanation is that there was not that much room for students' task-selection skills to improve (with the exception of the simple-to-complex-principle, which those who studied the video did follow more often), as the self-regulated learning condition already did quite a good job in selecting tasks that matched with most of the instructional design principles.

A second potential explanation, given that there was still room for some improvement, is that informing students about the principles only once may not have been sufficient to improve task-selection behaviour to such an extent that it enhances students' learning and motivation. For example, students received a lot of information they had to both understand and memorize in order to apply it during the learning phase later. Although we provided a short review/reminder at the end of the instructional video, it is possible they forgot some of the principles and/or how/when to use them during the learning phase. A solution might be to allow students to go back to the description and explanation of the principles during the learning phase. It is also questionable whether 'merely' informing students about instructional design principles and how to apply them would improve task-selection behaviour to such an extent that it enhances students' learning and motivation. To achieve those changes, it is considered important to ensure that learners also experience what the 'planned behaviour' actually brings them (i.e., to enhance their beliefs and commitment; McDaniel & Einstein, 2020). This might be achieved by additionally having students practice with and/or reflect on the information that is provided to them (e.g., Biwer et al., 2020; Endres et al., 2021). Finally, it would be interesting in this respect to also explicitly test whether students' (metacognitive) knowledge has actually been improved after watching such a video instruction. As increasing metacognitive knowledge could increase the likelihood an individual will modify and apply a strategy (e.g., Tullis et al., 2013; Yan et al., 2014), it is interesting to know whether this knowledge is actually enhanced after watching the instructional video.

Finally, results showed that more than one-third of the task selections made after problem-solving practice were likely not effective for learning. These results could suggest that students generally had a good sense of what to do (as their task-selections matched fairly well with the instructional design principles), but had some trouble in making adequate judgements of their learning needs at a specific moment and therefore did not always make relevant task-selections after problem-solving practice opportunities. For instance, increasing the level of complexity is a choice that generally aligns well with the principles, yet, if a student does so too quickly (i.e., without being able to perform the task on a lower level well enough), that would be an ineffective choice. In other words, students might have experienced some difficulties with self-assessing their performance after working on a practice problem and use this information to select a suitable follow-up task. Therefore, it might be necessary to link the instructional design principles more strongly to students' self-assessments of their understanding and performance (e.g., emphasize what to do when they do not yet master a task at a certain complexity level) or to target their self-assessment ability in the intervention (cf. Kostons et al., 2012; Raaijmakers et al., 2018).

4.1 | Limitations

This study does have several important limitations. First, it is an open question to which extent our findings are generalizable, because our sample –despite being novices– might have had prior experience with example-based learning and/or similar types of (math) tasks. Less experienced samples would likely show different (i.e., worse) task-selection behaviour. Therefore, it is unclear whether our instructional video intervention would have a more pronounced effect (i.e., improve task-selection, and thereby motivation and learning) under different circumstances, such as with less experienced samples. A particularly interesting avenue for future research would be to test this intervention with a sample that has previously been shown to show suboptimal task-selection behaviour when learning from examples and problems (e.g., Foster et al., 2018).

A second limitation is that, although our students had more responsibility and control over their learning relative to most example-based learning research, they still did not have full control over their learning. This choice was made to ensure that all three conditions would be comparable in all other respects (e.g., that all conditions studies 6 learning tasks). Yet in real learning settings there would likely be much more variation in the number (and type) of tasks selected, because an ideal task sequence hinges on students' prior knowledge, speed of learning, motivation, and effort investment and therefore varies from learner to learner. Therefore, future research could examine what choices students make when it is entirely up to them how many learning tasks they select.

A third limitation concerns the measurement of self-efficacy and perceived competence. There is research showing overlap between these two constructs, and more specifically that perceived competence may be a common core component of both self-efficacy and self-concept (e.g., Marsh et al., 2019; Schunk & Pajares, 2005). This idea is confirmed by the correlational analyses of these two constructs measured after the self-regulated learning phase in our study, $r = 0.860$, $p < 0.001$. As these measures seem to measure the same general feeling of competence regarding to what has been learned and how well someone considers him/herself capable in solving a similar task, it might be sufficient to use of one of the questionnaires in future research.

4.2 | Conclusion and implications for practice

To conclude, the findings suggest that the higher education students who participated in this study were relatively good at regulating their own learning with examples and problems in online learning environments (cf. Van Harsel et al., submitted). This is an important finding because providing students with control over their own learning is becoming more and more common, especially in higher education. Given that earlier studies painted a less rosy picture of students' self-regulated learning of problem-solving skills using examples and problems (e.g., Foster et al., 2018), and that the sample used in this study might have had some prior experience with similar mathematics problem-solving tasks, future research is needed to uncover under which circumstances students can and cannot regulate their learning of new problem-solving skills. Moreover, our findings also suggest that there is still room for some improvement in students' task selections. Informing students about evidence-based instructional design principles via an instructional video can help them to apply the simple-to-complex-principle more often, however, not to such an extent that it results in performance or motivational benefits. Therefore, future research should examine how the design and/or implementation of this intervention can be improved to (further) improve self-regulated learning of our population and other populations of higher education students.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHOR CONTRIBUTIONS

Milou van Harsel, Vincent Hoogerheide, Peter Verkoeijen, and Tamara van Gog contributed to the study conception and design. Milou van Harsel carried out material preparation, data collection, and data analysis. Milou van Harsel written the first draft of the manuscript. Vincent Hoogerheide, Peter Verkoeijen, and Tamara van Gog commented on subsequent versions of the manuscript. Milou van Harsel, Vincent Hoogerheide, Peter Verkoeijen, and Tamara van Gog read and approved the final manuscript.

INFORMED CONSENT

All participants gave their informed consent in the online learning environment.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/jcal.12589.

DATA AVAILABILITY STATEMENT

The datasets generated during and/or analyzed during the current study are available from the corresponding author on request.

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ENDNOTE

[1] Upon a reviewer's request, we explored whether the degree of applying the instructional design principles correlated with posttest performance. Results showed that total scores of how well students applied all the principles (total score) did not correlate with isomorphic task performance ($r = 0.135$, $p = 0.184$), conceptual task performance ($r = 0.150$, $p = 0.141$), or procedural transfer task performance ($r = 0.067$, $p = 0.513$).

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APPENDIX A.: EXAMPLES OF A CONCEPTUAL PRIOR KNOWLEDGE TEST QUESTION, ISOMORPHIC, AND TRANSFER POSTTEST TASKS

Conceptual prior knowledge test question

Question 6: What is the minimum required number of measurement points needed to be able to successfully apply the trapezoidal rule?

a. 0

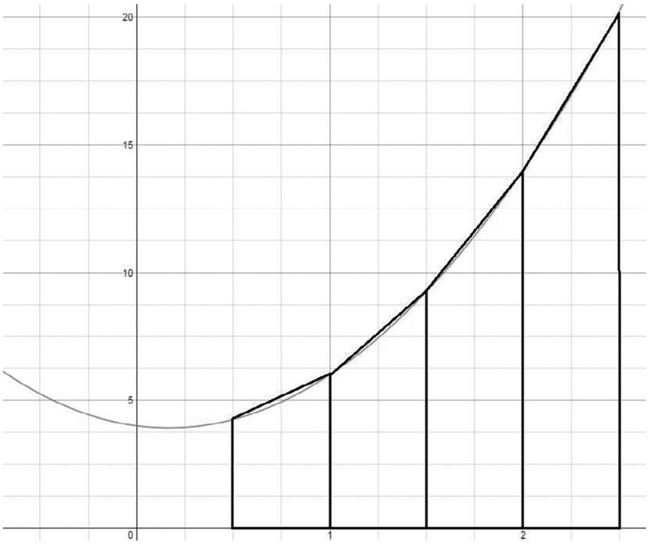
b. 1

c. 2

d. 3

Isomorphic posttest task

Rachel is an intern at a factory that produces different kinds of perfume. At one point, Rachel's supervisor asks her to examine how many litres of perfume is produced of the brand 'Scents' in two days. Rachel has measured this and plotted the results in a graph. The time (in days) is plotted on the horizontal axis and the litres (litre per day) are plotted on the vertical axis. By approaching the area under the graph, Rachel can determine how much litre has been produced during a certain amount of time.



Approaching the area under the graph can be done by using the trapezoidal rule:

$$\frac{(b-a)}{n}\left[\frac{1}{2}f(x_0)+f(x_1)+f(x_2)+\cdots+\frac{1}{2}f(x_n)\right]$$

The trapezoidal rule divides the area under a graph into 'strips'. By adding up the surface of the 'strips', you can approach the total area under the graph. To approach the area under the graph, you need the following information:

a: this is the left x value of the area that has to be approached;

b: this is the right x value of the area that has to be approached;

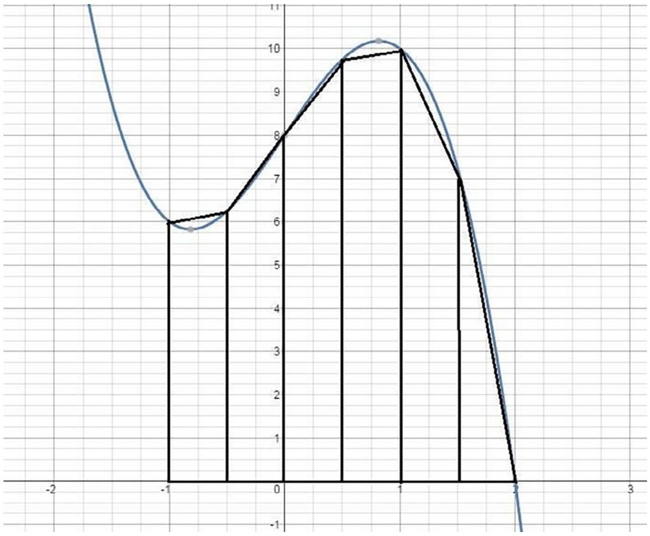
n: this is the number of 'strips' in which the area is divided;

xi: this is the x-value that belongs to the left- or right border of a 'strip' and it is calculated using the following function:

Approach the area under the graph using the information that is given. Write down all your intermediate steps and calculations.

Procedural transfer task

It takes energy to stop an elevator at a certain level. This energy is proportional to the distance between the current and desired position. Jimmy wants to determine how much energy is used to stop the lift three levels higher by measuring the distance during a certain amount of time. Jimmy has plotted the results in a graph. The time (in seconds) is plotted on the horizontal axis and the distance (in metres) is plotted on the vertical axis. By approaching the area under the graph, Jimmy can determine the energy that is needed.



Approaching the area under the graph can be done by using the Simpson rule:

$$\int_a^b f(x)dx \approx \frac{b-a}{6}\left[f(a)+4f\left(\frac{a+b}{2}\right)+f(b)\right]$$

The Simpson rule divides the area under a graph into 'strips'. By adding up the surface of the 'strips', you can approach the total area under the graph. To approach the area under the graph, you need the following information:

a: this is the left x value of the area that has to be approached;

b: this is the right x value of the area that has to be approached;

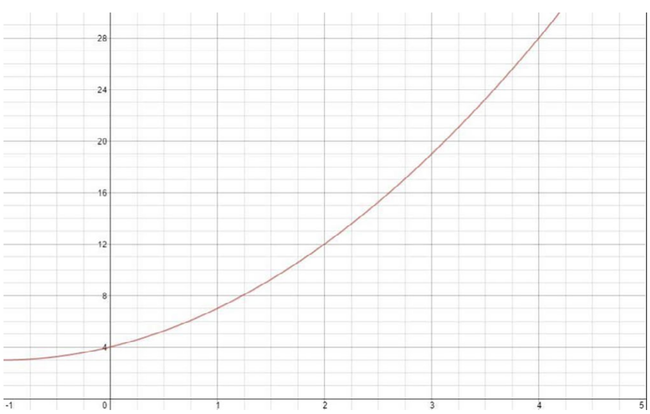
n: this is the number of 'strips' in which the area is divided;

xi: this is the x-value that belongs to the left- or right border of a 'strip' and it is calculated using the following function:

Approach the area under the graph using the information that is given. Write down all your intermediate steps and calculations.

Conceptual transfer item

Study the graph below (this is a part of a parabola):



You can approach the area under this graph with help of the trapezoidal rule in two ways:

A. Left border 2 and right border 4
B. Left border 7 and right border 9

Which surface will approach the exact surface at best? Choose one of the options and explain your answer.

APPENDIX B.: TRANSLATED SCRIPT FOR THE VIDEO INSTRUCTION (IN ENGLISH)

Soon, you will learn all about the mathematical subject 'the trapezoidal rule' in the online learning environment. You are free to choose six tasks that will help you to learn the trapezoidal rule to the best of your abilities. As you know, there are tasks at 3 levels of complexity. You can choose tasks at each of these complexity levels in the form of video modelling examples, worked examples, or practice problems. Do you already know what tasks you want to select to be able to solve all the tasks on the posttest? Here are four tips, derived from scientific research, that can help you learn as much as possible.

Tip 1: First, choose a task at the lowest complexity level and build up the complexity of the tasks.

If you start learning and you don't how to use the trapezoidal rule, it might be good start with a task that is not too difficult. Therefore, choose a task at the lowest complexity level. Do you feel you've mastered this level? Then, choose a task at a higher complexity level. This way, you build up the complexity of the tasks in such a way that it fits with what you already know.

Tip 2: Start with an example at each complexity level, especially when you feel you (still) know too little to solve the tasks.

If you don't know much about how to use the trapezoidal rule, it is not only useful to start with a task at the lowest complexity level, but also to learn more about how to solve such a task. By choosing an example, you will learn how to use the trapezoidal rule, because an example shows you how to solve a problem step-by-step. This prevents you from spending a lot of time figuring out the right solution procedure yourself. Starting with an example is therefore also very helpful when you want to choose a task at a higher complexity level.

Tip 3: Start at the very beginning with a video modelling example, then choose worked examples.

You can choose two different example formats. A video modeling example provides a lot of support during learning, because you can hear and see the solution procedure step-by-step. This is very useful if you are studying the trapezoidal rule for the first time. You can also opt for a worked example. In a worked example, you can only see the entire solution procedure. Whereas the information in a video modeling example quickly disappears, all steps are always visible in a worked example. This is very useful if you already understand part(s) of the solution procedure, but want to look up some more (difficult) steps.

Do you think you understand the solution procedure presented in the examples and want to check whether you do? Then, choose a practice problem so you can practice the task.

Tip 4: Alternate examples and practice problems.

As said before, it is recommended to select an example first before solving a practice problem when you want to move to a higher complexity level for the first time. This way, you can study the steps that you might find difficult. Moreover, you get an impression of the complexity of the task. When you think you understand the problem-solving procedure, then select a practice problem so you can test whether you actually understand the problem-solving task.

Before you start, here is a short summary of the tips:

Tip 1: First, choose a task at the lowest complexity level and build up the complexity of the tasks.

Tip 2: Start with an example at each complexity level, especially when you feel you (still) know too little to solve the problem.

Tip 3: Start at the very beginning with a video modeling example, then choose worked examples.

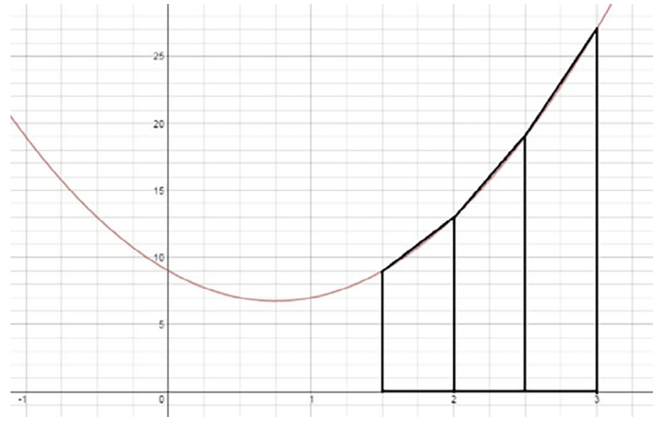
Tip 4: Alternate examples and practice problems.

And now it is time to get started, good luck!

APPENDIX C.: EXAMPLES OF FORMATS

Practice problem

Jalil has bought a solar cell and wants to know how much energy the solar cell supplies during a certain amount of time. Jalil has used an energy meter to examine how much energy the solar cell produces during a specific amount of time. Jalil has measured the energy at different time points and plotted the results in a graph. The time (in minutes) is plotted on the horizontal axis and the power the solar cell supplies (Joule per minute) is plotted on the vertical axis of the graph. By calculating the area under the graph, Jalil can determine how much energy the solar cell has produced during a certain amount of time.



Approaching the area under the graph can be done by using the trapezoidal rule:

$$\frac{(b-a)}{n}\left[\frac{1}{2}f(x_0)+f(x_1)+f(x_2)+\cdots+\frac{1}{2}f(x_n)\right]$$

The trapezoidal rule divides the area under a graph into ‘strips’. By adding up the surface of the ‘strips’, you can approach the total area under the graph. To approach the area under the graph, you need the following information:

a: this is the left x value of the area that has to be approached;

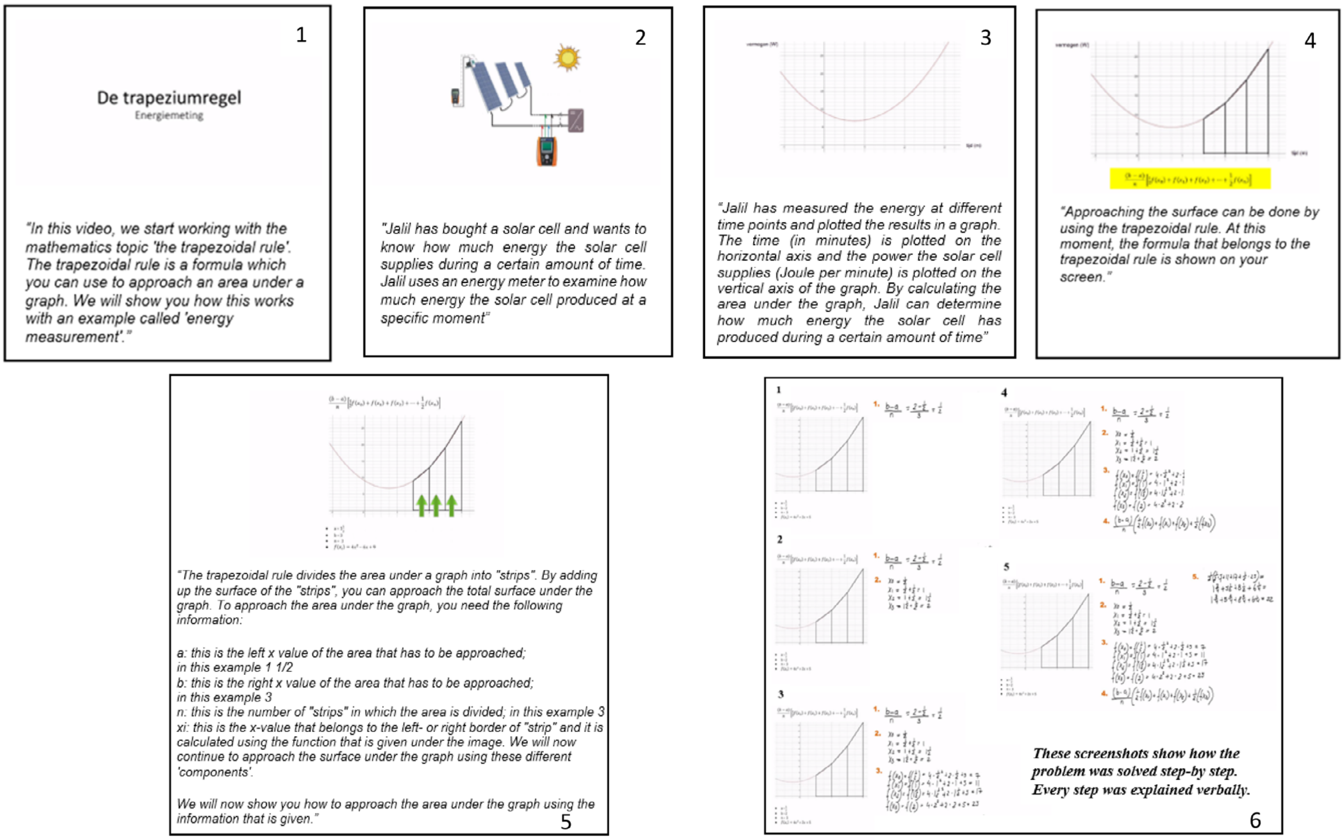
b: this is the right x value of the area that has to be approached;

n: this is the number of ‘strips’ in which the area is divided;

xi: this is the x-value that belongs to the left- or right border of a ‘strip’ and it is calculated using the following function: $f(x) = 3x^2 - 6x+$

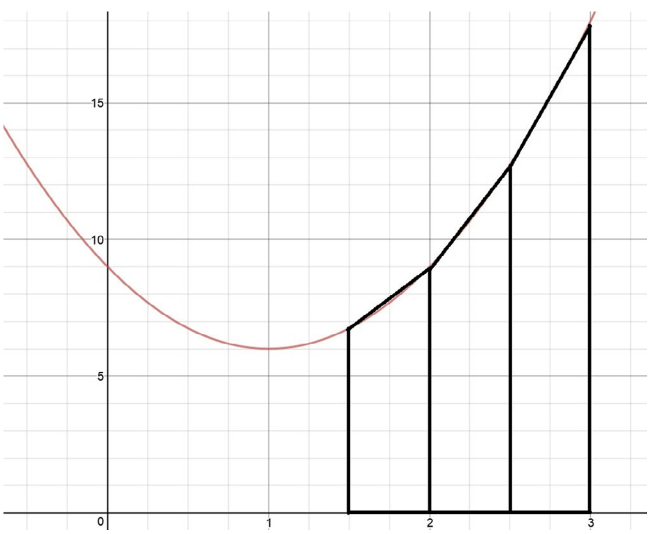
Approach the area under the graph using the information that is given. Write down all your intermediate steps and calculations.

Video modeling example



Worked example

Jalil has bought a solar cell and wants to know how much energy the solar cell supplies during a certain amount of time. Jalil has used an energy meter to examine how much energy the solar cell produces during a specific amount of time. Jalil has measured the energy at different time points and plotted the results in a graph. The time (in minutes) is plotted on the horizontal axis and the power the solar cell supplies (Joule per minute) is plotted on the vertical axis of the graph. By calculating the area under the graph, Jalil can determine how much energy the solar cell has produced during a certain amount of time.



Approaching the area under the graph can be done by using the trapezoidal rule:

$$\frac{(b-a)}{n}\left[\frac{1}{2}f(x_0)+f(x_1)+f(x_2)+\cdots+\frac{1}{2}f(x_n)\right]$$

The trapezoidal rule divides the area under a graph into 'strips'. By adding up the surface of the 'strips', you can approach the total area under the graph. To approach the area under the graph, you need the following information:

a: this is the left x value of the area that has to be approached, this is $a=1\frac{1}{2}$

b: this is the right x value of the area that has to be approached, this is $b=3$

n: this is the number of 'strips' in which the area is divided, this is $n=3$

xi: this is the x-value that belongs to the left- or right border of a 'strip' and it is calculated using the following function: $f(x)=3x^2-6x+9$

Step 1: Compute the step of each subinterval $\frac{b-a}{n}$

1. $b-a=3-1\frac{1}{2}=1\frac{1}{2}$
2. $\frac{1\frac{1}{2}}{3}=\frac{1}{2}$

Step 2: Calculate the x-values:

1. $x_o=a, \text{so } x_0=1\frac{1}{2}$

2. $x_1 = x_0 + \text{subinterval}, \text{so}\ x_1 = 1\frac{1}{2} + \frac{1}{2} = 2$
3. $x_2 = x_1 + \text{subinterval}, \text{so}\ x_2 = 2 + \frac{1}{2} = 2\frac{1}{2}$
4. $x_3 = x_2 + \text{subinterval}, \text{so}\ x_3 = 2\frac{1}{2} + \frac{1}{2} = 3$

Step 3: Calculate the function values for all x-values

1. $f(x_0) = f\left(1\frac{1}{2}\right) = 3.1\frac{1}{2}2 - 6.1 + 9 = 6\frac{3}{4} - 9 + 9 = 6\frac{3}{4}$
2. $f(x_1) = f(2) = 3.2^2 - 6.2 + 9 = 12 - 12 + 9 = 9$
3. $f(x_2) = f\left(2\frac{1}{2}\right) = 3.2\frac{1}{2}2 - 6.2\frac{1}{2} + 9 = 18\frac{3}{4} - 15 + 9 = 12\frac{3}{4}$
4. $f(x_3) = f(3) = 3.3^2 - 6.3 + 9 = 27 - 18 + 9 = 18$

Step 4: Enter the function values into the formula and calculate the area

Formula: $\frac{(b-a)}{n}\left[\frac{1}{2}f(x_0) + f(x_1) + f(x_2) + \frac{1}{2}f(x_3)\right]$

Adjusted formula with step 1 and 2 included:

$$\frac{1}{2}\left[\frac{1}{2}f(x_0) + f(x_1) + f(x_2) + \frac{1}{2}f(x_3)\right]$$

Adjusted formula with step 3 included and calculated:

$$\frac{1}{2}\left[\frac{1}{2}\cdot 6\frac{3}{4} + 9 + 12\frac{3}{4} + \frac{1}{2}\cdot 18\right] = \frac{1}{2}\left[3\frac{3}{8} + 9 + 12\frac{3}{4} + 9\right] = \frac{1}{2}\cdot 34\frac{1}{8} = 17\frac{1}{16}$$

The approached area under the graph is $17\frac{1}{16}$

APPENDIX D.: EXPLORATIVE ANALYSES OF DIFFERENCES AMONG SUBGROUPS IN THE ISRL-CONDITION

We explored to which degree participants in the ISRL-Condition followed the instructional design principles depended on whether they watched the entire, between half and three quarter, or less than half of the video. Results showed that these groups differed in following the lowest-level-principle ($H(2) = 7.55, p = 0.023$); however, post-hoc tests with a Bonferroni correction revealed no significant results (*ps* = 0.019; adjusted level of significance = 0.017). The groups also differed in following the simple-to-complex-principle ($H(2) = 13.45, p = 0.001$), and follow-up analyses showed that watching the entire ($U = 151, p = 0.002, r = 0.425$) or between half and three quarter of the video instruction ($U = 45.5, p = 0.014, r = 0.556$) resulted in higher scores on following the simple-to-complex-principle than watching less than half of the video. Finally, there was a difference among groups in the total score on following the principles ($H(2) = 7.77, p = 0.021$). Post-hoc tests showed that participants who watched the entire video instruction scored higher on following all of the principles than participants who watched less than half of the video instruction ($U = 152.5, p = 0.010, r = 0.357$).

We also explored whether there were performance and motivational differences among participants in the ISRL condition, depending on whether they watched the entire, between half and three quarter, or less than half of the video instruction. There were no significant differences among these groups on any of the outcome variables ($ps = 0.77$), except for participants' confidence in their own abilities before the learning phase, as indicated by a main effect on pretest self-efficacy ($H(2) = 10.46, p = 0.005$) and pretest perceived competence ($H(2) = 7.24, p = 0.27$). Post-hoc tests only showed one significant comparison on both motivational measures: relative to the participants who only watched between half and three quarter of the video, those who watched the entire video indicated lower levels of pretest self-efficacy ($U = 407, p = 0.003, r = 0.413$) and perceived competence ($U = 380.5, p = 0.016, r = 0.334$).