Effects of a Digital Math Training Intervention on Self-Efficacy: Can Clipart Explainers Support Learners?

Markus H. Hefter[a], Rudolf vom Hofe[b], and Kirsten Berthold[a]

Corresponding author: Markus H. Hefter (markus.hefter@uni-bielefeld.de)
[a]Faculty of Psychology and Sports Science, Department of Psychology, Bielefeld University, D-33501 Bielefeld, Germany
[b]Faculty of Mathematics, Bielefeld University, D-33501 Bielefeld, Germany

Keywords: clipart explainers, digital training intervention, self-efficacy, self-explanation, worked examples

Abstract

In the mathematics domain, learning from worked examples is a best practice method for initial skill acquisition. However, open questions refer to effective digital training interventions in the field. Subject to these questions are the potential effects of self-explanations on self-efficacy, and the role of clip art explainers currently in vogue (cartoon teachers plus explanations in speech bubbles). We thus developed and field-tested a short-term (approximately 45 minutes) digital training intervention on mathematical proportionality with 113 German secondary school students (M_{age}: 14.12 years). We applied a quantitative experimental research design to analyse learning processes and outcomes with tests and questionaires. To investigate the potential supportive effects of the clipart explainers, we compared two versions of our intervention: with clip art explainers (clipart condition) and without them (control condition). Our training intervention revealed a significant positive within-subjects effect on the learners' mathematical self-efficacy related to proportionality tasks. The clipart explainers had a significant negative between-subject effect on the subjective difficulty of the instructional material—with no indications of being detrimental to learning. Finally, we detected self-explanation quality and task engagement to be significant predictors for learning outcomes. Our findings underscore the importance of having learners deeply process the given materials.

Introduction

Imagine you want to bake cookies for 12 people, but your recipe calls for 600ml cookie dough, which is the recommended amount to satisfy only eight cookie-craving people. To compute the required amount of dough for 12 people, you first calculate the amount for one person (i.e. 600ml divided by 8). Then you multiply this result (i.e. 75ml) by 12, thus figuring out the required amount for 12 people (i.e. 900ml). You probably remember this type of calculation as the rule-of-three from schooldays. This is a worked example on the principles of direct proportionality in mathematics. Worked examples like this appear in manifold forms in mathematical schoolbooks, usually following instructional explanations of newly introduced principles (e.g. Bakenhus et al., 2013; Bierwirth et al., 2013; Eichenlaub-Fürst, Fischer, Liebau, Mohr, & Widl, 2019; Hecht et al., 2013). In particular, but not exclusively in the mathematics domain, learning from worked examples is a well-established, intuitively appealing, evidence-backed, best practice method for initial skill acquisition (e.g. Kirschner, Sweller, & Clark, 2006; Renkl, 2017).

However, open questions remain, as we will identify and address three research desiderata in the present paper: (1) testing a digital math training intervention based on worked examples in realistic field rather than artificial lab conditions, (2) analysing its effects on mathematical self-efficacy rather than mere knowledge gains, and (3) analysing potential effects of adding clipart explainers currently in vogue (i.e. cartoon teachers plus explanations in speech bubbles).

Effective learning from worked examples—self-explanation and example-set principles

Exhaustive research has backed the effectiveness of example-based learning for individuals with little or no prior knowledge (Renkl, 2014, 2017). This effectiveness is plausible because a worked example presents concrete solution steps to a given problem. These solution steps are principles that uninformed learners usually do not know yet. Thus, when confronted with a problem, there is nothing else for them to do but try to follow general or superficial solution strategies. As cognitive load theory suggests, this search for a solution exhausts learners' limited cognitive resources (Sweller, Ayres, & Kalyuga, 2011). Consequently, cognitive overload occurs, thus compromising learning. In contrast, processing a worked example instead of a problem frees learners from the search for a solution. Now, cognitive resources are spared to apply for learning. However, presenting concrete solutions steps in the shape of a worked example is only half the battle. Effective example-based learning requires the implementation of instructional guidelines (Renkl, 2021). This paper focuses on two crucial ones for the mathematical domain (i.e. *self-explanation* and *example-set principles*).

Self-explanation principle

For a start, learners need to deeply process the given examples to understand, memorise, and eventually apply their underlying principles later. That is where self-explanations come into play (*self-explanation principle*, Renkl, 2014). Generating self-explanations means explaining the worked examples' principles to oneself (Renkl, 2014) and thereby integrating and/or generalising knowledge (Rittle-Johnson, Loehr, & Durkin, 2017). This is a powerful and productive learning strategy that can promote learning outcomes such as conceptual or procedural knowledge (Wylie & Chi, 2014). As learners seldom engage spontaneously in self-explaining, so-called self-explanation prompts offer effective instructional support (e.g. Berthold & Renkl, 2010). Usually, such prompts simply request that learners explain the given solution steps to themselves and type their self-explanations in a text box. Learners commonly fulfil these requests, and researchers thus can rate the quality of learners' typed-in self-explanations (e.g. Hefter, Fromme, & Berthold, 2022). Such ratings of self-explanation quality are a measure of learners' performance in self-explaining, such as generating correct and exhaustive self-explanations. Overall, striving for high self-explanation quality is reasonable, as it is the quality of deeply processing to-be-learned principles in the form of knowledge integration and/or generalisation. Indeed, self-explanation quality was a significant mediator of immediate learning outcomes (e.g. Berthold, Eysink, & Renkl, 2009) as well as of learning outcomes in delayed posttests (e.g. Hefter, ten Hagen, Krense, Berthold, & Renkl, 2019; Hefter et al., 2022).

Example-set principle

Let us assume the aforementioned self-explanation principle is in action and learners successfully generate high-quality self-explanations. There is still another instructional guideline to consider for effective learning from worked examples in mathematics, which Renkl (2014) calls the *example-set principle*. According to this guideline, a set of examples should make the important to-be-learned principles salient to the learners. In mathematics, worked examples feature these to-be-learned principles (i.e. the structure) as well as some sort of arbitrary cover story (i.e. the surface). These little cover stories, like that about baking cookies or booking tickets, exemplify the to-be-learned principles.

For instance, a typical worked example's story is about a fictive person (Erik) who needs to bake cookies for 12 people but his recipe's amount of dough accounts for only eight people.

To calculate the amount for 12 people, Erik applies the principles of direct proportionality (divide the given amount by 8 and multiply it by 12). Another cover story for a worked example on direct proportionality is about buying tickets (without discount), when the number of people is in direct proportion to the ticket costs. Very similar but slightly more complicated, there are also the principles of inverse proportionality to consider. In our fictive case, Erik has a fixed amount of dough for eight people, but he expects 12 people. Thus, to bake more cookies from the same amount of dough, they—the cookies—need to be smaller. To calculate the mass of one cookie for 12 people, Erik needs to multiply the previous cookie mass by 8 and divide that product by 12. To concoct a similar ticket cover story for a worked example on inverse proportionality, consider a fixed ticket price for a group of people. Reducing the group size increases the ticket prize for each group member.

All in all, it is crucial that learners realise that they should focus on the examples' structure (here: principles of direct or inverse proportionality). They should not be tempted to assume that a certain cover story (here: cookies or tickets) implies a certain solution (Renkl, 2014). Hence, it is reasonable to implement structure-emphasising example sets (Quilici & Mayer, 1996) that vary both the examples' structure and surface, making the key learning principles salient. In the present case, this would mean a set of four worked examples combining both structure (here: principles of direct and inverse proportionality) and surface features (here: cookies and tickets cover story).

Overall, for our training intervention in the present study, we follow both instructional guidelines for example-based learning (i.e. self-explanation and the example-set principles). Moreover, we focus on the domain of mathematics. So did Rittle-Johnson et al. (2017), who analysed 26 published studies that compared self-explanations prompts with no self-explanation prompts in mathematics content. Learners' age varied from preschool to adulthood. However, only seven of these studies featured a realistic classroom environment, unlike the majority that took place in a laboratory environment. Rittle-Johnson et al. (2017) plausibly suggest less effort by learners in such realistic field conditions than in lab conditions. Hence, field-testing is an important research desideratum—combined with assessing learners' task engagement—, which we thus address in this paper.

Fostering self-efficacy through learning from worked examples

Another important research desideratum relates to self-efficacy. The concept of self-efficacy goes all the way back to Bandura (1977) and concerns—in a tiny nutshell—the belief about one's own confidence in the ability to successfully perform a particular given task. It is important to note self-efficacy's focus on specific tasks or problems. Ever since, a substantial body of research has identified self-efficacy's influence on performance, effort, persistence, and motivation (e.g. Dunlap, 2005; Lindstrøm & Sharma, 2011; Siegle & McCoach, 2007; Sharp, Rutherford II, & Echols, 2022). In light of this, it is not surprising that researchers have investigated how to improve learners' self-efficacy. For instance, Siegle and McCoach (2007) developed a teacher training intervention to improve students' self-efficacy by focusing on goals and feedback. Moreover, Dunlap (2005) showed positive effects on self-efficacy through a 16-week problem-based software engineering course. Finally, Hicks, MacDonald, and Martin (2017) fostered learners' science-related self-efficacy in their targeted intervention over a period of four weeks. Such long-term courses are all well and good, but what about short-term yet effective example-based learning interventions and their effects on self-efficacy?

Rittle-Johnson et al.'s (2017) meta-analysis provided a comprehensive overview of 26 published studies (i.e. 22 papers between 1998 and 2014) on short-term mathematical interventions built around self-explaining and worked examples. Notably, though, none of those 26 studies assessed self-efficacy. At least Crippen and Earl (2007) detected positive effects of a worked example with a self-explanation prompt on self-efficacy in their quasi-experiment in the chemistry domain. In a follow-up study, Biesinger and Crippen (2010) obtained mixed results of a web-based learning environment that included selective additional worked examples in the domain of chemistry on self-efficacy. Finally, Hoogerheide, Loyens, and Van Gog (2014) found positive effects of example-based learning on self-efficacy in two experiments across three different types of examples (worked examples, modelled examples with visible model, and modelled examples without visible model). Overall, the research on worked examples, self-explaining and self-efficacy is rather scant.

A possible explanation for this peculiarity is provided in Van Gog and Rummel's (2010) remarks on the difference between the two research perspectives on worked examples and on modelling examples. In short, worked examples rather focus on presenting (mostly written) solution steps to a learner, whereas modelling examples rather focus on presenting a model's demonstration of solving a problem (for an overview of both perspectives, see also Renkl, 2014). All commonalities and similarities aside, the research on modelling examples has tended to focus on how they affect learners' self-efficacy. By contrast, research on worked examples has focussed more on skill acquisition and cognitive load. Consequently, Van Gog and Rummel (2010) point out the potential of combining the strong points of both perspectives. Hence, we eagerly answer their call to analyse possible effects of (self-explaining) worked examples on self-efficacy in the present paper.

Moreover, we argue that an effective training intervention based on worked examples and self-explanation has the potential to foster mathematical self-efficacy in two ways. Studying worked examples might have an effect similar to expert modelling, improving self-efficacy (Schunk, 1981, 1996). Furthermore, Crippen and Earl (2007) identified no effect from the worked example on self-efficacy—until they added a self-explanation prompt. Thus, self-explaining might play a role in reinforcing a worked example's potential positive effect on self-efficacy and go the extra mile by experiencing mastery in the form of generating self-explanations.

Risks and potentials of providing additional clipart explainers

Besides following the aforementioned instructional guidelines, another rationale for developing an effective digital training intervention on mathematical proportionality was to employ authentic schoolbook materials. In recent years, small instructional measures that we call clipart explainers have emerged in various mathematic schoolbooks (e.g. Bakenhus et al., 2013; Bierwirth et al., 2013; Eichenlaub-Fürst et al., 2019; Hecht et al., 2013). They consist of a clipart or comic-like drawing of a young and supposedly hip person who provides short, simple explanations in a speech bubble. Clipart explainers are usually located on pages that introduce a new topic, accompanying instructional explanations and worked examples. Specific studies on the effect of these clipart explainers are sparse at best, but previous research offers food for thought about their potential and risks.

On the potential side, clip art explainers might help learners acquire deeper understanding because they might reduce the learning material's difficulty. Learning material consists of different representations such as texts, calculations, tables, etc. Hence, learners need to connect different representations in their working memory, which is considered difficult and cognitively demanding (Seufert & Brünken, 2006). They have to integrate information from multiple representations (Ainsworth, 2006). Concerning authentic schoolbook material on mathematical proportionality (e.g. Bierwirth et al., 2013), these multiple representations comprise at least two information sources: the worked example's written text (similar to this paper’s introduction) and a typical proportionality table. Figure 1 shows such a table from our intervention.

	Number of people	Amount of dough (in ml)	
	8	600	
: 8	1	75	: 8
• 12	12	900	• 12

Figure 1. Proportionality table for a worked example on direct proportionality

A clipart explainer that uses simple and short language might actually serve as support on a “deep structure level” (Seufert & Brünken, 2006), because it explicitly exposes how the corresponding structures are semantically connected. Figure 2 illustrates a clip art explainer such as the ones from our intervention.

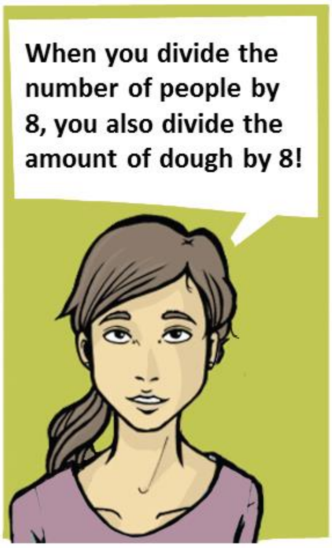

Figure 2. Clipart explainer for a worked example on direct proportionality. Illustrated by Carla Miller. Adapted with kind permission of Westermann Gruppe, Braunschweig, Germany, Copyright (2020).

On the downside, clipart might trigger side effects that jeopardise learning from a cognitive load perspective. First, adding such clip art explainers might be rather irrelevant for learning. However, they might catch learners’ interest (i.e. seductive details) and thus bind their limited cognitive resources (Mayer, Griffith, Jurkowitz, & Rothman, 2008). Their potential motivational and cognitive (side)-effects should therefore be carefully considered (Magner, Schwonke, Aleven, Popescu, & Renkl, 2014; Mayer & Moreno, 2003). Second, learners have to pay attention to both the clipart explainers and the material it accompanies, because they somehow need to integrate both information sources mentally. While doing or trying to do so, they are prone to the split-attention effect, which again bears the risk of binding their limited cognitive resources (Ayres & Sweller, 2014). Summing up, as open questions remain regarding the potential benefits and risks of these clipart explainers, we analysed their effects in the present paper.

Hypotheses

In light of these considerations and to address the initially mentioned research desiderata, we developed a short-term (~45 minute) digital math training intervention. We followed a twofold rationale: (1) Implementing state-of-the-art instructional guidelines for example-based learning (such as the self-explanation and example-set principles) and (2) using authentic and well-established schoolbook materials (such as worked examples and instructional explanations).

In particular, we assumed that…

H1: …our training intervention positively affects learners' mathematical self-efficacy.

H2: …self-explanation quality and task engagement positively influence learning outcomes.

Our final research desideratum was to investigate the supportive potential of clipart explainers during the training intervention. Thus, we analysed whether presenting clipart explainers…

H3: …affects learners' self-explanation quality and learning outcomes.

H4: …affects learners' subjective mental effort and perceived task difficulty.

Method

Sample and design

The ethics committee of Bielefeld University (No. 2019–159) approved the experiment. We recruited four classes at one German secondary school, yielding a sample of 113 students in the eighth grade. We received written informed parental consent for all participants ($N = 113$; $M_{\text{age}} = 14.12$, $SD_{\text{age}} = 0.67$; 61 female, 52 male; 53 native and 60 non-native speakers). Our study took place in the schools' computer room during regular mathematics lessons. The students were under our complete supervision in the presence of their mathematics teacher.

Our digital training intervention entailed a simple built-in randomisation routine for our experimental design with two conditions: Each participant had a 50/50 chance of starting one of two versions: (a) with clipart explainers (clipart condition, $n = 55$), (b) without clipart explainers (control condition, $n = 58$).

In general, we refrained from simply comparing the conditions training intervention versus no intervention for two reasons: First, to avoid triviality, because—as discussed in the introduction—there is already exhaustive research on example-based interventions' effectiveness on learning outcomes. Second, to avoid disadvantages for students who would not participate in the intervention during regular math lessons. Hence, learners in both conditions received our training intervention (albeit with or without additional clipart explainers). Consequently, we conducted between-subject comparisons to check for effects of the clipart explainers on learning processes and outcomes. To check for the effect of the whole intervention on self-efficacy, we conducted within-subject comparisons.

Digital training intervention on mathematical proportionality

Our digital training intervention featured the topic of mathematical proportionality. It was developed as a repetition of direct and inverse proportionality—concepts already introduced and taught in previous school years. We designed it to last approximately 45 minutes. Learners had no time limit and could move forward through the intervention via button click. We implemented four phases as shown in Table 1.

Table 1. Versions of the Digital Training Intervention

Phase	Content	Student Activity
Introduction Phase on Direct Proportionality	Instructional Explanation with Worked Example	Reading
Consolidation Phase on Direct Proportionality	Worked Example 1 Self-Explanation Prompt 1 Worked Example 2 Self-Explanation Prompt 2	Reading Self-Explaining Reading Self-Explaining
Introduction Phase on Indirect Proportionality	Instructional Explanation with Worked Example	Reading
Consolidation Phase on Indirect Proportionality	Worked Example 1 Self-Explanation Prompt 1 Worked Example 2 Self-Explanation Prompt 2	Reading Self-Explaining Reading Self-Explaining

The introduction phases provided the schoolbook's basic instructional explanations of the principles of direct/inverse proportionality (i.e. when the base amount increases, the mapped amount increases/decreases at the same rate) as well as a worked example (Bierwirth et al., 2013). During the introduction phases, the participants' only task was to carefully read the material and—whenever ready—click the button to proceed.

Each of the two consolidation phases (i.e. direct and inverse proportionality) consisted of two worked examples (cookies and tickets cover story). As mentioned above, we implemented structure-emphasising example sets. Hence, to make the key learning principles salient, we combined structure (here: principles of direct and inverse proportionality) and surface features (cookies and tickets cover story). A self-explanation prompt accompanied each worked example and encouraged the participants to generate an explanation of how the worked example had been calculated (e.g. "Explain, how Erik calculated the amount of dough for 12 people").

Participants in both experimental conditions underwent the same digital training intervention, except for one crucial difference: The clipart condition additionally featured six clipart explainers, one in each introduction phase and two in each consolidation phase. These clipart explainers are combinations of graphics and texts in the shape of cartoon teachers plus explanations in speech bubbles. Their purpose was to serve as coherence-formation support on a "deep structure level" (Seufert & Brünken, 2006). Therefore, they provided a simple and direct statement on how to calculate the first principle of proportionality (here: the amount of dough or the ticket price for *one* person). Figure 2 illustrates our intervention's clipart explainer.

Instruments

Prior math knowledge

To check and control for potential differences in prior math knowledge between conditions, we used two measures: First, we asked our participants to type in their last mathematics grades. In Germany, these grades range from 1 (*highest*) to 6 (*lowest*). Second, we gave them three simple calculation tasks that afforded to apply the so-called rule of three. We used the mean number of correct calculations from 0 (*lowest*) to 3 (*highest*) for another measure of prior mathematics knowledge.

Learning outcomes
Our digital training intervention's domain was mathematical proportionality. As a measure of learning outcomes, we thus assessed participants' knowledge about this domain in the posttest thereafter. Three tasks showed them a table featuring the so-called rule of three, and participants had to calculate a result. To assess mathematical proportionality knowledge, we used the mean number of correct calculations from 0 (*lowest*) to 3 (*highest*).

Mathematical self-efficacy
We assessed the participants' mathematical self-efficacy related to proportionality tasks before and after the intervention. We used a four-item test (see Appendix), with very high internal consistency (Cronbach's $\alpha_{pretest} = .95$ and Cronbach's $\alpha_{posttest} = .95$). Regarding validity, the mathematics grades correlated moderately with both pretest ($r = -.21$, $p = .026$) and posttest measures ($r = -.30$, $p = .002$). In other words, the better (i.e. lower in the German grading system) the mathematics grades, the higher the mathematical self-efficacy and vice versa. Moreover (and unsurprisingly), both pretest and posttest measures of self-efficacy are intercorrelated ($r = .44$, $p < .001$).

Self-explanation quality
We rated each participant's answer to each self-explanation prompt on a scale from 0 (*very low quality*) to 6 (*very high quality*) in relation to a correct solution. We gave the maximum of six for a correct and exhaustive self-explanation of how the rule of three is performed. Rating points were given for correctly naming which side of the table must be divided or multiplied by which number; in other words, naming the correct table column, operation, and factor scored. We used the mean rating of all four self-explanations to assess self-explanation quality. Internal consistency was high (Cronbach's $\alpha = .86$).

Task engagement
Task engagement represented the ratio of on-task answers that a participant typed into the input boxes during the whole study. An on-task answer was any noticeable attempt to answer the respective self-explanation prompt or calculation task including incorrect answers and comments such as "I don't know." By contrast, we counted comments such as "boring", "I'm so cool", or "your mother" as off-task answers. To calculate the ratio of on-task answers, we divided the number of off-task answers by the total number of answers, and subtracted the result from 1.

Subjective mental effort
We assessed participants' mean subjective mental effort during both our introduction and consolidation phases. For that purpose, we implemented a one-item 7-point rating scale from 1 (*lowest*) to 7 (*highest*) on the subjective invested mental effort (e.g. "How much effort did you invest in explaining how Erik calculated the amount of dough for 12 people?"). This scale was based on Paas' (1992) one item scale and is widely used (e.g. Schmeck et al., 2015).

Perceived task difficulty
Likewise, we assessed the mean perceived task difficulty with a one-item 7-point rating scale from 1 (*lowest*) to 7 (*highest*) (e.g. "How difficult was it for you to explain how Erik calculated the amount of dough for 12 people?"). Recent research has also used this scale widely to assess instructional interventions' cognitive demands (e.g. Schmeck et al., 2015).

Learning time

Learning time was the difference between the logged timestamps when participants started and finished working with the digital training intervention.

Procedure

At the beginning, participants filled out the pretests on mathematical self-efficacy and mathematical proportionality knowledge. They then worked individually and on their own with the digital training intervention according to their experimental condition (clipart or control condition). Finally, they completed the posttest on mathematical self-efficacy and mathematical proportionality knowledge, and filled out a demographic questionnaire.

Results

We applied an alpha-level of .05 for all analyses and used Cohen's *d* as the effect size measure for our *t* tests—qualifying values around 0.20 as small, values around 0.50 as medium, and values of 0.80 or more as large effects (Cohen, 1988). Table 2 shows all measures.

Table 2. Means (with standard deviations in parentheses) for all measures

Measure	Clipart condition	Control condition	Overall
Prior math knowledge			
Grades[1]	3.19 (0.94)	3.00 (1.08)	3.09 (1.01)
Test[2]	0.42 (0.33)	0.46 (0.37)	0.44 (0.35)
Learning Outcomes[2]	0.46 (0.40)	0.45 (0.37)	0.45 (0.38)
Self-Efficacy[3]			
Before	2.32 (1.22)	2.38 (1.32)	2.34 (1.27)
After	2.56 (1.36)	2.83 (1.45)	2.71 (1.41)
Subjective mental effort[4]			
Introduction phase	3.45 (1.92)	3.81 (1.95)	3.64 (1.93)
Consolidation phase	3.45 (1.94)	3.69 (2.01)	3.58 (1.97)
Perceived task difficulty[4]			
Introduction phase	2.85 (1.67)	3.40 (1.72)	3.13 (1.71)
Consolidation phase	3.00 (1.80)	2.94 (1.82)	2.97 (1.80)
Self-explanation quality[5]	1.77 (1.30)	2.16 (1.52)	1.96 (1.42)
Task engagement[6]	0.77 (0.25)	0.78 (0.28)	0.77 (0.26)
Learning time[7]	40.00 (16.87)	39.64 (17.01)	39.81 (16.87)

Notes. [1]School grades (German grading system) in math from 1 (highest) to 6 (lowest), [2]Number of correct proportionality calculations from 0 (lowest) to 3 (highest), [3]Scale from 1 (lowest) to 5 (highest), [4]Scale from 1 (lowest) to 7 (highest), [5]Scale from 0 (lowest) to 6 (highest), [6]Ratio of on-task answers, [7]Time in minutes

Control variables

There were no statistically significant differences between experimental groups with respect to prior mathematics knowledge, prior mathematical self-efficacy, or learning time. Nor was there any difference in the ratio of male/female or native/non-native speakers.

Effects on mathematical self-efficacy and learning outcomes

As our first hypothesis (H1), we assumed our training intervention would positively affect learners' mathematical self-efficacy. Indeed, participants described higher mathematical self-efficacy in the posttest than in the pretest, $t(103) = 2.56$, $p = .006$, $d = 0.27$ (one-sided within-subjects *t* test, small effect). Furthermore, with respect to our second hypothesis (H2), we detected a statistically significant regression to predict learning outcomes based on self-explanation quality and task engagement, $F(2, 76) = 8.83$, $p < .001$, $R^2 = .19$. Self-explanation quality was a statistically significant predictor, $\beta = .21$, $t(78) = 1.92$, $p = .030$ (one-sided *t* test), as was task engagement, $\beta = .33$, $t(78) = 3.07$, $p < .002$ (one-sided *t* test). Participants' learning outcomes amounted to 0.43 + 0.05 (self-explanation quality) + 0.87 (task engagement).

Specific effects of the clipart explainers

In our further hypotheses (H3 and H4), we addressed the clipart explainers' potential specific effects. We found no statistically significant effects on self-explanation quality, $t(104) = -1.38$, $p = .168$, on learning outcomes, $t(78) = 0.07$, $p = .944$, or on subjective mental effort, $t(111) = -0.64$, $p = .523$ (all two sided between-subjects *t* tests).

However, we did identify a significant effect on perceived task difficulty during the introduction phase. Learners in the clipart condition rated the introduction phase as less difficult than those in the control condition, $t(111) = -1.73$, $p = .044$, $d = 0.32$, (one-sided between-subjects *t* test, small effect).

Discussion

Theoretical contributions and practical implications

For a start, our findings make two contributions to the literature on learning from worked examples and self-explanations. First, the aforementioned majority of studies on self-explanations in the mathematics content featured artificial lab conditions (Rittle-Johnson et al., 2017). By contrast, our study featured a realistic classroom environment. As Rittle-Johnson et al. (2017) suggested, this classroom setting might cause learners to make less effort than they would in a laboratory setting. Hence, we assessed the participants' task engagement and found almost 25% of our participants' answers to be off-task. However, this finding highlights our effects, assuming they would be larger under lab conditions. Secondly, we contribute to the sparse research analysing worked examples and self-explanations' effects on self-efficacy. We answered Van Gog and Rummel's (2010) call to analyse possible effects of (self-explaining) worked examples on self-efficacy. Our findings show that our intervention's example-based effectiveness also arose regarding the learner's mathematical self-efficacy: Learners exhibited greater self-efficacy related to proportionality tasks after the digital training intervention than before. These results underscore the idea that studying worked examples has the potential to improve self-efficacy—similar to expert modelling (Schunk, 1981, 1996). Furthermore, as Crippen & Earl (2007) showed, the worked example's effect on self-efficacy might be caused by experiencing mastery in the form of generating self-explanations.

Under the perspective of cognitive load theory and instructional design, our study provided another novelty: we analysed the effects of additional clipart explainers. Our between-group comparisons revealed that our clipart explainers affected neither self-explanation quality nor learning outcomes. In other words, the quality of both experimental groups' self-explanations during the intervention did not differ statistically significantly; neither did either group's performance in the mathematical proportionality test after the intervention. As a reasonable interpretation for these results, note that both experimental groups received a concentrated intervention that combined authentic schoolbook materials with state-of-the-art instructional guidelines for example-based learning. The only difference between the two digital training-intervention versions was the implementation of small clipart explainers—six in total. We thus assume that both self-explanation quality and learning outcomes were robust enough to not be affected by such a relatively low-dose add-on to a training intervention already packed with effective instructional measures. Furthermore, the clipart explainers had no effect on the learners' self-rated mental effort. We assume that they did not induce higher cognitive demands on the learners because the subjective mental effort performance measures (self-explanation quality and learning outcomes) also remained unaffected by the clipart explainers. However, what was negatively affected was the perceived task difficulty during the introduction phase.

Concisely, clipart explainers have the potential advantage of making instructions appear easier to learners—with no indications of being detrimental to their learning. From a more practical point of view, this result could lead to a cautious recommendation: When carefully considering the potential risks of side effects (such as seductive detail and split-attention effects), there is hardly anything to be said against implementing clipart explainers.

Key predictors to learning outcomes turned out to be self-explanation quality and task engagement, as both exerted a significant positive influence on learning outcomes in our regression analysis. This finding underscores the importance of having learners deeply process the given materials. It is in line with previous research that identified self-explanation quality as a predictor of immediate (e.g. Berthold et al., 2009) and delayed (e.g. Hefter et al., 2022) learning outcomes.

Limitations and implications for future research

As one of this study's limitations, we used the topic of proportionality in the domain of mathematics. Thus, its generalisability to other domains that future studies might address is limited. We also used different tests to assess prior mathematics knowledge before the intervention and learning outcomes after the intervention. This approach had the advantage of preventing a memorisation effect due to identical tests, but came at the cost of within-subject analyses. Moreover, future studies might implement delayed posttests for assessing more long-term learning outcomes.

Furthermore, our short 45-minute intervention revised the concepts of direct and inverse proportionality, which students had already been taught in previous school years. Future studies might focus on longer interventions, which would then not just revise but actually introduce the concepts of proportionality. Moreover, direct and inverse proportionality might differ in their cognitive demands for learners. Comparing both concepts with respect to how self-explanations and clipart explainers might support learners to grasp them, seems promising. Summing up, our carefully designed digital training intervention based on worked examples combined instructional psychology guidelines with authentic schoolbook materials. It stood the field test and fostered mathematical self-efficacy. Additional clipart explainers were at least harmless, while at best, they reduced (perceived) task difficulty. The key to learning was engaging with the given tasks and deeply processing the materials by self-explaining the worked examples' principles.

Acknowledgements

We would like to thank all students who took part in our experiments, all teachers for their support, Christoph Carstens for his assistance in conducting the experiment, and Carole Cürten for proofreading..

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Appendix

Mathematical self-efficacy
4 items, 5-point-scale from 1 (*lowest*) to 5 (*highest*)

How confident are you that you are able to perform the following tasks?

1. I can explain direct proportionality.
2. I can apply the rule of three for direct proportionality.
3. I can explain inverse proportionality.
4. I can apply the rule of three for inverse proportionality.