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Generic preparation for upcoming explanations: intra- and inter-domain effects of a digital training intervention

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Abstract

Learning from instructional explanations is one of the most established, prevalent, and obvious ways of learning—but it carries the risk of shallow processing. Unlike previous research that focused on providing digital just-in-time support measures for learning with explanations, we strived to prepare learners on how to make the most of upcoming explanations. We thus developed a short-term computer-based training intervention on the focused processing of instructional explanations. In two experiments ($N_1 = 47$, $N_2 = 42$), we tested its effects on learning processes and outcomes of a subsequent learning phase. Our results revealed that the training intervention fostered domain-general knowledge about explanations. Furthermore, it enabled learners to benefit from future instructional explanations in other domains (inter-domain transfer for university students, Experiment 1) or at least on other topics (intra-domain transfer for primary school fourth graders, Experiment 2). The digital training intervention did not trigger more cognitive load in the subsequent learning phase. All in all, we describe an initial promising step toward a generic training effect that has the potential advantage of enhancing learning from explanations without altering the actual learning material.

Keywords: Digital training intervention, Focused processing, Explanations, Inter-domain effect, Intra-domain effect

Introduction

Imagine that you are intending to learn basic statistics and seek first introductory information about statistical hypothesis testing. Your source of knowledge is probably an instructional explanation read in a textbook, heard in a classroom or—in the digital age—swiped or clicked through in an online environment. The basic purpose of an explanation is to answer a question, implicit or explicit (Leinhardt, 2001, 2010). In our example, you have found and (preferably) also read or listened to instructional explanations that could answer your questions such as what statistical Type I and Type II errors are.

In a nutshell, instructional explanations are one of the most established, prevalent, and obvious means of instruction (Berthold, 2012). They are ubiquitous in everyday learning and cognition in general (Lombrozo, 2016). In fact, explanations “are central to our sense of understanding, and the currency in which we exchange beliefs” (Lombrozo, 2006, p. 464). Ideally, an instructional explanation simply provides correctness, completeness, and consistency—but it is not a no-brainer. Although it seems alluring to assume an instructional explanation can somehow transfer knowledge from teacher to student, many decades of human-brain research and even more decades of teachers’ practical classroom experience have debunked these assumptions. Passive learning via the Nuremberg funnel—that famous mechanical metaphor (Hirschfelder, 2006)—does not work. In our example, you cannot somehow upload the instructional explanation about statistical hypothesis testing into your brain and then simply “know” it. Rather, you need to re-construct knowledge actively via information processing in your working memory. In other words, a given instructional explanation is ineffective when not actively and deeply processed by the learner. Hence, developing effective instructional support measures for learning with explanations is of interest for theory and practice. Unlike previous research that focused on providing such support measures just in time (i.e., during the learning), we strove to prepare learners on how to make the most of upcoming explanations.

Previous research on digital just-in-time support to focused processing of instructional explanations

Even when learners are motivated and compliant enough to process instructional explanations, the risk remains that they will do so superficially (see e.g., Berthold & Renkl, 2010; Pressley et al., 1992). When engaged in such shallow processing, learners tend to summarize and reiterate the given explanations. But shallow processing leads to shallow knowledge and understanding. In our example, reciting an explanation about Type I and II errors by heart is unlikely to help you deeply understand the matter, let alone solve statistical problems. What would be more likely to help instead is deeply engaging with and focusing on the learning material, for example, by discerning its relevant principles, relating it to an example, and connecting it with your prior knowledge. In the present paper, we refer to these strategies as a form of *focused processing* (see also Renkl, 2015; Renkl & Atkinson, 2007)—in contrast to shallow processing.

As effective those strategies are, they are both scarce and hard to master—especially for learners with little or no prior knowledge. For instance, when provided with an instructional explanation about Type I and II errors, a student of basic statistics may have trouble focusing on the relevant and central principles and concepts. After all, the human working memory has its limitations and is thus prone to cognitive overload (Sweller et al., 1998, 2019). The complexity of the learning material itself—not only in statistics—requires a certain amount of learners' cognitive resources (i.e., *intrinsic cognitive load*), especially when they have low prior knowledge. Additionally, activities unrelated to learning goals (such as filtering irrelevant from relevant information) consume even more of one's resources (i.e., *extraneous load*). Finally, there simply might not be enough cognitive resources left for the actual learning processes, such as generating inferences or elaborating (e.g., *germane load*) (Sweller et al., 1998). Hence, instructional support should consider the learners' limited working memory and elicit focused processing of given explanations.

Consequently, a large body of instructional research has implemented the means to foster focused processing of instructional explanations directly in computer-based learning environments: Learners are provided with instructional support during their learning time—just in time, so to speak. Providing learners with information just-in-time bears resemblance to successful manufacturing and management concepts pioneered in Japan (Sayer, 1986; Sugimori et al., 1977). The just-in-time paradigm has since been applied in instructional models, such as the *Four Component Instructional Design Model* (4C/ID) by van Merriënboer (2019; see also van Merriënboer & Kester, 2014). This model recommends providing the prerequisite information that learners need to perform a specific task right at the time they actually need it. Such information usually refers to procedural information and/or how-to-instructions. Briefly, the 4C/ID model can be regarded as a "whole-task" model, a holistic approach so to speak, which describes full "educational programs for teaching complex skills or professional competencies" (van Merriënboer, 2019, p. 3). For the present study's literature review, however, we do not focus on measures that provide procedural information to learners as part of a whole instructional program. Rather, we focus on instructional support that aims at fostering the focused processing of instructional explanations during a short-term learning environment. We call these support measures "just-in-time" support measures, because—unlike our approach to a preparatory intervention—they are implemented within a learning environment and not handed out beforehand. One example of such just-in-time support is providing prompts that guide the learners' attention to the learning material's central principles. These prompts are often implemented as direct questions presented onscreen to the learners, sometimes called adjunct questions. To answer these questions, learners need to generate inferences referring to the explanations' central principles and concepts (Berthold & Renkl, 2010). Highly effective are a certain kind of prompts—so-called self-explanation prompts—that encourage learners to generate explanations to themselves and type them into text boxes (e.g., Atkinson et al., 2003; Berthold et al., 2011; Hefter, 2021; Hefter et al., 2019; Roelle & Renkl, 2020; Roelle et al., 2015). The range of further effective support measures for deep and focused processing include contrasting cases (Roelle & Berthold, 2015), adaptation (Roelle et al., 2014; Wittwer et al., 2010), color coding (Richter et al., 2016), and explanations on demand (Head et al., 2015; Renkl, 2002).

Summing up, there are well-studied and effective instructional support measures that foster learners' focused processing of explanations. In light of the cognitive load theory and instructional design, these support measures aim to reduce extraneous and increasing germane load by finding the sweet spot between too little and too much instructional support—appropriately called the *assistance dilemma* (Koedinger & Aleven, 2007).

Towards a digital generic preparatory training intervention on the focused processing of instructional explanations

The aforementioned measures provide effective instructional support for learners *during* their learning time. Hence, an instructor needs to supply the learning environment with more or less specific and detailed instructional support such as prompts and hints. In this research, however, we embark on a different approach that eschews the implementation of additional support to the learning material. Rather than enhancing the learning environment, we aim to enhance the learners—or at least their prior knowledge. We strive to foster prior knowledge about how to process explanations via a preparatory training intervention. This approach might have the potentially economical and practical advantage of using off-the-shelf learning material without having to alter it: Just hand the learners a short intervention beforehand.

The idea of providing some sort of training on processing strategies before presenting the actual learning material is not new. However, we will identify and address the research desideratum of developing and testing a more basic and generic approach. Previous research, for instance, yielded various training interventions on self-explaining (e.g., Ainsworth & Burcham, 2007; Hodds et al., 2014; McNamara, 2004). Generally, self-explaining is an effective cognitive endeavor that comprises generating an explanation about present learning material for one's self. It can be beneficial for acquiring various learning outcomes (see Wylie & Chi, 2014 and Chi, 2021 for an overview). McNamara (2004) developed an effective self-explanation training intervention for reading activities called SERT, which addressed strategies such as "comprehension monitoring", "using logic", or "prediction" (p. 3). For another example, Hodds et al. (2014) applied self-explanation training for mathematical proofs that addressed strategies such as "identifying key ideas in each line of a proof" and "explaining each line in terms of previous ideas presented in the proof" (p. 73). Overall, their self-explanation strategies seem to be quite sophisticated and specific to a certain domain such as mathematical proofs.

Our goal with the present paper was to train more low-key and basic strategies of how to process instructional explanations. Such basic strategies do not yet call for generating self-explanations, but rather just discern a given explanation's principles and relate them to a given example. Applying such strategies on instructional explanations can still be considered focused processing—at least more focused than the shallow processing of summarizing and reiterating that can occur with no support measures. Hence, pretraining such strategies might be beneficial for enhancing future learning from instructional explanations.

Furthermore, reasonable preparatory training on the focused processing of instructional explanations should have some sort of general effect that benefits the processing of upcoming explanations—regardless of their topic or even their domain. However, previous training concepts have often neglected such generic aspects, and did not focus on transfer effects. Rather, they implemented the same domain or even the same type of material for the (pre-)training phase and subsequent learning phase that followed the training. For instance, Bielaczyc et al. (1995) developed an effective training intervention on self-explanation and self-regulation. The intervention was part of a series of programming lessons for university students and thus featured the same domain (i.e., programming) as the remaining lessons. This "same domain" aspect also applies to the aforementioned training intervention in the domain of mathematical proofs (Hodds et al., 2014).

For the current paper, we aimed to develop and test a novel preparatory training intervention on the focused processing of upcoming instructional explanations. Summing up, the novelty of our approach arises from two aspects: First, unlike the aforementioned just-in-time measures, our intervention takes place *before* the actual learning phase. Handing learners the intervention before presenting existing off-the-shelf learning material has the potential advantage of circumventing the need to alter that existing material. Second, unlike the aforementioned pre-training phase of earlier studies, our intervention should foster basic and generic strategies of how to process upcoming explanations of topic and even of *any* domain. Thereby, it should enable learners to benefit from future instructional explanations in other domains (*inter-domain* transfer) or at least on other topics (*intra-domain* transfer).

Hypotheses and research question

We aimed to develop a computer-based generic preparatory training intervention on the focused processing of instructional explanations. As the first and most obvious hypothesis, we assumed that our intervention would foster…

H1: … domain-general knowledge, namely knowledge of strategies about learning from instructional explanations.

Furthermore, we assumed that our intervention would show beneficial effects for learners in a subsequent learning phase. During this subsequent learning phase, it should foster…

H2: … learning processes (i.e., notes' quality).

H3: … learning outcomes (i.e., domain-specific knowledge).

Finally, we aimed to shed light on cognitive load mechanisms. Berthold and Renkl (2010) argued that remembering and applying learned strategies of focused processing independently in the learning phase might increase the risk of cognitive overload. However, we could also consider that prior knowledge about strategies of focused processing might actually help to reduce cognitive load in the learning phase, because it provides knowhow about how to focus one's limited cognitive resources more thoroughly. Hence, we analyzed whether…

RQ: … our intervention would affect cognitive load during the subsequent learning phase.

Experiment 1

In Experiment 1, our goal was to test a digital preparatory training intervention on the focused processing of instructional explanations. We aimed to analyze its generic effectiveness in the university context and to shed light on cognitive load during subsequent learning.

Method

Sample and design

We recruited 47 university students ($N = 47$, 31 females, 16 males; $M_{age} = 24.60$; $SD_{age} = 6.12$) from psychology courses who received delicious candy and could fulfill part of their research participation requirement. Most of them (~53%) were in the second semester. After obtaining informed consent, we randomly assigned them to two experimental conditions: (a) with preparatory training (training condition, $n = 27$), (b) without preparatory training (control condition, $n = 20$). The difference in number of both subsamples was due to our automatic, simple randomization routine: Each participant had a 50/50 chance of ending up in the training or in the control condition—regardless of how large either subsample already was.

Intervention phase

Training condition. Participants in the training condition received our computer-based preparatory training intervention on the focused processing of instructional explanations. Our intervention featured the domain of biology and the topic of "heredity." It was built on materials by Berthold et al. (2010). Furthermore, our intervention comprised four components that followed the recommendations of effective training interventions (Friedrich & Mandl, 1997; Harris et al., 2008; Renkl, 2015; VanLehn, 1996): (a) learning goals, (b) theoretical introduction, (c) cognitive modelling, and (d) practice phase.

a) Learning goals: Making learning goals explicit to the learners can help them to focus their attention on these goals, concurring with Renkl's (2015) perspective of focused processing. It is a perspective that acknowledges the learners' cognitive resources—such as attention and working memory—as being limited and thus prone to becoming diverted to non-learning goal-related issues. Previous effective short-term training interventions therefore relied on presenting learning goals (e.g., Berthold & Renkl, 2010; Hefter et al., 2014). The preparatory training intervention in the present paper should enable learners to know and apply strategies of how to deeply process instructional explanations. Hence, a presentation of learning goals should make this very goal explicit to the learners and thereby focus them on achieving it. We presented the learning goals as statements, and told the learners that they should be able to agree with these statements after the intervention. The learning goals were "I know which strategies are essential for understanding explanations.", "I know those strategies' advantages, and when and how I should apply them.", and "I can process explanations on my own applying those strategies."

b) Theoretical introduction: We provided a 4-page presentation of introductory information about explanations and three essential strategies to process them. Those three strategies were "discerning the explanation's principles and concepts", "relating an example to an instructional explanation", and "understanding when and how to apply an explanation's principle." Figure 1 shows a visualization of one of the theoretical introduction's pages.

c) Cognitive modelling: For the intervention's core component, it makes sense to consider cognitive modelling. As a large body of research has shown (Hoogerheide & Roelle, 2020; Renkl, 2014, 2016, 2021), example-based learning can be very effective for fairly unexperienced and unskilled learners. It is considered the prototype of direct instruction

Understanding explanations

When you learn something, you often rely on explanations, such as from textbooks or from instructors.

However, research on learning and instruction has shown that learning from explanations is often not very effective.

The general reason for this is that learners (e.g., students) process the given explanations only in a shallow and superficial way, instead of really looking deep into the explanations.

To learn effectively from explanations, it is important to focus on the central concepts and principles.

Concepts are important terms and definitions that are key to a certain topic. For instance, in physics, a central concept is energy. Principles however are important relations and rules, such as the law of conservation of energy.

Discerning the explanation's principles and concepts is a prerequisite to fully understand and later apply the explanation.

Fig. 1 Visualization of the theoretical introduction (translated from German)

(Kirschner et al., 2006). Example-based learning can include not only learning from worked examples that present concrete solution steps, but also learning from models that demonstrate concrete skills. Here, we refrain from going into detail about those two interesting research backgrounds and their commonalties (see Renkl, 2014; van Gog & Rummel, 2010). Instead, we focus on the practical aspects of how to implement example-based learning within our training intervention. After all, the strategies to-be-learned should be modelled and made explicit to the learners. Then, learners can focus their limited cognitive resources on actually learning these strategies instead of the potentially overstraining task of finding these strategies on their own. Here, these strategies refer to how to deeply process instructional explanations. We presented explanations about homozygous versus heterozygous individuals and dominant-recessive versus intermediate heredity by providing an example about plants. Unlike motor skills for example, strategies of how to process explanations are internal cognitive strategies, though. They do not manifest in direct and thus observable action. Hence, these cognitive strategies need to be externalized via verbalization—similar to the modelling in the Cognitive Apprenticeship Approach (Collins et al., 1989; Minshew et al., 2021). For instance, Hefter et al. (2022) developed a digital training intervention on strategies for addressing students' misconceptions in physics. They implemented cognitive modelling by explicitly describing how a teacher would apply those strategies. For the present study, it therefore seems feasible to provide example cases that show a model verbalizing his/her thoughts about how to process given explanations. Hence, next to the explanations, there was a little clipart learner with a speech bubble that demonstrated how to process the given explanations. It modelled the three previously described strategies (see Figure 2).

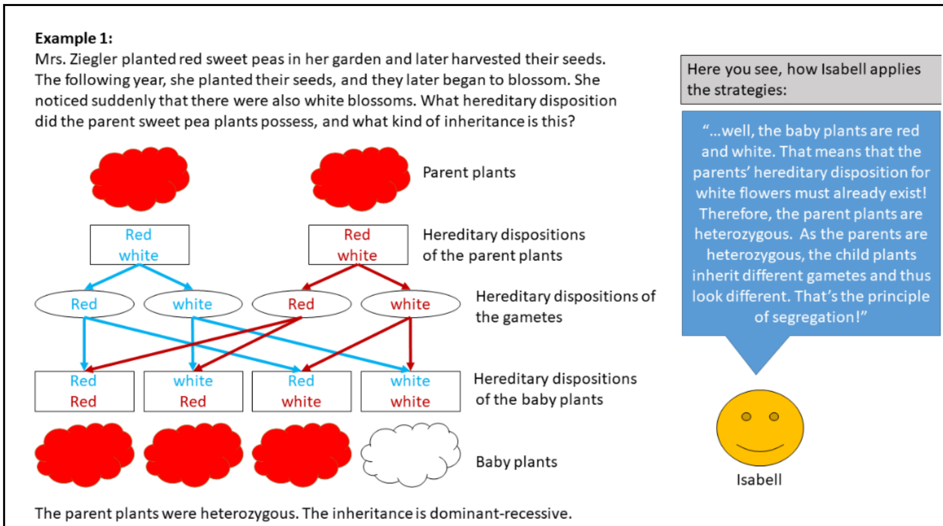

Fig. 2 Visualization of the cognitive modelling (translated from German)

d) Practice phase: Finally, the opportunity to apply and thereby practice these skills should follow the previous early phase of cognitive skill acquisition (e.g., VanLehn, 1996). After all, the learners' goal is to be capable of transferring these cognitive skills to new cases. Our intervention provided the learners with three short practice tasks. The first practice tasks showed three little clipart learners with speech bubbles. They were the same as in the previous cognitive modelling component. This time though, the participants had to select which one of the three given strategies the clipart learner is modelling. After selecting one of the three possible answers, a short feedback message popped up to inform the learners as to whether and why their answer was correct or not. The second practice task showed them the explanations about heredity from the previous cognitive modelling component, as well as an example regarding animals. This time though, the participants had the opportunity to apply the strategies themselves in a text box. The third and final practice task showed them all three strategies and asked them to each formulate a question that would encourage the participants to apply these strategies.

Control condition. Participants in the control condition received a similar computer-based environment with the same four-component structure. The components (c) cognitive modelling and (d) practice phase were identical to the pretraining condition. However, the components (a) learning goals and (b) theoretical introduction did not address strategies of processing explanations, but presented further information on the topic "heredity."

Application phase

The application phase was identical in both experimental conditions. It comprised a computer-based learning environment with a twofold purpose: It gave the participants an opportunity to process instructional explanations on a new domain and thus to apply their knowledge about how to process instructional explanations. It enabled us to analyze whether and how participants had benefitted from the preparatory training intervention. The application phase featured the domain of statistics, and the topic "introduction to statistical hypothesis testing" and consisted of two components: (a) a 12-page presentation of definitions and instructional explanations of basic concepts such as Type I and type II errors and (b) eight worked examples on basic statistical hypothesis testing. Those eight worked examples presented a word problem and its solution, thereby modelling four basic principles: null hypothesis, alternate hypothesis, type I, and type II error. Next to each worked example, a text box gave the learners the opportunity to take notes.

Instruments and measures

Mathematics and statistics grades. We asked the participants to state their final school grade in mathematics as well as their latest university grade in statistics (if available). In the German grading system, these grades range from 1 (*highest*) to 6 (*lowest*). The only reason we assessed these grades was to control for possible differences in prior knowledge between the experimental groups.

Training time. Training time was the time difference between the logged timestamps of the participants starting and finishing the training/control intervention.

Notes' quality. During the application phase, participants had the opportunity to type notes into a text field next to each of the eight worked examples. Those worked examples illustrated the four basic principles on statistical hypothesis testing, namely the null hypothesis, alternate hypothesis, type I, and type II error. We counted how many correct descriptions of these four principles our learners typed into each text field, ranging from 0 (*min*) to 4 (*max*).

An example of correct descriptions of all four principles was "null hypothesis: H_0, alternate hypothesis: H_1, type I error: reject true H_0, and type II error: don't reject false H_0 (translated from German)." The example note "this guy made a type II error by not rejecting the false H_0 (translated from German)" received a rating of 2. Because of very good interrater reliability for ~20% of the data (intraclass coefficient with measures of absolute agreement, ICC > .85) between two independent condition-blind raters (i.e., student research assistants), one rater scored the remaining data. We used the mean of all eight measures, as internal consistency was acceptable (Cronbach's $\alpha = 0.78$).

Cognitive load. We assessed the learners' cognitive load during the application phase based on Paas' (1992) one item scale. Four times—after every second worked example—participants answered an item on perceived difficulty "How difficult was it for you to understand the solutions of the last two word problems?" and an item on subjective mental effort "How much effort did you invest in understanding the last two word problems?" on a 9-point scale. We used the mean scores of each of the four items for our measures of perceived difficulty (Cronbach's $\alpha = .93$) and subjective mental effort (Cronbach's $\alpha = .88$).

Domain-general knowledge. We assessed the participants' knowledge about processing explanations via one item in an open format in the posttest: "A fellow student not participating in this training asks you for a clue on how to understand explanations better. What clues do you give them, and why?" We rated their answer on a 6-point rating scale from 1 (*very low quality*) to 6 (*very high quality*). To receive the maximum rating of 6, all three strategies that could be learned from our training had to be named or described. Interrater reliability for ~20% of the data was high (ICC > .85), so one rater rated the remaining data.

Domain-specific knowledge. Also in the posttest, we assessed the learners' domain knowledge, that is, basic knowledge about the topic "introduction to statistical hypothesis testing". To do that we used 16 open-format questions such as "You are supposed to conduct a pharma experiment. The medication in question should not impair driving behavior by delaying reaction times. Please decide which statistical error you prefer to be small in this case and give reasons for your decision." Each answer was rated on a 6-point rating scale from 1 (*very low quality*) to 6 (*very high quality*). One rater rated the rest of the answers because of high interrater reliability (ICC > .85). Internal consistency for all 16 questions was high (Cronbach's $\alpha = 0.83$). Thus, we used the mean of all 16 items as our measure of domain-specific knowledge.

Procedure

This experiment took place in our psychology departments' students computer pool room, providing computers for a maximum of nine people at a time. First, participants filled out a demographic questionnaire (about sex, age, and grades). Next came the intervention phase: According to their experimental condition, participants underwent either the training or control intervention. Then, all participants ran through an identical application phase while we assessed their *notes' quality* and *cognitive load*. Finally, participants were given posttests on *domain-general* and *domain-specific knowledge*.

Results

We applied one-sided *t* tests to test our directional hypotheses (otherwise two-sided) and used *d* as the effect size measure. We qualified effect sizes around 0.20 as small, around 0.50 as medium, and around 0.80 as large effects (Cohen, 1988). The alpha-level for all tests was .05. Furthermore, before our *t* tests, we applied Levene's test to check for homogeneity of variances (Field, 2013). In the rare case that the assumption of homogeneity of variances was violated, we reported a "*t* test for unequal variances" with adjusted degrees of freedom (df). Table 1 features all of Experiment 1's measures.

Table 1 Means (with standard deviations in parentheses) for all measures in Experiment 1

Measures	Training condition	Control condition
Mathematics grade[1]	2.00 (0.94)	2.25 (0.91)
Statistics grade[2]	1.99 (0.73)	2.51 (0.96)
Training time[3]	21.32 (9.72)	23.06 (5.92)
Notes' quality[4]	0.39* (0.40)	0.18 (0.27)
Subjective mental effort[5]	4.68 (1.62)	5.10 (1.81)
Perceived difficulty[5]	3.39 (1.57)	3.78 (2.44)
Domain-general knowledge[6]	2.89* (1.45)	1.79 (0.79)
Domain-specific knowledge[6]	3.57* (0.95)	2.85 (1.03)

Note. [1]Final school grades (German grading system) in math from 1 (highest) to 6 (lowest). [2]Latest grades (German grading system) in statistics from 1 (highest) to 6 (lowest). [3]Time in minutes. [4]Mean number of correct principle descriptions from 0 (min.) to 4 (max.). [5]Scale from 1 (very low) to 9 (very high). [6]6-point rating scale from 1 (very low quality) to 6 (very high quality). *$p<.05$

Learning prerequisites and time

We observed no statistically significant differences between the experimental groups in the participants' learning prerequisites, such as math grades, $t(44) = -0.91$, $p = .369$ and statistics grades, $t(19) = -1.42$, $p = .172$. Furthermore, there was no statistically significant difference in training/control condition time, $t(44) = -0.69$, $p = .493$.

Effects on domain-general knowledge

As assumed in the first hypothesis, participants in the training condition outperformed their fellow participants in the control condition regarding domain-general knowledge, $t(44) = 3.00$, $p = .002$, $d = 0.90$ (large effect).

Effects on subsequent learning processes

The notes' quality the participants produced during the application phase differed between experimental conditions. As assumed in Hypothesis 2, participants in the training condition generated more correct principle descriptions than those in the control condition, $t(45) = 2.06$, $p = .023$, $d = 0.61$ (medium effect).

Effects on subsequent learning outcomes

As assumed in Hypothesis 3, the trained participants also outperformed their non-trained fellows with respect to domain-specific knowledge, $t(45) = 2.48$, $p = .008$, $d = 0.73$ (medium effect).

Cognitive load

We detected no statistically significant differences between conditions in our cognitive load measures, namely subjective mental effort, $t(45) = -0.84$, $p = .403$, and perceived difficulty, $t(30.45) = -0.62$, $p = .540$ (t test for unequal variances).

Discussion

In Experiment 1, we tested the effects of training the focused processing of instructional explanations. As expected, our preparatory training intervention fostered domain-general knowledge about how to process explanations (H1).

In addition to this not too surprising result, we hypothesized more interesting effects with respect to subsequent learning after training. This application phase featured a different domain and took place right after the training intervention: First, the training intervention did indeed affect the learning processes during that phase. Trained learners wrote down more correct principle descriptions than non-pretrained learners (H2). Second, the training intervention affected subsequent learning outcomes positively. Trained participants outperformed their non-trained colleagues in the knowledge learned right after the training intervention (H3). This knowledge referred to the "introduction to statistical hypothesis testing"—a completely different domain than the training intervention's (i.e., biology). In other words, learning about how to process instructional explanations (exemplified in the biology domain) did help learning from instructional explanations in a different domain (i.e., statistics); a finding that reveals an inter-domain effect.

Concerning cognitive load during the subsequent learning phase (i.e., perceived difficulty and subjective mental effort, RQ), we detected no statistically significant difference between experimental conditions. This null-finding cannot prove that the training does not affect cognitive load, of course. At the very least, this result gives us no reason to assume any benefit or harm from the training intervention with respect to cognitive load. Furthermore—although widely used for decades—the shortcomings of our cognitive load assessments, which are subjective rating scales, need to be kept in mind (de Jong, 2010).

Nevertheless, our preparatory training intervention proved capable of providing an inter-domain effect for university students about to learn from instructional explanations. Admittedly, university students constitute a rather experienced sample, given that in all those school years they ought to be quite accustomed to handling instructional explanations. Hence, it would be interesting to seek similar transfer effects with younger learners who are less experienced and familiar with focused processing given explanations. Therefore, in Experiment 2, we concentrated on training primary school students.

Experiment 2

In Experiment 2, we aimed to build on Experiment 1 and conceptually replicate its findings with younger learners. Again, we analyzed the possible beneficial effects of our preparatory training intervention on the focused processing of instructional explanations. This time, however, we worked with primary school students and, accordingly, slightly modified training materials as well as different learning materials.

Method

Sample and design

We recruited 46 German primary school students (fourth graders). We had to exclude four due to language difficulties, and two students who were unable to complete our training intervention. Our final sample thus was $N = 42$ with 21 female and 21 male students ($M_{\text{age}} = 9.26$; $SD_{\text{age}} = 0.50$). After obtaining parental and teacher consent, we randomly assigned the students to two experimental conditions: (a) with preparatory training (training condition, n = 21), (b) without preparatory training (control condition, n = 21). During the whole experiment, we and the students' German teachers were present in the classroom.

Intervention phase

Training condition. As in Experiment 1, participants in the training condition underwent a computer-based preparatory training intervention on the focused processing of instructional explanations. Unlike in Experiment 1, the sample comprised of German primary school students. Hence, we needed a less complex topic than Experiment 1's topic "heredity", which was for university students. Therefore, to match the German primary school students' curriculum and level, the learning environment featured the domain of German grammar, focusing on the topic "tenses." This material was meant for German primary school fourth-grade students.

Structurally speaking, this intervention strongly resembled the one in Experiment 1 and comprised the same four components: (a) learning goals, (b) theoretical introduction, (c) cognitive modelling, and (d) practice phase.

However, to make the training intervention more suitable for primary school students, we made modifications to Experiment 1's intervention. The components (a) learning goals and (b) theoretical introduction were very similar to those in Experiment 1. In fact, the learning goals and strategies to-be-learned were the same as in Experiment 1, but we simplified the wording. For example, we rephrased Experiment 1's strategy "discerning the explanation's principles and concepts" into "noticing key words and rules."

We also reduced the complexity of the third component (c) cognitive modelling. In this component, we exemplified the theoretical information applying the "tenses" topic. We presented explanations and examples (in simple language) about when to use different tenses such as present, past (simple and perfect), or future. Similar to Experiment 1, a little clipart learner with a speech bubble modelled the three previously described strategies (see Figure 3). To make the material more accessible for primary school students, little captions told them that here they see "Lea's thoughts". Furthermore, we conducted the fourth component (d) practice phase not on the computers, but as a paper-pencil phase.

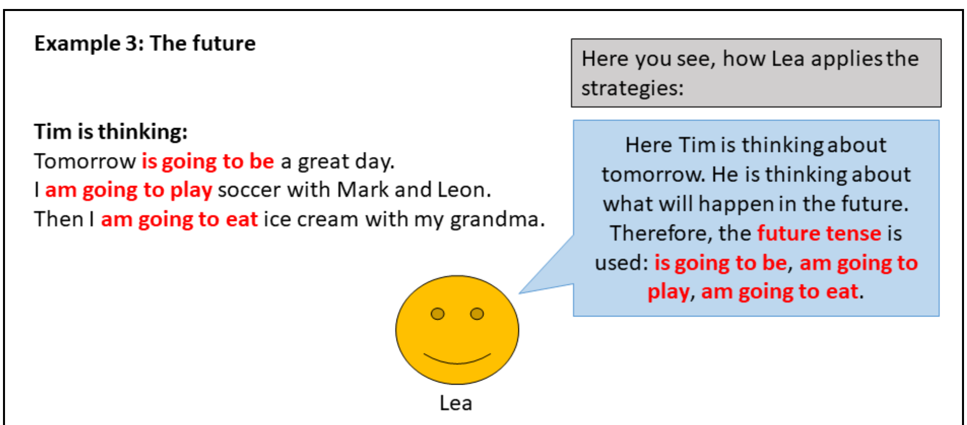

Fig. 3 Visualization of the cognitive modelling (translated from German)

Control condition. Analogous to Experiment 1, participants in the control condition received a computer-based environment very similar to the training condition's. Again, the components (c) cognitive modelling and (d) practice phase were identical to the training condition, whereas the components (a) learning goals and (b) theoretical introduction did not touch strategies of processing explanation. Instead, these components presented further information on the topic "tenses."

Application phase

The application phase that followed the intervention featured a learning environment identical in both experimental conditions. Its domain was grammar (topic "sentence constituents"), and its two components were: (a) a 6-page computer-based presentation of definitions and instructional explanations of sentence constituents and (b) paper-based worked examples on sentence constituents. We provided four worked examples—unlike eight worked examples in Experiment 1 because of the much younger sample. Each of those four worked examples presented a problem ("Read the following sentence and mark the subject red, mark the object green, and mark the predicate blue.") and its solution ("The boy is painting a picture."). Under each worked example, the words "Here you can take notes:" followed by free space gave the learners the opportunity to take notes. Just as in Experiment 1, the application phase gave participants the opportunity to apply their knowledge about how to process instructional explanations. We were thus able to analyze learners' potential benefits from the training intervention.

Instruments and measures

German grades. We asked the participants to name their last school grades in German, ranging from 1 (*highest*) to 6 (*lowest*).

Prior domain-specific knowledge. We assessed learners' prior knowledge in the domain of German grammar, more precisely basic knowledge about the topic "sentence constituents." This pretest consisted of four simple tasks, for instance color marking the subject, object, and predicate in a given sentence. We counted the number of correct solutions, ranging from 0 (*min*) to 4 (*max*), and used the mean of all four measures (Cronbach's $\alpha = 0.49$). The only reason for this pretest and for assessing the learners' grades was so that we could control for possible pre-experimental differences between groups.

Notes' quality. Similar to Experiment 1, the participants could take notes during the application phase. In this phase, worked examples illustrated three basic principles of sentence constituents, namely subject, object, and predicate. We simply counted how many correct descriptions of these three principles the participants wrote down, ranging from 0 (*min*) to 3 (*max*). An example of correct descriptions of all three principles for a rating of

3 was "subject = who or what?, object = (to) whom or what?, predicate = what is he/she/it doing? (translated from German)." The example note "The sheep is the subject (translated from German)." received a rating of 1, as it described one principle, namely the sentence constituent subject. Because of high interrater reliability for ~20% of the data (ICC > .85), one rater scored the remaining data. We used the mean of all four measures (Cronbach's $\alpha = 0.94$).

Cognitive load. Similar to Experiment 1, we also assessed the learners' cognitive load (i.e., subjective mental effort and perceived difficulty) during the application phase. There were two slight differences to Experiment 1 because of the much younger sample. First, the application phase featured four and not eight worked examples. This led to two and not four times the participants had to answer an item on perceived difficulty "How difficult was it for you to understand the solutions of the last two examples?" and subjective mental effort "How much effort did you invest in understanding the last two examples?". Second, we provided a 7-point and not a 9-point scale for easier rating. We relied on the mean scores of the respective two items for our measures of perceived difficulty (Cronbach's $\alpha = .79$) and subjective mental effort (Cronbach's $\alpha = .94$)

Domain-general knowledge. We assessed the participants' knowledge about how to process explanations the same way as in Experiment 1 with similarly high interrater reliability (ICC > .85).

Domain-specific knowledge. The learners' domain-specific knowledge refers to knowledge about the sentence-constituents topic. The posttest was longer than the pretest and comprised nine different questions. In addition to the color-marking tasks like those in the pretest, we also asked more complex open-format questions such as "Which three sentence constituents do you know?" and "How do you notice them?". As interrater reliability was high for each question (all ICC > .85), only one rater analyzed the rest of the data. Due to the different questions and items—unlike in Experiment 1 where we only used complex open-format questions—, we applied a *z* standardization and used the mean of all items (Cronbach's $\alpha = .89$).

Procedure

Experiment 2 study took place in the computer rooms at two different primary schools. The procedure resembled Experiment 1's: After filling out a demographic questionnaire (about sex, age, and grades), the participants started the intervention phase (training or control condition). During the subsequent application phase (identical in both conditions), we assessed their *notes' quality* and *cognitive load*. Finally, in the posttest, we assessed *domain-general* and *domain-specific knowledge*.

Results

As in Experiment 1, we checked for homogeneity of variances (via Levene's test), carried out one-sided t tests for our directional hypotheses (otherwise two-sided), used d as the effect size and applied .05 as the alpha-level. Table 2 features all of Experiment 2's measures.

Learning prerequisites

There were no statistically significant differences between the experimental groups with respect to school grades, $t(39) = -0.82$, $p = .415$, or prior domain knowledge, $t(40) = -1.65$, $p = .107$.

Effects on domain-general knowledge

We noted statistically significant differences between the two conditions in the posttest. The training group demonstrated higher domain-general knowledge than the control group, $t(30.73) = 8.36$, $p < .001$, $d = 2.58$ (large effect, t test for unequal variances). Such an effect was expected in our Hypothesis 1.

Effects on subsequent learning processes

We found differences between both experimental conditions with respect to the notes' quality the participants had written down when studying the worked examples in the application phase. As assumed in Hypothesis 2, the trained learners generated higher quality notes than their non-trained fellows, $t(31.28) = 2.80$, $p = .004$, $d = 0.86$ (large effect, t test for unequal variances).

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

Measures	Training condition	Control condition
German grade[1]	2.33 (0.91)	2.55 (0.76)
Prior domain-specific knowledge[2]	0.37 (0.26)	0.52 (0.34)
Notes' quality[3]	1.64* (1.13)	0.86 (0.63)
Subjective mental effort[4]	3.74 (1.27)	2.88 (1.51)
Perceived difficulty[4]	1.74 (0.63)	2.05 (0.99)
Domain-general knowledge[5]	4.86* (1.42)	1.91 (0.77)
Domain-specific knowledge[6]	0.48* (0.19)	-0.48 (0.49)

Note. [1]Last school grades (German grading system) in German from 1 (highest) to 6 (lowest). [2]Mean number of correct solutions from 0 (min.) to 4 (max.). [3]Mean number of correct principle descriptions from 0 (min.) to 3 (max.). [4]Scale from 1 (very low) to 7 (very high). [5]6-point rating scale from 1 (very low quality) to 6 (very high quality). [6]z-scores. *p<.05

Effects on subsequent learning outcomes

Furthermore, the training group demonstrated more domain-specific knowledge than the control group, $t(25.51) = 8.29$, $p < .001$, $d = 2.56$ (large effect, t test for unequal variances). This finding was expected in Hypothesis 3.

Cognitive load

No effects of condition on cognitive load measures could be found, neither on subjective mental effort, $t(40) = 1.99$, $p = .053$, nor on perceived difficulty, $t(40) = -1.22$, $p = .232$.

Discussion

As in Experiment 1, we tested the effects of training the focused processing of instructional explanations, but this time with primary school students. First, the preparatory training intervention fulfilled its basic purpose: It fostered domain-general knowledge about how to process explanations (H1).

Second, it also positively affected the learning that took place after the intervention. It fostered note taking (H2) as well as the actual learning outcome (H3). In other words, the trained participants demonstrated more knowledge after the subsequent learning phase than their non-trained classmates. Having learned about how to process instructional explanations (exemplified in the grammar domain, topic: tenses) helped the primary school students to learn from instructional explanations about a different topic in the same domain (sentence constituents), a finding that reveals an intra-domain effect.

As to our research question (RQ) whether training the focused processing of instructional explanations affects cognitive load (i.e., perceived difficulty and subjective mental effort) during subsequent learning, we could not find any effects. In addition to the aspects offered in Experiment 1's discussion, subjective rating scales may not be the ideal type of assessment method for such a young and unskilled sample.

General discussion

In this paper, we experimentally tested whether training the focused processing of instructional explanations has positive effects on subsequent learning from explanations. We used a short-term computer-based preparatory training intervention that teaches learners how to process instructional explanations. For a sample of university students in Experiment 1, we observed inter-domain effects from the domain of biology (topic: heredity) to the domain of statistics (topic: basic hypotheses testing). Training the focused processing of instructional explanations in the biology domain (topic: heredity) helped those university students during subsequent learning from explanations in the domain of statistics (topic: introduction to statistical hypothesis testing). For a sample of primary school students in Experiment 2, we did not aim for inter-domain effects. After all, primary school students in the fourth grade are much, much younger and thus less experienced in processing given explanations than university students—not to mention many years less advanced in their cognitive development… Therefore, in Experiment 2, we reduced the material's complexity and adjusted it to primary school students' curricular level. We aimed for and detected intra-domain transfer effects: Training the focused processing of instructional explanations in the grammar domain (topic: tenses) helped those primary school students during subsequent learning from explanations in the same domain's topic of sentence constituents.

In the bigger picture, enabling learners to apply and transfer knowledge from one domain to another has been one of the ultimate goals of instructors for decades (Hung, 2013). In the present study, showing learners how to optimally process given explanations in one domain obviously benefitted them to use these strategies in similar but not identical situations. This can be considered a so-called near transfer (Hung, 2013; see also Barnett & Ceci, 2002, for an overview of transfer taxonomy). First, our learners learned certain strategies (i.e., how to process given explanations) with a rather arbitrary topic. Then, immediately after this learning took place, experienced learners (here: university students) accomplished an inter-domain transfer: applying the same strategies they had just learned to another topic of another domain. Primary school students at least accomplished an intra-domain transfer: applying the same strategies to another topic in the same school subject (i.e., grammar). These effects demonstrate that a brief generic preparatory training intervention can support learning from upcoming explanations of another topic. Such a short and rather generic intervention might simply be handed out to learners before existing off-the-shelf learning material is taught—an economical and practical advantage.

Furthermore, the training intervention neither decreased nor increased cognitive load during the subsequent learning phase (i.e., perceived difficulty and subjective mental effort, RQ).

With respect to cognitive processes during the learning with explanations, our training intervention also showed statistically significant effects: when given the opportunity to take notes, trained learners generated more correct principle descriptions than non-trained learners. Apparently, the training intervention encouraged learners to take notes more thoroughly. These results suggest that training helped to ensure deeper processing of the learning material, which led to higher quality notes on that material. However, it should also be considered, that the learners' notes provided only limited insight into the actual learning processes. Of course, a learner could have also deeply processed the given materials without writing down high quality notes or even notes at all (for a similar argument regarding the task of learning protocol writing, see Nückles et al., 2020). Indeed, note-taking was voluntary in both experiments. Considering the rather low numbers of delivered notes, our learners obviously did not use this feature extensively. The university students used it much less than the primary school students, which seems plausible when considering the university students' greater experience, maturity, and independence in general. Nevertheless, future studies might shed more light on cognitive processes during the learning phase with more extensive analyses, such as eye-tracking or think-aloud-protocols.

Limitations and future research

Despite these promising results, there are some limitations and further suggestions for future studies to consider. The first point has to do with effect duration. Our study tested the training intervention's effects on learning processes and outcomes in a subsequent learning phase. This learning phase immediately followed the training. In future studies, we will need to also test for long-term effects: Do learners also benefit from our intervention when learning from future explanations both immediately and after some time has passed?

The second point relates to the more or less static nature of the computer-based preparatory training intervention. There are potential factors that would improve it, such as implementing explanations adapted to learners' prior knowledge (e.g., Roelle et al., 2014; Wittwer et al., 2010).

Another limitation of our study concerns cognitive load measurements. Various researchers have been applying und establishing the method we used for decades (de Jong, 2010). It remains a subjective rating of invested mental effort and perceived difficulty, though. It is thus probably not ideal—especially for primary school students, as they are undoubtedly less metacognitively skilled than university students.

Furthermore, our intervention is a short (< 30 min.) preparatory intervention that instructors could deploy as compact preparation for existing learning material. One of our intervention's key concepts is modelling the strategies to-be-learned, and making them explicit to the learners. This bears similarities to the "modelling" component of the Cognitive Apprenticeship Approach (Collins et al., 1989; Minshew et al., 2021). Briefly put, the Cognitive Apprenticeship Approach refers to "learning through guided experience" (Collins et al. 1989, p. 456). Unlike our dense direct instruction intervention, cognitive apprenticeship is a holistic approach for teaching complex skills, in which modelling is just one key concept besides coaching, reflection, articulation, and exploration (Dennen & Burner, 2007). Cognitive apprenticeship focuses on guided participation, which means that learners and teachers work alongside each other and interact socially for quite some time. For instance, Wedelin and Adawi (2014) developed and analyzed six weekly modules that included supervision and collective feedback and taught mathematics in engineering education. Bouta and Paraskeva (2013) examined a highly interactive and collaborative 8-

hour 3D virtual environment that featured elements such as avatars, chats, and reflective teacher questions. Likewise, Tsai et al.'s (2012) web-based learning program on argumentation featured continual reflection and interaction for 12 weeks. Finally, Liu's (2005) web-based learning program for pre-service teachers comprised a seven-week course and focused on observing, sharing, and discussing. Summing up, cognitive apprenticeship provides a framework for designing effective courses and learning programs, usually spread over many hours and featuring collaborative learning tasks. In contrast, our short and single-user intervention prepares learners for upcoming explanations. It only shares a fraction (i.e., modelling and explicating strategies) with the long and highly interactive and collaborative cognitive apprenticeship interventions designed to teach complex skills.

Finally, viewing our intervention from a wider perspective, it cannot—and is not meant to—replace the richness of school and non-school related learning and development opportunities. An instructional method, such as our intervention, should also be considered from a wider perspective of instructional goals, such as "taking charge of one's own learning" (see Kuhn, 2007, p. 112). The present preparatory intervention is more of a direct add-on for instructors, who work in a very structured and well-regulated learning environment, such as a platform that provides asynchronous online lectures. In such cases, instructors can rely on their previous learning material and simply offer a generic preparatory training intervention (such as ours), if learners need a preparation on how to process explanations. Ideally, the instructor needs to carefully decide about its appropriate application, providing neither too little nor too much instructional support (see also the assistance dilemma, Koedinger & Aleven, 2007). Thinking carefully about when and how to fade out structured and direct instructional support, such as the present intervention, should ensure that learners can develop self-regulated skills and independence.

Summing up, our main contribution to technology-enhanced learning research is experimentally demonstrating the benefits of a generic preparatory training intervention to learning from upcoming explanations. Such a domain-independent preparation might have practical and economic advantages. This is because it spares the implementation of digital just-in-time support measures—which are not only domain- but also application-specific (such as prompts and hints). Rather, a generic preparatory training might simply precede existing off-the-shelf learning material without altering it.

However, we did not directly compare preparatory with just-in-time instructional support in our experiments. In future studies, it would be interesting to experimentally seek possible effect differences between preparatory and just-in-time instructional support measures with regard to (long-term) learning processes and outcomes.

Conclusion

In light of our two experiments' findings, we come to the following conclusions. Developed against the background of instructional principles for effective short-term training interventions, a preparatory training intervention on focused processing instructional explanations enables learners to benefit from future instructional explanations in other domains, or at least on other topics. Our finding that even primary school students benefitted from such a preparation highlights its effectiveness. We thereby describe an initial and promising step toward a generic training effect. From a more practical perspective, such a generic preparatory training intervention might create economic and practical advantages. Instructors can rely on their previous learning material without implementing of digital just-in-time support measures. When necessary, they can simply prepend a computer-based generic pretraining intervention to their learners.

Abbreviation
4C/ID: Four Component Instructional Design Model

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Declarations

Competing interests
The authors declare that they have no competing interests.

Ethics approval and consent to participate
APA ethical standards in accordance with the 1964 Helsinki Declaration were followed in the conduct of the study. We received informed (parental) consent for all participants.

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