How Effective are Instructional Explanations in Example-Based Learning? A Meta-Analytic Review

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REVIEW ARTICLE

How Effective are Instructional Explanations in Example-Based Learning? A Meta-Analytic Review

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Abstract The worked example effect within cognitive load theory is a very well-established finding. The concrete effectiveness of worked examples in a learning situation, however, heavily depends on further moderating factors. For example, if learners improve their processing of worked examples by actively explaining the worked examples to themselves, they are usually better able to solve transfer problems. Another way to enhance example processing is to present learners with instructional explanations instead of prompting them to produce these explanations on their own. In this article, we review 21 experimental studies to address the issue whether instructional explanations support example-based learning. Meta-analytic results lead to three important conclusions: First, the benefits of instructional explanations for example-based learning per se are minimal. Second, instructional explanations are more helpful for acquiring conceptual knowledge than for acquiring procedural knowledge. Third, instructional explanations are not necessarily more effective than other methods supporting example processing such as self-explaining.

Keywords Cognitive skill acquisition · Instructional explanations · Learning from worked examples · Meta-analysis

Learning from worked examples, also called example-based learning, is an instructional method that has been intensively investigated in educational psychology. Typically, example-based learning is designed in the following way: First, learners receive a general instruction in which concepts and principles of a domain are introduced. Second, learners study worked examples that are an instance of these concepts and principles. The worked examples normally consist of three components presented to the learners: (1) the

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formulation of a definite problem (e.g., a combination problem), (2) the solution steps undertaken (i.e., operators; these steps are sometimes missing), and (3) the final solution itself (i.e., the goal). Third, in addition to studying worked examples, learners are often required to solve problems in the learning phase. There is abundant empirical evidence showing that example-based learning designed in this way is more effective than learning by solving problems alone. This is particularly true for early phases of cognitive skill acquisition (for overviews, see, e.g., Atkinson *et al.* 2000; Renkl 2005, manuscript submitted for publication). Hence, one of the best established findings within cognitive load theory (CLT) is the worked example effect (Sweller *et al.* 1998).

The effectiveness of studying worked examples for learning can be explained by CLT (Sweller 2005; Sweller *et al.* 1998) as follows: When confronted with a problem, learners who are unfamiliar with a knowledge domain usually engage in domain-independent solution strategies such as means-end-analysis to approach the current problem. This search, however, puts high demands on the limited capacity of the learners' working memory and normally does not lead to the construction of problem-solving schemata (e.g., Sweller and Chandler 1994). As a result, learners who are left to their own devices during problem solving are unlikely to achieve a satisfactorily deep understanding about the principles relevant to the solution process so that they fail to solve transfer problems (e.g., Renkl *et al.* 1996).

In contrast, providing worked examples prevents learners from engaging in irrelevant search processes and helps them to devote their attention to the presented problem states to solve a problem in a meaningful way. This frees up cognitive resources that can be used to actively engage in understanding the solution procedure, ideally, with reference to the underlying domain principle. Hence, worked examples create a lower demand on the learners' working memory and support them in constructing problem-solving schemata. Therefore, studying worked examples is helpful to acquire knowledge that can be flexibly applied to new problem-solving situations (for more details, see, e.g., Atkinson *et al.* 2000; Renkl 2005; Van Gog *et al.* 2004).

Although asking learners to study worked examples has been shown to be an effective means of instruction, successful learning from worked examples does not always occur naturally. For example, learners often simply acknowledge the information presented in worked examples without striving towards a deeper understanding (e.g., Renkl 1997). Therefore, learners usually need help to process the worked examples effectively. This might be accomplished, for example, through informing learners about the relevance of self-explanatory activities for learning such as principle-based explanations, explication of goal–operator combinations, or example comparisons (for details, see Renkl 1997, 2005) and through prompting them to generate such self-explanations (e.g., Atkinson *et al.* 2003). Empirical research has demonstrated that prompting and supporting self-explanations results in better learning outcomes (e.g., Berthold *et al.* 2009; Chi *et al.* 1989; Renkl 2005; Schworm and Renkl 2006).

Instructional Explanations and Processing Worked Examples

Sometimes, however, learners have difficulties with correctly explaining the principles underlying the worked examples to themselves (e.g., Berthold *et al.* 2009; Renkl 2002). Berthold and Renkl (2009), for example, found that the acquisition of procedurals skills was impaired when learners produced faulty self-explanations during example processing. In light of this finding, it can be expected that learners are better off when they are provided with instructional explanations that help them to understand the problem states displayed in the worked examples. Similarly, learners frequently have gaps in their understanding that they cannot fill in on their own or with the help of the worked examples alone. In these cases, providing instructional explanations can enable learners to overcome their difficulties and to develop a more complete understanding. Finally, learners are often prone to erroneously assume comprehension, although they actually fail to achieve a sufficient understanding (e.g., Otero and Graesser 2001). Under these circumstances, instructional explanations provided to facilitate example processing might help learners to detect inconsistencies in their own understanding, thereby preventing them from being caught by an illusion of understanding that inhibits further learning (e.g., Chi *et al.* 1994).

In addition, Van Gog *et al.* (2004) suggested that worked examples are not per se effective in supporting the acquisition of meaningful and flexible knowledge. This is because worked examples usually consist of prefabricated *product-oriented information* in terms of a problem formulation, solution steps, and a final solution. *Process-oriented information* about why some solution steps, for example, are undertaken (i.e., the rationale behind the problem) or how to select appropriate operators (i.e., strategic knowledge and heuristics), by contrast, is seldom provided in worked examples. Such information, however, might be immediately relevant to learning because it can support the understanding of the solution process and the development of a principle-based understanding. Therefore, to optimize learning from worked examples, Van Gog *et al.* (2004) suggest that instructional explanations in terms of process-oriented information should be added to worked examples. Referring to CLT, the researchers argue that process-oriented information can induce a germane load resulting in more effective learning.

Although there are theoretical assumptions in favor of adding instructional explanations to worked examples, the empirical evidence for the benefits of instructional explanations is inconclusive. Some studies found positive effects (e.g., Renkl 2002), some found neutral effects (e.g., Gerjets *et al.* 2006), and some found even negative effects (e.g., Ward and Sweller 1990). These mixed findings suggest that there are further factors influencing the effectiveness of instructional explanations for example-based learning.

First, Schworm and Renkl (2006) observed that instructional explanations were better for example-based learning than no instructional guidance. However, prompting learners to generate self-explanations during the study of worked examples was the best option. Hence, it can be assumed that providing explanations are an instructional means that make example-based learning not necessarily more effective than other instructional techniques such as self-explaining.

Second, instructional explanations typically provide learners with information about principles relevant to understanding the worked examples. Given that learners in example-based learning are usually at the early phase of cognitive skill acquisition (Renkl 2005), they might mainly acquire declarative knowledge from the explanations (e.g., knowledge about principles). In contrast, effects of instructional explanations on problem-solving performance are more indirect and thus might need more time to materialize because learning to solve problems requires the transition from declarative knowledge to procedural knowledge (e.g., Anderson 1982). However, in addition to presenting principles of a domain, instructional explanations can also provide information about operators that show learners how to approach the worked-out problem (e.g., Van Gog *et al.* 2004). Hence, it can be expected that instructional explanations that present not only information about principles but also information about operators are more likely to benefit example-based learning than instructional explanations that present only information about principles. For example, Kyun and Lee (2009) showed that worked examples containing both conceptual and procedural information resulted in more learning than worked examples containing only conceptual information or only procedural information.

Third, research has shown that example-based learning is more effective in those cases where the study of worked examples is combined with problems to be solved (e.g., Pashler *et al.* 2007). Accordingly, when provided with instructional explanations that aim to facilitate the processing of worked examples, learners who have the opportunity to apply their newly acquired knowledge by solving problems in the learning phase might more effectively profit from studying worked examples with instructional explanations than learners who study worked examples together with instructional explanations but are not provided with the opportunity to solve problems.

Fourth, it is a well-established finding that learning by studying worked examples loses its effectiveness with increasing experience of the learners (i.e., *expertise-reversal effect*; Kalyuga *et al.* 2003). This effect can be explained by the fact that learners who have already constructed problem-solving schemata might not need instructional guidance any longer. Hence, when continuously presented with worked examples, learners have to devote their attention to redundant information (i.e., worked examples), which might result in suboptimal learning processes (i.e., *redundancy effect*; Sweller 2005; Sweller *et al.* 1998). It can be assumed that in case worked examples are repeatedly provided with instructional explanations, learners have to invest even more cognitive capacity to process this redundant information. Hence, it might well be that worked examples that are enriched by instructional explanations are particularly harmful for learning under these circumstances. However, when learners have the possibility to choose whether or not they would like to have instructional explanations to support their example processing the redundancy effect might be diminished.

Research Questions and Hypotheses

In this article, we present a meta-analysis that was conducted to examine the influence of instructional explanations on example-based learning. In the meta-analysis, we contrasted learning by studying worked examples with instructional explanations against learning by studying worked examples without instructional explanations. In addition, we used meta-analytic techniques to investigate the role of different factors related to example-based learning with instructional explanations.

Specifically, we addressed the following research questions: First, due to the mixed patterns of results, we expected that the effect of instructional explanations on example-based learning averaged across all studies would be small. Second, even though there might not be a pronounced overall effect on learning, we hypothesized that instructional explanations would strongly affect the acquisition of conceptual knowledge. Third, we conjectured that the type of instructional explanations would make a difference in example-based learning. In particular, studying worked examples together with instructional explanations that presented information about both principles and operators should benefit learning. Fourth, we assumed instructional explanations to be more effective for example-based learning when contrasted against learning conditions in which learners were not supported in example processing as opposed to when contrasted against learning conditions in which learners were supported in example processing (i.e., through self-explanation elicitation). Fifth, we expected learning by studying worked examples in combination with instructional explanations to be more beneficial when learners were provided with the opportunity to solve problems in the learning phase. Sixth, we conjectured that instructional explanations would be more harmful for example-based learning in those cases where learners were repeatedly required to study worked examples. Seventh, we expected studying worked examples to be more beneficial when learners could actively choose whether they would need an instructional explanation or not. Eighth, we tested in an explorative way whether the domain to be learned would moderate the impact of instructional explanations on example-based learning.

Method

Selection of empirical studies

For inclusion in the review, we used the following criteria: First, we selected empirical studies that examined example-based learning under (at least) two experimental conditions: a condition in which instructional explanations were added to worked examples and a condition in which instructional explanations were not added to worked examples.[1] Second, we selected studies in which participants received a general instruction in the principles to be learned before they studied worked examples (e.g., as part of the experiment or as part of their studies)[2] because this sequencing is a key feature of learning by studying worked examples (e.g., Renkl, manuscript submitted for publication). Third, we selected studies that aimed to investigate the benefits of using instructional explanations for example-based learning so that it is reasonable to assume that instructional explanations were constructed in a way to promote learning.[3]

To identify relevant studies, we searched the SCI and SSCI (1973–2009), ERIC (1966–2009), PsycInfo (1887–2009), and Psyndex (1977–2009) databases using the following terms: *example-based learning*, *worked examples*, *explanation*, *elaboration*, *feedback*, and *information*. In addition, we examined the reference lists of individual articles and searched for studies that cited publications reviewing research on learning from worked examples (e.g., Atkinson *et al.* 2000; Renkl 2005).

Studies were included if the statistical means and standard deviations were presented or if a statistic (e.g., F statistics or binary data like events) was available from which an effect size could be computed. Therefore, we were not able to include empirical studies that failed to provide sufficient statistical information. All included studies used a between-subjects design and had at least one learning measure as dependent variable. In some control conditions of the studies in which instructional explanations were not added to the worked examples, learners were instructionally encouraged to generate self-explanations to improve their example processing. Overall, there were 21 experiments that were included in the meta-analysis. The experiments were located in 18 journal articles and 3 conference papers. Table 1 provides an overview over the studies.

[1] Some studies examined not only learning by studying worked examples but also by solving problems alone (e.g., Darabi *et al.* 2007a). The results for the experimental conditions with problem solving alone (i.e., without studying worked examples) were not included in the meta-analysis.

[2] In some studies, we inferred that participants were generally introduced into the principles to be learned from the fact that at least the topic (e.g., algebra) was introduced to them.

[3] Therefore, we excluded the study by Ward and Sweller (1990). The goal of this study (experiment 5) was to show that instructional explanations would have negative effects on example-based learning due to using a split-source format.

Table 1 Summary of Experimental Studies Included in the Meta-Analysis Together With the Effect Sizes and the Coded Categories of the Moderator Variables

Study	Year	Cohen's *d* (90% CI)	Learning measure	Learning domain	Number of learning opportunities	Combination of worked examples and problems	Prompted self-explaining in the control condition	Type of instructional explanation	Provision of instructional explanations
Atkinson, Exp. 1	2002	0.92 (−0.13 to 1.70)	Near transfer, far transfer	Mathematics	8	Yes	No	Operators	By default
Darabi, Nelson, & Paas	2007	−0.56 (−1.25 to 0.12)	Near transfer	Chemistry (science)	4	No	No	Operators and principles	By default
Darabi, Nelson, & Palanki	2007	0.50 (−0.01 to 1.00)	Near transfer	Chemistry (science)	4	No	No	Operators and principles	By default
Gerjets, Scheiter, & Catrambone, Exp. 2[a]	2003	0.34 (−0.23 to 0.91), −0.11 (−0.68 to 0.45)	Conceptual knowledge, near transfer, and far transfer	Mathematics	8	No	No	Operators and principles	By default
Gerjets, Scheiter, & Catrambone, Exp. 1[a]	2006	0.02 (−0.54 to 0.57), −0.29 (−0.90 to 0.33)	Near transfer, far transfer	Mathematics	8	No	No	Operators and principles	By default
Gerjets, Scheiter, & Catrambone, Exp. 2[a]	2006	0.60 (0.11–1.10), −0.17 (−0.66 to 0.32)	Near transfer	Mathematics	8	No	Yes	Operators and principles	By default
Große & Renkl, Exp. 1[a]	2006	0.24 (−0.21 to 0.68), −0.12 (−0.56 to 0.32)	Conceptual knowledge, near transfer	Mathematics	4	No	Yes[b] No[b]	Principles	By default
Hausmann & VanLehn[c]	2007	−0.04 (−0.50 to 0.42)	Near transfer, far transfer, and farther transfer	Physics (science)	7	Yes	Yes[b] No[b]	Operators and principles	By default
Hilbert, Schworm, & Renkl[a, d]	2004	−0.75 (−1.45 to 0.06), 0.40 (−0.27 to 1.08)	Near and far transfer	Instructional design	8	No	Yes	Principles	By default
Hohn & Moraes	1997/1998	0.78 (0.36–1.20)	Conceptual knowledge, situational knowledge, and near transfer	Programming (mathematics)[e]	4	No	No	Principles	By default
Hoogveld, Paas, & Jochems	2005	−0.74 (−1.42 to 0.06)	Near transfer	Instructional design	2	No	No	Operators and principles	By default
Meier, Reinhard, Carter, & Brooks	2008	0.03 (−0.50 to 0.56)	Near transfer	Biology (science)	1	No	No	Operators and principles	By default

Reed, Dempster, & Ettinger, Exp. 1 vs. Exp. 3	1985	0.45 (−0.58 to 1.47)	Near transfer, far transfer	Mathematics	3	Yes (problems serve as test items)	No	Operators and Principles	By default
Reed & Bolstad, Exp. 1	1991	0.34 (−0.33 to 1.01)	Near and far transfer	Mathematics	1	Yes (problems serve as test items)	No	Operators and principles	By default
Renkl	2002	0.45 (−0.04 to 0.94)	Near transfer, far transfer	Mathematics	Not fixed but at least 4	Yes (partly faded worked examples)	No	Operators and principles	On learner demand
Schworm & Renkl[c]	2006	−0.09 (−0.62 to 0.44)	Near and far transfer	Instructional design	8	No	Yes[b] No[b]	Principles	On learner demand
Stark, Gruber, Mandl, & Hinkofer	2001	−0.05 (−0.49 to 0.39)	Conceptual knowledge, strategic knowledge, and situational knowledge	Bookkeeping (mathematics)[e]	19	Yes	Yes	Operators and principles	By default
Stark, Kopp, & Fischer, Exp. 1[a]	in press	0.77 (0.38–1.16), −0.07 (−0.45 to 0.31)	Conceptual knowledge, strategic knowledge, and far transfer	Medicine (science)	6	No	No	Operators and principles	By default
Stark, Kopp, & Fischer, Exp. 2[a]	in press	0.85 (0.41–1.28), 0.34 (−0.09 to 0.76)	Conceptual knowledge, strategic knowledge, and far transfer	Medicine (science)	6	No	No	Operators and principles	By default
Van Gog, Paas, & Van Merriënboer	2006	−0.43 (−1.04 to 0.18)	Near transfer	Physics (science)	6	No	No	Operators and principles	By default
Van Gog, Paas, & Van Merriënboer[f]	2008	0.23 (−0.19 to 0.64)	Near and far transfer	Physics (science)	4	No	No	Operators and principles	By default

[a] The study includes two independent subgroups yielding two effect sizes

[b] The study includes two control conditions in which learners are (a) not supported in example processing or (b) supported in example processing by self-explanation elicitation

[c] The study included both an experimental condition with instructional explanations combined with self-explanation elicitation and an experimental condition with instructional explanations without self-explanation elicitation. For optimal comparison with the other studies, we did not include the experimental condition with instructional explanations combined with self-explanation elicitation in the meta-analysis

[d] In this study, learners of the experimental condition received a combination of instructional explanations and prompts for self-explaining

[e] The original learning domain of these studies is programming and bookkeeping, which we subsumed under the learning domain mathematics

[f] The study consisted of two learning phases. For optimal comparison with the other studies, we included only the results from the first learning phase in the meta-analysis

Moderator variables coded from each study

To include variables in the meta-analysis that potentially influenced (i.e., moderated) the magnitude of the effect of instructional explanations on example-based learning, we coded each experiment for the following moderator variables (see also Table 1):

Learning domain The studies differed in the domain in which the participants learned: mathematics, sciences (e.g., biology, physics), or instructional design.

Presentation of worked examples The studies differed in whether worked examples were presented in isolation or in combination with problems to be solved in the learning phase.

Number of learning opportunities The studies differed in how often learners were required to study worked examples and to solve problems in the learning phase. Each worked example to be studied and each problem to be solved was counted as a learning opportunity.

Type of instructional explanation added to worked examples The studies differed in whether the instructional explanations accompanying the worked examples presented information about operators, principles, or operators and principles. Operators are a set of actions undertaken to systematically approach a current problem (e.g., "In order to find the first event probability you have to consider the number of acceptable choices and the pool of possible choices," Gerjets *et al.* 2006, p. 106). A principle is a rationale underlying a problem. It informs about the relationship among elements (e.g., "In parallel circuits, the total current equals the sum of the currents in the parallel branches," Van Gog *et al.* 2006, p. 163).

Provision of instructional explanations The studies differed in whether the instructional explanations accompanying worked examples were available by default or only on learner demand.

Prompted self-explaining in the control condition Participants of the control conditions of the studies included in the meta-analysis always learned by studying worked examples without instructional explanations.[4] However, in some of the studies, the participants of the control conditions were, instead of receiving explanations, instructionally required to generate self-explanations during the study of the worked examples. In each of the studies, prompting learners to self-explaining was accomplished by asking questions to them.

Type of learning measure in the posttest All studies measured the learning effectiveness of worked examples by using at least one learning measure. The studies, however, differed in the types of learning measure used (note that the wording for the following seven types of learning measures needs not to be identical with the wording used in the studies).

> ***Near transfer***. A test required participants to solve problems that were structurally similar to the problems studied (i.e., the worked examples) in the learning phase.
> ***Far transfer***. A test required participants to solve problems that were not structurally similar to the problems studied (i.e., the worked examples) in the learning phase.

[4] There was one exception: In the second experiment conducted by Gerjets *et al.* (2006), learners in the control conditions received a combination of instructional explanations and prompts to generate self-explanations.

Farther transfer. A test required participants to solve problems from a domain different from the domain in which they learned during the learning phase.

Near and far transfer. A test required participants to solve problems that were either structurally similar or structurally not similar to the problems studied (i.e., the worked examples) in the learning phase. In the studies using this test, results on near and far transfer were not separately reported.

Conceptual knowledge. A test required participants to present their declarative knowledge about important principles and concepts acquired in the learning phase.

Situational knowledge. A test required participants to present their declarative knowledge about information relevant for solving a problem.

Strategic knowledge. A test required participants to present their declarative knowledge about strategies and heuristics relevant for solving a problem.

Computation and analysis of effect sizes

The effect sizes were calculated as Cohen's d defined as the difference between the means of the experimental conditions with and without instructional explanations divided by the pooled standard deviation (Hedges and Olkin 1985). If means and/or standard deviations were not available, we computed the effect size on the basis of other statistics (e.g., t, F, U) or on the basis of binary data (e.g., events). The sign of d is positive when adding instructional explanations to worked examples had a positive impact on learning, and the sign of d is negative when adding instructional explanations to worked examples had a negative impact on learning.

As the unit of analysis for computing effect sizes, we chose each independent group in an experimental study. For example, if an experimental study used a 2×2 factorial design and varied not only whether instructional explanations were added to worked examples (i.e., first factor) but also whether the worked examples were presented in different formats (i.e., second factor), we included each comparison between example-based learning with instructional explanations and example-based learning without instructional explanations resulting from each level of the second factor. For example, the study of Gerjets *et al.* (2006) varied not only whether instructional explanations were added to worked examples or not but also whether worked examples were presented in a modular or molar format. Hence, when we included this study in the meta-analysis, we took into account the comparisons between example-based learning with instructional explanations and example-based learning without instructional explanations for both the modular and molar format.

The inspection of the studies indicated that nearly all studies had multiple learning outcomes (e.g., performance on near and far transfer). In addition, some studies compared several experimental conditions in which different forms of example-based learning with instructional explanations were varied (e.g., instructional explanation with or without a pedagogical agent; Atkinson 2002) against a common control condition in which no instructional explanations were added to worked examples. In these cases, the studies yielded stochastically non-independent data whose effect sizes could not be separately included in the meta-analysis without producing biased results (e.g., Gleser and Olkin 1994). The best way to handle this problem is to employ multivariate techniques to take into account the correlational nature of the dependent learning measures (e.g., Gleser and Olkin 1994; Hedges and Olkin 1985). However, this was not possible because the majority of studies failed to provide information (e.g., information about correlations between learning measures within a study) necessary for performing such multivariate procedures. Therefore, we decided to compute the mean of the learning measures and the mean of the multiple comparisons in order to use these scores as the unit of analysis (Borenstein *et al.* 2009). In total, we had 28 independent pairwise comparisons.

To conduct the meta-analysis, we used a random-effects model. In contrast to a fixed-effect model, a random-effects model assumes the true effect size (i.e., the effect size in the population) to be not identical in all studies. Rather, the effect size depends on the specific characteristics of the individual study (e.g., learning domain, type of instructional explanation; cf. Borenstein *et al.* 2009). Each effect of the pairwise comparison was weighted by the inverse variance consisting of the variance of the within-pairwise comparison and the variance between the pairwise comparisons (Borenstein *et al.* 2009). For the analysis of the moderator variables, we also used a random-effects model to combine studies for each category of a moderator variable. To test for significant differences between the categories of a moderator variable, we used the Q test for heterogeneity (for more details, see Borenstein *et al.* 2009). A significant coefficient indicates that the averaged effect size for studies with one category of the moderator variable is significantly different from the averaged effect size for studies with the other category of the moderator variable. In case of more than two categories, we contrasted each category with the other categories of the moderator variable. In case of a continuous moderator variable, we performed a meta-regression. Note that the Q test usually has a relatively low statistical power when the number of studies is small (e.g., Huedo-Medina *et al.* 2006). Hence, given that our meta-analysis contained a relatively small number of studies, it was more difficult to detect significant effects (type 2 error). Therefore, we set the alpha level to 0.10 and report the 90% confidence interval. The software Comprehensive Meta Analysis Version 2 (2008) was used to perform the meta-analysis.

Results

Overall effect

The weighted mean effect size of the 28 pairwise comparisons was statistically significant, p=0.04 (90% confidence interval, 0.03–0.30). The effect size, however, was small, d=0.16. Hence, the effects of studying worked examples together with instructional explanations were minimal. To examine whether the effect sizes resulting from each pairwise comparison differed from each other systematically, we computed the Q statistic for fixed-effect models. The homogeneity statistic was significant, Q=49.89, df=27, p<.01. Thus, the variation in effect sizes of the pairwise comparisons did not occur by chance. This result indicates that it was legitimate to use a random-effects model for the meta-analysis (for more details, see Borenstein *et al.* 2009).

Effect of moderator variables

In Table 2, the results for the moderator variables are displayed. First, to examine the impact of studying worked examples with instructional explanations on the different types of learning measures, we computed separate meta-analyses due to the non-independent character of the learning measures (cf. Borenstein *et al.* 2009). The averaged effect sizes for studies measuring near transfer, far transfer, farther transfer, near and far transfer, situational knowledge, and strategic knowledge were not significant (see Table 2). In contrast, instructional explanations added to worked examples had a significant and positive effect on the acquisition of conceptual knowledge (see Table 2). As we conducted separate meta-

Table 2 Moderator Variables with Categories, Number of Pairwise Comparisons, Averaged Effect Sizes (*d*), and 90% Confidence Interval

Variable and category	Number of pairwise comparisons	*d*	90% Confidence Interval
Prompted self-explaining in control condition			
Yes	8	−0.01	−0.28 to 0.26
No	20	0.22**	0.05 to 0.38
Type of learning measure			
Near transfer	21	0.10	−0.04 to 0.24
Far transfer	15	0.23	−0.02 to 0.43
Farther transfer	1	−0.08	−0.54 to 0.38
Near and far transfer	3	0.15	−0.14 to 0.44
Conceptual knowledge	10	0.36**	0.17 to 0.55
Strategic knowledge	5	0.31	−0.12 to 0.74
Situational knowledge	2	0.37	−1.02 to 1.75
Learning domain			
Mathematics	14	0.22**	0.06 to 0.38
Science	10	0.21	−0.02 to 0.44
Instructional Design	4	−0.28	−0.71 to 0.16
Combined presentation of worked examples and problems			
Yes	4[a]	0.22	−0.10 to 0.54
No	22	0.13	−0.03 to 0.29
Type of instructional explanation			
Operators	1	0.92*	0.13 to 1.70
Principles	7	0.17	−0.12 to 0.462
Operators and principles	20	0.14	−0.02 to 0.29
Provision of instructional explanations			
By default	24	0.17**	0.04 to 0.32
On learner demand	4	0.04	−0.39 to 0.47

*$p<0.10$; **$p<0.05$

[a] In both studies conducted by Reed and Bolstad (1991) and Reed et al. (1985), problems had to be solved directly after studying worked examples. These problems, however, served as a learning measure. Therefore, we did not include these studies for analyzing the moderator variable.

analyses to avoid biased results, it was not possible to test whether the averaged effect sizes for studies with different types of learning measures varied significantly from each other.

Second, to investigate whether instructional explanations would benefit learning in cases where they presented not only information about principles but also information about operators, we performed a moderator analysis. There was one study with instructional explanations that provided learners only with information about operators. The effect size of this study was significant (see Table 2). The averaged effect size for studies with instructional explanations about principles and the averaged effect size for studies with instructional explanations about principles and operators were not significant (see Table 2). The significant effect size of the single study was not significantly different from the averaged effect size for studies with instructional explanations that provided learners with information about principles (Q=2.16, df=1, p=0.14) and from the averaged effect size for studies with instructional explanations that provided learners with information about principles and operators (Q=2.59, df=1, p=0.11). In addition, example-based learning together with instructional explanations about principles was not significantly different from example-based learning together with instructional explanations about principles and operators (Q=0.03, df=1, p=0.86).

Third, to see whether the effect of instructional explanations on example-based learning would differ as a function of whether or not learners in the control conditions were instructionally encouraged to self-explain the worked examples, we computed, due to the non-independence of the data, a further meta-analysis. In this analysis, we did not compute the means of multiple comparisons in those cases where the studies included both a control condition in which learners were instructionally supported in example processing by encouraging them to generate self-explanations and a control condition in which learners were not instructionally supported in example processing. As these control conditions were compared against the same experimental condition within a study (i.e., example-based learning with instructional explanations), we excluded the control condition with no instructional support for example processing from the meta-analysis to avoid producing biased results due to non-independent data. The averaged effect size for studies in which learners in the control conditions were presented with worked examples but not encouraged to self-explain the worked examples was significant (see Table 2). Hence, instructional explanations had a positive effect on learning outcomes as compared with conditions without self-explanation support. The averaged effect size for studies in which learners in the control conditions were presented with worked examples and encouraged to self-explain the worked examples was not significant (see Table 2). The averaged effect size for studies without self-explanation elicitation, however, was not significantly different from the averaged effect size for studies with self-explanation elicitation (Q=1.32, df=1, p=0.25).

Fourth, we tested whether studying worked examples together with instructional explanations would be more beneficial when learners were not only required to study worked examples but also provided with the opportunity to solve problems in the learning phase. The averaged effect size for studies with learning by worked examples only and the averaged effect size for studies with learning by worked examples in combination with problem solving were not significant (see Table 2). The averaged effect size for studies in which worked examples were presented together with problems to be solved in the learning phase was not significantly different from the averaged effect size for studies in which worked examples were presented alone in the learning phase (Q=0.16, df=1, p=0.69).

Fifth, we examined if instructional explanations would be more harmful for example-based learning in those cases where learners were repeatedly required to study worked examples (in combination with problem solving). To do so, we computed a meta-regression with the number of learning opportunities as the independent variable and the effect size of each pairwise comparison as the dependent variable. The regression slope (not displayed in Table 2) clearly failed to reach the level of statistical significance (Q=0.29, df=1, p=0.59).

Sixth, we tested whether example-based learning would be differently affected as a function of whether learners studied worked examples with instructional explanations that were provided by default or on learner demand. The averaged effect size for studies with instructional explanations provided by default was significant (see Table 2). In contrast, the averaged effect for studies with instructional explanations provided on learner demand was not significant (see Table 2). The averaged effect size for studies in which worked examples were presented together with instructional explanations by default was not significantly different from the averaged effect size for studies in which worked examples were presented together with instructional explanations on learner demand (Q=0.27, df=1, p=0.60).

Seventh, the averaged effect size for studies with mathematics as learning domain was significant, whereas the averaged effect sizes for studies with sciences or instructional design as learning domain were not significant (see Table 2). The averaged effect size for studies with mathematics as learning domain was not significantly different from the averaged effect size for studies with sciences as learning domain (Q=0.01, df=1, p=0.95) but significantly different from the averaged effect size for studies with instructional design as learning domain (Q=3.01, df=1, p=0.08).

Discussion

In order to shed light on the very mixed pattern of results on the effectiveness of instructional explanations added to worked examples, we reviewed and meta-analytically synthesized relevant literature in this research area. The identified 21 publications yielded 28 pairwise comparisons showing that the overall effects of instructional explanations for example-based learning were minimal. As indicated by the heterogeneity coefficient, there was a great variation in the effect sizes between the pair-wise comparisons. In other words, the meta-analysis contained experimental studies yielding positive effects (e.g., Hohn and Moraes 1997/1998) as well as negative effects (e.g., Hoogveld *et al.* 2005) of instructional explanations on example-based learning. To explain this variation, we analyzed the impact of moderator variables on the overall effect.

First, we observed a positive influence of adding instructional explanations to worked examples on the acquisition of conceptual knowledge. In contrast, transfer performance was not affected by whether worked examples were accompanied by instructional explanations or not. Obviously, instructional explanations that provide information about operators for achieving a certain goal or information about principles underlying a worked example can help learners to develop a substantial amount of declarative knowledge. It can be assumed that this knowledge is useful for the construction of problem-solving schemata (e.g., Anderson 1982; Rittle-Johnson *et al.* 2001). Even though the reviewed studies revealed no beneficial effects of instructional explanations on transfer performance, it can be assumed that conceptual knowledge acquired by receiving instructional explanations supports transfer performance in the long run. To test this assumption, future research on example-based learning with instructional explanations should implement delayed transfer tests.

Second, we found a positive effect of providing instructional explanations on example-based learning when learners in the control conditions were not supported in their self-explanation activities. By contrast, when learners in the control conditions were encouraged to engage in self-explaining during example processing, the benefits of instructional explanations disappeared. This pattern of results suggests that adding instructional explanations to worked examples can enhance learning under some circumstances. However, there are other ways, too, to support example processing such as generating self-explanations that make example-based learning at least as effective as adding instructional explanations to worked examples. It has to be noted that, due to the non-significant difference between the averaged effect size for studies without self-explanation elicitation and the averaged effect size for studies with self-explanation elicitation (cf. Borenstein *et al.* 2009), the finding on the benefits of instructional explanations observed in studies without self-explanation elicitation in the control conditions has to be interpreted with some caution.

Third, studies with mathematics as learning domain yielded a significant effect size. Obviously, adding instructional explanations to worked examples in this domain was helpful for learning. A tentative explanation might be that learners conceive mathematics as a particularly difficult learning domain in which they get unsure when they are left alone without instructional explanations (see also Schworm and Renkl 2006). Similarly, it is plausible to assume that instructional explanations are helpful in this domain because they can facilitate the understanding of the formal language used in mathematics. The averaged effect size for studies with mathematics as learning domain was significantly different from the averaged effect size for studies with instructional design as learning domain but not significantly different from the averaged effect size for studies with sciences as learning domain. Hence, the overall effect size was only in part systematically related to differences in the learning domain.

Fourth, we found a significant effect size for one study in which learners were provided with explanations presenting information only about operators (Atkinson 2002). In contrast, the averaged effect sizes for studies with explanations about principles and for studies with explanations about principles and operators failed to reach the level of statistical significance. As there was only this single study yielding a significant effect size for explanations about operators, it is problematic to generalize this result unless additional studies will provide further evidence. We also assumed that explanations focusing on principles and operators would benefit example-based learning more effectively than explanations focusing on principles alone. However, we found no empirical evidence in support of this assumption.

Similarly, we failed to obtain significant effects for other moderator variables. For example, our assumption that instructional explanations would be particularly helpful when the study of worked examples was accompanied by problem solving was not supported. Presumably, learners could not fruitfully use the instructional explanations for solving problems in the learning phase. Likewise, we failed to find a significant effect of the number of learning opportunities on learning. Apparently, the number of learning opportunities was still too small to evoke a redundancy effect (Kalyuga *et al.* 2003), which would have resulted in poor learning performance. Finally, the results of the meta-analysis did not confirm our assumption that learners would benefit more effectively from example-based learning when they were free to choose to have access to instructional explanations. It can be conjectured that learners might have difficulties in monitoring their understanding (Otero and Graesser 2001) and thus might not know when an instructional explanation could improve their example processing.

Although the overall variation in effect sizes between the pairwise comparisons could in part be attributed to the effects of the moderator variables under investigation, they did not fully account for the observed heterogeneity. Therefore, it can be assumed that further characteristics of the studies influenced the effectiveness of instructional explanations for example-based learning. In fact, each study included in the meta-analysis had specific characteristics that might have affected the effectiveness of instructional explanations. These characteristics, however, could not be coded for all studies and included in the meta-analysis. For example, in the study by Van Gog *et al.* (2006), more mental effort was invested by learners who were provided with instructional explanations for example processing as compared with learners who were not provided with instructional explanations. One explanation for this increased mental effort is that the instructional explanations and the corresponding diagrams of the learning material were not presented in an integrated format (*split-source effect*; Sweller 2005; Sweller *et al.* 1998; Ward and Sweller 1990). In this case, the learners might have been urged to put more cognitive effort into integrating both sources of information, which might have been detrimental to their learning. Similarly, Gerjets *et al.* (2006) observed in their first experiment that learners were able to acquire a substantial body of knowledge from studying worked examples in a specific instructional format. Therefore, when instructional explanations were added to these worked examples, they appeared to be redundant and had no additional benefits for learning (Sweller 2005; Sweller *et al.* 1998). This redundancy effect might also explain the results obtained by Van Gog *et al.* (2006) because learners were required to repeatedly study worked examples. Another aspect relevant to example-learning is the format in which the worked examples together with the instructional explanations were presented in the studies included in the meta-analysis. Whereas some studies explicitly examined the role of different example formats (e.g., Gerjets *et al.* 2006; Große and Renkl 2006), other studies did not provide detailed information about this aspect. For example, Atkinson (2002) investigated the modality of the instructional explanations that accompanied worked examples provided in a visual format. He found that instructional explanations provided in an aural format were particularly effective in fostering example-based learning. According to the *modality effect* (Mayer and Moreno 2003), this effect can be assumed to occur because working memory load is reduced when parts of the visual information are replaced by aural information.

In conclusion, the significant but small overall effect of instructional explanations challenges the notion that more direct instruction always results in more learning (cf. Koedinger and Aleven 2007). In other words, maximizing the instructional guidance in example-based learning through the provision of instructional explanations might not be beneficial in any circumstance. Instead, it is plausible to assume that the optimal design of instruction in example-based learning depends on specific learning goals. In this meta-analytic review, we found corroborating evidence for this assumption because the positive effects of instructional explanations were clearly more pronounced for the acquisition of conceptual knowledge. In addition, instructional explanations might be only one of many methods to support example processing. When compared to learners who were not instructionally required to engage in self-explaining, learners who received instructional explanations had higher learning gains. However, this effect was diminished when learners were encouraged to be actively on their own by generating self-explanations. This finding suggests that effective instruction is probably always characterized by a balanced mix of providing support (e.g., provision of worked solution steps) and eliciting learner activity (e.g., by self-explanation prompts; Koedinger and Aleven 2007). In further research, it might thus be fruitful to concentrate not only on the characteristics of the instructional explanations and related factors but also on instructional procedures that enhance the active processing and the further use of instructional explanations (Berthold and Renkl 2010; Wittwer and Renkl 2008).

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