

**SPECIAL ISSUE ARTICLE**

Example-based learning: New theoretical perspectives and use-inspired advances to a contemporary instructional approach

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Email: v.hoogerheide@uu.nl**Summary**

Decades of research has shown that example-based learning is an effective instructional strategy for learning new skills. The field of learning from examples is seeing a shift in focus towards more innovative and use-inspired research, in part because the use of examples for informal and formal learning purposes has mushroomed. This special issue comprises a set of eight papers in which students learned a procedural skill from worked examples or modeling examples. Each study characterizes a recent development towards more innovative example-based learning research. These developments are: (a) the integration of social-cognitive and cognitive example research, (b) the integration of example-based learning and analogical reasoning research, (c) the extension of traditional Cognitive Load Theory effects, (d) a greater focus on learning from (productive) errors, and (e) more research on individual differences. This special issue concludes with insightful commentary articles written by Prof. Dr. Katharina Scheiter and Prof. Dr. Richard Mayer.

KEYWORDS

example-based learning, cognitive load theory, modeling examples, problem solving, worked examples

1 | INTRODUCTION

Decades of research has shown that example-based learning is a powerful instructional strategy for novices to learn new skills (for a recent review, see Van Gog, Rummel, & Renkl, 2019). Most studies within the enormous body of literature on example-based learning have been conducted against the backdrop of two perspectives, which differ in the type of examples and outcome variables used as well as in the research questions examined (Renkl, 2014; Van Gog & Rummel, 2010). Firstly, research inspired by cognitive theories such as

Cognitive Load Theory (Sweller, Ayres, & Kalyuga, 2011) has focused on *worked examples*, which provide a text-based, step-by-step account of how to solve a problem (e.g., Cooper & Sweller, 1987). Commonly, a worked example shows the entire solution procedure in a didactical way, which means that the procedure is shown as novices should be learning the skill rather than how experts would actually perform it (Van Gog et al., 2019). Most cognitive research has shown that studying worked examples (alternated with practice problem solving) is more effective (i.e., enhances learning outcomes) and more efficient (attained with less effort and/or time investment in the learning phase) for acquiring new problem solving skills than (unaided) practice problem solving only (e.g., Paas, 1992; Van Gog, Kester, & Paas, 2011).

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Secondly, research inspired by social-cognitive theories (e.g., Social Learning Theory; Bandura, 1986) has focused on observational learning from live or video *modeling examples* in which someone else (i.e., the model, for example, another student or a teacher) explains and demonstrates how to solve a certain problem. This demonstration can either be of a didactical nature but could also be natural (e.g., Schunk, Hanson, & Cox, 1987). Aside from learning outcomes, the most common outcome variable is self-efficacy, which refers to people's beliefs about their capabilities to attain certain levels of performance (Bandura, 1997). Most social-cognitive research has focused on the question of whether the effect of modeling examples on self-efficacy and learning depends on who the model is in terms of characteristics such as gender (e.g., Hoogerheide, Loyens, & Van Gog, 2016), age (e.g., Hoogerheide, Van Wermeskerken, Loyens, & Van Gog, 2016), or expertise (e.g., Schunk & Hanson, 1985).

Worked and modeling examples arouse an important interest among both researchers and educational practitioners, and this interest has only increased in recent years. For instance, the use of video modeling examples has increased substantially in both formal (e.g., MOOCs, flipped classrooms) and informal settings (e.g., YouTube), because thanks to modern technological advances, it has become child's play to create and share them (De Koning, Hoogerheide, & Boucheix, 2018; Fiorella & Mayer, 2018; Van der Meij & Van der Meij, 2013). It is also becoming more common for learners to acquire new skills with the help of worked and/or modeling examples embedded in online learning environments (e.g., Foster, Rawson, & Dunlosky, 2018; Roll, Alevén, McLaren, & Koedinger, 2011; see also khanacademy.org).

This increased popularity of example-based learning has motivated researchers to shift their focus from the traditional research questions that long characterized (social-)cognitive research; instead, researchers are investigating novel questions by drawing on new theoretical perspectives and using new outcome variables, with the ultimate aim of uncovering how the effectiveness of example-based learning can be explained and further enhanced. This special issue comprises eight empirical studies that illustrate at least one of these innovative recent developments within example-based learning research. These innovative developments along with an introduction of the individual contributions will be presented below.

(1) The integration of cognitive and social-cognitive example-based learning research.

Two recent reviews integrated the social-cognitive and cognitive perspectives on example-based learning (Renkl, 2014; Van Gog & Rummel, 2010). Despite the similarities between the two perspectives, worked example (cognitive) and modeling example (social-cognitive) research used to function largely in isolation and not refer to each other much. In the conclusion section, Van Gog and Rummel stated that they "hope that future research on example-based learning will draw on both perspectives to identify and address novel research questions" (p. 168).

The integration of both research perspectives is precisely what happened. For instance, although self-efficacy used to only be a variable of interest in modeling example research (for an exception, see Crippen & Earl, 2007), recent research has shown that worked examples can also

foster self-efficacy beliefs (e.g., Hoogerheide, Loyens, & Van Gog, 2014). Similarly, recent research found that studying video modeling examples (alternated with practice problem solving) is more effective and efficient than problem solving only (e.g., Van Harsel, Hoogerheide, Verkoeijen, & Van Gog, 2019). A comparison of worked and modeling examples even showed no statistically significant differences between worked and modeling examples on learning outcomes, invested mental effort, or self-efficacy (Hoogerheide et al., 2014), suggesting that these two example types might yield similar effects.

The contribution of Van Harsel, Hoogerheide, Verkoeijen, and Van Gog (2020) nicely illustrates how the two different perspectives on example-based learning have become intertwined. Authors investigated the effects of different sequences of video modeling example study and practice problem solving (i.e., examples only, problems only, example-problem pairs, or problem-example pairs) on cognitive (i.e., cognitive load and learning outcomes) and motivational aspects of learning (i.e., self-efficacy, perceived competence, and topic interest), with four (Experiment 1) or eight tasks (Experiment 2) in the learning phase. The university students were novices to the task. How to sequence examples and problems has long been a key question in worked example research (e.g., Paas & Van Merriënboer, 1994) that only recently got introduced in the context of modeling example research (e.g., Coppens, Hoogerheide, Snippe, Flunger, & Van Gog, 2019; Kant, Scheiter, & Oschatz, 2017). The variation in sequence length is particularly interesting, because one could imagine that as example sequences become longer, example study would lose its effectiveness (cf. expertise-reversal effect; Kalyuga, 2007) or become demotivating (Sweller & Cooper, 1985), unless coupled with practice problem solving. Another innovative aspect is that Van Harsel and colleagues measured self-efficacy perceptions after every task in the learning phase, providing fine-grained insight into how (different sequences of) examples and problems affect novices' confidence in their abilities.

(2) Drawing connections between example-based learning and analogical reasoning research.

One of the developments that made Renkl's review unique is the integration of example-based learning research with research on analogical reasoning (about problems). Analogical reasoning refers to "reasoning on specific exemplars or cases" (Renkl, 2014, p. 10). As a result, the role of example comparison has received more attention. More specifically, building on a few "early" studies that had mainly focused on the role of within-category comparisons (i.e., several worked examples that instantiate the same principle) for noticing critical structural features and thus for schema abstraction (e.g., Gerjets, Scheiter, & Schuh, 2008; Quilici & Mayer, 1996; for research that focused on the comparison or several solution strategies that relate to the same or different problems see also Rittle-Johnson & Star, 2009), recent example-based learning studies have focused at optimizing both between- and within-category comparisons. For instance, Hancock-Niemic, Lin, Atkinson, Renkl, and Wittwer (2016) investigated the role of order (blocked vs. interleaved) and simultaneity (sequential vs. simultaneous) of examples in introducing learners to different but closely related principles.

The contribution of Schalk et al. (2020) builds on the study by Hancock-Niemic et al. as well as further previous research on the order and simultaneity of examples. Specifically, the authors addressed the research gap that in introducing learners to multiple closely related principles, which likely often is the case in educational settings such as school lessons, most studies have focused either on order or on simultaneity, or used incomplete (i.e., not fully crossed) factorial designs (the Hancock-Niemic et al. study is a rare exception). These issues make it hard to distinguish between and compare the effects of both factors (i.e., order and simultaneity) as well as understand the interplay between them. Furthermore, the authors point out that in previous research the learning material scarcely consisted of worked examples that were designed in accordance with main design guidelines (e.g., combining worked examples with self-explanation prompts, see Renkl, 2014) and that most studies differed concerning the learning process and outcome measures, which makes it hard to relate the studies to each other. Schalk and colleagues addressed these issues in an experiment with university students that followed a fully crossed 2x2-factorial design and in which several learning outcomes (i.e., conceptual knowledge, procedural knowledge, performance on verification tasks) and learning processes (i.e., cognitive load, feeling of flow, and learning time) were measured to illuminate the effects of both factors at a high level of detail.

The contribution of Loehr, Rittle-Johnson, Durkin, and Star (2020) contributes to extending our knowledge on the benefits of example comparisons as well. More specifically, the authors focused on the innovative question whether worked examples that follow main design principles such as the self-explanation principle (see Renkl, 2014) and that are combined with comparison prompts (here: comparison of different solution strategies for the same problem) protect learners from the detrimental effects of person-presentation of examples (i.e., examples that are presented with attribution to particular students), which have been found in previous research concerning transfer performance in particular (e.g., Riggs, Alibali, & Kalish, 2015). The authors make the case that such person-presentation of examples can often be found in mathematics textbooks, which renders the question whether appropriate example design can protect students from the detrimental effects highly relevant not only from a theoretical but also from an applied perspective. In close alignment with the applied goal of their study, the authors conducted a cluster-randomized experiment (teachers/classes were randomly assigned to the conditions) in actual classrooms. Using a posttest with three subscales (i.e., conceptual knowledge, procedural knowledge, and procedural flexibility), the authors managed to illuminate the effects of person-presentation in this setting in a detailed manner.

(3) Extending traditional Cognitive Load Theory research on worked examples.

Most worked example research has been conducted against the backdrop of Cognitive Load Theory (CLT; Sweller et al., 2011). The aim of CLT is to “explain how the information processing load induced by learning tasks can affect students' ability to process new information and to construct knowledge in long-term memory” (Sweller, Van Merriënboer, & Paas, 2019, p. 262). Its central premise is that

instructional designers should take into account that the cognitive system is heavily constrained by how limited our working memory is in terms of both capacity and duration. Consequently, it is important to ensure that learners allocate their resources to processes that are relevant for learning (germane load) rather than to processes that are irrelevant for learning (extraneous load). The third load type is intrinsic load, which concerns the complexity of the processed information and is commonly operationalized by how many interacting elements need to be processed simultaneously in working memory (Sweller, 1994).¹ Since its introduction in the 1980s (Sweller et al., 1998; Sweller & Levine, 1982), CLT has been in continuous development and led to an array of cognitive load effects (see Sweller et al., 2019).

Lu, Kalyuga, and Sweller (2020) report an experiment in which they examined whether the effectiveness of learning how to write complex Chinese characters could be improved with knowledge derived from two cognitive load effects. The traditional way of learning this skill involves studying and tracing whole characters from the start, which the authors hypothesized would overload novice learners' working memory capacity, because of the high levels of intrinsic cognitive load caused by the many interactive stroke movements. Firstly, building on the isolated elements effect which posits that for novices very complex information is at times better separated in individual elements first (Pollock, Chandler, & Sweller, 2002), authors hypothesized that learning would improve if novices are presented with isolated parts of a complex character before being presented with the whole character (i.e., isolated-integrated vs. integrated only). Secondly, drawing on the finding that adding variability across learning tasks helps learners construct more general knowledge and thereby boost test performance (i.e., the variability effect, see: Likourezos, Kalyuga, & Sweller, 2019; Paas & Van Merriënboer, 1994), Lu and colleagues hypothesized that presenting the isolated components in a variable manner would further improve learning relative to a blocked presentation. The innovative aspects of this study are the combination of the two cognitive load effects and the use-inspired aim of improving how novices learn to write Chinese characters.

(4) Learning from (productive) errors.

Another important ongoing development in the example literature is a greater focus on learning from (productive) errors. On the one hand, this development describes a rekindled interest in the role of erroneous information in examples (e.g., Richey et al., 2019; Schmitz, Schnabel, Stricker, Fischer, & Guttenstomsen, 2017). The focus on including errors in examples started early in social-cognitive research, where many studies compared the effects of mastery models showing an ideal performance to coping models showing and later on correcting performance errors (e.g., Schunk & Hanson, 1985). In the worked example literature, the incorporation of erroneous information only happened later in the form of asking students to locate and fix errors (e.g., Große & Renkl, 2007). On the other hand, this development addresses the extension of example-based learning research to research on productive failure (e.g., Glogger-Frey, Fleischer, Grüny, Kappich, & Renkl, 2015; Kalyuga & Singh, 2016). Productive failure research has shown that trying and failing to solve a problem before direct instruction improved novices' *conceptual*

knowledge acquisition compared to applying problem-solving strategies after direct instruction, without any detrimental effects on procedural knowledge (Kapur, 2012). This finding is particularly interesting from an example-based learning perspective, where research has shown that problem-solving first can impair procedural learning, at least for novices who lack the knowledge of how to proceed and therefore engage in inefficient and ineffective problem-solving strategies such as randomly trying out steps (Sweller, 1988).

The contribution of Jaeger, Marzano, and Shipley (2020) deals with the question whether the beneficial “locate and fix error”-effects that were found in worked examples research in the domain of mathematics (e.g., Große & Renkl, 2007) would generalize to learning in spatial science domains such as geology. More specifically, the authors had university students learn about 3D diagrams that showed vertical cuts into geologic structures. In addition to testing the benefits of erroneous examples in a new domain, a further innovative aspect is that the authors assessed both learning outcomes and learning efficiency (here: learning outcomes in relation to learning time), which provides a detailed picture of the effects of identifying errors in erroneous examples in comparison to copying correct ones and in comparison to a certain type of problem-solving (here: sketching).

The contribution of Barbieri and Booth (2020) adds to our understanding of the effects of erroneous worked examples as well. One of the innovative aspects of the study on which the authors reported is the inclusion of a “potential error” condition, in which learners received correct examples in conjunction with prompts that were designed to engage learners in thinking about potential errors that could occur in the respective solution procedures. From a theoretical perspective, it is highly interesting whether such a condition would yield similar effects as actual erroneous examples and whether similar or different learning processes drive these effects. From an applied perspective, the “potential error” instruction likely is highly useful as well for it could foster the degree to which students enjoy the benefits of learning about common errors: Providing correct examples and thinking about potential errors potentially convinces even practitioners who have concerns regarding displaying and discussing errors and who would thus not provide (beneficial) erroneous examples to their students. A further innovative aspect of the study is that potential moderating effects of prior knowledge for the benefits of learning from erroneous examples were explored.

The contribution of Hartmann, Van Gog, and Rummel (2020) deals with the effects of erroneous examples from a different angle. Situating in the productive failure framework by Kapur (2012), the authors investigated whether the preparatory effect of observing failed problem-solving attempts for subsequent learning from direct instruction can be enhanced by having learners observe not only the outcome of the failed process but also the process of failing. This innovative question has both theoretical as well as practical merit. In terms of theory, the innovative “observation of the process and outcome of failure” condition contributes to illuminating the active ingredients of (observed) failure that prepares learners for future learning. With respect to educational practice, the search for the active ingredients of future learning preparation via (observed) failure could

contribute to enhancing the efficiency of the preparation phase, which in the long-term could increase practitioners' willingness to incorporate such preparatory phases in their lessons.

(5) Individual differences in the preference for and effectiveness of example study.

Example-based learning is an effective instructional strategy for a wide variety of learners, ranging from young children to aging adults. Yet there is a severe paucity of research on the importance of individual differences that could moderate the preference for or effectiveness of example study. The exception to the rule is students' level of prior knowledge, which is an established moderating factor because example study becomes less effective or even hampers learning relative to practice problem solving when prior knowledge is high (Kalyuga, Chandler, Tuovinen, & Sweller, 2001). Note that a nice recent exception is provided by Schwaighofer, Bühner, and Fischer (2016): They found that the higher students' shifting ability (i.e., ability to flexibly switch between strategies or tasks) and fluid intelligence (i.e., ability to reason and solve novel problems), the less effective worked examples were relative to problem solving. The scarcity of research on individual differences motivated Van Gog et al. (2019) to issue a call for more research on this topic.

The longitudinal, observational study by Tempelaar, Rienties, and Nguyen (2020) answers this call. The authors followed 1,072 university students enrolled in an introductory math course with a blended format. Within this course, students worked in a digital learning environment and could select worked examples, practice problems, or tutored practice problems (i.e., problem-solving with feedback and hints). Tempelaar and colleagues assessed a variety of learning disposition variables prior to the course via questionnaires, such as epistemic emotions (e.g., anxiety and enjoyment) and attitudes to learning (e.g., interest and cognitive competence). These variables were then combined with prior knowledge, prior schooling, and learning behavior to find an answer to the question: Which type of students opt for worked examples, practice problems, and/or tutored practice problems? This dispositional learning approach allows for the identification of different cluster-based profiles of students, a very innovative approach for our field, which has traditionally been dominated by highly controlled experimental research with comparisons across different experimental conditions (for an early exception, see Zhu & Simon, 1987). The longitudinal nature and applied context of this study is another innovative feature, as example-based learning research is typically limited to single sessions in schools or research labs, which is precisely why Van Gog et al. (2019) recently highlighted investigating effects of example-based learning over time and in real classroom contexts as one of the key directions for future research.

2 | DISCUSSION

The final two papers of this special issue are commentary articles. The commentary by Scheiter (2020) draws on the special issue papers to shed light on the question of how the field has developed since the first extensive review on example-based learning published 20 years

ago (Atkinson, Derry, Renkl, & Wortham, 2000). In doing so, Scheiter focuses on three key research characteristics: which theories are used to understand the effects of example study (“theoretical foundations”), how is example study designed and implemented (“learning scenarios”), and what kind of skill do the examples portray (“domains”). Scheiter’s commentary ends with several methodological considerations that will be important to consider in future example research. Secondly, the commentary written by Mayer (2020) starts by addressing several “definition issues” in research on learning from examples (e.g., what is the presentation format of an example). Next, the individual contributions are discussed to find an answer to the question: What works and what does not work in designing example-based instruction?

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CONFLICT OF INTEREST

We have no conflict of interest to report.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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ENDNOTE

¹Note that in the most recent update to CLT, it is proposed that there are only two types of load (i.e., extraneous and intrinsic, see Sweller et al., 2019).

REFERENCES

- Atkinson, R. K., Derry, S. A., Renkl, A., & Wortham, D. (2000). Learning from examples: Instructional principles from the worked examples research. *Review of Educational Research, 70*, 181–214.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice Hall.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: Freeman.
- Barbieri, C. A., & Booth, J. L. (2020). Mistakes on display: Incorrect examples refine equation solving and algebraic feature knowledge. *Applied Cognitive Psychology, 34*, 862–878. <https://doi.org/10.1002/acp.3663>
- Cooper, G., & Sweller, J. (1987). Effects of schema acquisition and rule automation on mathematical problem-solving transfer. *Journal of Educational Psychology, 79*, 347–362. <https://doi.org/10.1037//0022-0663.79.4.347>
- Coppens, L. C., Hoogerheide, V., Snippe, E. M., Flunger, B., & Van Gog, T. (2019). Effects of problem-example and example-problem pairs on gifted and nongifted primary school students' learning. *Instructional Science, 47*, 279–297. <https://doi.org/10.1007/s11251-019-09484-3>
- Crippen, K. J., & Earl, B. L. (2007). The impact of web-based worked examples and self-explanation on performance, problem solving, and self-efficacy. *Computers & Education, 49*, 809–821. <https://doi.org/10.1016/j.compedu.2005.11.018>
- De Koning, B. B., Hoogerheide, V., & Boucheix, J. M. (2018). Developments and trends in learning with instructional video. *Computers in Human Behavior, 89*, 395–398. <https://doi.org/10.1016/j.chb.2018.08.055>
- Fiorella, L., & Mayer, R. E. (2018). What works and doesn't work with instructional video. *Computers in Human Behavior, 89*, 465–470. <https://doi.org/10.1016/j.chb.2018.07.015>
- Foster, N. L., Rawson, K. A., & Dunlosky, J. (2018). Self-regulated learning of principle-based concepts: Do students prefer worked examples, faded examples, or problem solving? *Learning and Instruction, 55*, 124–138. <https://doi.org/10.1016/j.learninstruc.2017.10.002>
- Gerjets, P., Scheiter, K., & Schuh, J. (2008). Information comparisons in example-based hypermedia environments: Supporting learners with processing prompts and an interactive comparison tool. *Educational Technology Research and Development, 56*, 73–92. <https://doi.org/10.1007/s11423-007-9068-z>
- Glogger-Frey, I., Fleischer, C., Grüny, L., Kappich, J., & Renkl, A. (2015). Inventing a solution and studying a worked solution prepare differently for learning from direct instruction. *Learning and Instruction, 39*, 72–87. <https://doi.org/10.1016/j.learninstruc.2015.05.001>
- Große, C. S., & Renkl, A. (2007). Finding and fixing errors in worked examples: Can this foster learning outcomes? *Learning and Instruction, 17*, 612–634. <https://doi.org/10.1016/j.learninstruc.2007.09.008>
- Hancock-Niemic, M. A., Lin, L., Atkinson, R., Renkl, A., & Wittwer, J. (2016). Example-based learning: Exploring the use of matrices and problem variability. *Educational Technology Research and Development, 64*, 115–136. <https://doi.org/10.1007/s11423-015-9403-8>
- Hartmann, C., Van Gog, T., & Rummel, N. (2020). Do examples of failure effectively prepare students for learning from subsequent instruction? *Applied Cognitive Psychology, 34*, 879–889. <https://doi.org/10.1002/acp.3651>
- Hoogerheide, V., Loyens, S. M. M., & Van Gog, T. (2014). Comparing the effects of worked examples and modeling examples on learning. *Computers in Human Behavior, 41*, 80–91. <https://doi.org/10.1016/j.chb.2014.09.013>
- Hoogerheide, V., Loyens, S. M. M., & Van Gog, T. (2016). Learning from video modeling examples: Does gender matter? *Instructional Science, 44*, 69–86. <https://doi.org/10.1007/s11251-015-9360-y>
- Hoogerheide, V., Van Wermeskerken, M., Loyens, S. M. M., & Van Gog, T. (2016). Learning from video modeling examples: Content kept equal, adults are more effective than peers. *Learning and Instruction, 44*, 22–30. <https://doi.org/10.1016/j.learninstruc.2016.02.004>
- Jaeger, A. J., Marzano, J. A., & Shipley, T. F. (2020). When seeing what's wrong makes you right: The effect of erroneous examples on 3D diagram learning. *Applied Cognitive Psychology, 34*, 844–861. <https://doi.org/10.1002/acp.3671>
- Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instructions. *Educational Psychology Review, 19*, 509–519. <https://doi.org/10.1007/s10648-007-9054-3>
- Kalyuga, S., Chandler, P., Tuovinen, J., & Sweller, J. (2001). When problem solving is superior to studying worked examples. *Journal of Educational Psychology, 93*, 579–588. <https://doi.org/10.1037//0022-0663.93.3.579>
- Kalyuga, S., & Singh, A. M. (2016). Rethinking the boundaries of cognitive load theory in complex learning. *Educational Psychology Review, 2015*, 831–852. <https://doi.org/10.1007/s10648-015-9352-0>
- Kant, J., Scheiter, K., & Oschatz, K. (2017). How to sequence video modeling examples and inquiry tasks to foster scientific reasoning. *Learning and Instruction, 52*, 46–58. <https://doi.org/10.1016/j.learninstruc.2017.04.005>

- Kapur, M. (2012). Productive failure in learning the concept of variance. *Instructional Science*, 40, 651–672. <https://doi.org/10.1007/s11251-012-9209-6>
- Likourezos, V., Kalyuga, S., & Sweller, J. (2019). The variability effect: When instructional variability is advantageous. *Educational Psychology Review*, 31, 479–497. <https://doi.org/10.1007/s10648-019-09462-8>
- Loehr, A., Rittle-Johnson, B., Durkin, K., & Star, J. R. (2020). Does calling it 'Morgan's way' reduce student learning? Evaluating the effect of person-presentation during comparison and discussion of worked examples in mathematics classrooms. *Applied Cognitive Psychology*, 34, 825–836. <https://doi.org/10.1002/acp.3670>
- Lu, J., Kalyuga, S., & Sweller, J. (2020). Altering element interactivity and variability in example-practice sequences to enhance learning to write Chinese characters. *Applied Cognitive Psychology*, 34, 837–843. <https://doi.org/10.1002/acp.3668>
- Mayer, R. E. (2020). Advances in designing instruction based on examples. *Applied Cognitive Psychology*, 34, 912–915. <https://doi.org/10.1002/acp.3701>
- Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive load approach. *Journal of Educational Psychology*, 84, 429–434. <https://doi.org/10.1037/0022-0663.84.4.429>
- Paas, F., & Van Merriënboer, J. J. G. (1994). Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive-load approach. *Journal of Educational Psychology*, 86, 122–133.
- Pollock, E., Chandler, P., & Sweller, J. (2002). Assimilating complex information. *Learning and Instruction*, 12, 61–86. [https://doi.org/10.1016/S0959-4752\(01\)00016-0](https://doi.org/10.1016/S0959-4752(01)00016-0)
- Quilici, J. L., & Mayer, R. E. (1996). Role of examples in how students learn to categorize statistics word problems. *Journal of Educational Psychology*, 88, 144–161. <https://doi.org/10.1037/0022-0663.88.1.144>
- Renkl, A. (2014). Toward an instructionally oriented theory of example-based learning. *Cognitive Science*, 38, 1–37. <https://doi.org/10.1111/cogs.12086>
- Richey, J. E., Andres-Bray, J. M. L., Mogessie, M., Schruggs, R., Andres, J. M. A. L., Star, J. R., ... McLaren, B. M. (2019). More confusion and frustration, better learning: The impact of erroneous examples. *Computers & Education*, 139, 173–190. <https://doi.org/10.1016/j.compedu.2019.05.012>
- Riggs, A. E., Alibali, M. W., & Kalish, C. W. (2015). Leave her out of it: Person-presentation of strategies is harmful for transfer. *Cognitive Science*, 39, 1965–1978. <https://doi.org/10.1111/cogs.12224>
- Rittle-Johnson, B., & Star, J. (2009). Compared with what? The effects of different comparisons on conceptual knowledge and procedural flexibility for equation solving. *Journal of Educational Psychology*, 101, 529–544. <https://doi.org/10.1037/a0014224>
- Roll, I., Aleven, V., McLaren, B. M., & Koedinger, K. R. (2011). Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning and Instruction*, 21, 267–280. <https://doi.org/10.1016/j.learninstruc.2010.07.004>
- Schalk, L., Roelle, J., Saalbach, H., Berthold, K., Stern, E., & Renkl, A. (2020). Providing worked examples for learning multiple principles. *Applied Cognitive Psychology*, 34, 813–824. <https://doi.org/10.1002/acp.3653>
- Scheiter, K. (2020). Embracing complexity in research on learning from examples and from problem solving. *Applied Cognitive Psychology*, 34, 906–911. <https://doi.org/10.1002/acp.3702>
- Schmitz, F. M., Schnabel, K. P., Stricker, D., Fischer, M. R., & Guttentormsen, S. (2017). Learning communication from erroneous video-based examples: A double-blind randomised controlled trial. *Patient Education and Counseling*, 100, 1203–1212. <https://doi.org/10.1016/j.pec.2017.01.016>
- Schunk, D. H., & Hanson, A. R. (1985). Peer models: Influence on children's self-efficacy and achievement. *Journal of Educational Psychology*, 77, 313–322. <https://doi.org/10.1037//0022-0663.77.3.313>
- Schunk, D. H., Hanson, A. R., & Cox, P. D. (1987). Peer-model attributes and children's achievement behaviors. *Journal of Education & Psychology*, 79, 54–61. <https://doi.org/10.1037/0022-0663.79.1.54>
- Schwaighofer, M., Bühner, M., & Fischer, F. (2016). Executive functions as moderators of the worked example effect: When shifting is more important than working memory capacity. *Journal of Educational Psychology*, 108, 982–1000. <https://doi.org/10.1037/edu0000115>
- Sweller, J. (1988). Cognitive load during problem-solving: Effects on learning. *Cognitive Science*, 12, 257–285. [https://doi.org/10.1016/0364-0213\(88\)90023-7](https://doi.org/10.1016/0364-0213(88)90023-7)
- Sweller, J. Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction*. 1994; 4 295–312. [https://doi.org/10.1016/0959-4752\(94\)90003-5](https://doi.org/10.1016/0959-4752(94)90003-5).
- Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. New York, NY: Springer.
- Sweller, J., & Cooper, G. A. (1985). The use of worked examples as a substitute for problem solving in learning algebra. *Cognition and Instruction*, 2, 59–89. https://doi.org/10.1207/s1532690xci0201_3
- Sweller, J., & Levine, M. (1982). Effects of goal specificity on means-ends analysis and learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 8, 463–474. <https://doi.org/10.1037/0278-7393.8.5.463>
- Sweller, J., Van Merriënboer, J. J. G., Paas F. Cognitive architecture and instructional design. *Educational Psychology Review*. 1998; 10 251–296. <http://dx.doi.org/10.1023/A:1022193728205>.
- Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, 31, 261–292. <https://doi.org/10.1007/s10648-019-09465-5>
- Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2020). Individual differences in the preference for worked examples: Lessons from an application of dispositional learning analytics. *Applied Cognitive Psychology*, 34, 890–905. <https://doi.org/10.1002/acp.3652>
- Van der Meij, H., & Van der Meij, J. (2013). Eight guidelines for the design of instructional videos for software training. *Technical Communication*, 60, 205–228.
- Van Gog, T., Kester, L., & Paas, F. (2011). Effects of worked examples, example-problem, and problem-example pairs on novices' learning. *Contemporary Educational Psychology*, 36, 212–218. <https://doi.org/10.1016/j.cedpsych.2010.10.004>
- Van Gog, T., & Rummel, N. (2010). Example-based learning: Integrating cognitive and social-cognitive research perspectives. *Educational Psychology Review*, 22, 155–174. <https://doi.org/10.1007/s10648-010-9134-7>
- Van Gog, T., Rummel, N., & Renkl, A. (2019). Learning how to solve problems by studying examples. In J. Dunlosky & K. Rawson (Eds.), *The Cambridge handbook of cognition and education* (pp. 183–208). New York, NY: Cambridge University Press.
- Van Harsel, M., Hoogerheide, V., Verkoeijen, P., & Van Gog, T. (2019). Effects of different sequences of examples and problems on motivation and learning. *Contemporary Educational Psychology*, 58, 260–275. <https://doi.org/10.1016/j.cedpsych.2019.03.005>
- Van Harsel, M., Hoogerheide, V., Verkoeijen, P., & Van Gog, T. (2020). Examples, practice problems, or both? Effects on motivation and learning in shorter and longer sequences. *Applied Cognitive Psychology*, 34, 793–812. <https://doi.org/10.1002/acp.3649>
- Zhu, X., & Simon, H. A. (1987). Learning mathematics from examples and by doing. *Cognition and Instruction*, 4, 137–166. https://doi.org/10.1207/s1532690xci0403_1

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