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Using heuristic worked examples to promote inquiry-based learning

Yvonne G. Mulder*, Ard W. Lazonder, Ton de Jong

University of Twente, Department of Instructional Technology, P.O. Box 217, 7500 AE Enschede, The Netherlands

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ABSTRACT

Inquiry learning can be facilitated by having students investigate the domain through a computer simulation and express their acquired understanding in a runnable computer model. This study investigated whether heuristic worked examples can further enhance students' inquiry behaviour, the quality of the models they create, and their domain knowledge. High-school students were offered a simulation of an electrical circuit and a modelling tool. Students in the experimental condition ($n = 46$) could consult heuristic worked examples that explained what activities were needed and how they should be performed. Students in the control condition ($n = 36$) did not receive this support. Cross-condition comparisons confirmed that heuristic worked examples improved students' inquiry behaviour and enhanced the quality of their models. However, few students created a model that reflected full understanding of the electrical circuit, and the expected between-group difference in posttest scores failed to appear. Based on these findings, improvements to the design of heuristic worked examples are proposed.

1. Introduction

Recent meta-analyses have concluded that inquiry learning can benefit students and can lead to superior student performance than more direct forms of instruction (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011; Minner, Levy, & Century, 2010). However, these meta-analyses also suggest that these benefits only hold when students are supported during their inquiry activities. This support is needed to compensate for students' modest inquiry skills, their prior knowledge deficits, or both. De Jong and van Joolingen's (1998) review revealed a broad variety of skill deficiencies in simulation-based inquiry learning. When students learn about phenomena through systematic experimentation with a simulation, they are generally unable to infer hypotheses from data, design conclusive experiments, engage in efficient experimentation behaviour, and attend to incompatible data. Similar problems arise when students engage in scientific modelling (hereafter: modelling) to create computer models of their understanding of scientific phenomena. Hogan and Thomas (2001), for example, noticed that students often fail to engage in dynamic iterations between examining output and revising models, and Stratford, Krajcik, and Soloway (1998) observed a lack of persistence in debugging models to fine-tune their performance.

Mulder, Lazonder, and de Jong (2010) examined whether these results generalize to a learning task where simulation-based inquiry and modelling are combined (cf. Basu, Dickes, Kinnebrew, Sengupta, & Biswas, 2013; van Joolingen, de Jong, Lazonder, Savelsbergh, & Manlove, 2005). This combined approach enabled students to learn about a scientific phenomenon by experimenting with a simulation. Once students had developed an initial understanding of the phenomenon, they built a runnable model to express their knowledge. This model can be thought of as a set of hypotheses students can test by running the model and checking its output against data from the simulation. Based on this evaluation students can refine their understanding through additional experimentation with the simulation and further revision of their model. Mulder et al. found that domain novices are quite capable of identifying which variables to include in their models, but have difficulty inferring how these variables are related. Instead of working step-by-step toward a full-fledged scientific equation to specify a relationship, novices tried to induce and model these equations from scratch, which proved to be ineffective given their lack of prior domain knowledge. These findings suggest that students could benefit from support that prevents them from 'jumping the gun' and that better attunes their inquiry and modelling activities to their level of domain knowledge (cf. Quintana et al., 2004).

This support can be offered in a non-intrusive way by organizing the learning task according to a simple-to-complex sequence that matches the students' increasing levels of domain understanding.

* Corresponding author. Tel.: +31 53 489 4857.
E-mail address: y.g.mulder@utwente.nl (Y.G. Mulder).

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This type of task structuring was first introduced by White and Frederiksen (1990), who termed it ‘model progression’. Model progression was found to lead to higher performance success in some studies (Alessi, 1995; Eseryel & Law, 2010; Rieber & Parmley, 1995; Swaak, van Joolingen, & de Jong, 1998), but other studies report less favourable results (de Jong et al., 1999; Quinn & Alessi, 1994). These differential effects might be attributable to the use of slightly different configurations of the simple-to-complex sequencing. Some studies introduced students to all of the learning content at once and engaged them in increasingly specific reasoning about the task content (i.e., model order progression) whereas students in other studies engaged in specific reasoning from the start and were confronted with increasingly elaborate task content (i.e., model elaboration progression).

Mulder, Lazonder, and de Jong (2011) implemented both types of model progression in a simulation-based inquiry and modelling task about the charging of a capacitor in an electrical circuit. Both types divided the task into three successive phases, but differed with regard to the sequencing principle that determined how task complexity increased across these phases. *Model order progression*, the predicted optimal variant, gradually increased the specificity of the relations between variables. In Phase 1, students had to identify all relevant variables and relations and sketch the model outline. In Phase 2, they had to indicate a general direction of the effect for these relations, and in Phase 3 they had to specify these relationships quantitatively in the form of an equation. *Model elaboration progression*, by contrast, gradually expanded the number of variables in the task. Students had to investigate and model an electrical circuit with a voltage source and one light bulb in Phase 1. An additional light bulb was introduced in Phase 2, and a capacitor was added in Phase 3. Students who were supported by either type of model progression outperformed students from an unsupported control condition. A comparison between the two model progression variants further showed that students in the model order group outperformed those from the model elaboration group on the construction of relations in their models.

However, in this study even students in the best-performing model progression group produced mediocre models. In a follow-up study, attempts to optimize model progression also failed to substantially improve students' performance (Mulder, Lazonder, de Jong, Anjewierden, & Bollen, 2012). Unfortunately, it is not uncommon that scaffolding has little success in enhancing what students learn from modelling tasks. For instance, the Manlove, Lazonder, and de Jong (2009) studies showed that students often do not take full advantage of the support offered by regulative scaffolds, which causes their performance to remain somewhat poor. Likewise, Roscoe, Segedy, Sulcer, Jeong, and Biswas (2013) provided students with hints that offered content feedback. Although these hints were positively associated with students' performance, students gradually came to rely on this tool. This was considered a shallow strategy development, as it negatively impacted the efficacy of the learning task. As such, offering direct support has the risk of affecting students' learning activities, but not their learning outcomes. In a recent review, VanLehn (2013) thus argues that scaffolds for learning should guide students through the learning process instead of providing only content feedback. Hence, students might benefit from a more explicit account of what the activities in each model progression phase entail and how they should be performed.

Such support could take the form of worked examples, which have proved to be a fruitful means to enhance problem-solving performance (e.g., Atkinson, Derry, Renkl, & Wortham, 2000; Sweller & Cooper, 1985). Worked examples essentially include a problem statement, a step-by-step account of the procedure to solve the problem, and the final solution. Worked examples have traditionally been applied to well-structured problems that have a straightforward, algorithmic solution process. Research has shown that studying a series of worked examples, either to prepare for or instead of problem-solving practice, is more effective than conventional, unsupported problem solving (see, for a review, Atkinson et al., 2000; Sweller, Ayres, & Kalyuga, 2011). Other studies have tried to optimize the presentation and use of worked examples. To minimize shortcomings such as only rote recall of the information, worked example instruction can be enhanced by eliciting self-explanations (Atkinson, Renkl, & Merrill, 2003; Chi, Bassok, Lewis, Reimann, & Glaser, 1989), presenting the rationale behind the presented solution (van Gog, Paas, & van Merriënboer, 2008), or offering meta-level feedback (Moreno, Reisslein, & Ozogul, 2009),

However, the effectiveness of problem-solving support methods does not necessarily generalize to inquiry learning tasks. Inquiry and modelling are iterative processes in which the scientific reasoning skills of hypothesizing, experimenting, and evaluating evidence are performed repeatedly. The nature of the hypotheses, the way they are examined, and the outcomes of these investigations all determine what would be the next logical step in order to induce and model the characteristics of the phenomenon at hand (Klahr & Dunbar, 1988; White, Shimoda, & Frederiksen, 1999). Capturing this complex cognitive activity in a fixed, algorithmic sequence of action steps would neither be possible nor do justice to the true nature of the inquiry and modelling process—and would therefore presumably cause students to develop a limited understanding of the task content.

Hilbert and colleagues acknowledged this limitation of traditional worked examples, and proposed a variant that can be applied in non-algorithmic problem-solving situations (Hilbert & Renkl, 2009; Hilbert, Renkl, Kessler, & Reiss, 2008). These so-called heuristic worked examples do not emphasize the specific action sequence students should follow to solve a problem, but exemplify the heuristic reasoning underlying the choice and application of this action sequence. This shift in focus has broadened the application of worked examples from well-structured, algorithmic problem-solving tasks to more ill-structured, and hence more complex learning tasks. Recent reviews of worked-examples research have demonstrated that heuristic worked examples can be applied effectively in a variety of domains such as mathematical proofs, concept mapping, and second language learning (Renkl, Hilbert, & Schworm, 2009; Sweller et al., 2011).

Heuristic worked examples also hold promise for supporting students' inquiry and modelling activities. Both processes are iterative by nature and require students to consider previously performed activities and results in order to decide which actions to perform next. These decisions have been found to be problematic because students have an insufficient understanding of the inquiry and modelling process (Mulder et al., 2011). Heuristic worked examples could help alleviate this problem by exemplifying these processes (i.e., hypothesis generation, experimentation, and evidence evaluation) and showing the heuristic reasoning for cycling through these processes effectively. As the design of informative simulation experiments is challenging for students (de Jong & van Joolingen, 1998), explicit attention was given to the design of unconfounded experiments using the Control-of-Variables Strategy (CVS; Chen & Klahr, 1999). The heuristic worked examples also show how the interpretation of data from these experiments can subsequently lead to an (initial) understanding of the phenomenon, which can then be represented and tested in a model. In this way, students are shown how to set up systematic experiments with the simulation, and how modelling can be integrated into the inquiry process.