Learning from erroneous models using SCYDynamics

Yvonne G. Mulder, Lars Bollen, & Ton de Jong

Abstract

Dynamic phenomena are common in science education. Students can learn about such system dynamic processes through model based learning activities. This paper describes a study on the effects of a learning from erroneous models approach using the learning environment SCYDynamics. The study compared three conditions. Two experimental conditions where students had to correct errors in a model were contrasted to working with a correct model. The experimental conditions differed on whether or not the students had to detect the errors before correcting them. Results indicate that this approach enhanced students' model testing and revising activities. Furthermore this approach was found to have a beneficial effect on learning common errors. Contrary to expectations this approach showed no learning effect on domain knowledge acquisition. The discussion further elaborates on improvements that might enhance this learning from erroneous model approach.

Keywords: System Dynamics, modeling, learning, erroneous examples

Introduction

Science education often requires students to learn about dynamic systems, which are notoriously difficult to understand. An example of such a complex dynamic system commonly found in high school biology curricula, is the topic of the human glucose regulatory system. Students are taught that the human body constantly needs glucose as it is the basic source of energy. However, the glucose level should stay within a narrow range as either too high or too low blood glucose levels can cause damage to nerves, blood vessels, and organs. The dynamic process of glucose-insulin regulation keeps the blood glucose level within this narrow range. Students often have difficulties understanding this system because it consists of multiple variables that are interrelated in intricate ways. Also the dynamic behavior of this complex system in which glucose accumulates and recedes over time is difficult to understand (Grösser and Schaffernicht, 2012) and requires reasoning on multiple levels (i.e., on the structure of the system and the behavior over time).

To facilitate students' learning of such complex dynamic systems, the potential of learning by modeling approaches is increasingly recognized in the Netherlands and elsewhere around the world (CCSSO, 2013; NGSS Lead States, 2013; van Dijk *et al.*, 2013). System Dynamics (Forrester, 1968) models (hereafter: models) have the opportunity to aid students' understanding of dynamic systems as they provide an overview of the relevant variables and

their intricate relations (Grösser and Schaffernicht, 2012; Mulder, Lazonder, and de Jong, 2014). Moreover, when these models have the form of an executable computer model, they can show the behavior of the entire system over time. As such, these models give students the opportunity to explore the effects of the components and their relations on the behavior of the system as a whole.

Model based learning activities typically require students either to learn from an existing model, or to construct a model themselves (e.g., Alessi, 2000; de Jong and van Joolingen, 2008). Existing models give students a direct overview of the model structure. Through simulation, students can explore the model by changing the values of input variables and observe the resulting behavior of the system. In contrast, the learning by creating models approach requires students to first construct the model from scratch before it can be simulated. The learning by creating models approach is in line with the basic ideas behind constructionism, and as such presumably enhances knowledge acquisition. Through iterative phases of model building, testing, and revising (cf. Hogan and Thomas, 2001) students acquire a deeper understanding of the domain. Unfortunately, the advantages of this learning by creating models approach are often hindered by students' lack of model building activities in science education in order to reap the benefits (e.g., Louca and Zacharia, 2012; Mulder, Lazonder, and de Jong, 2010; VanLehn, 2013).

As creating models from scratch is too difficult for novice students, we propose an alternative model based learning activity (i.e., erroneous model approach) which might bridge the gap between learning from existing models and learning by creating models. Like learning from existing models, this alternative approach presents students with a pre-constructed model. However, to actively engage students in the modeling process, the provided model contains errors which students have to correct. Learning from erroneous models requires students' to *detect* and *correct* the errors. In this manner, students have to engage in testing and revising behavior like during learning by creating models, but students are less likely to become overwhelmed by the actual model construction process.

Learning from erroneous examples is gaining interest in a variety of domains, such as math (e.g., Booth *et al.*, 2013; Durkin and Rittle-Johnson, 2012; Große and Renkl, 2007; Isotani *et al.*, 2011; Tsovaltzi *et al.*, 2012) and concept mapping (e.g., Chang, Sung, and Chen, 2002; Hilbert, Nückles, and Matzel, 2008). Große and Renkl (2007) summarize multiple arguments in favor of learning from erroneous examples, indicating that encountering errors during the learning process might lead to deeper understanding (e.g., because errors can trigger reflections). Several studies have shown that compared to problem solving or learning from correct examples, learning from erroneous examples leads to higher learning gains (e.g., Booth *et al.*, 2013; Chang *et al.*, 2002; Durkin and Rittle-Johnson, 2012; Große and Renkl, 2007; Hilbert *et al.*, 2008; Tsovaltzi *et al.*, 2012). However some studies could not find this effect (e.g., Hilbert *et al.*, 2008; Isotani *et al.*, 2011).

These mixed findings suggest students do not always reap the benefits of this approach. One of the risks of learning from erroneous examples is that students fail to detect and correct the

errors and instead gain incorrect knowledge. To compensate for this pitfall, Hilbert and colleagues conclude that a prerequisite for effective learning from erroneous examples is the availability of feedback. In learning by modeling, students have the opportunity to engage in testing and revising activities by simulating their models. This gives them feedback on the quality of the model and will indicate the errors in the model. Additionally, to compensate for lack of error detection, the errors in the model can be indicated (for instance by highlighting) leaving students with only the correction task. As such it could be expected that applying a learning from erroneous examples approach in modeling will have a positive effect on students learning.

Research design and Hypotheses

The study described in this paper assessed the effects of a learning from erroneous model approach and the differential effects of detecting and correcting the model errors. To do so this study contrasted three conditions. Students in the first experimental condition (i.e., detection and correction; D&C condition) received an incorrect model where they had to detect and correct the mistakes. Students in the second experimental condition (i.e., correction only; C condition) also received an incorrect model where the errors were highlighted and thus they only had to correct the mistakes. To assess the effects of the learning from erroneous model approach, both experimental conditions were contrasted to a control condition (i.e., simulation; S condition) where students received a correct model which they could simulate. Contrasting both experimental conditions will shed light on the differentiated effect of detecting and correcting errors in models. It is expected that both detecting and correcting errors increases students' testing and revising behavior and enhances students' knowledge of the domain.

Learning environment SCYDynamics

All students worked with the learning environment SCYDynamics. SCYDynamics is a standalone modeling tool that originates from the SCY project (de Jong *et al.*, 2010) where it was created to allow students to build and work with System Dynamics models in an interactive fashion. The main part of this learning environment is the model editor (Figure 1) where students can create, inspect, and adjust their models. Additionally the tool provides two tabs where students can get feedback on the structure (bar chart) and dynamic behavior (graph tool) of their models (Figure 2). SCYDynamics is intended for secondary school students to learn about system dynamic phenomena from the biology, chemistry, or physics curricula.

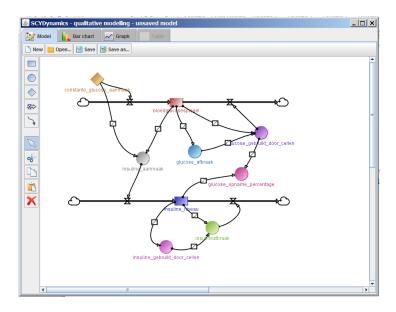


Figure 1. Model editor tab

Model editor. In the model editor part of SCYDynamics the students can represent and structure their knowledge of a particular domain in an executable computer model. As shown in Figure 1 the editor uses principles from the System Dynamics formalism (Forrester, 1968).

In addition to the typical language elements in this context, e.g. stocks, constants, flows, relations and auxiliary variables, SCYDynamics provides a selection of qualitative relation types that can be used to describe the nature of a relation between a stock and an auxiliary variable or between two auxiliaries (e.g. linear, parabolic, or sigmoid). Internally, SCYDynamics replaces the qualitatively specified relation with a quantitative relation to create an executable model. The quantitative representation is taken from a set of pre-defined functions that can be specified by a teacher or a modeling expert. This feature alleviates the mathematical complexity and skills needed by a learner to create sound models of complex phenomena.

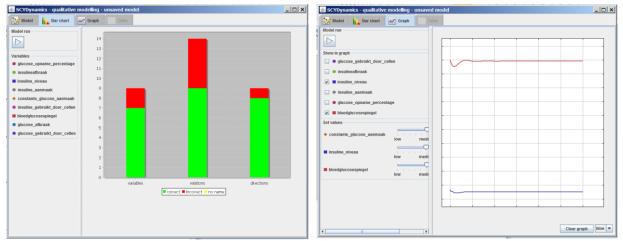


Figure 2. Bar chart (left panel) and graph tool (right panel)

Feedback. Whilst constructing their models, students can get instant feedback from the SCYDynamics tool on their model by means of a bar chart and graph tool. The bar chart offers feedback on the current structure of the model, by indicating the number of correct, incorrect, and non-specified variables, relations, and directions of relations. Using the graph tool, students can inspect and learn about the dynamic behavior of their model by running the model and evaluating the output. The information about correct and incorrect variables and relations is derived from the above mentioned expert model, which also provides the quantitative representations of qualitative relations.

Modeling task. In this study the SCYDynamics tool was used to teach all students about the glucose insulin regulatory system. Students could find information about the glucose-insulin regulatory system in an instructional text. This text described the 'supply and demand' mechanisms that ensure that cells in the human body receive blood that contains the right amount of sugar. Students received an assignment that was based on three scenarios: (1) the case of homeostasis, where the blood glucose level reaches an equilibrium over time, (2) eating high-calorie food, which creates a spike of glucose in the blood glucose level. The first scenario, homeostasis, served as a starting point as all students were instructed to inspect and get feedback on the model, and correct any errors in the model. The subsequent scenarios required students to apply the model to real life cases that affect the glucose-insulin regulation process.

Although the assignment was identical for all students, the pre-defined model with which students started the assignment differed across conditions. Students in the experimental conditions started with a pre-defined model containing errors in the variables and relations as well as in the type of relations. Consistent with studies on erroneous concept maps by (Chang *et al.*, 2002) and (Hilbert *et al.*, 2008), 30% of the model was incorrect which resulted in a total of six errors (2 elements, 2 relations and 2 relation types). In Figure 3 these errors are indicated by highlighting. Students in the D&C condition started with the non-highlighted version of this model and had to detect and correct the errors in this erroneous model. Students in the C condition received a highlighted erroneous model as shown in Figure 3, so they only had to correct the errors. Students in the S condition worked with a correct version of the model.

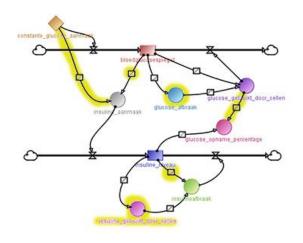


Figure 3. Erroneous model

Procedure

Participants were 62 Dutch high school students aged 15-17 years. Participants were matched to conditions based on class-ranked prior knowledge test scores (S (Simulation) condition: n =21; C (Correction only) condition: n = 22: D&C (Correction & Detection) condition: n = 19). Data were collected during two sessions: a 50-minute introduction, and a 100-minute experimental session that were carried out in regular classrooms where students worked individually. During the introductory session participants first completed a domain knowledge pretest, then received a brief plenary introduction on learning by modeling, which was followed by a brief tutorial that familiarized students with the learning environment. During the experimental session participants first read an instructional text about the glucose-insulin regulatory system before students worked on the modeling task. The learning environment SCYDynamics stored all participants' actions in a logfile, so students' testing and revising activities could be retrieved as the number of times students ran their models to inspect the bar chart and graph tools. At the end of the experimental session, students filled out a domain knowledge posttest and an error recognition test. The domain knowledge posttest was identical to the domain knowledge pretest and consisted of 9 items addressing key domain concepts and students' understanding of the glucose-insulin regulatory system. Students' answers to the items were scored using a rubric that allocated one point to each correct response. The Cohen's k inter-rater reliability estimate of this rubric was 0.89. The error recognition test required students to indicate and correct the six errors on a paper version of the models. The coding rubric of this test allocated one point for each correctly identified error, and one point for each correctly corrected error, leading to a 12 point maximum score. The Cohen's κ inter-rater reliability estimate of this rubric was 0.98.

Analysis of Results

Table 1

Summary of Participants'	Performance	
	S (<i>n</i> = 21)	С (

	S (<i>n</i> = 21)		C (<i>n</i> = 22)		D&C (<i>n</i> = 19)	
	М	SD	М	SD	М	SD
Domain knowledge pretest scores	2.76	1.34	3.14	1.46	2.63	1.38
Domain knowledge posttest scores	4.10	0.94	4.36	1.09	4.47	1.54
Error recognition test scores	3.90	1.97	7.41	3.29	6.95	2.70
Testing and revising activities						
Bar chart runs	8.95	6.35	23.27	14.68	34.32	26.80
Graph runs	6.14	7.18	3.64	3.98	3.95	5.15

Table 1 reports students' scores on the knowledge tests and the number of times students ran their models to inspect the bar chart and graph tool. Students' overall scores on the domain knowledge pretest was 2.85, indicating that students in our sample had little prior knowledge of the glucose-insulin regulation. Univariate analysis of variance (ANOVA) were performed which confirmed that the slight between-group differences in pretest scores did not significantly differ between conditions, F(2,59) = 0.74, p = .482.

The number of times students ran their models to inspect the bar chart and graph tools as shown in Table 1 are an indication of students' testing and revising activities. Multivariate analysis of variance (MANOVA) produced a significant effect for experimental condition, F(4,118) = 4.82, p < .001, indicating that the learning from erroneous model approach influenced students' testing and revising activities. Subsequent ANOVA's showed that the learning from erroneous model approach significantly affected the number of times students ran their models to inspect the bar chart, F(2,59) = 10.48, p < .001, but not the number of times students ran their models to inspect the graph tool, F(2,59) = 1.26, p = .292. Planned contrasts were performed to pinpoint the effects of detecting and correcting errors on the number of times students ran their models to inspect the bar chart. Significant differences were found contrasting the S condition to both experimental conditions, t(61) = -4.20, p < .001, r = .47, and when contrasting the C condition to the D&C condition, t(61) = -2.00, p = .050, r = .25. This indicates that both detecting and correcting of errors independently increase how often students use the bar chart for testing and revising activities.

Having established the influence of detecting and correcting errors on students' testing and revising behavior, additional analyses were performed to reveal the influence of the learning from erroneous model approach on students' learning. The domain knowledge posttest scores reflect students' understanding of the glucose-insulin regulatory system following the

modeling task. A mixed-design ANOVA was performed which combined the between-group variable condition and the repeated-measures variable domain knowledge scores (on both pretest and posttest), to analyze the effect of erroneous examples on students' domain knowledge increase. There was a significant main effect of the repeated-measures variable domain knowledge scores, F(1,59) = 49.35, p < .001, which indicates that the students learned during the experiment. There was no significant main effect of the between-groups variable condition, F(2,59) = 0.55, p = .579, nor was there an interaction effect of the between-group variable and the repeated-measures variable, F(2,59) = 0.78, p = .455. This means that we found no indication that the learning from erroneous model approach influences students' performance on the domain knowledge posttest, nor that this approach influences students' increase on domain knowledge. Together this shows that both erroneous model learning and learning from existing models approaches enhanced students' learned from the domain during the modeling activity.

The error recognition test score reflects how well students' recognize errors and how capable they are in correcting these errors following the modeling task. Students' overall score on the error recognition task was 6.08, indicating that, on average, students recognized (and were able to correct) about half of the errors in the model. As can be seen in Table 1, there were large differences between conditions on the number of recognized errors. ANOVA confirmed that these between-group differences were significant, F(2,59) = 10.32, p < .001. Next, planned contrasts were performed to pinpoint the effects of detecting and correcting errors on the number of errors students recognized. Significant differences were found contrasting the S condition to both experimental conditions, t(61) = -4.48, p < .001, r = .49, but not when contrasting the C condition to the D&C condition, t(61) = 0.54, p = .590. This indicates that correcting a model increases the number of errors that students recognize, but that detecting errors in a model has no added effect on the recognition of errors.

Discussion

The aim of the study presented in this paper was to assess the effects of a learning from erroneous model approach and to further differentiate on the effects of detecting and correcting model errors. Compared to learning from (correct) existing models, detecting and correcting errors was expected to increase both students' testing and revising behavior and to enhance students' knowledge of the domain.

First, in line with expectations, detecting and correcting errors in models was found to influence students' testing and revising behavior. As expected, students used the bar chart most often when they had to detect and correct errors in the model and least often when they only had to simulate a correct model. However, contrary to expectations, this effect of detecting and correcting errors was not found regarding the number of times students ran their model with the graph tool. This could easily be explained in terms of the feedback function of these tools. When confronted with an erroneous model, testing and revising activities are more likely to occur compared to when confronted with a correct model. Furthermore, two-thirds of the errors in the erroneous model regarded the structure of the model. Since the bar chart tool offers direct feedback on the model structure, it makes sense that the effect of the

erroneous models in this study on testing and revising activities was more pronounced in the number of times the students used the bar chart tool compared to the graph tool.

Second, the hypothesized effect of detecting and correcting errors in models on students' domain knowledge acquisition was partially confirmed. The model based learning activities in the three conditions were all found to increase students' learning of the domain. However, the effect of detecting and correcting errors on students' learning only showed with regard to how well students' can recognize errors and are capable of correcting these errors, but not with regard to acquiring knowledge of the domain. These results could help explain why the existing research on the effectiveness of learning from erroneous examples paint a mixed picture as only some, and not all, studies report that erroneous examples leads to higher learning gains (Booth *et al.*, 2013; Chang *et al.*, 2002; Durkin and Rittle-Johnson, 2012; Große and Renkl, 2007; Hilbert *et al.*, 2008; Isotani *et al.*, 2011; Tsovaltzi *et al.*, 2012). This study indicates that erroneous examples only influences acquisition of knowledge on the targeted errors.

However, this conclusion is not in line with the Hilbert *et al.* (2008) study, where learners were found to acquire incorrect knowledge during a concept map correction task. Based on their findings, Hilbert and colleagues conclude that feedback is essential for a learning from erroneous examples approach, as to prevent the students from acquiring incorrect knowledge. Students in the current study did have this suggested feedback option and did not show acquisition of incorrect knowledge. This supports Hilbert's conclusion that feedback is a prerequisite in order for a learning from erroneous examples approach to be effective.

The results of this study have a clear practical implication for science education. The learning from erroneous models might be a fruitful approach in teaching students about dynamic phenomena on which students typically have persistent misconceptions. By creating models which harbor these misconceptions and having students correct these errors, students gain a more correct understanding of the domain. As this study showed no difference between the experimental groups on learning, the most practical approach is to highlight the errors in the model so students can fully focus their attention on correcting them.

Future research in this area should focus on advancing this learning from erroneous model approach, in such a way that it also enhances students' acquisition of domain knowledge. The question remains whether, and how, erroneous models can facilitate acquisitions of correct domain knowledge. The present findings suggest that students focus only on the errors in the model and neglect the correct aspects and the system as a whole. Traditional learning from worked example approaches are typically enhanced by applying self-explanation prompts. These prompts trigger self-explanations during the learning activity which are commonly known to substantially foster learning outcomes (e.g., Chi *et al.*, 1989; Renkl, 1997).

A first attempt to apply these prompts to erroneous examples by Große and Renkl (2007) showed no effect of these prompts, presumably because the errors in the model diminished the quality of students' self-explanations. Future research should find a means to compensate for this negative side effect. Instead of a general self-explanation prompt, students should receive prompts that specifically direct them to explain the whole model and not only the errors. This

might pave the way for a broad practical application of the learning from erroneous models approach.

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