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Can Learning by Qualitative Modelling Be Deployed as an Effective Method for Learning Subject-Specific Content?

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Abstract. Modelling can help understanding dynamic systems, but learning how to model is a difficult and time-consuming task. The challenge is to foster modelling skills, while not limiting the learning of regular subject matter, or better, to also improve this learning. We investigate how learning by qualitative modelling can be as successful as a regular classroom setting that uses an active and stimulating approach. 74 students from two high schools participated in two Biology lessons. Particularly, in the school 2 study, students in the modelling condition improved as much as students in the control group.

1 Introduction

One way in which thinking about dynamic systems can be supported is through the use of models [1, 2]. Creating models from scratch is seen as a higher order skill within the larger set of systems thinking skills [3]. Although widely believed, evidence that active modelling can help students develop such understanding is scarce [4]. Moreover, learning how to model takes time. This learning time is especially important: the time spent on learning how to model cannot be spent on learning subject-specific content.

In the studies reported here, the effect of qualitative modelling on subject-specific understanding was investigated. An experiment was developed in which participants were assigned to a modelling or a control condition. The modelling instruction was integrated in the first lesson, which served as a *modelling learning phase (LP)* for students in the modelling condition. In the second lesson, the *modelling application phase (AP)*, these students were expected to be able to apply their modelling knowledge on the second topic. In the control condition, the same topics were treated, making it possible to assess progress of both groups for the LP and for the AP. These control condition also used computers, but created alternative representations (using PowerPoint).

It was expected that in the LP students in the control condition would improve more than students in the modelling condition with regard to subject-specific knowledge. In the control condition, students would only have to concentrate on the subject-specific content, while students in the modelling condition also have to concentrate on modelling.

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In the AP, students in the modelling condition were expected to improve more with regard to subject-specific knowledge than students in the control condition, as the acquired modelling skills were expected to be helpful for understanding this content.

2 Method

Two schools participated in the study with their Biology class (school 1: 44 students, mean age = 16.99, SD = 0.56, 45% girls & school 2: 30 students, mean age = 16.67, SD = 0.72, 83% girls). Students were in their 5th year of pre-university secondary education (grade 11). As the schools made the study part of their program, all students were expected to participate. Each school visited the research location twice within the single week, during which the students followed one lesson. School 2 participated in the study one month after school 1 had done so.

When settled in the room the study was introduced and students took the pre-test (30 min). Next, students worked on the lesson individually (1.5 h, with a short break halfway). The visit event ended with the post-test (10 min). During the second visit, students started immediately with the lesson. After two hours (including a short break) the students took the post-test (25 min). During the school 1 visit, two teachers were present at both days. During the school 2 visit, a different teacher accompanied the students on each of the days. A teacher or a researcher was always present in the room to answer questions. All students were randomly assigned to the conditions.

Students followed two lessons (one on trophic cascades and one on eutrophication). Learning goals were addressed in the same order in both conditions. The lessons were worksheet-based, minimizing the need for instruction by the teachers. Students were instructed to work alone, although they could ask fellow students, their teacher or the researcher for help. In both conditions the lessons were similarly structured: students were given a small amount of information at the beginning of each lesson, on which they were asked to formulate an initial hypothesis. As students gathered more information during the lesson, either through texts provided in the assignment, modelling or looking up information on the internet, students were asked to revise their previous answers or models. As such, a discovery learning element was added and students understanding of the subject matter was built up step-by-step. This was expected to aid students' conceptual understanding of the system they were studying.

In the *modelling condition*, students created as part of the lesson a model from the system that was the principal subject of the lesson. For this, the newly developed software DynaLearn-Web (https://DynaLearn.nl) was used. This instrument is available as an online tool (using web browsers) and implements aspects of the DynaLearn workbench [5] focusing on features which are hypothesized to facilitate effective learning by qualitative modelling. When creating a model with this tool, a student starts by defining entities. These entities can be connected as in a concept map using configurations, but the student can also define any number of quantities for each entity. A quantity is a measurable property of an entity, and can be related to any other quantity. These dependencies can be positive or negative. Furthermore, each quantity has a change rate that can be set to decrease, steady or increase. A simple model is shown in Fig. 1. It depicts part of the eutrophication process in which underwater sunlight is blocked by algae. The entity *waterbody* is connected to three other entities: *algae*, *sunlight* and *water plants*. These all have quantities related to the available amount of the entity. Moreover, the amount of algae is negatively related (P−) to the amount of sunlight, as algae float at the water surface and thus block sunlight under water. The amount of sunlight is positively related (P+) to the amount of water plants, as these plants need sunlight to grow. All three quantities have a change rate, depicted by ∂. Only the change rates at the beginning of a causal chain need to be defined, in this case that of algae. In this example, it is defined as increasing. When the model is simulated, the inferred (green) arrows indicate that sunlight decreases and that because of that the water plants also decrease. This example uses only a few model ingredients. The students were asked to make more elaborate and complex models, such as the one shown in Fig. 2.

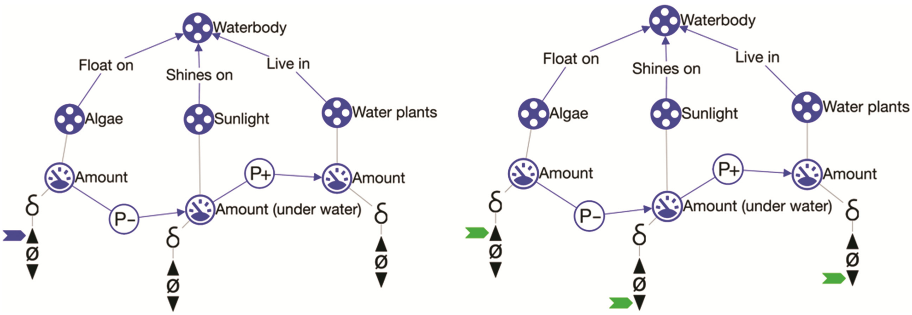

Fig. 1. Example DynaLearn-web model. Right-hand side shows the model in building mode (blue arrow specifies initial changes: Algae increase). Left-hand side shows simulation mode (green arrows denote inferred directions of change). (Color figure online)

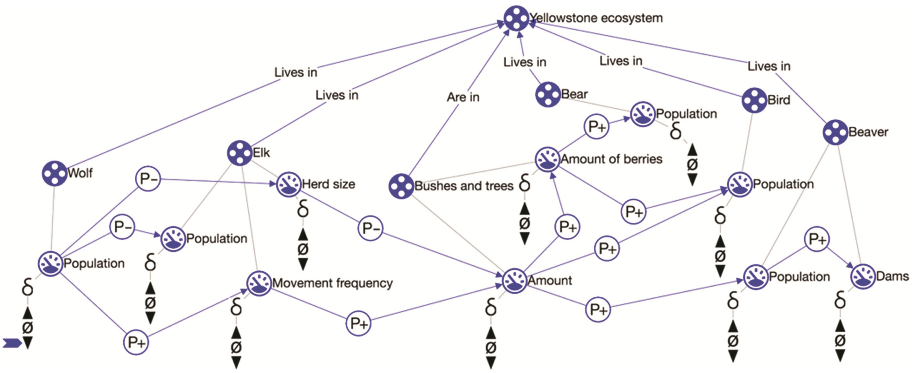

Fig. 2. Model of trophic cascade in the Yellowstone ecosystem.

In the current study, students had to learn how to use 5 out of the 15 possible DynaLearn-Web ingredients. As such, the models were relatively simple and without feedback loops or other complicated causal structures. In the first lesson students were guided through the modelling process. In the second lesson, students were expected to know how to create a model with DynaLearn-Web but were still supported in their decisions as to what ingredients to include. This was done through the assignments.

In the *control condition*, the same texts were presented to the students and similar questions asked regarding the ecosystems: what are the elements in this ecosystem, what properties do they have and how are these properties related? However, students were not asked to show these in a model but in textual answers to questions. Additional computer assignments were added to control for possible effects of computer usage. In the first lesson this consisted of making a PowerPoint on all animals in that lesson. In the second lesson this consisted of looking up information on the internet.

To assess content knowledge pre- and post-tests were developed. For both topics 5 questions were asked: 2 reproduction, 2 comprehension, and 1 application. To allow for comparability, questions were constructed such that for each question on cascade there would be a similar question on eutrophication. Reproduction scored 2.5 and 3 points, comprehension 3 and 4 points, and application 5 points. The pre- and post-test were identical per topic. Test scores thus range from 0 to 17.5 points.

3 Results

Worksheet completion was assessed as a measure of treatment integrity. On average, between 85% and 99% of the worksheet was completed. Students who finished less than 60% of their worksheet were excluded from analyses on content learning, as it was believed that these students did not participate seriously enough.

To assess the acquisition of subject knowledge, pre- and post-tests were administered before and after the lessons. Table 1 shows the school 1 results. Form the 44 participants, 39 could be used to compute results during the LP and 36 to compute results during the AP. During the LP students in the control condition significant improved on their test scores. Students in the modelling condition also obtained a significant change, however, in the opposite direction, as if they unlearned something. During the AP, the students in both conditions improved, with the improvement in the control condition being significant. However, there was a large difference on the pre-test scores, with the students in the control condition scoring significantly lower.

Table 1. Test scores school 1 – Learning & Application phase

Condition	N	Pre-test		Post-test		Average (= *Post* − *Pre*)	p
		Mean	SD	Mean	SD		
Learning phase (LP)							
Modelling	20	7.18	2.41	5.93	1.59	−1.250 (0.575)	.034*
Control	19	6.37	1.23	7.63	2.29	1.263 (0.590)	.036*
Application phase (AP)							
Modelling	17	8.32	1.83	9.35	2.66	1.03 (0.65)	.120
Control	19	5.70	2.74	7.66	2.66	1.96 (0.62)	.002*

The school 2 study happened a month after the school 1 study. Care was taken to conduct this second study more orderly and homogenous across the two conditions. In addition, because in the school 1 study it appeared that some students lost interest, a situational interest questionnaire was administered at the end of the school 2 study.

Form the 30 participants, 27 could be used to compute results during the LP and 23 to compute results during the AP (Table 2). During the LP, both conditions improved on their average scores. For the modelling condition this increase was statistically significant. During the AP, both conditions increased on their average scores. Both being statistically significant, although the increase in the modelling condition was higher.

Table 2. Test scores school 2 – Learning & Application phase

Condition	N	Pre-test		Post-test		Average (= *Post* – *Pre*)	p
		Mean	SD	Mean	SD		
Learning phase (LP)							
Modelling	13	6.88	2.22	9.00	2.18	2.12 (0.713)	.004*
Control	14	7.89	2.67	8.89	3.27	1.00 (0.687)	.151
Application phase (AP)							
Modelling	11	6.50	2.47	10.55	2.69	4.05 (0.81)	<.001*
Control	12	6.31	2.09	9.10	3.03	2.79 (0.78)	<.001*

4 Discussion

In the school 1 study, students in the control condition improved on average scores in both phases. However, students in the modelling condition obtained a significant lower average score during the LP on the post-test. This seems to suggest that they had unlearned subject-specific content, which is specifically remarkable because the questions in the pre- and post-test were the same (albeit differently ordered). The students did improve on average during the AP, but not significantly.

Informal observations showed differences as to how orderly the experiment was conducted. In general, the implementation was more orderly the control condition than in the modelling condition. This may have prompted students in the modelling condition to take the experiment less seriously, which may explain the decline in scores for these students during the LP. A few students also left early, and may not have filled out the post-test with sufficient dedication. The poor learning during the LP may also have had an effect on students modelling abilities resulting in less improvement during the AP. A few students in the modelling condition did not show up for the AP. These were some of the less well performing students. This may explain the higher average score on the pre-test in the modelling condition during the AP, and consequently reducing the size of learning effect within this group.

For the school 2 study, care was taken to ensure orderly conduct of the experiment and to have comparable experiences for both conditions. In accordance with the expectations, the results of the second study show that students in all conditions obtained higher average scores. The increase was significant for the students in the modelling condition for both the LP and AP. For the students in the control condition this was only the case in the AP. Consequently, it seems fair to conclude that students in de modelling condition did not fall behind due to the extra cognitive load imposed by the need to model. On the contrary, they even obtained higher average scores than the students in the control condition.

Overall the experiment was demanding for all students. Students were expected to work individually for almost three hours per session. This is considerably longer than the duration of most experimental studies [6] and may have asked a lot of the students' attention span. Although we tried to keep lessons fairly similar in terms of workload, students in the modelling condition did work on a larger number of learning goals and had a larger number of questions on their worksheets. This demand may have affected the scores on the post-test, which was the last activity in the three hours lasting event.

New tests were developed to measure learning. However, the reliability of these tests was found to be low, with Cronbach's α being .074 (pre-test 1), .483 (post-test 1), .409 (pre-test 2), and .435 (post-test 2). It is possible that this imprecision resulted in not finding essential differences between conditions. Another cause of imprecision relates to the pre- and post-test being identical. It appeared to demotivate students, who pointed out that they had already made these questions when filling out the post-test.

5 Conclusion

Learning by modelling is expected to induce better understanding of the subject matter, but deployment in secondary education is hampered by the extra effort it takes for learners to become proficient in modelling. The challenge is to overcome this problem and foster modelling skills, while not limiting the learning of regular subject matter. This paper reports on two studies that investigated whether the newly developed instrument for learning by 'creating qualitative models' (DynaLearn-Web) would be able to address this challenge. Particularly, the results of the school 2 study show that students in the modelling condition performed as well as students in the control condition. This supports the hypothesis that modeling can facilitate subject-specific learning without being hindered by the extra effort needed to acquire modelling skills.

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