Learning by modelling: A study of individual differences

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Abstract

Modelling is a useful cognitive skill that is becoming increasingly important in many domains, especially in science. Learning by creating computer models actively engages students in their knowledge construction and offers students the possibility to test their acquired understanding. In practice, however, novice modellers experience several difficulties, whereby learning gains often fail to show. This study investigated whether self-explanations can overcome these difficulties and enhance student's domain knowledge and the quality of their models. High school students (n= 34) were asked to perform a modelling task that required them to construct a coherent model of the effects of alcohol consumption on the human body. During the entire modelling task students were asked to think aloud. Students were post hoc classified as either high self-explainers, i.e., students that generated a minimum of 11 self-explanations; n= 24, or low self-explainers, i.e., students that generated less than 11 self-explanations; n= *10*. The main results were derived from between-group analysis of knowledge gain scores and model performance scores. The between group analyses concerning knowledge gain scores showed that there were significant differences between high and low self-explainers in favour of the former. However, no student constructed a model that reflected a complete understanding of the alcohol processes, and differences between high and low self-explainers in model performance scores failed to show.

- ***Key-words: Learning by modelling, self-explanations, learning gains.***

Samenvatting

Modelleren is een nuttige cognitieve vaardigheid die steeds belangrijker wordt in diverse gebieden, vooral in de wetenschap. Leren door het creëren van computermodellen zorgt er voor dat studenten actief kennis construeren en biedt studenten de mogelijkheid om hun verworven kennis te testen. In de praktijk blijkt echter dat beginnende modelbouwers verscheidene problemen ondervinden, waardoor de gewenste leerwinsten vaak uitblijven. Deze studie onderzocht of zelf-verklaringen tijdens het modelleren deze problemen kunnen verminderen of voorkomen, en of zelf-verklaringen daarmee in staat zijn om domeinkennis te vergroten en de kwaliteit van modellen te verbeteren. Middelbare scholieren (*n*= 34) werden gevraagd om een modelleer taak uit te voeren waarbij ze een samenhangend model moesten construeren van het effect van alcoholconsumptie op het menselijk lichaam. Gedurende de gehele modelleer taak werden de studenten gevraagd hardop te denken. Studenten werden post hoc ingedeeld in frequente zelf-uitleggers, studenten die een minimum van 11 zelf-verklaringen genereerden; *n*= 24, of sporadische zelf-uitleggers, studenten die minder dan 11 zelf-verklaringen genereerden; *n*= 10. De belangrijkste resultaten vloeiden voort uit de uitgevoerde tussen groepen analyses van leerwinst scores en modelprestatie scores. Een tussen groepen analyse betreffende leerwinst scores toonde aan dat er significante verschillen waren voor frequente en sporadische zelf-uitleggers. De gemiddelde leerwinst score was veel hoger voor frequente zelf-uitleggers dan voor sporadische zelf-uitleggers. Echter construeerde geen enkele student een model dat een volledige weergave van de alcohol processen gaf. Daarnaast bleken er geen verschillen te zijn tussen frequente en sporadische zelf-uitleggers betreffende modelprestatie scores.

- ***Steekwoorden: Leren via modelleren, zelf-verklaringen, leerwinsten.***

Table of contents

1. Introduction 4
1.1 Present study and hypotheses 7
2. Method 8
2.1 Participants 8
2.2 Materials 8
2.2.1 Modelling program 8
2.2.2 Modelling task 9
2.2.3 Instructional text 9
2.2.4 Knowledge test 9
2.3 Procedure 10
2.4 Coding and scoring 11
2.4.1 Coding and scoring of self-explanations 11
2.4.2 Coding and scoring of learning outcomes 12
2.4.3 Coding and scoring of model run scores 12
2.4.4 Coding and scoring of performance success 12
2.5 Analyses 13
3. Results 14
4. Discussion 17
5. References 21
6. Appendices 23
Appendix A 23
Appendix B 26
Appendix C 28
Appendix D 29
Appendix E 30
Appendix F 31
Appendix G 35

1. Introduction

Modelling is a useful cognitive skill that is becoming increasingly important in many domains, especially in science. There are three main purposes of modelling: (a) to produce simpler forms of objects or concepts; (b) to provide stimulation for learning or concept generation, and thereby support the visualization of some phenomenon; (c) to provide explanations for scientific phenomena (Coll & Lajium, 2011). Students benefit from modelling in several ways, first of all modelling is able to show how processes behave of the course of time, this allows students to develop a dynamic understanding of complex concepts (Campbell, Zhang, & Neilson, 2011). In addition learning by modelling actively engages students in their knowledge construction and offers students the possibility to test their acquired understanding (Mulder, Lazonder, & Jong, 2010). This active construction of knowledge takes place because students are able to interact with the modelling program, by requesting feedback on their ideas throughout the whole process of creating a model. Learning by modelling should therefore be well suited for enhancing students' understanding of complex phenomena and for providing a deeper and more accurate mental representation. A recent review of VanLehn (2013) supports the idea that in theory modelling should be able to provide several advantages. However the construction of a model is a complex task, and beginners are easily overwhelmed by the demands of modelling. When involved in modelling students should ideally go to four disguisable stages: (1) model sketching, (2) model specification, (3) data interpretation, and (4) model revision (cf. Hogan & Thomas, 2001). Students are often provided with a start model were all elements are given, which can be seen as a first solution step, thereafter student must independently go through the four stages. It appears that many students lack insights into their own knowledge and knowledge gaps and fail to evaluate these. In practice this results in several problems for novice modellers.

Among the most pertinent problems are their inability to engage in dynamic iterations between examining output and revising models (Hogan & Thomas, 2001) and their lack of persistence in debugging models to fine-tune their performance (Stratford, Krajcik, & Soloway, 1998). Due to these difficulties performance scores are often quite modest for novice modellers and learning gains fail to appear. To overcome these problems and ineffective behaviour a few studies developed and tested different forms of scaffoldings. In which the study of Manlove, Lazonder, and Jong (2009) they developed a supporting computer tool with regulatory guidelines that contained a set of goals and (sub)goals that outlined the phases students should had to go through. In addition for each (sub)goal there were hints that proposed strategies for goal attainment. However, results showed that students often did not take full advantage of the offered support from regulative scaffolds, therefore their performance scores remained somewhat poor. They research of Roscoe, Segedy, Sulcer, Jeong, and Biswas (2013) provided students with hints that offered content feedback. It appeared that these hints were positively associated with students' performance, however students gradually came to rely on this tool. This direct form of support did affect students learning activities but not their learning outcomes. Another more promising form of scaffolding was developed by Mulder, Lazonder, and de Jong (2014), namely worked-out examples.

Proving students with worked out examples, which consist of the specification of a problem, the solution steps, and the final solution itself has been found to compensate for students lack of insight into their own knowledge and knowledge gaps to some extent (Sweller, Ayres, & Kalyuga, 2011). Worked-out examples serve as models for how to solve certain types of problems. Previous research has provided empirical evidence that learning from worked-out examples is of great importance to the deduction of initial skills in well-structured domains such as physics, programming, and mathematics (Renkl, 1997).

Recent research of Mulder et al. (2014) has shown that worked-out examples in an adapted version could also be used as a scaffolding method for learning by modelling. Typical worked-out examples could not be used in modelling as students than would not have to construct a model anymore. They therefore chose to provide worked-out examples that demonstrated the process and examples that only showed a part of the solution. Results were promising and showed that the worked-out examples could further enhance students modelling behaviour and the quality of the models they create. However, in their study few students created a model that reflected full understanding of the topic, and the expected between-group difference in post-test scores failed to appear. Additionally the worked-examples led to substantial individual differences in post-tests scores which suggest that some students benefit more from the worked-out examples then others (Mulder et al., 2014).

The findings of Mulder et al (2014) concerning individual differences are consistent with the findings of the study of Chi, Bassok, Lewis, Reimann, and Glaser (1989). They have shown that the extent to which students benefit from learning with worked-out examples differs significantly among individuals, and that these differences depend on how well a student explains the solutions steps to her/himself. This phenomenon was called the *self-explanation effect.* To be more precise, self-explanation is a constructive activity that engages students in active learning and ensures that learners attended to the material in a meaningful way while effectively monitoring their evolving understanding. Several key cognitive mechanisms are involved in this process, including (1) generating inferences to fill in missing information, (2) integrating information within the study materials, (3) integrating new information with prior knowledge, and (4) monitoring and repairing faulty knowledge. So self-explanations can be given in multiple forms, but they always include an explanation or a statement. Research by Chi et al. (1989) and a replication by Renkl (1997) about the application of worked-out examples on a simple task showed that students could be divided into good or poor problem solvers based on the number of employed self-explanations. It turned out that the students who applied significantly more self-explanations learned a lot more from the task. We can therefore say that in case of well-structured domains learning with worked-out examples needed the amplification of self-explanations. In other words, self-explanations were of such essential importance, that without applying them much less learning effect of worked-out examples could be shown. However, learning by modelling differs in critical ways from learning in well-structured domains with worked-out examples. Learning with worked-out examples in contrast with learning by modelling prevents learners from using load-intensive strategies, this enables them to focuses their attention on the principles to-be-learned. With learning by modelling students independently have to build a coherent model versus learning with worked-out examples were students are guided through the entire process. So we cannot just assume that learning by modelling will also benefit from self-explanations.

On the other hand there is a reason to believe that modelling could also benefit from self-explanations. Hilbert et al. (2008) investigated the effect of self-explanation in a concept mapping task, and found results that were consistent with the original findings of Renkl (1997). Concept mapping is a method of graphically representing concepts and their interrelations, which closely resembles the core characteristics of modelling. In both concept mapping and modelling a lot is asked from students: they have to engage in several processes at a time. Hilbert et al. (2008) showed that there were significant differences in learning gains between students who were prompted to generate self-explanations during a concept mapping task and students who were not prompted. We have therefore reason to believe that students can also benefit from self-explanations in less structured learning methods. According to Renkl and Atkinson (2003), self-explanation activities may be considered effective in concept mapping because, although it increases cognitive load even more, it also directly contributes to mental model construction. As concept mapping is very comparable with modelling, it seems plausible that students will also benefit from self-explanations when learning by modelling. However, in contrast with concept mapping we have also reason to believe that self-explanations will arise spontaneously. Modelling includes the stage data interpretation, data interpretation is supposed to occur when students run the model. When they run the model the results of their input will be shown (Mulder et al., 2010). Not all the information about the rationale of the answer that is necessary for understanding the solution procedure is included in the runs. It seems therefore likely that this data interpretation phase will lead to self-explaining. When students actively explain the information the run provides to them, it is likely that students are better capable of learning successfully.

1.1 Present study and hypotheses

The purpose of the present study was to answer the general research question: *Is frequency of generated self-explanations related to how much students benefit from a learning by modelling task?* This study therefore utilized an observational design that observed the generation of spontaneous self-explanations. The learning environment was designed in accordance with Mulder et al.'s (2011). To be able to register the generated self-explanations students were asked to think-aloud during the entire modelling task.

To answer the research question three hypotheses were investigated. The first hypothesize concerned the learning gains. Consistent with Renkl (1997) and Hilbert and Renkl (2009), students who evidenced more self-explanations were expected to learn more from the task than students who generated fewer self-explanations. Said differently, *a higher frequency of generated self-explanations during a modelling task will enhance learning gains (Hypothesis 1).* The second hypothesis concerned the reason why some students will generate more self-explanations then others during a modelling task. Following the presumption that data interpretation will lead to self-explanations, and that data interpretation supposed to occur during a model run we hypothesize that: *The more often a model run is performed the more self-explanations will be generated (Hypothesis 2).* Previous research on self-explanations only investigated whether self-explanations were a predictor for learning gains. As it seems plausible that students who learned more also performed better, it was in this study also investigated whether self-explanations were also a predictor for performance success. We hypothesize that: *A higher frequency of generated self-explanations during a modelling task will lead to a higher performance score (Hypothesis 3).*

2. Method

2.1 Participants

The sample consisted of 34 Dutch high school students (23 men, 11 women). The average age of the students was 16.53 years (*SD*= 0.79) All participants were enrolled in the interdisciplinary beta subject NLT (nature, living, & technique). The sample consisted of a lot more men than women, which was due to the fact that all students had an NT (nature & technique) or an NH (nature & health) profile, in the Netherlands in general more men than women choose these exact profiles. The sample consisted of two groups, one Havo group (general higher secondary education) of (11 men, 3 women) and one Vwo group (pre university education) of (12 men, 8 women); these two levels of education are above average.

2.2 Materials

2.2.1 Modelling program

Participants engaged in a modelling task using the modelling program SCYDynamics. This program can be used to create and run models in the system dynamics modelling language. Models created with SCYDynamics have a graphical structure that consists of variables and relationships a (see Figure 1). Variables are the constituent elements of a model and relations define how two or more variables are related. When participants have created a model or a part of it they can see the output of these creations when they run the model. The output can then be analysed through a bar chart, or graph tool. When participants were confused about the meaning of certain tools of the program they could consult a modelling manual that offered an explanation and examples of the operation of the tools.

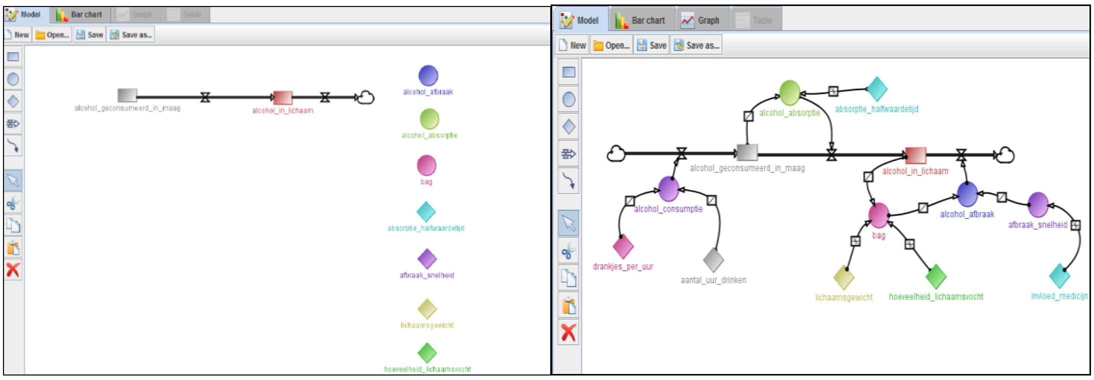


Figure 1. Screen capture of the model editor tool with the start model, (left panel) and the reference model (right panel)

2.2.2 Modelling task

The task was to create a coherent model of the effects of alcohol consumption on the human body. As the creation of a coherent model is a complex task and to keep students motivated the modelling task was divided over three scenarios (Louca & Zacharia, 2012). The first scenario consisted of two phases. During Phase 1 students had to place the model elements at the right place in the model and indicate which variable had influence on each other by creating relationships. In Phase 2 students had to specify the relationships by providing a qualitative specification of each relationship (e.g., a linear descending relationship: if weight increases, then blood alcohol concentration decreases). In both phases students could get feedback on their model quality, in Phase 1 this could be done by consulting the barchart, in Phase 2 this could be done by consulting the graph. After completing the first scenario there were two scenarios left in which students were asked to adjust their model to situations in which the effect of changes in quantity of an element could be shown. In the second scenario students needed to let the model calculate what happens when a person consumes alcohol for a long time. During the third and final scenario students needed to let the model calculate what happens when elimination rate becomes dependent on another element, in this case the element medicine. Students here again needed to run the model to see the effect of their input. The assignment paper instructed that participants should only go the next phase if the previous phase was completed. However, as there were no restrictive phases it could not be checked whether students actually adhered to this instruction. SCYDynamics stored all participants' actions in a log file.

2.2.3 Instructional text

During the modelling task students could infer domain knowledge from an instructional text (Appendix F). This instructional text provided a clear and coherent account of the ingestion, absorption and elimination of alcohol. The text gave a clear description of the elements that influences these three processes. The instructional text consisted of 744 words.

2.2.4 Knowledge test

A knowledge test was used to assess participant's knowledge of the alcohol domain. The test consisted of nine items, and was divided in three sections that addressed three different kinds of knowledge. The first section consisted of two items that addressed conceptual knowledge about alcohol. Both items were designed as true/false statements (e.g., Indicate if the following statement is true or false: A small amount alcohol provides a greater feeling of relaxation: true / false). The second section consisted of four items, about the key processes at stake during alcohol consumption, including the ingestion, absorption, spread and elimination of alcohol. These items were graphically designed such that participants needed to show one relationships per item, so only one process was assessed per question, therefore these questions were considered to be testing process knowledge (e.g., For a healthy person there is a relation between the amount of consumed alcohol and the blood alcohol content of this person. Display this relation in the graph below). The third section consisted of three items that assessed deep understanding of the model as a whole. These three questions referred to the three different scenarios of the modelling task, and were again designed graphically (e.g., Imagine you are in a bar and you have consumed four drinks. Look at the graph. Displayed is the course of the amount of alcohol in your stomach over time if you didn't drink alcohol for the rest of the evening. Draw the corresponding graph for the amount of alcohol in your body).

2.3 Procedure

All participants engaged in two sessions, one joint introduction session and one individual experimental session of each 50 minutes. The introduction session was divided into four parts. During the first participants received an explanation of what modelling is, what purposes it serves, and what was expected from them during the study. These instructions took approximately 10 minutes. In the second part students completed the knowledge test to assess their initial understanding of the task content. The maximum time to complete this test was 10 minutes. The third part was an interactive exercise that tested whether students had understood the given explanation of the first part. Students had to give examples of models and explain what purposes these models served. After this it was assumed that students obtained a sufficient knowledge of what modelling involves, but not how a coherent model could be constructed. In cooperation with the students, the experimenter created an example model to show how a model could be built. This interactive section took approximately 10 minutes. During the fourth part students were familiarized with SCYDynamics. They received a modelling manual and completed an introduction lesson in modelling. They had a maximum of 20 minutes to complete this introduction.

The experimental session was divided into three parts. During the first part students received an explanation of what was expected from them during the modelling task. Students were told that they were going to take part in an individual modelling task concerning alcohol processes. Students were then told that the experimenter would like to know how they approached the task, and were therefor asked to verbalize their thoughts during the entire modelling task. The corresponding instruction was structured according to the guidelines of Ericsson and Simon (1993). The participants were told to talk aloud and verbalize anything that comes to their mind. Participants were not instructed to provide any special information. In this manner only spontaneous self-explanations were generated. To make sure participants understood what was expected from them the think aloud procedure was practiced with a warm-up problem (making a bowline knot). Participants were told that when they did not think aloud for more than one minute during the modelling task the experimenter would gave them a prompt (e.g. ‘‘please keep thinking-aloud’’). After completing the think-aloud example students received the final instruction; they were told that they could only ask the author for help concerning technical issues during the modelling task, this first part of the experimental session took approximately five minutes. During the second part students actually started working on the modelling task, first the audio program (Camtasia studio) was activated by the experimenter, then students were told to start SCYDynamics and log in with their own name. At the same time participants received the instructional text, the modelling task and the modelling guide from the author. They had a maximum of 40 minutes to work on the modelling task, the experimenter gave a warning when five minutes were left to work on the task. When students finished the task, or when time was up, they were told to save their work and close the modelling program. The experimenter would then stop the audio program and close Camtasia studio. During the third and final part students again completed the knowledge test. Students had a maximum of 10 minutes to complete the post-test.

2.4 Coding and scoring

Data was collected during the introduction session and the experimental session. Four variables were assessed: frequency of generated self-explanations, learning outcomes, model run scores, and performance success.

2.4.1 Coding and scoring of self-explanations

The first variable under investigation was *frequency of generated self-explanations*. The think-aloud protocols were not entirely segmented only the frequency of generated self-explanations were tallied. A self-explanation may differ in length from a few seconds to more than a minute. A self-explanation was ended when the student brought up a new topic or remained silence for at least 10 seconds. A coding schema was developed to facilitate the recognition of self-explanations, several examples were provided (Appendix A). Self-explanations were scored using a table that distinguishes the three scenarios of the modelling task, each self-explanation should be scored at the scenario wherein it was generated (e.g., self-explanations that were generated during the first scenario, defining of the relationships, were scored in the first row) (Appendix G).

To establish the reliability of the coding schema for self-explanations, a pilot study was conducted with two volunteers who performed the same modelling task as the participants in the actual study. The pilot participants' think-aloud protocols were audio taped. These protocols were entirely segmented; recordings were segmented with a segmenting program (Elan, 2013). A new segment began when a new topic had arrived or when a silence of more than 10 seconds had occurred. The segments were either coded as a self-explanation or no self-explanation. The segments were independently coded by both the experimenter and a second coder. An inter-rater reliability Cohen's κ of .85 was obtained over 173 segments. Any major discrepancies among coders were resolved through a discussion. To establish whether the experimenter kept consistent in coding the think-aloud protocol of the participants three audio recordings of the actual participants were segmented. Again these protocols were entirely segmented and coded by both the experimenter and a second coder. The recordings were randomly chosen, one at the beginning, one at the middle and one at the end of the research. The overall Cohen's κ inter-rater reliability was .84 obtained over 234 segments.

2.4.2 Coding and scoring of learning outcomes

Learning outcomes were indicated by participants gain scores on the knowledge test. A rubric was designed to score students answers for the nine items on the knowledge tests, one point was assigned to each correct answer. For the three different knowledge sections separate total scores were computed, for conceptual items a maximum of two points could me obtained, for process items a maximum of four points and for coherent understanding items a maximum of three points could be obtained. Then for each student gain scores on the knowledge tests were computed. The experimenter and a second coder used the designed rubric to score the nine items for a randomly selected set of 30 knowledge tests. The overall Cohen's K inter-rater reliability was .97 (section 1: 1.00; section 2: .96; section 3: .92). The instances where the two raters differed were discussed and clarified prior to the final coding of all knowledge tests.

2.4.3 Coding and scoring of model run scores

Students' model run scores were a composite score and existed of students barchart scores and graph scores. Barchart scores indicated how often students requested feedback from the barchart; graph scores indicated how often students runned the model with the graph tool. Barchart and graph scores were filtered from the log files by a software agent, there after the scores were summed.

2.4.4 Coding and scoring of performance success

Performance success indicated the quality of the students' models. Two separate scores were computed, a model structure score and a model concept score (Kopainsky, Pirna, Dummer, & Alessi, 2012). Model structure scores were assessed from participants' final models, this was done by a software agent that filtered the information from the log files. For the scoring of the model structure the rubric of Mulder et al. (2014) was employed in an adapted version (Appendix B). The model structure score of the total model represented the number of correctly specified variables and relations in the model. The reference model was used to determine whether variables and relations were scored as correct (right panel of Figure 1). Concerning the variables that needed to be created during scenario two and three, one point was given for each correctly named variable, an additional point was given if that variable was of the correct type. (e.g., two points would be assigned for the element 'hours_drinking' if the correct name was given to it, if it was correctly represented as a constant element). With regard to relationships, one point was assigned to each correct link between two elements. One extra point could be earned for a right direction of the relationship, and one extra point for the right nature of the relationship (i.e., a qualitative specification), (e.g., three points would be earned if a relation between BAC and alcohol elimination was made, the relation was directed from BAC to alcohol elimination and the qualitative specification was set to linear). The maximum model quality score was 49.

Model concept scores were assessed for students' created concepts. The total model consisted of five concepts: including ingestion, absorption, distribution, elimination, and elimination extension. The concepts were scored by a software agent that filtered the information from the log files. A scoring rubric was designed that assessed the five concepts separately (Appendix C). A concept was seen as correct when it included all the belonging elements and relationships, when this was the case one point were assigned. For the concepts ingestion and elimination extension, one or more elements needed to be created by the students themselves, therefore these concepts could only be scored as correct when the variables belonging to a concept were created correctly (the right name and the right kind). All concepts could earn one additional point when the correct qualitative specifications were chosen, so a maximum of two points could be achieved per concept. The maximum model concept score was 10 points.

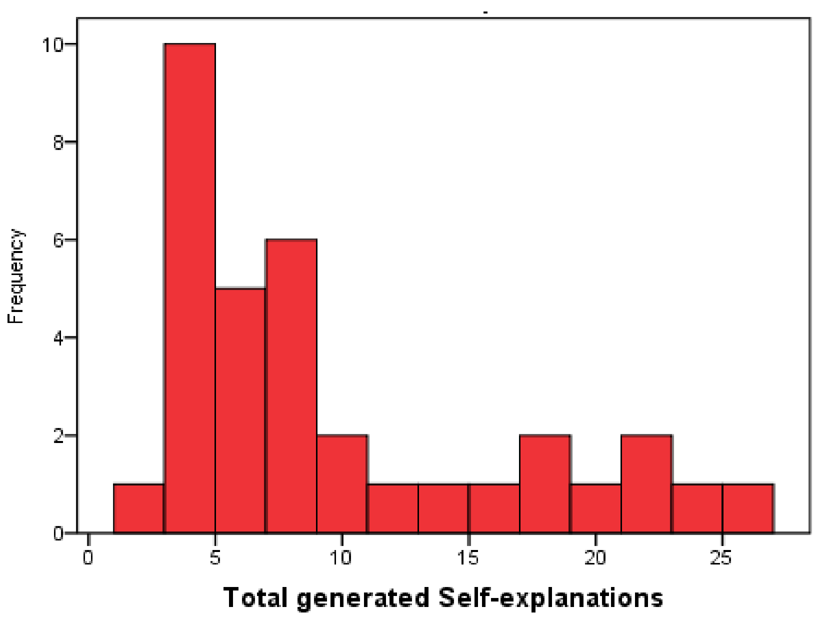
2.5 Analyses

To test the hypotheses that were established in the introduction the following statistical analyses were conducted. First, knowledge gain scores were computer by subtracting the pre-knowledge scores from the post-knowledge scores, then a paired sample t-test was performed to determine whether post-test scores significantly differed from pre-test scores. To determine if significant differences for high and low self-explainers concerning, pre-knowledge scores, gain scores, amount of feedback requested, model structure and model concept scores existed analyses of variance where conducted. Finally, correlation analyses were performed to provide insights into the interdependence of all the used variables.

3. Results

Individual differences were reported by dividing the sample into "high" and "low" self-explainers. These two groups were defined post hoc, using the students' number of generated self-explanation scores. It appeared that the self-explanation data was not normally distributed and that the data was very skewed to the right, which indicated that most students generated a very low amount of self-explanation against a few students that generated al lot of self-explanations (Figure 2). The histogram shows a clear transition from a few to a lot generated self-explanations at 11. Students were therefore defined as high self-explainers when a self-explanation score of at least 11 was obtained. Students who generated less than 11 self-explanations were defined as "low" self-explainers.

Figure 2
Distribution of Generated Self-explanations



To determine whether students in general learned from the modelling task a paired sample t-test was performed. The mean score for post-knowledge (M= 3.88, SD= 1.72) was higher than the mean score for pre-knowledge (M=2.86, SD=1.22). It appeared that the scores were significantly different, t (33) = -4.27, p = <.001. Table 1 summarizes the descriptive statistics for participants' scores in the high self-explainer and the low self-explainer group. Univariate analysis of variance (ANOVA) revealed no significant differences between the high and low self-explainer groups concerning prior knowledge scores F(1, 34) = 0.054, p= .818.

Table 1
Summary of Participants Scores

	High explainers (*n*= 10)		Low explainers (*n*= 24)	
	M	*SD*	*M*	*SD*
Knowledge scores:				
Pre-knowledge	2.60	1.17	2.71	1.27
Post-knowledge	5.80	1.23	3.08	1.18
Knowledge gain	3.20	0.92	0.38	1.06
Performance scores:				
Model structure	21.10	10.49	16.79	5.90
Model concepts	0.70	0.48	0.92	0.78
Model run	29.80	11.43	24.08	12.06

To test Hypothesis 1, that self-explanation scores influenced knowledge gain scores, a univariate ANOVA was performed. Results yielded a main effect for self-explainer group (high/low), $F(1, 34) = 54.26$, $p = <.001$, such that the average gain score was significantly higher for high self-explainers than for low self-explainers. Hypothesis 2 predicted that a students' model run scores could predict self-explanation scores. To analyse this hypothesis a univariate ANOVA was performed and revealed that there were no significant differences for high and low self-explainers concerning the average amount of runs performed $F(1,34) = 1.63$, $p = .211$. Hypothesis 3 predicted that self-explanation scores could enhance performance success. As the scores of the dependent variables model structure and model concept score were not normally distributed, Mann Whitney U tests for two independent samples were conducted to test this hypothesis. The first analysis determined whether the model structure scores varied as a function of whether students were defined as high ($MR= 21$) or low ($MR= 16.04$) self-explainers, the results were not significant, $U = 85$, $p= .182$. The second analysis determined whether the model concept scores varied as a function of whether students were defined as high ($MR= 16$) or low ($MR= 18.13$) self-explainers, these results were also not significant, $U = 105$, $p= .518$.

Table 2 summarizes the performed correlations analysis. Two correlations appeared to be significant. As expected self-explanation scores and knowledge gain scores were highly correlated. The correlation between self-explanation scores en model structure scores was less strong but appeared also significant. The remaining correlations were not significant.

Table 4
Summary of Correlation Analyses

	Self-explanation	Knowledge Gain	Model run	Model structure	Model concept
Self-explanation	-	.81*	.25	.35*	-.21
Knowledge Gain		-	.09	.30	-.26
Model run			-	.05	.05
Model structure				-	-.34
Model concept					-

*. Correlation is significant at the 0.05 level

4. Discussion

The purpose of the present study was to answer the general research question: *Is frequency of generated self-explanations related to how much students benefit from a learning by modelling task?* This study compared the learning outcomes and performance success of students who either were defined as high self-explainers or low self-explainers. It was expected that the high self-explainers had learned more from the modelling task and therefore had obtained higher gain scores (Hypothesis 1). We also had an expectation concerning where individual differences in the amount of generated self-explanations might stem from. As we assumed that self-explanations were often generated after a model run was performed, this study also compared the amount of model runs performed by high and low self-explainers (Hypothesis 2). As self-explanation scores were assumed to be a predictor for learning gains, it was logically expected that self-explanation scores also predicted performance success. It was therefore expected that significant differences for high and low self-explainers concerning performance success could be found (Hypothesis 3).

Hypothesis 1 was confirmed. Students defined as high self-explainers obtained significantly higher gain scores, confirming that a higher frequency of self-explanations indeed led to higher knowledge gains. These results are consisted with the results founded in the study of Chi et al. (1989), who found that students that were defined as good students (high self-explainers), learned significantly more from the worked-out examples than the students that were defined as poor students (low self-explainers). It is also consistent with the study of Hilbert and Renkl (2008) on concept maps, were students who were prompted to generate self-explanations obtained significantly higher learning gains then the group that was not prompted. We can therefore say that this study confirmed that self-explanations are able to enhance learning gains and that a less structured learning method like modelling can also benefit from self-explanations.

Hypothesis 2 could not be confirmed, a between group comparison of the number of model runs determined that no significant differences between high and low self-explainers could be found. This suggests that there was no relation between frequencies of generated self-explanations and the amount of feedback that was requested. A possible explanation might be the perceived difficulty of the task. Because the task was appeared very difficult for the students a lot of students randomly drawn relationships between variables and checked the barchart to see whether the barchart might become greener. As they had no idea of why a particular relation might be right in the first place, they also could not give an explanation to the provided information in the barchart. These students often said something like ‘‘Ok, now I have one more relationship wright’’ they did not gave any additional explanation of why it might be right, this resulted in little generated self-explanations and very much feedback requests. So this explanation suggests that because the modelling task was so hard, students did often consult the barchart but were unable to generate self-explanations during this data interpretation phase. However it is also possible that it was not due to the difficult modelling task that a high frequency of generated self-explanations was not related to the amount of feedback requested. It was assumed that self-explanations arose during the data interpretation phase which should take place during a model run. However, not every model run has to lead to (extensive) data interpretation. It possible that model runs were performed when a small change was made, and that students would only look if the model was still correct and then moved on without applying self-explanations.

Hypothesis 3 could not be confirmed as there were no significant differences between high and low self-explainers concerning model structure and model concept scores. Correlation scores for model structure and model concepts were however not so straightforward. For example, there appeared to be a significant positive correlation between self-explanation scores and model structure scores. This suggests that the frequency of generated self-explanations was associated with model structure scores. On the other hand the correlation between model concept scores and self-explanation scores appeared to be weak negative one and not significant. So students were able to obtain a reasonable model structure score, but they were not able to obtain a reasonable model concept score. The model structure score was seen as a more superficial score, students could check the barchart and just randomly change relationships until they were right. As the high self-explainers runned the model slightly more, it seems therefore plausible that a positive correlation between self-explanations and model structure was found. For model concept scores a deeper understanding was requested, students could only obtain points when they had understood a concept completely. The barchart was in this case less helpful, because it did not say how much element and relationships a concept should contain. The model concept scores therefore provide a more clear understanding of how "poor" students actually performed, in general not even one of the five concepts was completely correct. As we showed that high self-explainers learned a lot, on average 3.20 points from the modelling task, we may assume that they did obtain a better understanding of the concepts after the modelling task. The statistics on the model concepts however appeared very low, this suggest that the high self-explainers were able to learn from the modelling task through self-explaining, but still found it very difficult to externalize their ideas of the concepts in the learning environment. These results not only apply for modelling, novice concept mappers also experience difficulties in externalizing their ideas in an abstract manner (Hilbert & Renkl, 2009). This may be explained the neurological research of Binder, Westbury, McKiernan, Possing, and Medler (2005). Which emphasise that students often find it more difficult to think in abstract ways rather than concrete ways. In their study it appeared that abstract words activated left inferior frontal regions which were previously linked with working memory processes. This suggests that abstract thinking provides a higher load in working memory. The research of Kapur (2008) provides a different explanation, this study demonstrates an existence proof for productive failure. Engaging students in solving complex, ill-structured problems without the provision of support structures can be a productive exercise in failure. In the study of Kapur (2008) there were two groups, one who solved ill-structured problems and one who solve structured problems. The ill-structured group struggled with defining and analyzing the problems, resulting in poor quality of solutions. However, despite failing during the task, these students outperformed their counterparts in the well-structured condition on near- and far-transfer measures. Suggesting that high learning gains do not immediately imply high performance success.

So it appeared that self-explanations led to a complex relation between the model performance and students' knowledge gains. Students' model performance was quite low which is very contrasting with the high knowledge gains. There are two possible conclusions concerning the effect of self-explanations, (1) self-explanations were able to enhance learning gains but were not able to enhance model performance, or, (2) high self-explainers did understand the task but did not take the effort to adjust their models correctly. This is quite possible because students knew they did not receive a grade for the modeling task. The existing research on self-explanations only tested if self-explanations were an indicator for learning gains, but they did not test if self-explanations could be a predictor for performance scores. So we cannot say if this is consistent with earlier research on self-explanations. What we can say is that for modelling in general performance scores are often quite modest and that learning gains often fail to show (Mulder et al., 2010). So the modest performance scores in our study resemble those of earlier studies on modelling.

Of course, the present study not only provided answers to the research questions, it also provides suggestions for future investigations. This study established that learning by modelling can benefit from self-explanations. In order to ensure that in the future all students are able to benefit from self-explanations further research should develop self-explanation prompts just as was done for concept mapping in the research of Hilbert and Renkl (2008). The research of Atkinson et al. (2003) also showed the effectiveness of self-explanation prompts, the prompts were used for a new worked-out example method whereby more and more worked-out solution steps were removed as learners transition from relying on examples to independent problem solving, to facilitate this transition self-explanation prompt were added.

To even further enhance the effects of self-explanation prompts on learning gains, a distinction between different forms of self-explanations should be made to develop the most effective prompts. In the research of Renkl (1997) five self-explanation categories and two monitoring categories were established. It appeared that certain self-explanation categories were able to enhance learning gains much more than others. Principle based explanations and anticipative reasoning were seen as the two most successful categories. Principle based explanations, indicated in their study that students referred to the principles of probability calculation and explained these principles to themselves. In the case of modelling a possible example of a principle based explanation could be "This relationship must be linear, because when X increases Y also increases ". Anticipative reasoning indicated in their study that students were making connections between examples and thinking ahead, in the case of modelling a possible example could be "This element is shaped as a diamond, and I know that this element cannot change over time, so this mean that all other diamonds are also constant ". When a combination of these two categories was used even more learning gains were obtained.

In the case of modelling there is however an obstacle concerning the timing of the prompts. For learning with worked-out examples it is very logical were to give prompts as this method is very structured, but for modelling it would be rather difficult to find those critical points. A possible solution to overcome this problem could be to look at the timing were students with very high knowledge gain scores generated self-explanations.

In conclusion it can be said that self-explanations are able to enhance learning by modelling. Further research should concentrate on the development of prompts, so that in the future all students are able to benefit from self-explanations during modelling.

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6. Appendices

Appendix A
Codering self-explanations

1. Omschrijving self-explanation

Self-explanations: Het aan je zelf uitleggen van een opdracht, tekst, programma etc. Self-explanation is dus een constructieve activiteit waarin actief kennis wordt verworven. Self-explanations kunnen betrekking hebben op verschillende onderwerpen maar bevatten altijd een uitleg of verklaring van het betreffende onderwerp.

2. Codeer instructies:

- ❖ Er bestaan verschillende vormen van self-explanations, deze worden duidelijk in het schema hieronder. Deze dienen als hulp bij het coderen, maar tijdens het coderen worden in deze vormen geen onderscheidt gemaakt.
- ❖ Alleen de frequentie self-explanations worden gecodeerd niet de frequentie geen self-explanations.
- ❖ Wanneer je twijfelt of iets een self-explanation is kun je de voorbeelden raadplegen.

3. Self-explanations schema + voorbeelden:

Self-explanations:	**Voorbeelden:**
Uitwerkingen van de probleem situatie:	1. Oké, even kijken ik heb dus 9 variabelen en die moeten dus op de goede plek komen om een goed model te maken 2. Ik moet dus een samenhangend model maken met deze elementen door er relaties aan toe te kennen. 3. Dus ik moet hier relaties definiëren zodat de relatie ook betekenis krijgt en wat kan laten zien.
Uitleggen van principes:	1. Ik verbind bag met hoeveelheid lichaamsgewicht omdat het gewicht volgens de tekst invloed blijkt te hebben heeft op de hoogte van het bag. 2. Deze relatie is lineair omdat wanneer x groter wordt y ook groter wordt. 3. Dit element is constant omdat deze niet kan veranderen door een ander element.
Uitleggen van de functies van het programma:	1. Een ruitje betekent een constante waarde, dus kies ik voor aantal drankjes een ruitje want die veranderd niet. 2. Met een stroompijl kun je dus aangeven dat de voorraadgrootheid toe of afneemt. 3. In de barchart kan ik bekijken of de relaties die ik maak goed zijn toch, dus ga ik dat zo vaak mogelijk doen. 4. Met de graph kan ik straks controleren of ik de relatie goed gedefinieerd heb. 5. Volgens mij kan ik alleen definiëren als ik in next fase ben, want zo deden ze het in de handleiding ook.
Het uitleggen van de informatie uit de bar chart of uit de graph:	1. De barchart zegt me nu dat ik dus 7 goede relaties heb en 9 goede elementen, dus dat betekent dat ik alles goed heb en dat ik verder kan gaan. 2. Er is dus 1 richting fout, dat betekent dus dat ik de relatie moet omdraaien. 3. Uit de grafiek blijkt dat bag stijgt naarmate het lichaamsgewicht daalt. Dus hoe zwaarder je bent hoe minder last je hebt van alcohol.

4. Overgang self-explanations schema + voorbeelden

Overgang van self-explanations:	**Voorbeelden:**
Bij verandering van onderwerp	1. Bijv. eerst vertellen of wat invloed heeft op het bag en dan bijv. verder gaan op absorptie halfwaardetijd.
Bij een stilte langer als 10 seconden	1. Wanneer de persoon langer dan 10 seconden stil blijft is de self-explanation afgelopen, ook als hij/zij daarna weer verder gaat over het zelfde onderwerp.

5. Geen self-explanations schema + voorbeelden:

Geen self-explanations	**Voorbeelden:**
Vragen die geen betrekking hebben op de opdracht	1. Mag het raam dicht? 2. Hoeveel tijd heb ik nog?
Opmerkingen die geen betrekking hebben op de opdracht	1. De computer vraagt om een update. 2. De stoel wiebelt.
Opmerkingen over het programma	1. Wat een rot programma. 2. De grafriek werkt niet goed.
Letterlijk hardop voorlezen van de opdracht	1. Delen of de hele opdracht hardop voorlezen.
Letterlijk hardop voorlezen van de tekst	1. Delen of de hele tekst hardop voorlezen.
Opnoemen acties, zonder uitleg waarom ze dat doen.	1. Even kijken wat ik moet doen. 2. Ik ga even de tekst lezen. 3. Dat ga ik opzoeken in handleiding. 4. Ik verbind bag met lichaamsvocht.
Monitoren dat iets wel of niet lukt.	1. Yes, het is gelukt! 2. De barchart zegt dat het klopt 3. Nu loop ik helemaal vast.
Alle losse woorden.	1. Afzonderlijk voorlezen elementen dus bag, alcohol afbraak, absorptie halfwaardetijd. 2. Oké, hmm, ja, nee, klopt. 3. Graph, barchart, stroompijl. 4. Raar, vreemd.

Appendix B

<u>Punten systeem voor de model kwaliteit</u>

***Variabelen waaraan punten worden gegeven**

Variabele naam:	*Variabele soort:*	pnt
1. Alcohol consumptie	Rekengrootheid	2
2. Drankjes per uur	Constante	2
3. Aantal uur drinken	Constante	2
4. Invloed medicijn	Constante	2
5. Afbraak snelheid (scenario 3)	Rekengrootheid	2
		Totaal pnt: 10

***Relaties waar punten voor worden gegeven:**

Relaties	Pnt
1. Alcohol consumptie beïnvloedt alcohol in de maag	3
2. Drankjes per uur beïnvloedt alcohol consumptie	3
3. Aantal uur drinken beïnvloedt alcohol consumptie	3
4. Alcohol geconsumeerd in maag beïnvloedt alcohol absorptie	3
5. Absorptie half waarde tijd beïnvloedt alcohol absorptie	3
6. Alcohol absorptie beïnvloedt alcohol geconsumeerd in de maag en alcohol in het lichaam	3
7. Alcohol in het lichaam beïnvloedt bag	3
8. Lichaamsgewicht beïnvloedt bag	3
9. Hoeveelheid lichaamsvocht beïnvloedt bag	3
10. Bag beïnvloedt alcohol afbraak	3
11. Afbraak snelheid beïnvloedt alcohol afbraak	3
12. Alcohol afbraak beïnvloedt alcohol in het lichaam	3
13. Invloed medicijn beïnvloedt de afbraak snelheid	3
	Totaal pnt: 39

***Uitleg variabelen:**

Aan variabelen kunnen maximaal 2 punten worden toegekend:
1 punt voor de juiste naam van de variabele
1 punt wanneer de juiste soort variabele is gekozen

***Uitleg relaties:**

Aan relaties kunnen maximaal 3 punten worden toegekend:
1 punt voor elke juiste link tussen variabelen
1 punt voor de juiste richting tussen deze variabelen
1 punt voor de juiste kwalitatieve specificatie

Appendix C
<u>Punten systeem voor model begrip</u>

***Concepten waaraan punten worden gegeven**

Concepten:	Pnt:
1. Inname	
2. Absorptie	
3. Verspreiding	
4. Afbraak	
5. Afbraak uitbreiding	
	Totaal pnt: 10

***Uitleg concepten :**

Aan concepten kunnen maximaal 2 punten worden toegekend.
1 punt werd toegekend wanneer het gehele concept juist is weergegeven. Met juist wordt bedoeld dat het concept alle behorende *variabelen en *relaties bevat.

*Juiste variabelen zijn variabelen die behoren tot het betreffende concept.(Met betrekking tot de concepten inname en afbraak 2: Variabelen worden gezien als juist wanneer zij behoren tot het concept en zij de juiste naam hebben, en van de juiste soort zijn).

* Juiste relaties worden hier gezien als relaties met de juiste link en met de juiste richting *(wanneer de juiste kwalitatieve specificaties ook zijn weergegeven wordt in zijn geheel 1 extra punt gegeven).*

Inname:	Drankjes per uur en aantal uur drinken beïnvloeden alcohol consumptie, alcohol consumptie beïnvloedt alcohol in de maag.
Absorptie:	Alcohol geconsumeerd in maag beïnvloedt alcohol absorptie, absorptie half waarde tijd beïnvloedt alcohol absorptie, alcohol absorptie beïnvloedt alcohol geconsumeerd in maag en alcohol in lichaam.
Verspreiding:	Alcohol in lichaam beïnvloedt bag, lichaamsgewicht en hoeveelheid lichaamsvocht beïnvloeden bag.
Afbraak:	Bag beïnvloedt alcohol afbraak, afbraak snelheid beïnvloedt alcohol afbraak, alcohol afbraak beïnvloedt alcohol in het lichaam.
Afbraak uitbreiding:	Bag beïnvloedt alcohol afbraak, invloed medicijn beïnvloedt afbraak snelheid, afbraak snelheid beïnvloedt alcohol afbraak, alcohol afbraak beïnvloedt alcohol in het lichaam.

Appendix D
Codeerschema kennis toets:

Vraag 1:
1: Wanneer alle stellingen juist zijn beantwoord.
0: Wanneer 2,1, of 0 goede antwoorden zijn gegeven.
Vraag 2:
1: Wanneer alle stellingen juist zijn beantwoord.
0: Wanneer 2,1, of 0 goede antwoorden zijn gegeven.
Vraag 3:
1: Wanneer een constante lijn is weergeven, de hoogte van de lijn in de grafiek maakt hierbij niet uit.
0: Wanneer er geen constante lijn is weergegeven.
Vraag 4:
1: Wanneer een lineaire lijn is weer gegeven die links onder begint en rechtsboven eindigt.
0: Wanneer geen lineaire lijn is weergegeven.
Vraag 5:
1: Wanneer een constante lijn is weergeven, de hoogte van de lijn in de grafiek maakt hierbij niet uit.
0: Wanneer er geen constante lijn is weergegeven.
Vraag 6:
1: Wanneer een dalend lineaire lijn is weergegeven, die links boven begint en rechts onder eindigt.
0: Wanneer geen dalend lineaire lijn is weergegeven.
Vraag 7:
1: Wanneer een lijn is weergegeven die begint bij het begin punt van alcohol in de maag en blijft stijgen tot het punt waar alcohol in de maag op een 0 punt is (de alcohol in het lichaam mag niet boven het hoogste punt van alcohol in maag uitkomen), en vanaf dat punt gaat dalen met een snelheid gelijkmatig aan die van de stijging, daarna komt deze ook op een 0 punt en blijft constant.
0: Wanneer aan 1 of aan meerdere voorwaarden niet is voldaan.
Vraag 8:
1: Wanneer een lijn is weergegeven die links onder begint en verder stijgt dan het hoogtepunt van alcohol in de maag en blijft stijgen tot voorbij het hoogste punt van alcohol in de maag, daarna zal de lijn lineair dalen.
0: Wanneer aan 1 of meerdere voorwaarden niet is voldaan.
Vraag 9:
1: Wanneer een lijn is weergegeven die links onder begint en blijft stijgen tot het hoogtepunt van alcohol in de maag, wanneer alcohol in de maag op een 0 punt is zal de lijn van alcohol in het lichaam heel minimaal gaan dalen, dit blijft zo gedurende de rest van grafiek.
0: Wanneer aan 1 of meerdere voorwaarden niet is voldaan.

‘

Appendix E
Beoordeling schema kennis toets

Naam:	
Leerling nummer:	

Sectie 1 punten:
Vraag 1:
Vraag 2:
Totaal:
Sectie 2 punten:
Vraag 3:
Vraag 4:
Vraag 5:
Vraag 6:
Totaal:
Sectie 3 punten:
Vraag 7:
Vraag 8:
Vraag 9:
Totaal:
Subtotaal:

Appendix F
<u>Inleidende tekst & opdracht</u>

Afbraak van alcohol in het lichaam

Deze tekst beschrijft hoe het menselijk lichaam geconsumeerde alcohol afbreekt. Velen ervaren het als prettig dat alcohol ervoor kan zorgen dat je je meer ontspannen voelt, maar als je meer drinkt krijg je ook de nadelige effecten van alcohol op je geheugen, je reactiesnelheid en je coördinatie. Gelukkig zorgt je lichaam ervoor dat alcohol ook weer afgebroken wordt, zodat al deze effecten verdwijnen.
Na het lezen van deze tekst zou je moeten weten:

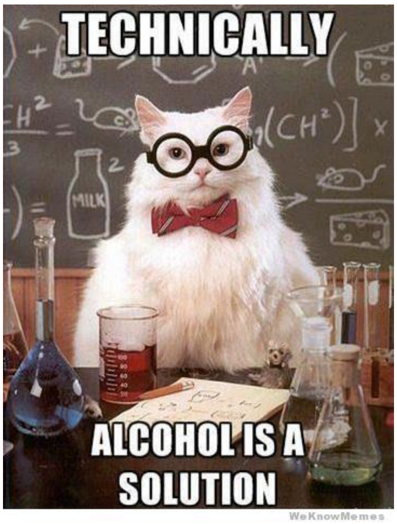
- hoe alcohol wordt opgenomen door je lichaam;
- hoe alcohol zich verdeelt over je lichaam;
- hoe alcohol ook weer wordt afgebroken.

Wist je dat alcohol heel snel in het lichaam opgenomen wordt, maar ongeveer een uur nodig heeft om afgebroken te worden?
Als je alcohol houdende drankjes, zoals bier, wijn of mixdrankjes drinkt, heeft dat een invloed op het functioneren van je lichaam. In eerste instantie zorgen deze drankjes vaak voor een prettig gevoel, remmingen nemen enigszins af, je wordt vrolijker, spraakzamer en je voelt je waarschijnlijk meer ontspannen. Drink je meer dan een paar glazen, dan heeft dat gevolgen voor je lichamelijke en psychische gesteldheid en je gedrag. Het vermogen om sociale situaties goed te beoordelen neemt af, risico's worden minder goed ingeschat, het geheugen wordt beïnvloed en de reactiesnelheid en het coördinatievermogen nemen af. Daarnaast kan het zijn dat je overdreven emotioneel gaat gedragen of agressief wordt. In een verder stadium is er ook een grote kans op misselijkheid en overgeven). Maar goed dus dat alcohol ook weer afgebroken wordt in je lichaam.
Alcohol wordt heel snel in het lichaam opgenomen, maar een drankje heeft 1 tot 1,5 uur nodig om afgebroken te worden. Bij een inname van 1 drankje per uur is er dus sprake van een soort evenwicht. Maar als je drie drankjes in een half uur drinkt, is de innamesnelheid niet meer gelijk aan de afbraak snelheid, je wordt dus een stuk sneller dronken omdat je lichaam de inname niet meer bij kan houden.

Hoe wordt alcohol opgenomen in je lichaam?
Na het drinken komt alcohol in de maag terecht. Via de maagwand wordt een deel van de alcohol in het bloed opgenomen. Hoeveel dit is hangt af van je maagvulling. Voedsel in je maag zorgt ervoor dat de alcohol gelijkmatiger en langzamer wordt opgenomen in je maag. Wanneer je een lege maag hebt wordt de alcohol dus sneller opgenomen dan wanneer je een volle maag hebt. De rest van de alcohol gaat via de maag naar de dunne darm. In de dunne darm wordt de rest snel in het bloed opgenomen. Via het bloed bereikt de alcohol na een minuut of 10 de hersenen en vanaf dat moment ben je onder invloed.

Hoe verdeeld alcohol zich over je lichaam?

Met het bloed verspreidt de alcohol zich door je lichaam. Omdat lichamen verschillen heeft het drinken van alcohol dus niet bij iedereen dezelfde effecten. Daarom wordt vaak gekeken naar de relatieve hoeveelheid alcohol in je lichaam. Dit wordt aangegeven met de term Bloed Alcohol Gehalte oftewel BAG. BAG is het aantal gram alcohol per liter bloed, ook wel het alcoholpromillage genoemd. Het drinken van alcohol zorgt niet bij iedereen voor hetzelfde bloedalcoholgehalte, er zijn grote individuele verschillen: de ene drinker is de andere niet. De hoeveelheid lichaamsvocht blijkt van invloed op het bloedalcoholgehalte. Gewicht is hier natuurlijk van belang; bij een zwaarder persoon kan hetzelfde glas alcohol zich over meer kilo's verdelen dan bij een lichter persoon. Ook blijkt de hoeveelheid lichaamsvocht per kilo per persoon te verschillen. Het lichaam van een vrouw bevat een lager percentage lichaamsvocht per kilo dan dat van een man. Daarom wordt de alcohol bij vrouwen minder verdund en zijn vrouwen gemiddeld sneller onder invloed dan mannen.



Hoe wordt alcohol weer afgebroken?

Alcohol wordt ook weer door je lichaam afgebroken. Gelukkig maar, anders zou je constant dronken zijn. Alcohol wordt voornamelijk afgebroken door de lever. Via je bloedbaan komt alcohol in je lever. Daar wordt het afgebroken door twee enzymen. Het enzym alcoholdehydrogenase (ADH) zet de alcohol om naar acetaldehyde. Dit is een stofje wat erg irriterend is en voor een groot deel bijdraagt aan een kater. Het enzym Aldehydedehydrogenase (ALDH) breekt deze stof vervolgens verder af naar azijnzuur en uiteindelijk naar het onschadelijke kooldioxide en water. Hoe snel alcohol wordt afgebroken is afhankelijk van de afbraaksnelheid, deze is ongeveer 7 gram per uur. Een alcoholconsumptie bevat 10 gram. De lever doet er dus 1,5 uur over de afbraak van 1 standaardglas alcohol.

---- …. ----

De opdracht

Je hebt net de tekst gelezen over de afbraak van alcohol in het lichaam. In deze les ga je zelf met dit onderwerp aan de slag. Voor deze opdracht ga je voor drie situaties aan de slag met een model:
Jouw opdracht bestaat uit 3 delen:

1. Maak een computermodel over de afbraak van alcohol in het lichaam (situatie 1).
2. Controleer je model door te bekijken wat er gebeurt als je door blijft drinken (situatie 2).
3. Controleer je model door de gevolgen van medicijngebruik te bekijken (situatie 3).

1. Maak een computermodel (situatie 1)

Gebruik SCYDynamics om een model te maken van de afbraak van alcohol in het lichaam. Richt je hierbij op de *processen* die zich in het lichaam afspelen en **niet** op de organen en enzymen die daarbij betrokken zijn. Het model moet deze processen weergeven die een rol spelen bij de **afbraak** van alcohol in het lichaam.
Je maakt het model in twee fasen: Om je een beetje op weg te helpen, krijg je alvast een deel van het model dat je verder kunt afmaken.

Fase 1: Model schetsen

1. Zet de gegeven elementen op de juiste plaats in je model.
2. Teken relatiepijlen om aan te geven hoe elementen uit het model elkaar beïnvloeden.
3. Gebruik het staafdiagram om te zien hoeveel goede elementen en relaties je model bevat.

Fase 2: Relaties definiëren

1. Bedenk bij elke relatiepijl in je model hoe de verbonden elementen elkaar beïnvloeden. Is de relatie bijvoorbeeld lineair (als A groter wordt, wordt B ook groter), curvilineair (als A groter wordt, bereikt B een maximum), of anders?
2. Kies in SCYDynamics voor elke rekengrootheid de meest passende relatie.
3. Run het model om te testen of de uitkomst klopt met de informatie uit de tekst.
4. Pas je model net zolang aan totdat alle relaties kloppen.
5. Sla je model op onder de naam '*situatie1'*, als je model af is.

2. Controleer je model: doordrinken (situatie 2)

Verschillende drankjes zoals bier, wijn of mixdrankjes bevatten een bepaalde hoeveelheid alcohol. Hoeveel kun je zien aan het alcoholpercentage. Bier bevat minder alcohol dan bijvoorbeeld wijn, maar omdat een bierglas groter is dan een wijnglas is de hoeveelheid alcohol die je binnenkrijgt ongeveer gelijk per soort drankje. Dit heet een standaard glas. De hoeveelheid alcohol die in je lichaam binnenkomt hangt dus af van het aantal glazen wat je drinkt per uur en natuurlijk aan hoe lang je dit volhoudt.
Je kunt je model laten doorrekenen wat er gebeurt als gedurende een langere tijd drinkt. Omdat in deze situatie dus gedurende een bepaalde tijd de hoeveelheid geconsumeerde alcohol nog toeneemt zal het langer duren voordat alle alcohol weer uit je lichaam verdwenen is. Je kunt dit gegeven gebruiken om je model te controleren. Dit doe je als volgt:

1. Pas je model aan zodat de hoeveelheid geconsumeerde alcohol afhankelijk wordt van het aantal drankjes dat je per uur drinkt en het aantal uur dat je drinkt:
   a. Voeg een stroompijl toe die aangeeft dat de hoeveelheid geconsumeerde alcohol toeneemt.
   b. Voeg de elementen <u>alcohol consumptie</u>, <u>drankjes per uur</u>, en <u>aantal uur drinken</u> toe.
   c. verbind deze variabelen zodat het model kloppend wordt.
   d. Verlaag de beginwaarde van de hoeveelheid geconsumeerde alcohol en geef goede waarden voor de variabelen 'drankjes per uur' en 'aantal uur drinken'.

2. Kijk in de grafiek naar de hoeveelheid geconsumeerde alcohol en naar de hoeveelheid alcohol in het lichaam. En vergelijk deze grafiek met de grafiek van situatie 1.

Je ziet dat de hoeveelheid geconsumeerde alcohol langere tijd boven nul licht. Dit heeft een effect op de hoeveelheid alcohol in je lichaam: in vergelijking met situatie 1 stijgt de hoeveelheid alcohol in je lichaam langer, wordt dus ook hoger en heeft dus ook weer langer de tijd nodig om uit je lichaam te verdwijnen. Als jouw grafiek andere resultaten laat zien, klopt je model niet met de werkelijkheid. Is dat het geval, dan moet je je model verbeteren.

3. Sla je model op onder de naam '*situatie2'*, als je model af is.

3. Controleer je model: (situatie 3)

In een normale situatie breekt de lever alcohol met een snelheid van ongeveer 7 gram per uur af. Hierin zitten wel individuele verschillen, van zo'n 5 tot zo'n 13 gram per uur. Medicijnen (waaronder paracetamol) kunnen de afbraak van alcohol vertragen. Je kunt het model laten doorrekenen wat er gebeurt stel dat medicijnen de afbraak van alcohol ernstig tot volledig vertragen. Dit doe je als volgt:

1. Pas je model aan zodat de afbraak van alcohol door medicijnen vertraagd wordt
    a. Voeg het element <u>medicijnen</u> toe.
    b. verbind deze variabele zodat het model kloppend wordt.
    c. Stel de waarden voor de variabelen in.

2. Kijk in de grafiek naar de hoeveelheid geconsumeerde alcohol en naar de hoeveelheid alcohol in het lichaam. En vergelijk deze grafiek met de grafiek van situatie 1.

Je ziet een grafiek waarin de hoeveelheid alcohol in het lichaam niet meer in verhouding staat tot de hoeveelheid geconsumeerde alcohol. De hoeveelheid alcohol in het bloed is ontregeld en vooral toe. Dit kan ernstige gevolgen hebben.
Als jouw grafiek andere resultaten laat zien, klopt je model niet met de werkelijkheid. Is dat het geval, dan moet je je model verbeteren.

3. Sla je model op onder de naam '*situatie3'*, als je model af is.

Appendix G
Coding table self-explanations

Naam:	
Leeftijd:	
Leerling nummer:	
Havo/Vwo:	
Geslacht:	

Opdracht Fases:	**Frequentie self-explanations:**
(Situatie 1) Schetsen & Definiëren **Tijdstip:**	
Totaal aantal minuten:	**Totaal aantal frequenties:**
(Situatie 2) Controleer je model **Tijdstip:**	
Totaal aantal minuten:	**Totaal aantal frequenties:**
(Situatie 3) Controleer je model **Tijdstip:**	
Totaal aantal minuten:	**Totaal aantal frequenties:**
Subtotaal:	**Subtotaal:**