

ANALYSIS OF LEARNING WITH DYNAMIC MODELS AND EXPERIMENTS IN OPTICS

Albert Teichrew and Roger Erb

Goethe University, Frankfurt am Main, Germany

Modelling is an essential step in acquiring scientific knowledge, serving as the basis for experimenting and interpreting collected data. The teaching and research project presented in this paper used an online learning environment to prepare students for experiments in optics, implementing dynamic models created with GeoGebra to encourage virtual exploration. The results support the idea that the learning environment enables model-based hypothesis formation. In this mixed-methods study, screen recordings, videos and questionnaires were used to explore how learning with dynamic models and experiments works.

Keywords: Dynamic Visualisation Tools, Video Analysis, Inquiry-based teaching

INTRODUCTION

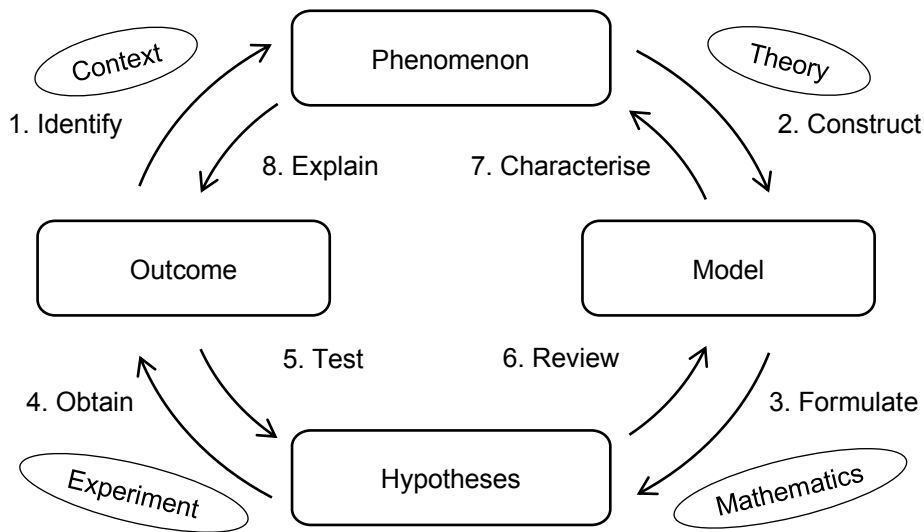
Experimentation is considered the central process of scientific knowledge acquisition in classrooms. However, it is not possible to obtain knowledge from an experiment if subject-specific knowledge and theoretical assumptions are not well presented. One possible way to improve results, explored here, is for students to engage with dynamic models of the phenomenon under instruction.

Scientific knowledge acquisition with dynamic models

Working with models is considered a key capability for research and learning processes (Bailer-Jones, 2009; Thiele et al., 2005). Structural models for scientific thinking or experimental competence aim to depict knowledge acquisition as a problem-solving process with several steps (Mayer, 2007). In general, these are steps to plan, carry out and analyse experiments (Nawrath et al., 2011; Theyßen et al., 2016). However, a model that combines modelling and experimentation in a united problem-solving process would be more appropriate. As a design aid for learning environments, we constructed the cycle of knowledge acquisition shown in Figure 1 (Teichrew & Erb, 2018). The components include four topics (rounded rectangles), which are developed in several steps (arrows) with suitable tools (ovals).

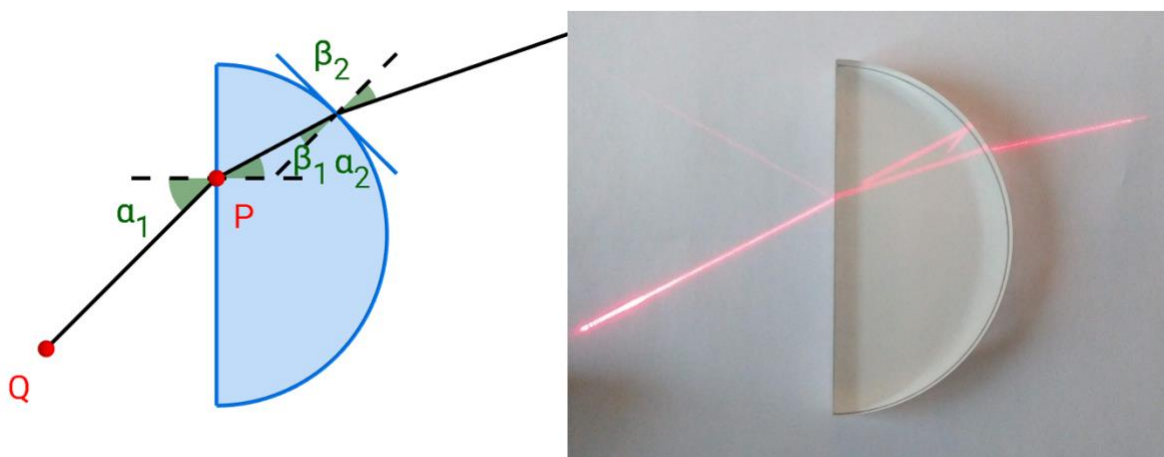
In the first steps, students learn that in order to understand something unknown, they must construct a model for the phenomenon, learn how their model behaves and build their hypotheses from it. The hypotheses are then used to get an experimental outcome. In each of the first four steps, they need input from the learning environment, such as context of the investigation, a scientific theory, mathematics and experimental material. The later steps encourage reflection on the process. Students are directed to test their hypotheses, review their model and identify the limits of it. Finally, they should be able to characterise the phenomenon based on the model and explain new observations with their knowledge of different phenomena.

Figure 1. Cycle of knowledge acquisition with modelling and experimentation.



With dynamic geometry software like GeoGebra, learners can create or work with interactive models, while directly observing the result (Erb, 2016). In this way, they use dynamic representations to construct their own understanding (also referred to as mental models, see Schnotz & Bannert, 2003). At the same time, this exploratory learning activity should produce hypotheses that can be tested experimentally. In this study a dynamic model of refraction of light through a semi-circular disc was used (Fig. 2, left). It contains several variables, principally the entry angle and entry point can be varied in order to analyse different light paths. The instructional materials for the corresponding “real” experiment direct students to produce different paths of light through the disc and the task is to compare observations with the results of the model (Fig. 2, right). At first glance, it is apparent that reality is more complicated and differs from the model. Some reflections distract from the subject under investigation, the refraction of light through the disc.

Figure 2. Example of a dynamic model (left) and the corresponding experiment (right).



Teaching and research project

In order to answer the general research question of the influence on learning outcomes through the interaction with dynamic models and experiments, it is necessary to clarify how to

characterise students' approaches. Therefore, we pursued in a mixed-methods study three exploratory research questions:

Q1: How do students interact with dynamic models and experiments in an open learning environment?

Q2: How does hypothesis formation based on a dynamic model work?

Q3: Do cognitive or affective factors have an influence on this learning process and if so which?

Overall, 41 students participated in all parts of the study and answered several questionnaires. Using an online learning environment at home throughout the semester students took part in several lessons on light propagation, reflection and refraction. The core of each lesson was a dynamic model that encourages free exploration and formulation of hypotheses followed by practical work on optical experiments during contact hours at the university. However, research focus was on learning activities related to refraction. First, the participants interaction with the model in Figure 2 on a tablet screen was recorded. After writing down their hypotheses and answering questions about their impressions of the modelling process, the experimentation process with the refraction lab equipment was also recorded.

METHODS

In order to answer the research questions, an integration of qualitative and quantitative data shown in Table 1 was produced. On the one hand, videos were used to measure time on task during modelling and experimentation, adding up the time to read the instructions and modify the model (or work with the equipment). On the other hand, a deductive content-coding, based on the usage possibilities in the model or experiment was carried out. In this case, 12 goals can be achieved in the model and the experiment, whereby following interactions have been counted: Whether a variable was varied (moving one part of the model or the experiment), whether extreme cases were explored (wide variation of a variable), whether relevant settings were found (setting several variables to a certain value).

To answer the second question, hypotheses formulated by the students after their work with the model were inductively coded and divided into three levels with five categories each (111 or 2.8 statements per student in total). Declarative statements about refraction that are probably known from the previous lecture are assigned to Level 1 (55 statements). More complicated hypotheses that included relevant settings for the experiment based on the model are at Level 3 (32 statements). A level in between contains other ideas and observations (24 statements).

In addition, questionnaires were integrated into the learning environment to measure various types of perceived self-efficacy (PSE) such as mathematics, computer use or experimentation (according to Bescherer, 2004; Spannagel & Bescherer, 2009; Körner & Ihringer, 2016). Besides that, various dimensions of intrinsic motivation were measured immediately after interacting with the model (according to Wilde et al., 2009). In this way, influence of different factors can be analysed, such as enjoyment, perceived competence, perceived choice or external pressure. The internal consistency of most factors is satisfying. Furthermore, the students have previously passed a subject knowledge test containing 18 Rasch-calibrated items

on the topic of refraction from an item pool from previous studies (Weber et al., 2017). The results were used to estimate prior knowledge using the maximum likelihood method based on item response theory.

Table 1. Mean values and standard deviations of the analysed data.

<i>Constructs measurements</i>	<i>and</i>	<i>n</i>	<i>M</i>	<i>SD</i>	<i>No. of items</i>	<i>α</i>	<i>Scale</i>
Modelling time (modtim)		37	358	160	1	-	in s
Experimentation time (exptim)		39	208	161	1	-	in s
Modelling goals (modgoa)		41	6.41	2.93	1	-	from 0 to 12 goals
Experimentation (expgoa)	goals	41	5.68	2.56	1	-	from 0 to 12 goals
Number of Hypotheses							from 0 to 5 statements
→ Level 1 (hyplv1)		41	1.34	1.13	1	-	
→ Level 2 (hyplv2)		40	0.53	0.68	1	-	
→ Level 3 (hyplv3)		40	0.73	0.75	1	-	
Subject knowledge value (subkno)	ability	41	4.81	1.86	1	-	from 0.96 for 7 of 18 answers to 8.86 for 17 of 18 answers
Perceived self-efficacy							Likert from 1 to 5
→ Mathematics (mse)		41	3.96	0.56	9	.89	
→ Computer use (cse)		40	3.76	0.74	7	.91	
→ Experimentation (ese)		35	3.81	0.32	8	.88	
Intrinsic motivation							Likert from 1 to 5
→ Enjoyment (enj)		39	3.68	0.54	3	.82	
→ Perceived competence (com)		41	3.07	0.74	3	.84	
→ Perceived choice (cho)		39	3.62	0.50	3	.69	
→ External pressure (pre)		41	2.96	0.93	3	.83	reversed

Annotations: N = 41. Adjusted sample sizes result from the omission of outliers.

RESULTS

The interaction with the dynamic model and the corresponding experiment was very heterogeneous in terms of time and goals achieved. That is the consequence of an open learning environment in which no precise learning steps are specified. On average, students spent significantly more time on the model than on experimental verification of it (asymptotic Wilcoxon test: $z = -3.62$, $p < .001$, $n = 35$, $r = .61$), but achieved about the same amount of goals ($z = -.90$, $p = .369$, $n = 41$). The correlation matrix in Table 2 shows that goals correlate stronger with time than with other factors. This result replicates the known connection between time on task and learning outcomes.

Nevertheless, the interaction with the model allowed all learners to formulate their observations as hypotheses. However, the majority were simple statements that had no relation to the special geometry of the refraction medium (Level 1 and 2), but there is a correlation between successful work with the model and the number of Level 3 hypotheses. Overall, the number of formulated hypotheses had no measurable influence on the experimentation process (time and goals).

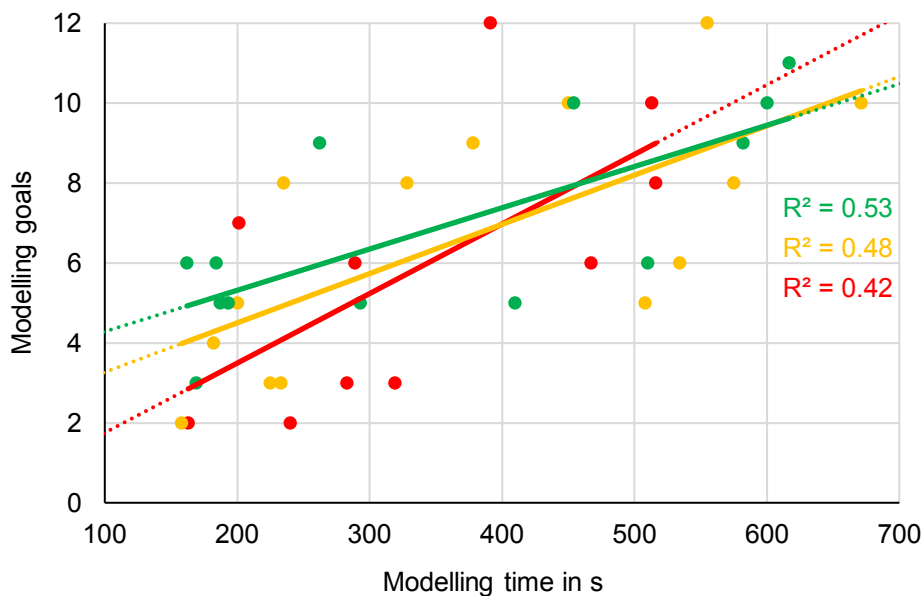
Furthermore, the correlation matrix shows that PSE in mathematics qualifies as a predictor for successful work with the model, in contrast to PSE in computer use and experimentation. In addition to PSE in computer use, it also appears to be helpful for a variety of Level 3 hypotheses. Besides that, motivational factors such as a high level of perceived competence and the absence of external pressure in the modelling process had a positive effect. The correlation matrix also shows that more experimentation goals were achieved by students reported enjoying the modelling phase.

Table 2. Shortened correlation matrix of constructs and measurements.

	modtim	exptim	modgoa	expgoa	hyplv1	hyplv2	hyplv3
modtim	1						
exptim	.	1					
modgoa	.672**	.	1				
expgoa	.	.616**	.	1			
hyplv1	1		
hyplv2	1	
hyplv3	.	.	.386*	.	.	-.309	1
subkno	-.448**	.	.432**
mse	.	.	.346*406**
cse320*
ese
enj406*	.	.	.
com389*
cho
pre429**

Annotations: Values between -.300 and .300 are hidden. The correlation is significant at the level of *0.05 or **0.01 (2-sided).

Figure 3. Scatter plot of modelling time and goals divided into tertiles based on prior knowledge.



Annotations: Low prior knowledge group in red (n = 10), medium in orange (n = 14) and high in green (n = 13).

Finally, prior knowledge only has a negative correlation with the number of Level 1 hypotheses and therefore a positive correlation with Level 3. On the one hand, this confirms the validity

of the content analysis. On the other hand, it seems that the developed learning environment enables a successful interaction with dynamic models and experiments in optics, regardless of the amount of prior knowledge. This impression is confirmed by the graphic analysis of the scatter plot in Figure 3. The low knowledge group achieves less on average in a short time than the high knowledge group, but the students who invest more time can also achieve many of the modelling goals.

DISCUSSION AND CONCLUSIONS

The exploratory research questions were aimed at generating data-based hypotheses about learning with dynamic models and experiments. The study shows that not all students reach their modelling goals in an open learning environment. However, none of the dimensions of intrinsic motivation were measurably responsible for this. The number of modelling or experimentation goals strongly depends on the time invested. At the same time, it was found that the better the prior knowledge, the faster goals can be achieved. As for the formulated hypotheses, more subject knowledge results in a higher quality, but more modelling goals also occur with more Level 3 hypotheses. Based on the results, we expect that using a good learning environment, advanced hypotheses can be formulated based on a dynamic model without much prior knowledge, given enough time. Furthermore, an improved instructional design could help more students to find all the relevant settings for the model and to formulate functional hypotheses. We suggest that this would lead to a purposeful experimentation process and a better understanding of the physics, which will be examined in subsequent studies.

ACKNOWLEDGEMENT

This research was supported by Joachim Herz Foundation. We thank Julian Weide, Laura Sührig and Jelka Weber for assistance with video content analysis.

REFERENCES

- Bailer-Jones, D. (2009). *Scientific models in philosophy of science*. University of Pittsburgh Press.
- Bescherer, C. (2004). *Selbsteinschätzung mathematischer Studierfähigkeit bei Studienanfängerinnen und -anfängern. Empirische Untersuchung und praktische Konsequenz*. [PhD Thesis]. <http://nbn-resolving.de/urn:nbn:de:bsz:93-opus-16269>
- Erb, R. (2016). *Optik mit GeoGebra*. De Gruyter.
- Körner, H.-D., & Ihringer, S. (2016). Selbstwirksamkeit beim Experimentieren – Mädchen und Jungen in den Naturwissenschaften. In C. Wiepcke & M. Kampshoff (Eds.), *Vielfalt geschlechtergerechten Unterrichts: Ideen und konkrete Umsetzungsbeispiele für die Sekundarstufen* (1st ed., pp. 106–140). epubli.
- Mayer, J. (2007). Erkenntnisgewinnung als wissenschaftliches Problemlösen. In D. Krüger & H. Vogt (Eds.), *Theorien in der biologiedidaktischen Forschung* (pp. 177–186). Springer.
- Nawrath, D., Maiseyenko, V., & Schecker, H. (2011). Experimentelle Kompetenz. Ein Modell für die Unterrichtspraxis. *PdN Physik in Der Schule*, 60(6), 42–49.

- Schnotz, W., & Bannert, M. (2003). Construction and interference in learning from multiple representation. *Learning and Instruction, 13*(2), 141–156.
- Spannagel, C., & Bescherer, C. (2009). Computerbezogene Selbstwirksamkeitserwartung in Lehrveranstaltungen mit Computernutzung. *Notes on Educational Informatics - Section A: Concepts and Techniques, 5*(1), 23–43.
- Teichrow, A., & Erb, R. (2018). Implementierung modellbildender Lernangebote in das physikalische Praktikum. *PhyDid B - Didaktik Der Physik - Beiträge Zur DPG-Frühjahrstagung*.
- Theyßen, H., Schecker, H., Neumann, K., Eickhorst, B., & Dickmann, M. (2016). Messung experimenteller Kompetenz. Ein computergestützter Experimentiertest. *PhyDid A - Physik Und Didaktik in Schule Und Hochschule, 15*(1), 26–48.
- Thiele, M., Mikelskis-Seifert, S., & Wünscher, T. (2005). Modellieren. Schlüsselfähigkeit für physikalische Forschungs- und Lernprozesse. *PhyDid A - Physik und Didaktik in Schule und Hochschule, 1*(4), 30–46.
- Weber, J., Winkelmann, J., Erb, R., Wenzel, F., Ullrich, M., & Holger, H. (2017). Ein Fachwissenstest zur geometrischen Optik. In C. Maurer (Ed.), *Implementation fachdidaktischer Innovation im Spiegel von Forschung und Praxis* (p. 107). Gesellschaft für Didaktik der Chemie und Physik, Jahrestagung in Zürich 2016.
- Wilde, M., Bätz, K., Kovaleva, A., & Urhahne, D. (2009). Überprüfung einer Kurzsкала intrinsischer Motivation (KIM). *Zeitschrift für Didaktik der Naturwissenschaften, 15*.