



**HAL**  
open science

## Researching the Impact of Innovative Learning Materials Within STEM Education

Cindy De Smet, Tammy Schellens, Bram de Wever, Pascale Brandt-Pomares,  
Martin Valcke

► **To cite this version:**

Cindy De Smet, Tammy Schellens, Bram de Wever, Pascale Brandt-Pomares, Martin Valcke. Researching the Impact of Innovative Learning Materials Within STEM Education. AERA 2014 Annual Meeting. The Power of Education Research for Innovation in Practice and Policy, Apr 2014, Philadelphia, United States. hal-02366900

**HAL Id: hal-02366900**

**<https://hal.science/hal-02366900v1>**

Submitted on 16 Nov 2019

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# **Researching the Impact of Innovative Learning Materials Within STEM Education**

**Cindy De Smet, Tammy Schellens, Bram De Wever,  
Pascale Brandt-Pomares, Martin Valcke**

## **Please cite as:**

De Smet, C., Schellens, T., De Wever, B., Brandt-Pomares, P., & Valcke, M. (2014). Researching the impact of innovative learning materials within STEM education. In the Annual Meeting of the American Educational Research Association 2014, Philadelphia, USA.

# Objectives

This research takes place within the field of STEM (science, technology, engineering and mathematics) education. STEM innovation is internationally recognised as a very important factor for a country's economic and political status. Although STEM education leads to good jobs and a high standard of living, youngsters seem to have little interest in science as a possible career path (U.S. Department of Education, 2007; National Governors Association, 2007). Special interest goes to the gender gap. Several studies (European Commission, 2012) revealed that females are underrepresented in science.

Given the performance of girls in science education, the Programme for International Student Assessment 2006 (PISA) showed no difference in average science performance between males and females, but unveiled that males thought significantly more highly of their science abilities than females do. This was in line with earlier research by Eccles (1994) where women were found to enter less likely occupations linked to mathematics and physical sciences, because they have less confidence in their abilities and place little subjective value on these fields. Furthermore, Eccles argued that girls rate social values high and prefer studying academic subjects that have social implications and enable them to 'do something worthwhile'.

Within the field of Computer Supported Collaborative Learning (CSCL) researchers try to find an answer to narrow the gender gap. Eg. Slotta, Linn (2009) found that web-based collaborative inquiry can be helpful in maintaining positive attitudes towards science instruction. A recent research (anonymized) found that low achieving girls benefited from this type of intervention.

The goal of this study is to research if girls benefit from web-based collaborative learning paths within a biology course. Besides the impact of group composition, two types of learning paths were created to examine the impact of visual representations on learning outcomes.

## Theoretical framework

### Visual representations

The creation of our technology enhanced learning objects is theoretically based on the work of the Cognitive Load Theory or CLT (Sweller, 1994; Van Merriënboer, Sweller, 2005) and the Cognitive Theory of Multimedia Learning or CTML (Mayer, 2001, 2003, 2005). CTML represents a framework to direct instructional design and results in the definition of practical principles for multimedia learning material.

CLT is based on the assumption that individual learners can only process a certain working memory (WM) load, in contrast to an unlimited long-term memory (LTM). As soon as WM goes over its limits, meaningful learning will not take place (Baddley, 1986). Sweller, Van Merriënboer, Paas (1998) argue that information is organized into schemas that determine how to deal with new information. A schema is a cognitive structure that can hold a big amount of information, is processed as a single unit in WM and stored in LTM.

CLT assumes three types of cognitive load that can occur when processing information in WM: intrinsic, extraneous or germane (Sweller et al., 1998). Intrinsic cognitive load is affected by the intrinsic nature of the material (number of elements and the interactivity between them). Extraneous cognitive load (the effort required to process information) and germane cognitive load (the effort required to construct schemas) are altered by the presentation of the material and by the learning activities required.

CLT leads to the challenge that meaningful learning requires cognitive processing (i.e. understand, organise and integrate new material) and that cognitive load should be avoided (Sweller, 1999; van Merriënboer, 1997). Different techniques were researched to avoid cognitive load, among others worked examples (Chi et al., 1989; Ward, Sweller, 1990). Atkinson et al. (2000) define worked examples as instructional devices that include a problem statement and a procedure to solve the problem and that illustrate a principle or pattern. Instances of worked examples are diverse: from the usage of diagrams and schemas within learning material to the number of sources being used. It was found that worked examples decrease extraneous cognitive load (Van Merriënboer, Kirschner, Kester, 2003), facilitate the construction of schemas (Sweller, Van Merriënboer, Paas, 1998), and lead to better transfer performance (Paas, Gog, 2006).

### **Group composition**

The term 'collaborative' as opposed to 'cooperative' refers to the engagement of all participants to solve a problem together (Roschelle, Teasley, 1995), so tasks are not devised amongst the participants. As this research is based on CLT and CTML, both focusing on the cognitive architectures of individual learners, we will not consider the group itself as the unit of analysis, but concentrate on the learning of each individual group member. This leads to 'more informative and straightforward results' than conclusions based on individual versus group performance (Kirschner, Paas, Kirschner, 2009).

Several researchers concluded that placing learners in a group does not guarantee spontaneous collaboration (Cohen, 1994) or effective learning behavior (Soller, 2001). Instructional support improving the collaborative learning process and the individual learning outcomes was provided by using scaffolds or scripting (Kollar, Fischer, Hesse, 2006).

Scripts were implicit to the learners within the learning environment, but were made explicit for the teachers via a lesson plan. By using scripts we reduce extraneous cognitive load and help the learner to maximise those cognitive processes that help construct schemas (Sweller, Van Merriënboer, Paas, 1998).

### **Hypotheses**

Students studying a learning path following Mayer's guidelines (CTML) and designed and optimised with the framework by Atkinson in mind (CLT) should perform better.

Collaborative learners perform better than individual learners.

## **Data sources**

### **Participants**

Eight teachers (3 males, 5 females) from six different secondary schools in Flanders (Belgium) participated. As most of the instructors had several groups following the same course, we invited all of their classes (N=29) to participate in this study. All lessons took place in a computer lab.

The student sample consisted of 511 students, nevertheless only 360 students (167 males, 193 females) were taken into account as they completed the full course. They were all third year secondary school students (Flemish school system). Students were on average 15 years old (89,4%).

### **Procedure**

Learning paths were created with eXe learning, an open source authoring tool (eXe, 2013).

Figure 1: screenshot learning path

Hoe planten bacteriën zich voort?

Uit de proef bleek dat als de omstandigheden gunstig zijn, bacteriën zich heel snel kunnen voortplanten. Bacteriën planten zich ongeslachtelijk voort door celdeling (mitose). In gunstige omstandigheden ontstaat zo na 20 minuten een nieuwe generatie. Deze dochtercellen kunnen op hun beurt na 20 minuten terug een nieuwe generatie bacteriën vormen.


Activiteit

In gunstige omstandigheden kunnen na 20 minuten uit 1 bacterie twee dochtercellen ontstaan ( $2^1$ ). Na 40 minuten ontstaan dan uit elke dochtercel opnieuw 2 bacteriën, er zijn dan in totaal 4 bacteriën ( $2^2$ ). Na 60 minuten zijn er zo al 8 ( $2^3$ ).

Stel dat de bacteriën uit de proef zich aan die snelheid hebben voortgeplant. Uit hoeveel bacteriën bestaat zo'n kolonie dan?

Als het gewicht van één bacterie  $1 \times 10^{-12}$ g is, hoeveel weegt de hele kolonie bacteriën dan? Kan dat?

Waar hebben we een fout gemaakt?



Within the biology course, the bacteria topic was chosen. In order to simulate a real-world setting, two recently graduated biology teachers created learning materials following the official network lesson plan for biology. Subsequently, these materials were reviewed and modified by 18 pre-service teachers majoring in biology under the supervision of their lecturer. This resulted in learning path version 1, a 'traditional' learning path created by in-service and pre-service teachers.

Version 2 was an optimised and extended version of learning path 1, based on the worked example framework by Atkinson, Derry, Renkl, Wortham (2000) and Mayer's multimedia guidelines (2003).

Both are a combination of several learning objects: pictures, texts, schemas and web-based exercises.

As defined by Kollar, Fischer, Hesse (2006), all scripts contain an objective, engage learning activities, sequence all required actions, specify and distribute roles and contain a type of representation for the instructions to the learners. A lesson plan containing these scripts was created for the 4 different conditions: individual use of learning path 1 (= reduced version), collaborative use of learning path 1, individual use of learning path 2 (= amplified version) and collaborative use of learning path 2. Complete classes ( $N = 29$ ) were assigned to the four different conditions.

## Methods

Students were offered three knowledge tests in three different moments: a pre-test (before starting the bacteria course), a post-test (immediately after completing the course) and a retention-test (a month after completion). The tests consisted of 20 multiple choice true/false questions, on which guessing was allowed. Teachers were asked not to announce any of the tests.

MLwiN software (Centre for Multilevel Modelling, University of Bristol) was used to analyse the hierarchical data (Rabash et al., 1999). Following Van Der Leeden (1998), we consider repeated measures as a hierarchical structure where measurements are nested within individuals.

A two-step procedure was followed to analyse the effects of 3 explanatory variables (visual representation, group composition and gender) on the dependent variables, i.e. learning outcomes

First, we created a four-level conceptual null model serving as a baseline model. This unconditional null model (without any predictor variables) provides the overall pre-test, post-test and retention score across all students, classes and schools. This null model answers, by means of the Intra-Schools-Correlation, the question if the outcome measures vary across students, across classes and across schools.

The second step concerned the input of the three main explanatory variables.

# Results

The models built following the two-step procedure are presented in Table 1.

Table 1

*Multilevel parameter estimates for the four-level analyses of learning outcomes*

Parameter	Model 0	Model 1
<i>Fixed part</i>		
Intercept	57.20 (1.50)	59.90*** (2.59)
Post (test)	7.31 (1.09)	-2.66 (2.59)
Retention (test)	14.74 (1.13)	12.93*** (2.59)
Amplified representation		1.39 (4.02)
Collaborative setting		-1.60 (3.57)
Woman		-4.85*** (3.03)
Post*Amplified representation		17.88*** (4.18)
Retention*Amplified representation		-1.03 (4.25)
Post*Collaborative setting		7.59 (3.62)
Retention*Collaborative setting		2.04 (3.64)
Post.Woman		11.45 (3.74)
Retention*Woman		-0.43 (3.74)
Amplified representation*Collaborative setting		-2.43 (7.66)
Amplified representation*Woman		-0.53 (4.57)
Collaborative setting*Woman		4.95 (4.13)
Post*Amplified representation*Collaborative setting		-14.07*** (8.78)
Retention*Amplified representation*Collaborative setting		0.00 (0.00)
Post*Amplified representation*Woman		-10.37*** (5.73)
Retention*Amplified representation*Woman		6.58 (5.88)
Amplified representation*Collaborative setting*Woman		-10.27 (8.54)
Post*Collaborative setting*Woman		-10.28*** (5.09)
Retention*Collaborative setting*Woman		1.48 (5.11)
Post.Amplified representation*Collaborative setting*Woman		8.05 (11.01)
Retention.Amplified representation*Collaborative setting*Woman		0.00 (0.00)
<i>Random Part</i>		
Level 4: School		
Intercept/Intercept	3.19 (6.60)	0.00 (0.00)
Level 3: Class		
Intercept/Intercept	26.15 (10.86)	18.91 (7.68)
Level 2: Student		
Intercept/Intercept	39.57 (9.62)	42.24 (9.40)
Level 1: Knowledge test		
Intercept/Intercept	208.56 (11.41)	195.89 (10.73)
<i>Model fit</i>		
-2*loglikelihood:	8568.341	8512.92
$\chi^2$		55.42
df		22
p		<.001
<i>Reference model</i>		Model 0

Note. Standard errors are in parentheses \*  $p < .05$  \*\*  $p < .01$  \*\*\*  $p < .001$

Given our repeated measures approach, the conceptual unconditional null model (model 0) predicts the overall pre-test (=the intercept, or 57.20 out of 100), post-test (= 64.51, 7.31 + 57.20) and retention-test score (71.94, 14.74 + 57.20) across all students, classes and schools.

The total variance of the scores is 277,464. After calculation of the Intra-class Correlation, we can state that 1.15 % of the total knowledge score variance lies at school level, the proportion variance due to differences between classes is 9.42%, 14.26 % of total variance lies at student level and finally 75.17% is within-students, between-tests (level 1) variance.

These variances in scores on the four levels are significantly different from zero and, except for the school level, significant at the  $p < .001$  level.

Based on the theoretical framework visual representation, group composition and gender were entered in the model as potential explanatory variables. All predictors were included in the models as fixed effects. Table 1 shows the results of this factorial model with main and interaction effects added to the model. The reference category is a boy working alone and following a reduced learning path. Adding these variables to the null model resulted in a better model fit ( $X^2 = 55.42$ ,  $df = 22$ ,  $p < .001$ ).

The results presented in model 1 indicate that a significant main effect was found for gender, but not on visual representation and group composition. However, the interaction effects involve all three explanatory variables. In order to facilitate the interpretation of model 1, Table 2 was composed.

	MIndRed	MGrRed	MIndAmp	MGrAmp	FIndRed	FGrRed	FIndAmp	FGrAmp
<i>N</i>	59	63	37	8	54	71	50	18
Pre	59,903	58,299	61,293	57,259	55,057	58,407	55,921	46,569
Post	57,245	63,229	76,515	66,001	63,853	64,51	72,224	54,161
Ret	72,834	73,272	73,19	71,198	67,557	62,668	67,387	64,43
	MIndRed	MGrRed	MIndAmp	MGrAmp	FIndRed	FGrRed	FIndAmp	FGrAmp
Post-Pre	-2,658	4,93	15,222	8,742	8,796	6,103	16,303	7,592
Ret-Post	15,589	10,043	-3,325	5,197	3,704	-1,842	-4,837	10,269
Ret-Pre	12,931	14,973	11,897	13,939	12,5	4,261	11,466	17,861
<i>Note. Overview individual test scores and learning gains achieved between the different tests.</i>								
<i>Two learning paths were created, a reduced version (Red) and an amplified version (Amp).</i>								
<i>Both learning paths were offered to students working alone (Ind) or in group (Gr).</i>								
<i>These 2 conditions are further subdivided between male (M) and female (F).</i>								

Table 2 shows one outlier on the pre-test (46,57) and post-test (54,16), i.e. the female students within the GrAmp condition. Given the results of the other female groups, the outlier could be due to the small group size ( $N = 18$ ). However, the learning gain between the pre-test and the post-test (7, 59) is in line with the progress by the male students of the GrAmp condition and the females within the IndRed and GrRed condition. The results are also supported by the significant interactions  $post*amp$ ,  $post*amp*woman$  and  $post*col*woman$ . Further on, although not significant, we notice that the score on the retention-test of the females in the GrAmp condition is in line with the other three female conditions (FIndRed, FGrRed and FIndAmp). This shows that at the moment of the retention test, the girls in the GrAmp condition have mastered the bacteria topic and suggests that these low achieving girls benefited from the intervention.

On the post-test, most amplified conditions, except the female students within the GrAmp condition, outperform the reduced scores, especially the students working alone. These results are supported by the significant interactions  $post*amp$  and  $post*amp*woman$ .



## Scientific significance

Evidence was found for the importance of how content is visually represented. Students working within an amplified condition performed better than their cohorts within the reduced condition. However, no evidence was found for the relevance of collaborative learning. A possible explanation could be that our collaboration scripts were too vague. A main effect was found for gender and several interaction effects. Unfortunately, due to a small group size, some of these results are hard to interpret.

A number of limitations are to be considered. First, group composition was not reported, although the gender of group members can play an important role (Webb, 1991). Second, the number of students within some conditions might have impacted the results. Follow-up research taking care of these limitations is currently analysed.

Despite some limitations, this research shows the importance of how content is presented. This is extremely important in an educational context where tablets, MOOC's and e-learning are making their way.

## References

Atkinson, R. K., Derry, S. J., Renkl, A., & Wortham, D. (2000). Learning from examples: Instructional principles from the worked examples research. *Review of educational research*, 70(2), 181-214.

Baddeley, A., Gathercole, S., & Papagno, C. (1998). The phonological loop as a language learning device. *Psychological review*, 105(1), 158.

Chi, M. T., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive science*, 13(2), 145-182.

Cohen, E. G. (1994). Restructuring the classroom: Conditions for productive small groups. *Review of educational research*, 64(1), 1-35.

Eccles, J. (1994). Understanding women's educational and occupational choices. *Psychology of women quarterly*. Retrieved from <http://onlinelibrary.wiley.com/doi/10.1111/j.1471-6402.1994.tb01049.x/abstract>

European Commission (Ed.). (2012). *She figures 2012. Gender in research and innovation*. [http://ec.europa.eu/research/science-society/document\\_library/pdf\\_06/she-figures-2012\\_en.pdf](http://ec.europa.eu/research/science-society/document_library/pdf_06/she-figures-2012_en.pdf)

eXe (2013). In Exelearning.org Wiki. Retrieved from <http://exelearning.org/wiki>

Kirschner, F., Paas, F., & Kirschner, P. A. (2009a). A cognitive load approach to collaborative learning: United brains for complex tasks. *Educational Psychology Review*, 21(1), 31-42.

Kollar, I., Fischer, F., & Hesse, F. W. (2006). Collaboration scripts—a conceptual analysis. *Educational Psychology Review*, 18(2), 159-185.

Mayer, R. E. (2001). *Multimedia learning*. Cambridge, MA: University Press.

Mayer, R. E. (2003). The promise of multimedia learning: using the same instructional design methods across different media. *Learning and Instruction*, 13, 125–139.

Mayer, R. E. (Ed.) (2005). *The Cambridge handbook of multimedia learning*. Cambridge: University Press.

National Governors Association. (2007) *Innovation America: Building a Science, Technology, Engineering and Math Agenda*. Washington, D.C.

Organisation for Economic Co-operation and Development. (2006). *Assessing scientific, reading and mathematical literacy. A framework for PISA 2006*. Paris: OECD.

Paas, F., & Van Gog, T. (2006). Optimising worked example instruction: Different ways to increase germane cognitive load. *Learning and Instruction*, 16(2), 87-91.

Anonymized. *Web-based Collaborative Inquiry to Bridge Gaps in Secondary Science Education*. Manuscript accepted for publication in *Journal of the Learning Sciences*.

Rasbash, J. et al. MLwiN Beta version: multilevel models project. London: Institute of Education, University of London, 1999.

Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. In *Computer supported collaborative learning*, 69-97. Springer Berlin Heidelberg.

Slotta, J. D., & Linn, M. C. (2009). *WISE Science: Web-based Inquiry in the Classroom*. Technology, Education Connections. Teachers College Press. 1234 Amsterdam Avenue, New York, NY 10027.

Soller, A. (2001). Supporting social interaction in an intelligent collaborative learning system. *International Journal of Artificial Intelligence in Education (IJAIED)*, 12, 40-62.

Sweller, J. (1994). Cognitive load theory, learning difficulty and instructional design. *Learning and Instruction*, 4, 295-312.

Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, 10, 251-295.

Sweller, J. (1999). *Instructional design in technical areas*. Camberwell, Australia: ACER Press.

U.S. Department of Education. (2007) *Report of the Academic Competitiveness Council*. Washington, D.C.

Van der Leeden, R., 1998. Multilevel analysis of repeated measures data. *Quality and Quantity*, 32, 15-19.

Van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive Load Theory and Complex Learning: Recent Developments and Future Directions. *Educational Psychology Review*, 17, 147-177.

Van Merriënboer, J. J. G. (1997). *Training complex cognitive skills*. Englewood Cliffs, NJ: Educational Technology Press.

Van Merriënboer, J. J. G., & Kirschner, P. A. (2007). *Ten steps to complex learning*. Mahwah, NJ: Lawrence Erlbaum.

Van Merriënboer, J. J., Kirschner, P. A., & Kester, L. (2003). Taking the load off a learner's mind: Instructional design for complex learning. *Educational psychologist*, 38(1), 5-13.

Van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review*, 17, 147-177.

Ward, M., & Sweller, J. (1990). Structuring effective worked examples. *Cognition and Instruction*, 7, 1-39.

Webb, N.M. (1991) Task related verbal interaction and mathematics learning in small groups. *Journal for Research in Mathematics Education*, 22 (5), 366-389.