How do personalized visualizations influence students self-regulated learning?

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Abstract

This contribution reports on two experimental studies that explore how data from Adaptive Learning Technologies(ALTs) can be used to support students' Self-Regulated Learning(SRL). While students learn using adaptive learning technologies on tablets, they leave rich traces of data that capture many details of their learning processes. These data are used to support students to apply SRL effectively during learning. In study A, students received a goal-setting and reflection intervention in which they set goals at the start of each lesson and were asked to reflect on these goals based on ALT progress measures after each lesson. In study B, students in the experimental condition followed the same procedure as in study A, but were also shown dashboards with personalized visualizations based on Moment-by-Moment Learning Curves. These personalized visualizations serve as reference for students to better understand how they regulate their learning during a lesson. Both goal setting and personalized visualizations are expected to support students' self-regulated learning. For study A, we found that students in the goal setting condition outperformed students in the control condition with respect to learning. Effects on students' effort and accuracy are currently analyzed as well as the data from study B. The effects of personalized visualizations derived from the data and based on moment-by-moment learning curves are expected to serve as an additional references for students to improve their SRL. The contribution of our research is the design of two SRL interventions based on ALTs trace data.

Extended summary

Background

This contribution investigates how students' data from Adaptive Learning Technologies ALTs) can be used to support students' self-regulated learning(SRL). Students learning with adaptive learning technologies on tablets leave rich traces of data that capture many details of their learning process(Gašević et al., 2015). Although ALTs successfully use student data to adjust instructions to learners performance, they fail to use the captured data to support self-regulated learning(Winne & Baker, 2013). SRL theory defines learning as a goal-oriented process in which students make conscious choices working toward learning goals(Zimmerman, 2000). The students' data traces in ALTs provide indications of students' ongoing progress towards their learning goal and can show how students regulate their effort and accuracy over time(Authors et al., 2018). Hence the data can be used to help students explicitly reflect on their progress on their learning goals. Interventions that support goal setting and reflection have been found to affect learning(Hattie & Timberly, 2007) and can potentially influence SRL. Moreover, data shown to students in learner-faced dashboards supports SRL(Jivet et al. 2018). Moment-by-Moment Learning Curves(Baker et al, 2013; authors et al, 2018) derive specific patterns that are not only associated with student learning but also students' regulation of accuracy and effort. Hence, these patterns could potentially help learners to understand the development of their effort and accuracy during a lesson, subsequently triggering planning and monitoring. Therefore in two experimental studies, we investigate how the application of students' ALTs data in a goal setting-reflection intervention and a personalized visualization intervention support students' learning and self-regulation.

Method

In study A, 71 students in grade 4 were divided over the experimental goal setting condition (n=37) and the control condition (n=34). In study B, 78 students were divided over the experimental personalized visualizations condition (n=40) and the control condition (n=38).

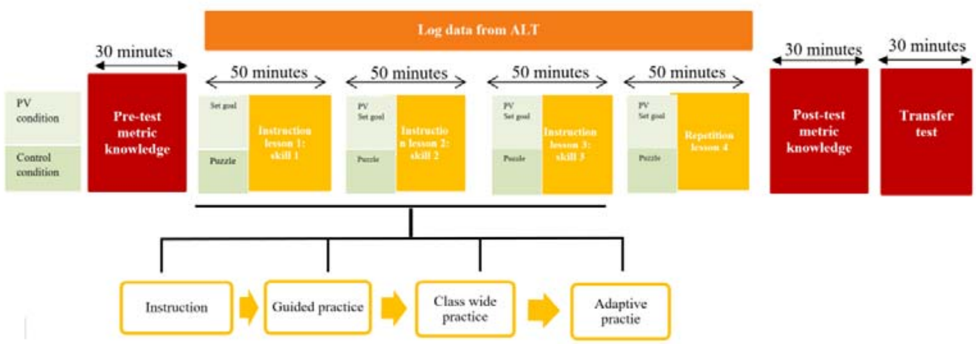


Figure 1. Study design

In study A, students in the goal setting condition were asked to set a goal at the start of each lesson by indicating on a scale from 0 to 100% how much they expected to learn in this lesson. At the start of the next lesson students were asked to reflect on their actual learning based on the ability score displayed in the ALT and set goals for the next lesson. In study B students in the personalized visualization condition followed the same procedure as in study A and additionally they were shown personalized visualizations indicating how their learning evolved during the practice activities. The personalized visualizations were based on the Moment-by-Moment Learning Curve , of which 5 types were shown: immediate drop, immediate peak, double spikes, close multiple spikes and separated multiple spikes (Authors et al. 2018).

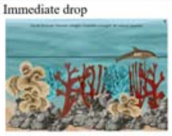
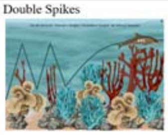
Personalized dashboards	Planning	Monitoring	Personalized dashboards	Planning	Monitoring
Immediate drop 	You already know this skill. Please continue to practice a different skill.	Accuracy is high because you know this skill	Close multiple spikes 	You are learning this skill somewhat slowly. Please continue with adaptive practice that will be better for you.	Please monitor your accuracy and during practicing.
Immediate peak 	You have learned this skill quickly after the teacher explained it. You can practice until you have reached our goal and then continue on the next skill.	Your accuracy is high, well done!	Separate multiple spikes 	You are learning this skill very slowly. Please continue to practice in adaptive mode and if you cannot master this skill please notify your teacher.	Please monitor your accuracy and during practicing.
Double Spikes 	You have learned this skill in two stages during guided instruction and class wide practice. You can practice until you have reached our goal and then continue on the next skill.	Please monitor your accuracy during class wide practice.			

Figure 2. Personalized dashboards

Both studies followed a similar design in which students worked on 3 arithmetic skills in 4 lessons of 50 minutes, see Figure 1. The lessons consisted of a mix of teacher instruction and practice activities. The three skills were increasing in difficulty. Students' learning was measured with a pre and post-test and a transfer-test. The logs of the ALT stored data of students' practice activities: a time stamp, an exercise id, a student id and the correctness of the answer. Based on this data students' effort(number of unique problems and problem solving attempts) and accuracy(percentage of correctly answered problems) were measured. The Moment-by-Moment Learning Curves were derived based on the algorithm developed by Baker et al.(2013).

Results

Study A. The results showed a significant main effect of Time $F(1, 69) = 89.13$, $p < .001$. All students post-test scores ($M = 19.01$, $SD= 3.56$) were higher compared to the pre-test scores ($M = 14.03$, $SD= 5.31$). We also found a significant interaction effect between Time *Condition $F(1, 69) = 4.09$, $p = 0.05$. Students in the experimental condition made more progress ($M = 6.00$, $SD= .25$) than students in the control condition ($M = 3.88$, $SD= .26$). There also was a significant difference on the tranfer test $F(1,69) = 5.15$, $p = .026$. Students in the experimental condition scored lower on the transfer test ($M = 10.19$, $SD= 3.97$) than students in the control condition ($M = 11.97$, $SD= 2.36$). Differences between the conditions in effort and accuracy regulation are currently analyzed to futher understand these findings.

Study B. We expect that students in the personalized vizualisation condition will outperform students in the control condition both on learning outcomes as well as their effort and accuracy regulation.

Scientific significance

This research indicated that a goal-setting and reflection intervention indeed improved students learning, but did not enhance transfer of students' knowledge. If differences in student effort and accuracy are also found, this will imply that the intervention also affects how students regulate their learning. Additional effects of providing personalized visualizations as a reference to further support regulation will be presented at EARLI. This contribution provides two examples of interventions to support students SRL based on trace data from ALTs.

References

Baker, R. S., Hershkovitz, A., Rossi, L. M., Goldstein, A. B., & Gowda, S. M. (2013). Predicting robust learning with the visual form of the moment-by-moment learning curve. *Journal of the Learning Sciences*, 22(4), 639-666.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends,* 59(1), 64-71.

Greene, J. A., & Azevedo, R. (2010). The measurement of learners' self-regulated cognitive and metacognitive processes while using computer-based learning environments. *Educational psychologist*, 45(4), 203-209.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018, March). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 31-40). ACM.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of educational research*, 77(1), 81-112.

Winne, P. H., & Baker, R. S. (2013). The potentials of educational data mining for researching metacognition, motivation and self-regulated learning. *JEDM-Journal of Educational Data Mining*, 5(1), 1-8.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13-39). San Diego, California: Academic Press.