Designing Dashboards to support learners' Self-Regulated Learning

Inge Molenaar
Behavioural Science Institute, Radboud University Nijmegen
i.molenaar@pwo.ru.nl

Anne Horvers
Behavioural Science Institute, Radboud University Nijmegen
a.horvers@pwo.ru.nl

Rick Dijkstra
Behavioural Science Institute, Radboud University Nijmegen
rick.dijkstra@student.ru.nl

Ryan Baker
University of Pennsylvania
ryanshaunbaker@gmail.com

ABSTRACT: This contribution reports on the development of two learner-faced dashboards that support learners' self-regulated learning during practice activities in an adaptive learning technology (ALT). While learners learn using adaptive learning technologies on tablets, they leave rich traces of data that capture many details of their learning processes. The data can be used to create dashboards that support learners to make valid inference about how they regulate control and monitor their learning. Such personalized visualizations are a new tool to support learners regulation. In this paper we describe two designs of personalized dashboards supporting SRL. The first dashboard is drawn by learners themselves based on ALT achievement data. Learners are asked to set goals at the start of each lesson and add their achievements after each lesson. This is used as input to monitor progress and determine whether adaptation is needed to reach their goals. Learners draw elements of the dashboard themselves and hence make their own personalized visualizations. The second dashboard follows the same logic, but the visualization process is automated in an app. Again learners set their goal at the start of each lesson and view their achievement and progress in the dashboard after each lesson. Additional, learners also are presented with their learning path based on Moment-by-Moment Learning Curves and cues to translate data into actionable feedback to efficiently reach learning goals. The contribution of this paper is to discussion the design and rational for the two dashboards that support young learners SRL based on ALTs trace data.

Keywords: Adaptive Learning Technologies, Self-Regulated Learning, Personalized Visualisations

1 BACKGROUND

This contribution describes two approaches to translate learners' trace data from Adaptive Learning Technologies (ALTs) into personalized visualizations that function as dashboards to support learners' self-regulated learning (SRL). In the Netherlands alone, over 250,000 students in primary education learn Mathematics, Dutch and English using adaptive learning technologies (ALTs) such as Snappet, Muiswerk, Taalzee/Rekentuin, Got it, and PulseOn on a daily basis (Kennisnet, 2014). These systems provide learners with instructional materials and practice opportunities that are aligned with the current level of learners' knowledge (Aleven, McLaughlin, Glenn, & Koedinger, 2016a; Klinkenberg, Straatemeier, & Van Der Maas, 2011a). When learners learn with adaptive learning technologies on tablets, they leave rich traces of data that capture many details of their learning process (Gašević, Dawson, & Siemens, 2015). Although ALTs successfully use learner data to adjust instructional materials to learners performance, supporting learners' self-regulated learning is not a focus of most ALTs being used at scale (Winne & Baker, 2013). Even though the important role of self-regulated learning (SRL) has been emphasised in the field of learning analytics and quite a few learner-faced dashboards have been developed aimed to support SRL (Winne & Baker, 2013), these dashboards do not use trace-data nor support learners to translate data into appropriate actions (Bannert, Molenaar, Azevedo, Järvelä, & Gašević, 2017).

Dashboards are loosely defined as: "*Single displays that aggregated different indicators about learners, learning processes and or learning contexts into one or multiple visualizations*" (Schwendimann et al., 2017). Research around dashboards traditionally has a strong focus on the learning analytics and educational data and less attention is paid to the pedagogical value and connection to learning sciences (Jivet, Scheffel, Specht, & Drachsler, 2018). Although SRL theory is the most common foundation for learner-faced dashboards, most of these dashboards only visualize indicators of learner achievement to support students awareness or reflection (Bodily & Verbert, 2017). Dashboards often fail to support learners in translating awareness into actions to improve regulation. Moreover, none of the dashboards reviewed in a recent review by Jivet et al (2018) used trace data to support SRL. This is especially surprising considering the well-established measurement problems with self-report measurements of SRL (Azevedo, 2009). The relative rarity of trace data used as support for SRL can be explained by the challenges to understand what learner trace data reveal about SRL (Bannert et al., 2017; Molenaar & Järvelä, 2014). Hence the purpose of this contribution is to explore how trace data from ALTs can be used to develop dashboards that supports learners' SRL and provide learners with actionable feedback. Especially for young learners in primary education learner-faced dashboard have been under represented in research and we are unaware of any learner-faced dashboard supporting SRL with trace data (Jivet et al., 2018). This contribution starts with the pedagogical basis for this dashboards discussing SRL theory and explicitly grounding the dashboard design in SRL theory. Next, we discuss the dashboard design including the data used, explanation of the visualizations selected and the interaction techniques and implementation in the educational setting and workflow.

1.1 SRL theory as basis for the design of the dashboards

SRL theory defines learning as a goal-oriented process in which learners make conscious choices working toward learning goals (P. H. Winne & Hadwin, 2017; Zimmerman, 2000). Self-regulated learners use cognitive activities (read, practice, elaborate) to study a topic, use metacognitive activities (orientation, planning, monitoring, and evaluation) to control and monitor their learning, and motivate themselves to engage in an appropriate level of learner effort (Azevedo, Moos, Greene, Winters, & Cromley, 2008). Following the COPES model (Winne, 2018; Winne & Hadwin, 1998) regulation unfolds in 4 loosely coupled phases: i) the task definition phase in which learners generate an understanding of the task, ii) the goal setting phase in which learners set their goals and plan their actions, iii) the enactment phase in which learners execute their plans working towards their goals and finally iv) the adaption phase which is activated when progress towards the goals is not proceeding as planned and adjustments in strategies, actions or tactics are required. These phases occur in the context of task conditions, standards that learners set to represent their goals and operations performed by learners that lead to new products in the form of knowledge or skills. The control and monitoring loop are at the heart of COPES model. In cognitive evaluations learners relate their achieved products to their standards in order to assess progress towards their goals. Although the COPES model explains how learners' internal feedback functions, it is well established that learners often face a utilization deficiency (Winne & Hadwin, 2013). This is the failure to adequately activate control and monitor loop during learning. Dashboards are potentially a powerful tool to overcome this utilization deficiency as they can help learners with objective data about the current products obtained (achievement), how they relate to learning goals (progress) and how that relates to standards (Molenaar, Horvers, & Baker, 2019). This form of external feedback can consequently drive the adaptation phase, helping learners' adjust learning behaviour leading to optimized strategies, adjustments to plans or different actions in the enactment phase.

Hence when internal feedback fails, dashboards can support learners with external feedback to adjust the regulation during learning (Butler & Winne, 1995). Learners often receive external feedback from the teacher or the ALT indicating the correctness of an answer to a problem (Aleven, McLaughlin, Glenn, & Koedinger, 2016b). Although this supports local corrections, this type of feedback does not provide sufficient information to adjust control and monitoring. Specifically, this feedback does not trigger cognitive evaluation which is important for learners that do not regulate their learning sufficiently (Azevedo et al., 2008). Different techniques (e.g., prompts (Bannert, Hildebrand, & Mengelkamp, 2009), scaffolding (Azevedo et al., 2008), intelligent tutor systems (Azevedo et al., 2016)) have been used to assist learners' regulation in ALTs. Although these techniques are initially effective, they are less successful in sustaining regulation during learning in absence of the tools. A drawback of these techniques is that they do not help learners to make explicit inferences about how their actions are related to progress towards learning goals (Winne & Hadwin, 2013). The fit between achievement (products) and internal representations of the learning goals (standards) remains underspecified and the contribution of actions to progress is unclear. In order to engage in cognitive evaluations learners need reliable, revealing, and relevant data in order to be able to draw valid inferences about their own learning process (Winne, 2010). Data from ALTs can be used to provide learners with continuous feedback about their achievement, progress and above all to understand how progress towards their learning goal is related to their actions. This entails that the role of dashboards needs to be extended from discussing *what* learners learned to also incorporate *how* learners learned. Hence dashboard can be the basis for developing a promising way to overcome learners' utilization deficiencies of regulatory strategies, and consequently increase learners' SRL skills for future learning.

Learner-faced dashboards have just recently become a more prominent way of providing SRL support e.g. Bodily et al., (2018), although visualizations on learners' achievements have been used in some learning systems for some time (Arroyo, et al. 2007; Koedinger et al., 2007). However, a recent review by Jivet (2018) and colleagues indicates that most of these dashboards do not provide actionable information for learners to improve their regulation. Following the learning analytics process model learners need to translate awareness into action (Bodily & Verbert, 2017). They need a 'representative reference frame' to interpret the data (Wise, 2014). Both achievement and progress can be valuable ways to create such a reference frame, but as described above only when learners have internal standards, against which they are evaluated (Winne & Hadwin, 2013). These standards help learners to set criteria that indicate *how* to know that a learning goal is reached. Frequently, learners are in need of additional external help to create standards. This is also referred to as *feed-up*, which represents an external trigger to support learners to articulate *when* learning goals are reached (Hattie & Timberley, 2007). Feed-up interventions can be used to support learners to explicitly set standards. Consequently, this can support learners' cognitive evaluations in the enactment phase. Only when learners establish that there is a difference between their achievement and standards set, they realize that progress is not as anticipated and adaptation is needed. This may cue re-evaluation of plans and adjustment of strategies, but only when learners are able to determine next steps to reach the learning goal. External feedback to articulate this is named *feed-forward* (Hattie & Timperley, 2007), when a learner's verbalizes how to adapt learning strategies and actions to ensure future learning. Thus, next to assessment feedback that indicates how a learner is doing on one task (feedback), *feed-up* and *feed-forward* are external feedback that can help learners to effectively monitor and control their learning. A comprehensive approach towards learner-faced dashboards includes both the assessment of learners achievement on a cognitive level (feed-back on achievement) as well as information on progress to stimulate cognitive evaluation by supporting the monitoring loop (feed-up) and recommendations to drive adaptations in the control loop to proceed towards the learning goal (feed-forward).

The learners' data traces in ALTs provide indications of learners' achievement and progress towards their learning goal (Molenaar et al., 2019) and specifically the relation between learning actions and progress i.e. the learning path. Therefore the data can be used to help learners explicitly reflect on achievement and progress towards their learning goals (Winne, 2010). To indicate the relation between actions and progress explicit we use Moment-by-Moment Learning Curves (Baker, Hershkovitz, Rossi, Goldstein, & Gowda, 2013; Baker, Goldstein, & Heffernan, 2011). These curves show how much the learner is likely to have learned at each problem-solving opportunity, which is a representation of progress over time. This may function as a tool to show learners how they regulate their learning over time. Research has shown that Moment-by-Moment Learning Curves show specific patterns that are not only associated with learning but also regulation of accuracy (Molenaar, Horvers, & Baker, submitted). Hence, these patterns could potentially help learners understand the development of progress during a lesson and subsequently triggering adaptation. Consequently, dashboards visualizing achievement, progress towards learning goals and the learning path may play a central role in guiding learners to optimize their regulation.

2 THE DASHBOARD DESIGN: DATA, VISUALIZATION AND INTERACTION TECHNIQUES

In this contribution we explore two possible types of dashboards to support SRL and serve as an form of external feedback for learners. The dashboards are developed in the context of ALT which also generates the data used.

2.1 Data from the adaptive learning technology

The *adaptive learning technology (ALT)* used in this study is widely used for spelling and arithmetic education throughout the Netherlands. This technology is applied in blended classrooms in which the teacher gives instruction after which learners practice on their tablets. First, learners solve non-adaptive problems, which are the same for each student in the class. After this, the learners work on adaptive problems. Adaptive problems are selected after each problem solved based on an estimate of the learner's knowledge called the ability score (Klinkenberg, Straatemeier, & Van Der Maas, 2011b). This score is calculated by a derivative of the ELO algorithm (ELO, 1978). Based on the learner's ability score, the ALT selects problems with a probability of 75% that the learner will answer the problem correctly. After a learner has answered approximately 25 problems, the system has a reliable indicator the ability score. This ability score is used as indicator of *achievement*. The difference between the previous ability score and the new score is the indicator of *progress*.

Next to adaptive problems, Learners are given direct feedback (correct or incorrect) after entering an answer to a problem and teachers can follow learners in teacher dashboards (Molenaar & Knoop-van Campen, 2018).

The log data from the ALT consist of: A date and time stamp, learner identifier, problem identifier, learning objective identifier, ability score after the mentioned problem and the correctness of the answer the learner gave.

2.2 Techniques to transform data: Moment-by-moment learning curves

The ALT data are used to create M*oment-by-Moment Learning Curves* (MbMLC) using an algorithm developed by Baker, Hershkovitz, Rossi, Goldstein, & Gowda (2013). These curves are used to visualize a learner's learning over time. The probability a learner has just learned a skill is plotted across the learner's problem solving attempts over time while practicing on a specific skill. A newly developed Python script is used to label the MbMLC based on Baker et al. (2013) following the rules in Table 1. A peak is defined as a point more than 0,015 higher than the point before or after. A new common pattern was found, with two peaks, so this pattern is added as 'double spike'.

Table 1: Rules for coding moment-by-moment learning curves.

Curve	Rules
Immediate drop	The curve starts high, drops quickly after solving problems and remains low afterwards.
Immediate peak	The curve starts low, peaks within the first 10 problems and remains low afterwards.
Double spikes	The curve starts low and shows 2 peaks over the course of problem solving.
Close multiple spikes	The curve starts low and shows more than 2 peaks within the first 25 problems and remains low afterwards.
Separated multiple spikes	This curve starts low and continues to show multiple peaks, even after 25 problems

2.2.1 Dashboard A: drawing your own dashboard

In study A learners are asked to draw their own dashboard. At the start of first three lessons, learners are asked to answer four questions regarding their learning goals: 1. How skilled do you want to become at that particular subskill? 2. How many lessons do you need to reach that goal? 3. How skilled do you want to become in this particular lesson? These questions are answered on a scale from 1 (not very good) to 6 (excellent). Also, learners are asked which percentage of problems they wanted to solve in one attempt (0% to 100%). Learners answered by drawing the bars below the questions, see the left side of Figure 1. The chosen colour represent different levels of achievement also used in the ALT to indicate achievements. This stage was designed to act as a *feed-up* intervention in which learners clearly articulated their learning goal and set their standards to evaluate progress.

After the first three lessons, learners are asked to reflect on their learning by answering three questions: 1. What is your current knowledge on the subskill studied today?; 2. How much effort did you put in today's lesson?; 3. What is percentage of problems you solved in one attempt? Like above, learners answered by drawing the bars below the questions, see the left side of Figure 1. Learners based their answers with regard to *achievement* on the ability score indicated by the ALT. Next, students were asked to compare part 1 with part 2 to determine their *progress* and to see how far they are from reaching their goal. This stage was designed to act as a *feed-forward* intervention in which learners clearly articulated progress towards their learning goal and engage in cognitive evaluation.

Before the rehearsal lesson, the learners were asked to review all their dashboards and determine which subskills they need to work on in the rehearsal lesson. Again students set goals for the rehearsal lesson and evaluate on those before working on the post-test. Thus the feed-up, feed-forward cycle is repeated 4 times during the experiment.

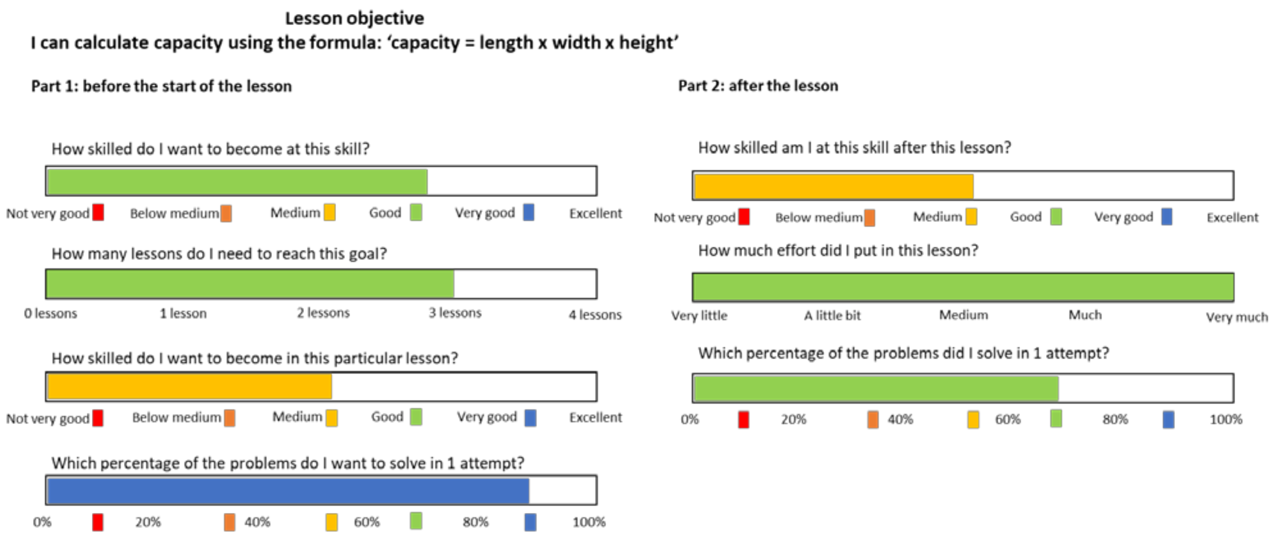


Figure 1. Dashboard drawing by a learner.

2.2.2 Dashboard B: The learning path app

In study B, learners were asked to set a goal at the start of each lesson in the *learning path app*[1]. In the overview screen, learners clicked on the dolphin of a particular arithmetic subskill. Then they were shown the goal setting screen, see Figure 2. In this screen, learners were asked to indicate how skilled they wanted to become at that particular subskill and what their goal was for this lesson. The learners filled in their goals by moving the flag on a scale from 0 to 100%. This stage was designed to act as a feed-up intervention in which learners clearly articulated their learning goal and set their standards to evaluate their progress.

After the lesson, learners were asked to look at their progress in the overview screen and in the goal setting screen. On the overview screen learners can see their combined progress on all the three subskills which was communicated by the position of the dolphin. The position of the dolphin on the horizontal level indicates the ability score of the learner as calculated by the ALT. Hence the more to the right the better you know this subskill. Additionally, the size of the dolphin increases with the number of problems solved so this gives an indication of the number of problems a student made for the progress made. Moreover, the dolphins colour provides information about the progress in relation to the overall learning goal set. A grey dolphin indicates no learning goal is set, an orange dolphin indicates the learners has not yet reached their personal learning goal and a green dolphin shows that the learning goal is reached. The hoop around the dolphin indicates that the lesson goal is reached, but the end goal for this skill is not yet reached. This stage was designed to act as a feed-forward intervention in which learners clearly articulated progress towards their learning goal and engage in cognitive evaluation.

When learners click on a dolphin, they go to the goal-setting screen with more detailed information on the learner' progress. The blue bars indicate progress based on the ability score as calculated by the ALT. When the ALT did not yet provide an ability score, learners were shown a grey bar. The colour of the flag shows how this progress is related to the goals set. An orange flag indicates that the learner has not reached their goal yet and a green flag indicates that particular goal is reached.

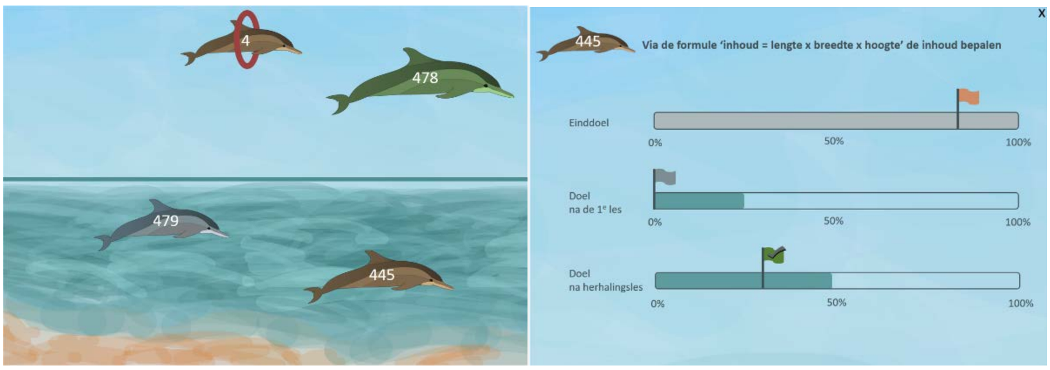


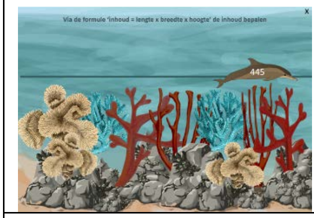
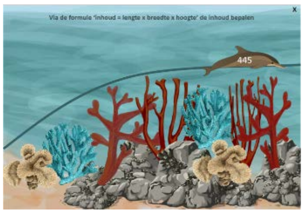
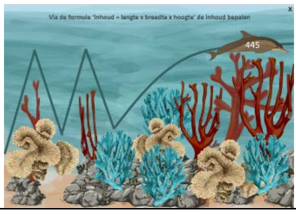
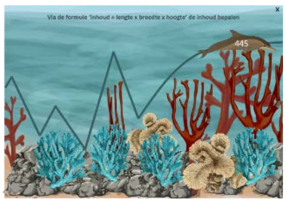
Figure 1. Goal setting screen

When learners click on the progress bars, they go to the p*ersonalized visualizations screens.* Here learners see the learning paths they followed for a particular subskill. The learning paths show how

[1] Leerpaden app in the google appstore

a learner's learning evolved during the practice activities. The personalized visualizations are based on the Moment-by-Moment Learning Curves calculated based from the ALT data. Learners were shown 5 types of learning paths called high swimmer (immediate drop), quick swimmer (immediate peak), climber in two steps (double spikes), slow climber (close multiple spikes) and climber and descender (separated multiple spikes), see Figure 3. The learning path visualize how learners actions contribute to their achievement and show their progress over time. To make these visualizations actionable, learners are explained the meaning of the learning paths. On the poster students are also given actionable feedback to adapt their learning. For example, when a learner showed a close multiple spikes this means that he/she learned the skill slowly and that more practice is still needed. Students are advised to actively monitor their accuracy and increase their effort to ensure they are practicing at their level. Hence, these patterns may help learners understand the development of their effort and accuracy during a lesson and subsequently triggering adaptation.

The feedback is printed on posters that are positioned central in the classroom for all learners to see. Additionally, teachers are given instructions to support learners to understand the learning paths and their implications. A protocol was provided to the teachers that explicitly discusses the function of each step in the intervention. Moreover, teachers are instructed to help learners formulate which actions they could take depending on their learning paths

Personalized dashboards	**Planning**	**Monitoring**
High swimmer: Immediate drop 	You already know this skill. → Please practice a different skill.	Your accuracy is high, well done!
Quick riser: Immediate peak 	You have learned this skill quickly after the teacher explained it. → You can practice until you have reached proficiency (green dolphin) and then continue on the next skill.	Your accuracy is high, well done!
Riser in two stages: Double Spikes 	You have learned this skill in two stages during guided instruction and class wide practice. → Please practice until you have reached proficiency.	→ Please monitor your accuracy during practice. → Do you feel that you can put in a little more effort? Try to become a quick riser!
Slow riser: Close multiple spikes 	You are learning this skill somewhat slowly. → Please continue to practice in adaptive mode until you have reached proficiency.	→ Please monitor your accuracy during practicing. → Do you feel that you can put in a little more effort? Try to become a riser in two stages!

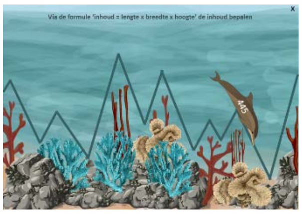
Riser and descender: Separate multiple spikes 	You are learning this skill quite slowly. → Please continue to practice in adaptive mode → If you cannot master this skill please notify your teacher	→ Please monitor your accuracy during practicing. → Do you feel that you can put in a little more effort? Try to become a slow riser!

Figure 3. Personalized dashboards

3 EVALUATION FRAMEWORK

We have evaluated the dashboards in two experimental studies. The experiments examine the effects of the dashboard intervention on learning outcomes and transfer of knowledge. Effort and accuracy are included as indicators of self-regulated learning.

Study A evaluates dashboard A and consisted of 71 learners in grade 4 who were divided over the experimental goal setting condition (n=37) and the control condition (n=34). Study B investigates the learning path app with 93 learners divided over the experimental personalized visualizations condition (n=63) and the control condition (n=30). Both studies followed a similar design in which learners worked on 3 arithmetic skills in 4 lessons of 50 minutes, see Figure 4. The lessons consisted of a mix of teacher instruction and practice activities. The three skills were easy, medium and hard in terms of difficulty. Learners' learning was measured with a pre and post-test and a transfer-test.

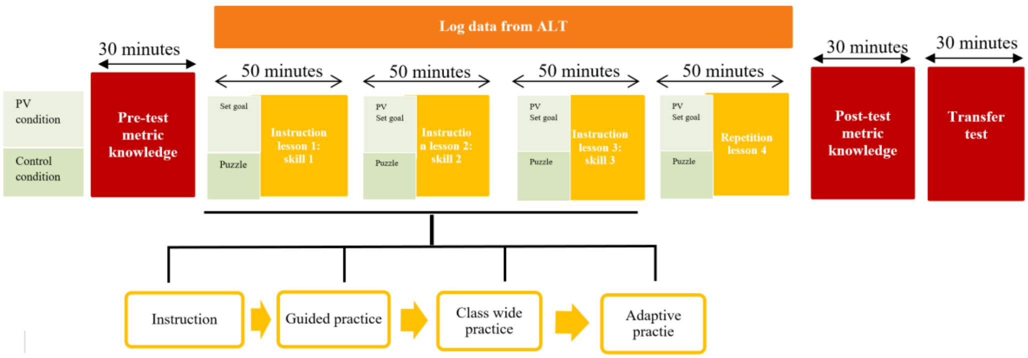


Figure 4. Study design

3 PRELIMINARY RESULTS

Study A. A repeated measurement ANOVA was used to investigate the effect of the dashboard on learning with pre and post-test as within subject variables and condition as between subject variable. The results showed a significant main effect of Time $F(1, 69) = 89.13$, $p < .001$. All learners 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. Learners in the experimental condition made more progress (*M* = 6.00, *SD*= .25) than learners in the control condition (*M* = 3.88, *SD*= .26). An ANOVA showed a significant difference on the transfer test $F(1,69) = 5.15$, $p = .026$. Learners in the experimental condition scored lower on the transfer test (*M* = 10.19, *SD*= 3.97) than learners in the control condition (*M* = 11.97, *SD*= 2.36).

Study B. Data are currently analysed and will be ready for presentation at the workshop. We expect that learners in the personalized visualization condition will outperform learners in the control condition both on learning outcomes as well as their effort and accuracy regulation.

4 SCIENTIFIC SIGNIFICANCE

In this paper we outlined the design of two dashboards to support learners' regulation. These dashboards are grounded in the COPES theory of self-regulated learning. We propose a comprehensive approach towards learner-faced dashboards that includes learners' achievement, information on progress and the learning path which connects learners' actions to their progress. This transforms the role of dashboards from discussing *what* learners learned to also incorporating *how* learner learned. In this way dashboards could be a promising way to overcome learners' utilization deficiencies to effectively apply self-regulated learning. Unique to these dashboards is that trace data is used to help students understand their regulation in learning paths. MbMLC are used to help learners understand how their actions relate to progress.

These dashboards are designed to function as a reference for learners and to support learners to engage in cognitive evaluation. Prior to learning, the feed-up intervention ensures students set standards and formulate learning goals. After learning, the feed-forward intervention helps learners to translate the dashboard data into adaptations that help them to proceed towards their goals. The explicit instructions show how learners can be supported to follow up on the provide data on achievement, progress and learning paths. This provides a very transparent interface into how data are transformed into actionable feedback for learners.

The preliminary results indicate that these dashboard indeed improved learners learning, but did not enhance transfer of learners' knowledge. When differences are found in learner effort and accuracy, this may imply that the intervention also affects how learners regulate their learning. Additional effects of personalized visualizations will be presented at the workshop.

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