# Using enhanced Learner-facing Visual Interfaces to support Self-regulated Learning

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**ABSTRACT**: Visualisations provide a rapid way for learners to gain insight into their learning process which, in turn, may promote their self-regulated learning. Yet few learner-facing visualisations have been developed to support learners' self-regulation. In this paper, we propose a collection of personalised, theory-based and empirically driven visual interfaces. We harnessed trace data from multiple channels to generate clear and actionable recommendations for learners to improve their regulation. Guided by a quasi-experimental study in a university context, we investigate the critical learning processes in SRL, describe the environment to collect multimodal and multichannel data about those processes, and suggest visualizations that can rely upon these data sources— to prompt learners to engage in metacognitive monitoring using visualisations to support their regulation and learning.

Keywords: self-regulated learning; enhanced trace data; dashboards; learning analytics

## **1** INTRODUCTION

Providing learners with visualized information about their learning process may prompt them to reflect upon their prior and adapt their future studying, i.e., engage in metacognitive monitoring and control that are essential to productive self-regulated learning (Azevedo, Taub, & Mudrick, 2015; Roll & Winnie, 2015). Data reported in a visual form, e.g., a histogram displaying the frequency of learning strategies a student enacted over a period of observation, can cast a light on multiple elements that interplay during learning and allow researchers and educators to understand complex processes such as goal settings, enactment of learning strategies and adaptation to learning behaviours. Equally important, visualized data may afford learners the opportunity to better oversee their learning process and adapt accordingly.

We collected data from a pilot study in a university setting (n=25), where students were asked to engage in an essay writing task over the period of 45 minutes. In the task, students had to integrate three topics: Artificial Intelligence, Differentiation in the classroom and Scaffolding of learning into a 300-400 words vision essay about learning in school in 2035. The learning environment (Figure 1) consists of six areas of interest (AOI). The AOI zones included the catalogue zone on the left, the reading and writing zones in the middle, the note taking interface (annotation tool), the planner tool, timer tools and an essay writing interface, that opens as an overlay on the screen. The choice of tools integrated and the visualisations produced were guided by the COPES model of SRL (Winne & Hadwin, 1998).

According to the COPES model, self-regulated learning spans the four phases: i) in the task definition phase, learners develop an understanding of the task, ii) during the goal setting phase, learners set their goals and plan their learning, iii) in the enactment phase, learners execute their plans and control and monitor progress iv) in the adaptation phase, adjustments are made when progress towards the goals is not proceeding as planned.

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Figure 1: Learning environment including the six (6) AOI

#### 2 SRL MEASUREMENTS

We collected rich traces of these temporally unfolding SRL processes that emerged from our various data channels such as LMS log, enhanced log, eye-tracking data and interactions with external systems. Table 1 lists a subset of multichannel data sources and corresponding actions (both unobtrusive trace and self-reported data) that was captured.

Table 1:	List of multi-channel data sources and their interactions that can assist self-regulation

Data Source	Event/Action	
LMS Log	Content Reading, Re-reading, Content Search, Navigation Sequence	
	Catalogue Access, Task Attempts	
Enhanced Log	Mouse movements, Mouse clicks on pages, Page scroll	
	Keyboard strokes	
Eye-Tracking	Repeated number of fixations on AOIs, Sequential patterns of	
	fixations, Revisits to AOIs, Saccades, Smooth pursuit eye movements	
External Systems	Annotation Tool: Annotation Created, Deleted, Searched, Read	
	Essay Writing Tool: Essay Write, Essay Save	
	Timer Tool: Time Tracker Viewed	
	Planner Tool: Planner Viewed, Planner Updated	

Informed by the COPES model and the framework proposed by Siadaty, Gašević & Hatala (2016), we labeled the raw trace data into theoretically meaningful learning actions. We then interpreted the obtained patterns of learning actions as SRL processes based on our theoretical framework. These processes (Planning, Content Consumption, Working on Task, Monitoring, Evaluation) informed our design. The detailed action library and SRL labelling process can be accessed via this <u>link</u>.

# 3 FRAMING SRL SUPPORT THROUGH VISUALISATIONS: AN EXAMPLE

As highlighted earlier, our conceptual framework incorporates the COPES model that focuses on the *four phases* of SRL. Figure 2 outlines these *four phases* and the corresponding visual interfaces that are enacted to support the learners self-regulation during the experimental task, that is to write an essay. To maintain the relevance and efficacy of SRL visualisations, we tried to coordinate the visualizations (such as percentage complete, etc.) within the standard interface of the tools (such as Planner and Essay writer) for maximum potential of facilitating monitoring and regulation.

To support time-management, which is considered an important element in SRL (Pintrich, 2004), we captured the amount of time each learner spent on the various tools. Using the actions posited in Table 1, Figure 3 visually represents a few examples of how student's low-level interactions can be mapped onto theoretically meaningful learning actions attending to SRL criteria. Such visualisations

(histogram showing SRL processes) presented in real-time can give valuable insights to learners on their current strategies with respect to time management.



Figure 2: Interfaces enacted in line with the four phases of COPES model to support self-regulation

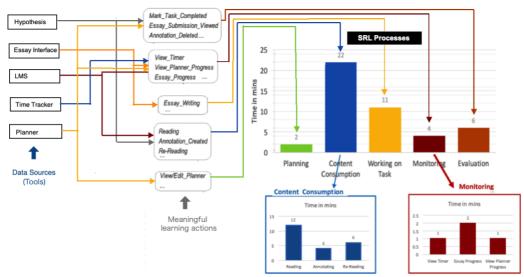


Figure 3: Visually mapping data sources and log events to specific SRL processes

### 4 DISCUSSION AND NEXT STEPS

Through this preliminary data analysis, we prototyped how multimodal multichannel learning data can be aligned to theoretical principles of SRL to support learners to accurately monitor and regulate their learning. An attempt has also been made to keep the balance between simple to understand and abstract monitoring indicators to maintain learner's cognitive load and reflection on one's affective reactions. Our next step is to deploy the SRL focused visual interface and catalogue of detailed visuals in an experimental study, in which students of the experimental group will have access to the personalized visualization interfaces supporting SRL and the students of the control group will not have access to these interfaces. While the current design of the learning analytics dashboard for SRL is primarily intended to be used in the laboratory setting, the overarching research program is to create the tool instrumentation (i.e., user interfaces) that can replace, to some extent, apparatus that is used in a laboratory setting (e.g., eye-trackers). This will enable our design to be used in authentic learning settings.

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