Relevance of learning analytics to measure and support students' learning in adaptive educational technologies

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ABSTRACT
In this poster, we describe the aim and current activities of the EARLI-Centre for Innovative Research (E-CIR) "Measuring and Supporting Student's Self-Regulated Learning in Adaptive Educational Technologies" which is funded by the European Association for Research on Learning and Instruction (EARLI) from 2015 to 2019. The aim is to develop our understanding of multimodal data that unobtrusively capture cognitive, meta-cognitive, affective and motivational states of learners over time. This demands for a concerted interdisciplinary dialogue combining findings from psychology and educational sciences with advances in computer sciences and artificial intelligence. The participants in this E-CIR are leading international researchers who have articulated different emerging perspectives and methodologies to measure cognition, metacognition, motivation, and emotions during learning. The participants recognize the need for intensive collaboration to accelerate progress with new interdisciplinary methods including learning analytics to develop more powerful adaptive educational technologies.

CCS Concepts
Algorithms, Experimentation, Human Factors, Standardization, Theory, Verification.

Keywords
Adaptive Educational Technologies; Educational Data Mining; Learning Analytics; Multimodal Data; Self-Regulated Learning

1. INTRODUCTION
Even though the recent influx of tablets with learning technologies in education is promising, the challenge lies in improving adaptive educational technologies to support students' self-regulated learning. These technologies offer immediate individualized instruction including personalized feedback from real-time data of learner actions and performance. Driven by the emerging field of learning analytics, these technologies seek to tailor learning experiences based on learners' progress through the measurement, collection, analysis and reporting of multi-modal cognitive, metacognitive, affective, and motivational data.

Current adaptive educational technologies focus on students' performance (cognition) to adapt learning materials and largely neglect important aspects, such as students' metacognition, emotion and motivation. However, multimodality online trace data such as log-files, eye gaze behaviours, transpiration, facial expressions of emotions, heart rate and electro-dermal activity can enhance our understanding of students' processes during learning [1]. For example, eye gaze data reveals the learners' focus at different points of time and is indicative of the level of cognitive load. Measurement of transpiration, heart rate and skin galvanic conductivity reveals emotional reactions. More specifically, combining multimodal data can reveal both cognitive and affective states of the learner and can detect arousal levels and the valence of emotional reactions. In a learning situation, students are confronted with a variety of cognitive challenges (e.g. lack of prior knowledge, task difficulty) which can result in emotional reactions (e.g. frustration, boredom). Therefore, this cooperation aims to develop our understanding of multimodal data that unobtrusively capture cognitive, metacognitive, affective and motivational states of learners over time in order to design adequate instructional support and scaffolds.

2. NEED OF COMPLEMANTARY EXPERTISE AND RESEARCH QUESTIONS
Valid online-measures of multimodal data during learning and their analysis demand for a concerted interdisciplinary dialogue combining findings from psychology and educational sciences with advances in computer sciences and artificial intelligence. The participants in this E-CIR are leading international researchers who have articulated different emerging perspectives and methodologies to measure cognition, metacognition, motivation and emotions *during* learning. The participants recognize the need for intensive collaboration to accelerate progress with new interdisciplinary methods to develop more powerful adaptive educational technologies which would not be possible within individual labgroups.

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To guide our E-CIR, we outlined two research questions which are also highly relevant in the field of learning analytics:

1. How can we analyze multimodal, trace data from existing adaptive educational technologies using different channels (e.g., verbalization, phsysiology, navigation behavior) to measure students' cognitive, metacognitive, emotions and motivation during learning?
2. How can these measurements be used to enhance current adaptive learning technologies supporting learners' self-regulated learning through visualisation and recommendation tools?

3. E-CIR RESEARCH ACTIVITIES

Our research questions will be addressed in regular meetings where we present and discuss research of individual members and plan collaborative research projects in order to investigate the research topics as a joint effort among lab groups (see Table 1).

Table 1. Overview of E-CIR Activities

Focus	Issues
Review of existing methods for trace and multimodal-data collection and analysis	Specifying different channels (e.g. eye-tracking, physiological) and methods (e.g. process-mining, video-analysis)
Consolidation of methods	Analyzing each other's datasets
Multiple data-streams	Discussing approaches to multiple data-streams
Application in education	Visualization of data for learners and teachers
Multiple data-streams	Sharing of results and planning new publications
Application in education	Recommendation services
Standardization of methods	Discussing different settings
Research agenda for next decade	Outline remaining research issues

The meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, Bannert et al. [2] are using process mining techniques to analyse verbal protocols collected during self-regulated learning. Especially, they are interested if instructional scaffolds affect not only the amount of different SRL activities but also the temporal structure and if so, whether the temporal structure of learning events corresponds with different dimensions of learning performance.

Molenaar's group studies time and order in self and socially regulated learning using single or multiple data streams. Specifically, sequential characteristics of S-SRL consider which actions follow each other, for example planning was shown to play a critical role in transitions between low and high cognitive activities [3]. Temporal characteristics indicate when those actions are taken during learning and how actions fluctuate other over time. For example, successful learners are more likely to engage in metacognitive activities early in the learning process compared to less-successful learners. Recently, this group has begun to analyze logs of adaptive technologies to assess students' regulation of effort and learning over extended time periods.

Azevedo [1] and colleagues' research has focused on examining the role of cognitive, metacognitive, affective, and motivational (CAMM) self-regulatory processes during learning with advanced learning technologies. More specifically, the overarching research goal has been to understand the complex interactions between humans and intelligent learning systems by using interdisciplinary methods (e.g., log-files, physiological sensors, facial expressions of emotions, etc.) to measure CAMM processes and their impact on learning, performance, and transfer. To accomplish this goal, his team conducts laboratory, classroom, and in-situ (e.g., medical simulator, construction site) studies and collect multi-channel data to develop models of human-computer interaction; examines the nature of temporally unfolding self- and other-regulatory processes (e.g., human-human and human-artificial agents); and, designs intelligent learning and training systems to detect, track, model, and foster learners, teachers, and trainers' self-regulatory processes.

Järvelä et al. [4] have been exploring what multimodal data can tell us about SRL processes in authentic collaborative learning tasks. They have investigated how multichannel data can be used for identifying markers that characterize successful SRL and learning progress and help in understanding and increasing the evidence about (a) interactions between different facets of regulation (i.e., cognition, motivation, emotion) (b) temporality and cyclical processes of regulation, and (c) the occurrence and temporality of different types of regulation (SRL, CoRL, and SSRL).

Finally, Gašević and his colleagues [5] have been working on analytical methods for the theory-informed study of self-regulated learning. Their work involves a broad range of methods for analysis of clickstream, discourse, and more recently psychophysiological data. Data are generated in learning activities performed in laboratory experiments and ecologically valid and open-ended learning environments including flipped classrooms and (massive open) online courses. The methods are based on unsupervised and supervised machine learning, sequence and process mining, automated text analysis, and social and epistemic network analysis. The use of these methods allows for detection of a) learning strategy; b) cognitive, metacognitive, motivational, social, and affective processes; and c) interaction between different self-regulatory processes. To allow for triangulation with psychophysiological data collected typically as continuous data streams, methods for time series analysis and digital signal processing will be explored in the future work.

4. ACKNOWLEDGMENTS

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