Relevance of Learning Analytics to Measure and Support Students’ Learning in Adaptive Educational Technologies

Maria Bannert
Technical University of Munich
Arcisstrasse 21
Munich, Germany
+49 89 289 24390
maria.bannert@tum.de

Inge Molenar
Radboud University
Montessorilaan 3
Nijmegen, The Netherlands
+31 24 3611942
I.molenaar@pwo.ru.nl

Roger Azevedo
North Carolina State University
2310 Stinson Drive
Raleigh, NC, 27519, USA
+1 919 515 2254
razeved@ncsu.edu

Sanna Järvelä
University of Oulu
P.O.Box 2000,
FIN-90014 University of Oulu
+35 8405 77 7164
sanna.jarvela@oulu.fi

Dragan Gašević
The University of Edinburgh
10 Crichton Street
Edinburgh, EH9 9AB, UK
+44 131 651 3837
dragan.gasevic@ed.ac.uk

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 COMPLEMENTARY 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.
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, physiology, 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

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

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 and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation. For example, the meetings will be informed by research of each team members and will stimulate their future research cooperation.

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

Our thanks to EARLI for funding our E-CIR.

5. REFERENCES


