Drachsler, Hendrik; Schneider, Jan

JCAL special issue on multimodal learning analytics [editorial]

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E d i t o r i a l

JCALSpecialIssueonMultimodalLearningAnalytics

The transition of our world from an analogue to a digital one affects all aspects of society and, thus, also the educational sector. In recent years, we have gained insights into learning behaviour by investigating existing data sources such as learning management systems, mobile applications, and social media environments with analytic methods (Drachsler & Kalz, 2016; Greller & Drachsler, 2012).

While these data sources can still provide a rich ground for research, a new wave of technological innovations is taking place with the Internet of Things (IoT) and the maker movement. IoT devices provide new applications and affordances for everyday life. Wearables, eye-trackers and other camera systems and self-programmable microcomputers such as Raspberry Pi and Arduino create new data sources which can be used to investigate learning. These new data sources are creating so-called multimodal data sets as they combine different data sources from physical activities and physiological responses to learning situations with more traditional learning data such as user logs from learning management systems. Alternative to traditional learning data collections, multimodal data sets require manifold data collection methods to combine the diverse data streams.

New multimodal data research approaches promise to provide a more holistic picture of learners and the success factors for learning, but multimodal data is much more diverse and heterogeneous than data available from traditional learning environments. It is challenging to combine various data types such as text, assessments, activities, physiological data, and video for research purposes and gaining meaningful results.

In line with the scope of the Journal of Computer Assisted Learning, we were interested in empirical studies that take advantage of multimodal data sources to enrich or investigate learning and teaching. We therefore explicitly looked for research that can show effects of multimodal data on learning and teaching sciences, but as Multimodal Learning Analytics is such a young field, we explicitly encouraged literature studies and results of technology infrastructures with new insights for this special issue.

The special issue looked for contributions touching the following, non-exhaustive topics:

- multimodal representation of learning
- multimodal learning behaviour modelling
- real-time data collection
- multimodal data mining technologies
- multimodal data interpretation
- open data sources
- learning analytics
- wearable computing for learning
- new educational approaches with multimodal learning
- supporting feedback and reflection with multimodal data

In the current special issue, we have collected seven articles from various backgrounds.

1. Dimitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018). From signals to knowledge. A conceptual model for multimodal learning analytics. https://doi.org/10.1111/jcal.12288

Description:
The Special Issues begins with a conceptual overview of the field of Multimodal Learning Analytics (MMLA). The authors describe the landscape of sensors and wearable trackers that can be used for learning support, as well as the required data collection and analysis methods. Based on a literature review of experiments using multimodal data, the authors provide a conceptual model for the young research field of Multimodal Learning Analytics. The review explored the multimodal data used in related studies (the input space) and the learning theories selected (hypothesis space). It finally results in a first Multimodal Learning Analytics Model (MLeAM) that aims to map the use of multimodal data for learning, shows how to combine machine learning with multimodal data, and aims to establish a shared terminology for the main communities moving the MMLA field, namely, the field of machine learning and learning science.

2. Junokas, M. J., Lindgren, R., Kang, J., & Morphew, J. W. (2018). Enhancing multimodal learning through personalized gesture recognition. https://doi.org/10.1111/jcal.12262

Description:
This article presents a study where gestures are used to interact with a multimodal learning environment. The article describes an adaptable model that enables students to define their own gestural interactions with computer-assisted learning environments. The authors argue that these interactions are foundational to developing stronger connections between students' physical actions and digital representations within a multimodal space. Results from the study showed that the described “one-shot” model approach for personalized gesture definition had higher recognition accuracy than the compared “pre-trained model” in repeatability and recall tasks.

3. Yu, L. C., Lee, C. W., Pan, H. I., Chou, C. Y., Chao, P. Y., Chen, Z. H., … & Lai, K. R. (2018). Improving early prediction of academic failure using sentiment analysis on self-evaluated comments. https://doi.org/10.1111/jcal.12247

Description:
This article presents a model that helps with the early identification of students who are at risk of failing and academic course. The model is based on sentiment analysis from text-based self-evaluated comments written by students. Results from the study show that the proposed sentiment analysis yields a significant improvement in early-stage prediction quality of at risk students. Moreover, results point out the limited predictive value of early-stage structure data, such as homework completion, attendance, and exam grades. Therefore, the authors argue that applying sentiment analysis to unstructured data (e.g., self-evaluation comments) can play an important role in improving the accuracy of early-stage predictions, thus offering educators an opportunity to provide students with real-time feedback and to support them to become self-regulated learners.

4. Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. https://doi.org/10.1111/jcal.12263

Description:
This article investigates the use of diverse sensors, including computer vision, user-generated content, and data from the learning objects (physical computing components), to record high-fidelity synchronized multimodal recordings of small groups of learners interacting. The authors used these recordings to investigate the students' interaction features that able to predict team success in open-ended tasks with physical computing. To conduct this investigation, the authors explored different supervised machine learning approaches (traditional and deep learning techniques) to analyse the data coming from multiple sources. The results of the study illustrate that state-of-the-art computational techniques can be used to generate insights into understanding the learning process in students' project-based activities.

5. Beardsley, M., Hernández-Leo, D., & Ramirez-Melendez, R. (2018). Seeking reproducibility: Assessing a multimodal study of the testing effect. https://doi.org/10.1111/jcal.12265

Description:
This article presents the replication of a multimodal wordlist experiment. The authors measured the brain activity of participants with the purpose to investigate whether the retrieval during learning supports the encoding of subsequent learning. This is measured by performance on recall tests and reflected by changes in alpha wave oscillations. In the reported study, authors were able to replicate behavioural results but not the physiological ones. They conclude the paper by highlighting the challenges of replicating previous work with the aim to facilitate the reproducibility of their own experiment.

6. Barmaki, R., & Hughes, C. E. (2018). Embodiment analytics of practicing teachers in a virtual immersive environment. https://doi.org/10.1111/jcal.12268

Description:
This article presents a series of studies with an interactive virtual training environment designed to support candidate teachers who need to sharpen their classroom communication skills. Using tracking sensors and improvements for existing gesture recognition utilities, authors created a gesture database that was used for the implementation of a real-time feedback application. For the described studies, the authors explored the use of haptic and visual feedback. The article describes the importance of recognizing nonverbal communication in the teaching context and reports on the positive impact of the proposed feedback application.

7. Pijeira-Díaz, H. J., Drachsler, H., Kirschner, P. A., & Järvelä, S. (2018). Profiling sympathetic arousal in a physics course: How active are students? https://doi.org/10.1111/jcal.12271

Description:
This article presents a study that investigated the arousal level of students in the classroom (how active students are) and examined how activation levels relate to achievement. Authors studied sympathetic arousal during two runs of an elective advanced physics course in a real classroom setting, including the course exam. Authors used electrodermal activity to index the arousal in students. Results from the study showed that arousal was positively and highly correlated with achievement as measured by students' grades. The authors discuss the needs to

address low arousal states in learning, the potential of applications for biofeedback, teacher intervention, and instructional design.

When we look through the collection of articles accepted for this special issue of JCAL, we see a variety of advances that bring together the best ideas of Multimodal Learning Analytics with important advancements for Computer Assisted Learning in general, such as the conceptualization of a Multimodal Learning Analytics Model that maps the use of multimodal data for learning, capturing gestures to support different learning activities, and using multimodal data to get insights about the learning process. It is gratifying to see the expansion of studies conducted in this area that open up truly new way to analyse learning behaviour and provide new ways of feedback, and even more gratifying to see the increased diversity of open source tools that are available for this challenging research that enables more researchers to benefit and participate in this new research field.

So, we are entering what may well become the golden age of Multimodal Learning Analytics research, and this is a well-timed volume to help bring those new to the field up to speed.

Hendrik Drachsler: Open University of the Netherlands OTEC, Netherlands

Jan Schneider: Das Deutsche Institut für Internationale Pädagogische Forschung – DIPF Educational Technologies, Germany

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