

Wolfgang GRELLER¹ (Vienna) & Ulrich HOPPE (Duisburg)

Editorial: Learning Analytics: Implications for Higher Education

1 Motivation

The increased use of digital systems to support learning and teaching in higher education goes along with the increased possibility to collect data on students' behaviour in those systems. It is now possible to gather data unobtrusively on when and what students contribute to a discussion forum, when they open a webcast lecture, when and how they take an assignment or test.

The term “Learning Analytics” refers to the use of such data and results of processing these data for educational purposes. A commonly used definition (SIEMENS, 2011) is: “Learning Analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs.” The abundance of learning-related data has resulted in a diverse set of research questions and research approaches (for an overview of pertinent issues: GRELLER & DRACHSLER, 2012). Some researchers advocate a bottom-up approach encouraging the use of data mining techniques, others argue that educational data sets and technical analyses only become meaningful when guided by a learning theory. We believe that a good combination of both ingredients is most desirable and promising. At least two questions emerge in this respect: what information to provide, and, how to present it (e.g. ALI, HATALA, GASEVIC & JOVANOVIC, 2012).

¹ E-mail: wgreller@gmail.com



For higher education institutions, ownership of learner data originating from the delivery systems and learning platforms offers new ways to evaluate their learning services, success rates and student support requirements, and may help in reducing drop-out and failure. Learning Analytics has the claimed potential for “evidence-based” decision taking.

Current discussions about learning analytics do also pertain to ethical issues (SLADE & PRINSLOO, 2013). These are concerned with the sharing and exploitation of educational datasets for wider use within and outside educational institutions for a variety of purposes including research as well as commercialisation. Ways to make learner data more accessible without jeopardising personal privacy and independent learner control over their own learning are questions that are still awaiting viable solutions (DRACHSLER & GRELLER, 2016). Steps in this direction have been undertaken by policy makers at the Open University (2014) and through the JISC Code of Practice (SCLATER & BAILEY, 2015).

In addition to the ongoing scientific and technical developments in the domain, there is increased activity at institutional level to put learning analytics into everyday teaching and learning practice. These efforts begin to show signs of impact on the learners, teachers, and the organisation as a whole. The current volume explores various examples and real life experiments with student data that demonstrate the potential in supporting student learning in various ways.

2 Contributions

This Special Issue gathers recent experiences and research examples concerning the use of Learning Analytics in higher education contexts of online and blended learning. All featured articles span across technically enabled data collection and processing/analysis, on the one hand, and, pedagogically motivated decision making by learners, teachers and other stakeholders on the other.

Focusing on gaining actionable results from data and ensuing analyses, *Tempelaar, Rienties and Nguyen* report on results from an introductory blended learning course on mathematics and statistics using worked out examples as part of the SOWISO learning environment. They adopt the perspective of “Dispositional Learning Analytics” (DLA) and argue that this allows for linking data to concrete pedagogical decisions as actionable results. The variable that they take into focus is the frequency and timing of calls for worked out examples on the part of the students. As a main finding, early usage appears to go along with better overall performance. They also study interaction with dispositions of learning emotions such as enjoyment, curiosity, frustration, or anxiety. These data are made available to both learners and tutors with the aim of informing and influencing self-regulation processes. This work makes a case for making learning data actionable and not just using them for predictive purposes.

From the perspective of optimising Higher Education based on course data, the article by *Greller, Santally, Boojhawon, Rajabalee, and Sungkur* reports on findings from a freshman course in a “Web and Multimedia Programme” of the University of Mauritius. This course is offered in blended learning mode with a dominance of online modules (three out of five). The study is based on two complete cohorts from two consecutive years. In its core, the analysis is based on the correlations between six normalised variables including gender, High School Certificate scores (prior to entering the programme) and scores within the course with specific dependencies corroborated through ANOVAs and regression analyses. Interestingly, based on the respective marks, online modules appear to rather go along with continuous assessment, whereas face-to-face modules assessment appears to favour summative examinations. There is an overall gender effect indicating a slightly better performance of female students. The dependency between regularity of participation and marks was stronger in the online modules as compared to the face-to-face modules. Based on these findings, the authors discuss strategies for further improving the delivery quality of the specific course and possible generalisations. Thus, this article exemplifies the value of summative analytics using higher education course data on quality improvement and course design.

The verification of student workload is the topic of an analysis by *Samoilova, Keusch and Wolbring*. It uses a contrastive method of comparing students' self-assessed work efforts with system data using interaction logs from video files, including number of videos watched, how much of a video was watched, how long videos were played for, and how much video material was covered. The student estimates were collected using survey data. Rather unsurprisingly, the results between self-reporting and system data diverged substantially, with students generally overestimating their time spent. The authors conclude among other things that over-reporting may be due to social desirability, but refined measuring would also be required. In any case, the article proposes to expand Learning Analytics to the new area of workload research, which can be considered important for curriculum development and comparability of degree courses.

A look at classical methodologies forms the basis of the argument by *Ledermüller and Fallmann*. They aim to show that classical factors that used system-generated data are valuable for learning effectiveness. Among those classical factors that they validate for effective learning are prior knowledge and invested learning time. The validation of their argument used a Learning Analytics approach to confirm the hypothesis for self-regulated learning scenarios with system data.

Khalil and Ebner look at massive open online courses (MOOCs) comparing student activities and engagement with success rates. In their mind, the high drop-out rates associated with MOOCs can be tackled with activity-motivation analytics that uses gamified feedback to students to stimulate persistence and motivation to learn and towards course completion. In their approach, the authors look at student interaction patterns on discussion forums, quizzes, and video lectures over the duration of a course. They find that certified users invested distinctively more time in these activities. Following from these conclusions, Khalil and Ebner develop a motivation prototype that visualises the variety of activities with charging levels of a battery. Full charge can only be achieved via performance in all four defined activity areas. They express the hope that this type of visualisation represents an aid for students against falling off in their engagement, and, avoid early drop-out of the course.

3 Future Directions

As originally predicted by the Horizon Report (New Media Consortium, 2011), Learning Analytics is no longer a theoretical concept, but is in the process of entering teaching and learning practice. Early experimentation as demonstrated in the presented contributions widens the perceived potential use of analytics to several additional and innovative ways to manage and organise teaching and learning in higher education. Among the ones highlighted here are:

- Making data-based information actionable
- Student motivation research
- Workload measurement
- Curriculum and course design to suit student needs and backgrounds
- Confirmation of classical theories and empirical evidence

Interestingly, these topics are on a different line of investigation as the growing body in predictive analytics that aims to anticipate student success or failure. In the areas mentioned here, there is, instead, a clear focus on everyday delivery and a better understanding of student needs.

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Editors



Univ.-Doz. Dr. Wolfgang GRELLER || Vienna University of Education || Grenzackerstraße 18, A-1010 Vienna

www.phwien.ac.at

wolfgang.greller@phwien.ac.at



Prof. Dr. H. Ulrich HOPPE || Research Group COLLIDE / Department INKO, University of Duisburg-Essen || Lotharstr. 63, D-47057 Duisburg

<http://www.collide.info>

hoppe@collide.info