Editor's Note

One of the most well-known requirements in educational settings is the need to know what happens in a course, lesson plan or full academic programme. That is true for any type of education but in particular for Open Education with the multiple dimensions of openness (Stracke, 2018). On the one hand, educators (i.e. teachers, professors, tutors, etc.) and practitioners in Open Education need to reshape the course plan according to the actual features of the learners (e.g., learning styles, motivation, performance, et cetera) and therefore they require real-time analytical information to supervise, assess, adapt and offer feedback to the learners. On the other hand, Open Education offers specific opportunities through online learning using Open Educational Resources (OER) and providing Massive Open Online Courses (MOOCs) (Corbi & Burgos, 2015). The online environments and platforms provide huge amount of data on all activities (a huge Excel sheet, labelled as Big Data). More importantly, Open Education with open teaching and learning is now commonly shaped by a learner-centred approach that pushes the learners to be the driver of their own learning. That is, learners require awareness to self-assess their progress along the course and make decisions for their next steps. In short, Open Education is now an always changing process that requires effective support for the decision making process by the educators and the learners.

In addition, Open Education at any time requires a big deal of flexibility, as an overall strategy for achieving learning quality and success: flexible learning means to get knowledge, retrieve information and provide feedback at any time, from anywhere; flexible teaching requires to assess from multiple locations and devices and to provide coaching in a large variety of formats; flexible academic management, to combine personal objectives with group goals along with institutional vision and accreditation requirements; flexible content authoring, to integrate open educational materials from the best sources, no matter if proprietary or not; flexible policies, to match competences with official credit recognition from those open sources.

To this extent, the emergence of big data in the open educational arena pushes the research of data mining and analytic techniques in order to describe and understand facts and processes in the course context. Learning Analytics is a relatively recent research field that provides techniques and methods to extract information from learning scenarios, to process the data for automatic discovery of information that goes beyond the raw data, and to report back the findings to the participants of the learning process (i.e. learners, educators) (Picciano, 2014). As a general approach, the human judgement plays a central role in the sense-making process of Learning Analytics systems, while the automatized discovery is a tool to accomplish this goal.

According to the International Conference on Learning Analytics and Knowledge, Learning Analytics refers to “the measurement, collection, analysis and reporting of data about learners and their contexts, for [the] purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens, 2012). It is one of the fastest growing field in technology enhanced learning research (Baker & Yacef, 2009; Ferguson, 2012; Romero & Ventura, 2007). McGrath (2010) and Romero et al. (2008) provide sample use cases of how challenges of tracking learner activities are met with data mining techniques in the context of Learning Management Systems (LMSs). Jivet et al. (2017 and 2018) present a literature review of Learning Analytics dashboards and Scheffel et al. (2017) propose an evaluation framework for Learning Analytics dashboards.

Research is very active in the Learning Analytics field, but there is yet a need for a real impact on daily activities of the end-users. Learners, educators and academic managers require a more flexible and open paradigm to integrate the best of materials, ideas, resources, strategies and any other component of the learning path. This special issue on big data and open education combines a number of excellent outcomes in the field, which can provide a real impact in both, current and future trends and research directions in the research area and the related application contexts. The special issue focuses on the full process of Learning Analytics in Open Education: from data collection methods, through innovative use of analysis techniques in the educational world, and up to information representation methods, with a clear stress on improving a flexible and personalised approach to open and distance settings, for every single shareholder in the learning process.

Analytics techniques are used for the early identification of learners at risk, for score prediction, and as a straightforward way to help learners self-assess their performance on a course. This problem is addressed by a well-known area called ‘academic analytics’ (Campbell et al., 2007), of which there are several examples in the literature. Macfadyen & Dawson (2010) present an ‘early warning system’ for educators that mines data from the LMS; Munoz-Organero et al. (2010) establish a relationship among usage patterns of LMS and learner motivation; Romero-Zaldivar et al. (2012) analyse the correlation between learner involvement on a course and the score they obtain; and Swan (2016) closes the gap between analytics, learning and visualisation.

Visual analytics techniques also use graphical representations for synthesising information and deriving insights from large amounts of dynamic, ambiguous and often conflicting data; they are used to detect the expected and discover the unexpected (Keim et al., 2008). They also increase learner retention (De Freitas, 2015) and boost the open paradigm to education (El-Assady et al., 2018). The idea behind visual analytics is to let a computer program filter and pre-process the data, arrange it visually and then let the user perform an interpretation. Given that the field of visualisation is so relevant for supporting educators and learners, Santos et al. (2013) and Bodily et al. (2018) discuss the concept of ‘learning dashboards’ and identify its empirical evaluation as a research challenge. De Laet et al. (2018) present a framework for the creation of learning dashboards, considering different roles in the learning process and allowing for their integration with third-party systems.

Beyond the logical technical risks and challenges of working with real-time information, process speed and information accuracy, however, practical daily implementation of these visualisation techniques remains a challenge. The practical adoption by non-technical educators of such dashboards requires closer integration with the educational methodology, the learning scenario and the lecturer's profile. Although there is great potential to improve the relation between learner, educator, scenario, institution and other potential practitioners and stakeholders, the field of visual learning analytics requires a clear connection with the end user (educators as well as learners) from basic to expert level, so that they become widely adopted and increasingly useful to the educational community.

The expected impact of Learning Analytics strategies ranges from the promotion of the learners' self-reflection, to the reshape of institutional educational strategies, through the support to educators. It copes with many various areas such as OER and MOOCs, formal and informal learning, face-to-face contexts, blended learning and distance scenarios. In addition, the impact on the actual learning situation highly depends on when the discovered information is presented to

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the practitioners. If the information is analyzed and provided after the course, it allows for a refinement of the educational strategy in future courses (summative approach). On the contrary, when the findings are provided during the course, then the course participants can lively adapt resources and efforts in order to get their expectations accomplished (formative approach).

Research is very active in the fields of Learning Analytics and Open Education, but there is yet a need for a real impact on daily activities of the end users and on improving the learning quality (Stracke, 2018). Learners, educators and academic managers require a more flexible and open paradigm to integrate the best of materials, ideas, resources, strategies and any other component of the learning path. This special issue on Big Data and Open Education combines a number of excellent outcomes in the field, which can provide a real impact in both, current and future trends and research directions in the research area and the related application contexts. The special issue focuses on the full process, from data collection methods, through innovative use of analysis techniques in the educational world, and up to information representation methods, with a clear stress on improving a flexible and personalised approach to open and distance settings, for every single shareholder in the learning process.

In summary, Open Education can benefit from Big Data and Learning Analytics used and analysed in the right way as well as Open Education can be the enabler for a broader implementation and acceptance of Big Data and Learning Analytics, again if realized in the correct way. Recent research shows the upcoming relevance of Big Data in Open Education through decision support systems aiming at learners and educators, usually representing the information with information visualization techniques and dashboards. There are a lot of on-going research projects related Learning Analytics and Open Education that are producing interesting results to improve learning quality and to achieve societal impact. In this special issue, we present just a selection of fine papers focused on analytics (Moreno et al.), an intelligent assistant (Lodhi et al.), higher education (Hamoud et al.), vocational education (de Lange et al.), employment (Peñalvo et al.), gamification (González-González et al.), augmented reality (Medina et al.) and Open Educational Resources (Idrissi et al). We hope that the reader enjoys as much as we did, as editors of this double-blind, peer-reviewed compilation.

Prof. Dr. Daniel Burgos

Prof. Dr. Roumen Nikolov

Assoc. Prof. Dr. Christian M. Stracke

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