Module 5 •

Data Activism in higher education, a scholarly commitment •

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• Summary •

In this module we will explore the concepts of readability, agency and negotiability applied to learning analytics. We will learn how datafication in the field of educational platforms affects university teachers and their work. We will finish this journey by suggesting that the technological advances that lead to the use of data-driven techniques cannot be passively experienced by teachers. Rather, they must be continuously active in pushing for the readability of data infrastructures and participating in the negotiation processes related to the oversight and privacy of students and of the teachers themselves. University teachers' ultimate goal is to be involved and committed, to play an active role, i.e., to have "agency" with respect to data technologies and infrastructures, in a journey that is made at the same time as the technology is developed, rather than passively accepting it after the event. This is why we will speak of "data activism". As learning analytics become more popular and some experimental and commercial applications are rolled out, university teachers need to pay attention to how technologies become part of their educational experiences and what values and imaginaries are assigned to data in teaching and learning. Specifically, it is necessary to consider the economic interests and the desire to control behaviour underlying many of the technological solutions put forward as a panacea producing information that makes teaching better, easier or more accurately targeted. Thus, our journey will start from the exploration of the concept and applications of learning analytics and its objective of supporting more effective behavioural patterns in teachers and students. Going beyond the techno-solutionism that has frequently permeated discourses and research on learning analytics, we will focus on critical literature concerning the use of educational data and, in particular, the associated ethical concerns. In order to find a balance between techno-enthusiasm and techno-disillusionment, we will look at cases that examine data in education from complex, interdisciplinary and participatory perspectives. Finally, we will consider the value of data activism in education, as a mindset and attitude that implies a critical and transformative perspective towards

the evolving techno-structure, requiring agency, negotiability and readability as the means to build fair data cultures in higher education and in society.

• Learning outcomes •

1. To understand the concept of learning analytics as the most recent expression of the strategic use of digitized educational data, including types, technological possibilities and pedagogical design.
2. To know the brief but forceful historical development of the concept of learning analytics.
3. To reflect on the ethical implications of the use of students' data and the pitfalls linked to a naive conception of learning analytics.
4. To reflect on the value of data activism concerning learning analytics and data in education as a means to build "fair" data cultures in higher education.

• Lessons •

- 5.1. Learning analytics: basic research, types and applications.
- 5.2. Fair learning analytics : an oxymoron?
- 5.3. The necessary (but insufficient) ethical discourse on the use of students' data.
- 5.4. Data activism as a scholarly commitment: building fair data cultures in higher education

• **Multimedia** [video - podcast] •

- Bonnie Stewart (2019) The ProSocial Web: Why Open Digital Practices Matter in the context of datafication – Webinar Series Fair Data Cultures in Higher Education (UOC-UWINDSOR) https://youtu.be/4RXAvHe0Mq0
- Regina Motz, Patricia Díaz (2020) - Fair learning analytics: design, participation and transdiscipline within the technostructure - Webinar Series Fair Data Cultures in Higher Education (UOC-UDELAR) https://youtu.be/O2QgvvcIXH0
- Paul Prinsloo - Will the future of Higher Education be evidence-based? - Paul Prinsloo UNISA – Lecture – UOC UNESCO CHAIR IN EDUCATIONAL TECHNOLOGIES FOR SOCIAL TRANSFORMATION - https://www.youtube.com/watch?v=UK7flnbzZ4c
- Raffaghelli, J.E. (2021) El sentido de los datos en el ecosistema educativo. "Educar con Sentido" series, 2021 edition, Eds. Rivera-Vargas, P., Miño, R., Passeron, E., Faro Digital & Grupo de Investigación Esbrina (University of Barcelona). https://youtu.be/Y9xuGSx4cuA
- Adell, J. (n.d.). Seminar 'Analíticas del aprendizaje: Una perspectiva crítica' | CENT. https://cent.uji.es/pub/jordi-adell-analitica-aprendizaje [In Spanish only]

• Recommended reading •

1. Broughan, C., & Prinsloo, P. (2020). (Re)centring students in learning analytics: in conversation with Paulo Freire. Assessment and Evaluation in Higher Education, 45(4), 617–628. https://doi.org/10.1080/02602938.2019.1679716

2. Ebbeler, J., Poortman, C. L., Schildkamp, K., & Pieters, J. M. (2016). Effects of a data use intervention on educators' use of knowledge and skills. Studies in Educational Evaluation, 48, 19–31. https://doi.org/10.1016/j.stueduc.2015.11.002

3. Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. International Journal of Technology Enhanced Learning, 4(5–6), 304–317. https://doi.org/10.1504/IJTEL.2012.051816

4. Ferguson, R. (2019). Ethical challenges for learning analytics. Journal of Learning Analytics, 6(3), 25–30. https://doi.org/10.18608/jla.2019.63.5

5. High-Level Expert Group on AI. (2019). Ethical guidelines for Trustworthy AI. Brussels. Retrieved from https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai

6. Milan, S., & van der Velden, L. (2016, October 10). The Alternative Epistemologies of Data Activism. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2850470

7. Nunn, S., Avella, J. T., Kanai, T., & Kebritchi, M. (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. Online Learning, 20(2). https://doi.org/10.24059/olj.v20i2.790

8. Raffaghelli, J. E. (2018). Educators' Data Literacy Supporting critical perspectives in the context of a "datafied" education. In M. Ranieri, L.

Menichetti, & M. Kashny-Borges (Eds.), Teacher Education & Training on ICT between Europe and Latin America (pp. 91–109). Rome: Aracné. https://doi.org/10.4399/97888255210238

9. Raffaghelli, J. E., Manca, S., Stewart, B., Prinsloo, P., & Sangrà, A. (2020). Supporting the development of critical data literacies in higher education: building blocks for fair data cultures in society. International Journal of Educational Technologies in Higher Education, 17(58). https://doi.org/https://doi.org/10.1186/s41239-020-00235-w

10. Raffaghelli, J. E., & Stewart, B. (2020). Centering complexity in 'educators' data literacy' to support future practices in faculty development: a systematic review of the literature. Teaching in Higher Education, 25(4), 435–455. https://doi.org/10.1080/13562517.2019.1696301

11. Shum, S. J. B. (2019). Critical data studies, abstraction and learning analytics: Editorial to Selwyn's LAK keynote and invited commentaries. Journal of Learning Analytics, 6(3), 5–10. https://doi.org/10.18608/jla.2019.63.2

12. Siemens, G. (2013). Learning Analytics. American Behavioral Scientist, 57(10), 1380–1400. https://doi.org/10.1177/0002764213498851

13. Slade, S., & Prinsloo, P. (2013). Learning Analytics, Ethical Issues and Dilemmas. American Behavioral Scientist, 57(10), 1510–1529. https://doi.org/10.1177/0002764213479366

14. Stewart, B., & Raffaghelli, J. E. (2020). Why should we care about datafication? Critical data literacies in Higher Education | Zenodo. Barcelona. https://doi.org/http://doi.org/10.5281/zenodo.3744135

15. Tsai, Y.-S., & Gasevic, D. (2017). Learning analytics in higher education --- challenges and policies. In Proceedings of the Seventh International Learning

Analytics & Knowledge Conference on - LAK '17 (pp. 233–242). New York, New York, USA: ACM Press. https://doi.org/10.1145/3027385.3027400

16. Vuorikari, R., Ferguson, Rebecca., Brasher, Andrew., Clow, Doug., Cooper, Adam., Hillaire, Garron., Mittelmeier, J., & Rienties, Bart. (2016). Research Evidence on the Use of Learning Analytics (p. 148). Joint Research Center - Publications Office of the European Union. https://doi.org/10.2791/955210

• Glossary •

DATA ACTIVISM – This social practice is based on data technologies and infrastructures to challenge the forms of power that are contained in the search for social and ethical justice. It emerged from existing activist cultures, such as the hacker or the free software movements. It is a type of activism made possible and delimited by the growth of datafication and data-driven practices (based on extractive techniques). It may involve using open data to collect data on a voluntary basis in order to challenge power, but it also includes hacking data from existing platforms.

DATA CULTURE – It refers to the principle established in business practices in the private and public sectors. It initially referred to the requirement that those involved in processes and activities must understand and use data sources in order to make decisions in organizational processes. More recently, however, based on the debate on data ethics, it has taken on greater meaning, touching on the design of data infrastructures, the monitoring and assessment of practices based on data and the need for change to ensure the impact of using data in an organizational and community context is appropriately balanced. Rahul Bhargava and Catherine D'Ignazio at MIT Media Lab introduced the concept of data culture into their work on data literacy in popular big data, establishing that data is for everyone and should circulate freely in order to empower people. Raffaghelli applied this concept to her work in the context of higher education, taking into account the need for a fair data culture. She defined this concept as a set of practices and narratives that contextualize the approaches and perceptions that an institution's members have about data and its use in that specific context. A fair data culture will be transparent, will allow its participants to take part in practices and decisions, and will encourage an ethical discourse so that all stakeholders, not just those at the top of the hierarchy, benefit from the use of data.

DATA ETHICS – Big data ethics, or data ethics in general, refers to systematizing, developing and recommending concepts of correct and incorrect conduct in relation to data, in particular personal data or information. Data ethics can be applied directly to the field of learning analytics and, in fact, has given rise to a central debate in this area. The issues raised include privacy, as well as how personal data can be monetized without the end-users/participants in an analytics system having a complete understanding of it.

EVIDENCE-BASED EDUCATION (EBE) – It is the principle whereby any educational practice should be based on the best evidence or scientific proof, rather than allowing tradition, educators' judgement, or other influences, to guide educational processes and practices. This principle is related to others such as evidence-based teaching, evidence-based learning, and school effectiveness research. As learning analytics has developed, it has become accepted as a source of the "best evidence". The massive, extractive logic underlying it seemingly overcomes the biases and issues inherent in experimental and observational methods of educational research.

LEARNING ANALYTICS – It is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.

5 • 1 • Learning analytics: basic research, types and applications •

In the keynote speech at the 1st conference on Learning Analytics and Knowledge in 2011 (LAK11 https://tekri.athabascau.ca/analytics/) it was noted that:

> *Learning institutions and corporations make little use of the information "discarded" by students in the process of accessing learning materials, interacting with teachers and colleagues and creating new content. At a time when educational institutions are under growing pressure to reduce costs and increase efficiency, analytics is a promising tool for identifying and planning changes in courses and at the institutional level.*

The emphasis on the opportunity provided by data collection led to the emergence in that period of a field of research dedicated to examining the link between the data tracked in digital learning environments and its continuous feedback to teaching staff, to help them make decisions, and to students, to support them in the (self-)regulation of their learning processes.

Siemens (2007) was one of the first to define this emerging field of study, *learning analytics*, based on his work with MOOCs. Together with Gasevic (another researcher who made a major contribution to the sector, as we will see later), he defined analytics as:

> *"the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Gasevic, (2012), p. 1)*

The UK's Open University, a major on-line higher education institution, went on to carry out the earliest experiments, setting up a work group that led the development of the discipline, and later producing a critique (Herodotou et al., 2019; Knight et al., 2014;

Rienties et al., 2016). Rebecca Ferguson, from the same group, developed a view of the complexity of a field in which tracking data is combined with a complex view of the possibilities of pedagogical research into the same data (Ferguson, 2012). This group of authors also emphasises that tracking data must go far beyond eLearning platforms to include their interoperability with other systems and lay solid foundations for the pedagogical constructs adopted (Knight et al., 2014; Herodotou et al., 2019). As indicated in the seminal work by Long & Siemens (2011), based on the development of themes in the LAK conference (Baker et al., 2021), areas of research in higher education were also being divided according to their relationship with:

- Efficacy of the system (preventing dropouts)
- Supporting teaching decisions (preventing failure, focusing attention, guiding further studies, etc.)
- Supporting independent studies or "self-regulation".

The different types of analytics were defined according to the data tracking technology involved and the algorithmic operations applied, as illustrated in Table 1.

DATA PROCESSING APPROACHES	TYPE OF ANALYTICS
Recording present events, ex-post analysis	Descriptive Analytics
Recording present events, ex-ante analysis	Diagnostic Analytics
Recording past events, subsequent probability	Predictive Analytics
Recording past events, modelling and recommending	Prescriptive Analytics

Table 1 - Types of Analytics

Figure 1 expands the definition by typologies showing the levels of automation and its relationship with human intervention in pedagogical processes mediated by learning analytics.

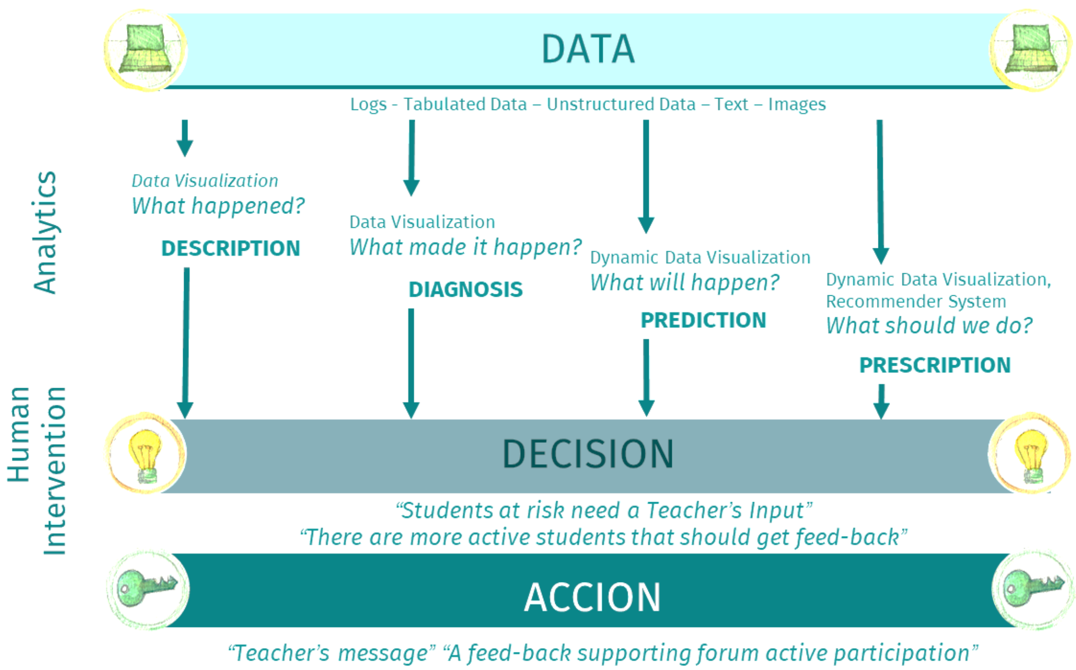


Figure 1 - Types of analytics according to the levels of automatism-human intervention interaction.

A total automation of processes is frequently assumed, but in reality, there is a great dependence on human action in the interaction with analytical systems. Furthermore, it is desirable that the teacher understand these levels of interaction as a kind of "post-human teamwork" in which the levels of automation do not compete with human action but rather support it.

Since these early beginnings, interest in analytics has grown unceasingly, partly driven by the interest of the education and computational science interdisciplinary research community. This growth was associated with the potential for applying data, especially the business opportunities detected. However, based on their experiments, researchers and developers noted a number of pitfalls that impede the use of a large part of the analytics developed or which meant that they were unreliable. This formed the basis for a socio-technical critique of analytics that took off from 2014, with contributions from authors such as Paul Prinsloo and Sharon Slade in South Africa (Prinsloo, 2017; Slade & Prinsloo, 2013) and Dragan Gasevic (Tsai & Gasevic, 2017) based on his work at the Centre for Research in Digital Education at the University of Edinburgh, which has always taken a socio-critical approach to digital technologies.

This was the background to a new debate on the quality of analytics that had not taken place prior to 2015.

Central to understanding why issues arose related to characterizing analytics systems is the complexity intrinsic to the data architectures needed to generate representations (diagnostic analytics) and systems for making recommendations (prescriptive systems) that are useful, usable and fundamentally relevant to users.

The illustrations below (Figures 2, 3 and 4) show that one of the key issues to focus on is the fact that all analytics are based on a pedagogical concept, which is a theoretical or technical construct whose features can be "tracked" using the data associated with it. For example, a "potential dropout" indicator could be less time spent on a learning platform (a simple example, for the purposes of illustration).

Figure 2 contains some of the sources of data that could form the inputs for an analytics system.

Figures 3 and 4 contain examples of learning analytics dashboards (such as Moodle plugins or experimental projects).

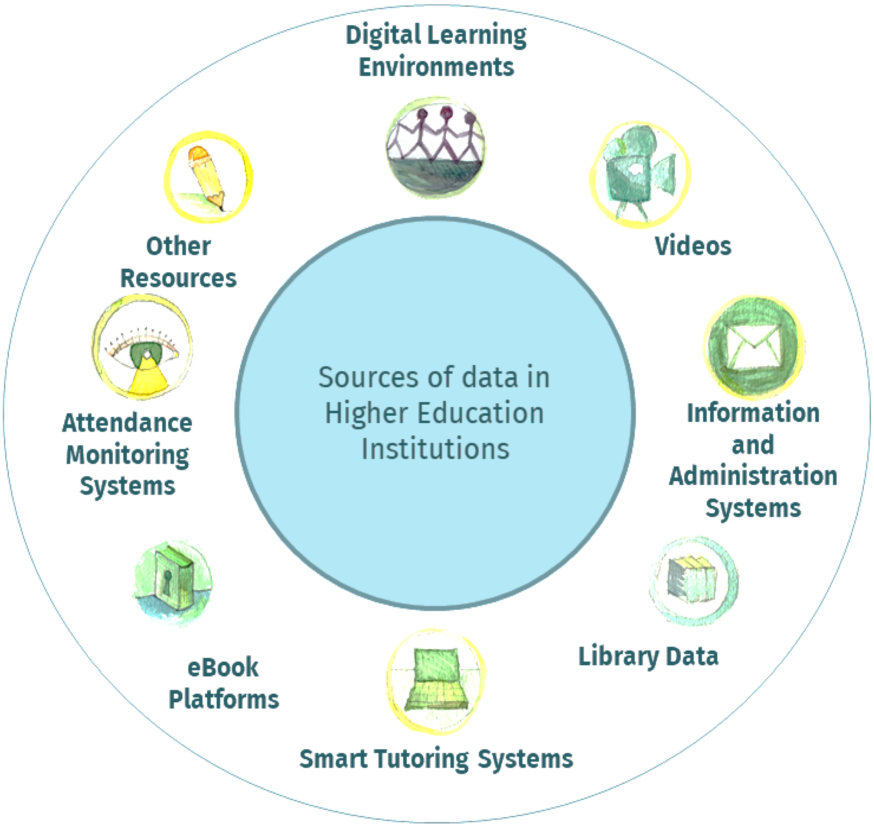
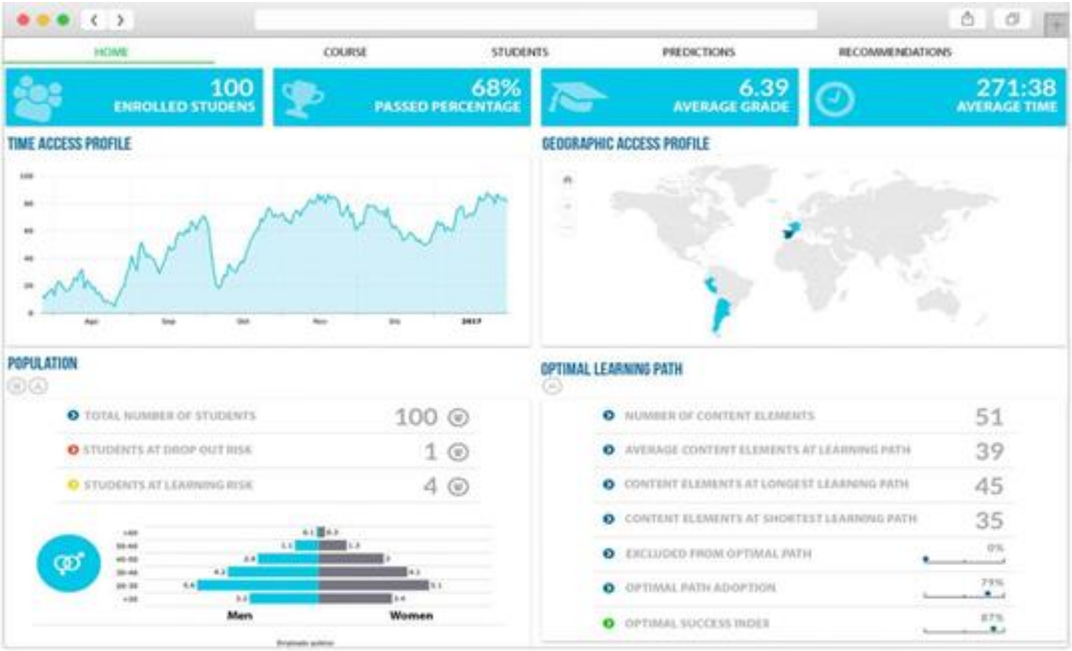


Figure 2 - Data systems used as sources for Learning Analytics

Moodle Plugins: SmartKlass - https://moodle.org/plugins/local_smart_klass



IAD Learning- https://www.iadlearning.com/learning-analytics-dna/

Figures 3 and 4 – Analytics dashboards that support students' and teachers' work

As can be seen, there are many sources of data used in existing developments, which have been published in the literature. For example, projects analysing dropout rates use a combination of student records (results obtained in previous courses), time spent in the library, enrolment in various subjects at the same time, and even personal data such as the district the student lives in (an indicator of socio-economic status).

These data are used to establish systems that predict dropout risk, which may or may not generate alerts addressed to the student at risk. Many dashboards, however (such as the first example above), are based only on information collected from the campus or online classroom. It must be borne in mind that in these cases the type of data collected may not be sufficient or relevant for making predictions. For example, in hybrid contexts, or face-to-face courses supported by some online activities, this virtual space is clearly insufficient, unless the teacher establishes and subsequently monitors attendance parameters.

And in any case how relevant can this information be, compared with direct pedagogical relations and communication?

• Further thoughts •

According to Williamson (2016, p. 404)

"Educational data science is an emerging transdisciplinary field formed from an amalgamation of data science and elements of psychological, cognitive and neuroscientific knowledge about learning, or learning science."

• In a nutshell •

- The collection of digital data in educational settings leads to the generation of diagnostics and systems for making recommendations (or prescriptions) to guide the behaviour of teachers and students based on an underlying pedagogical "conception" depending on who designs the system.
- This conception is not always visible, transparent or shared.
- We should note that a greater number of data sources means more opportunities for the algorithms to make connections, making it more likely that complex learning constructs such as "dropout risk" can work correctly.
- The dashboards are the end result of the preparation and handling of digital data and are designed to influence the behaviour of the user (teacher or student).

5 • 2 • Fair learning analytics: an oxymoron? •

Over time, as we noted in the section above, we would expect growing big data processing capacity, advances in research into algorithms and the testing of interfaces for human-computer interaction for visualizing data to provide increasing support for vital tasks such as pedagogical guidance for teachers, supporting at-risk students, empowerment, personalization and self-regulation (Viberg et al., 2018). The focus of learning analytics has expanded rapidly to encompass all levels of education (school, higher education and vocational training) and types of learning (formal, informal and non-formal). In each case, questions arise as to the viability of applying analytics systems, and the difficulties of tracking and compiling data swiftly enough for users to have effective access to a system of recommendations and visual representations that guides their behaviour in the desired direction. Analytics developers' concerns give rise to questions on the *quality* of the analytics that go beyond issues relating to the technology and human interaction. Nevertheless, these concerns about quality have not gone any further than efforts to ensure that the systems generated work *correctly*. Issues that go beyond this, taking into account aspects of quality such as inclusion, social justice and, generally speaking a critique of the use of technological development in the service of a neoliberal concept of development, have not, it seems, been considered.

- In infant and primary education, we are seeing an increasing use of toys connected to web applications, giving rise to the concept of the "internet of toys". Children's activities are digitally tracked to inform parents about their play routines and cognitive development, producing opportunities for education and stimulating early learning. In this example, commercial interests enthusiastically embrace pedagogical theory and neuroscientific advances (Chaudron et al., 2017; Holloway & Green, 2016).

- In school (primary and secondary education), the same digital architectures are applied to the analysis of multimodal learning. Wearable sensors, mobile eye-tracking as well as audiovisual and accelerometry data from sensors worn by the teacher enable the collection of data on complex classroom processes, such as orchestration graphs of collaborative activities (Prieto et al., 2018), or the social regulation of group learning (Noroozi et al., 2018). Another example from a school setting is the research carried out by the University of Oulu into developing dashboards that are more user-friendly for educational researchers, teachers and students (https://www.oulu.fi/let/) (Noroozi et al., 2018). Meanwhile, Tallinn University (https://www.tlu.ee/en/dt/centre-educational-technology) in collaboration with the Swiss Federal Institute of Technology Lausanne (https://chili.epfl.ch/) is analysing how to improve the performance of the model initially available via the interfaces, in order to reproduce classroom orchestration graphs for teacher training purposes (Prieto et al., 2018). The technical gaps in the compiling, cleaning, organization, modelling and conversion of real-time data into actionable graphics for teachers and students clearly show that this field is still in its technological infancy (Blikstein & Worsley, 2016). The initial concerns about the quality of these systems raised by researchers in the field are related to technical aspects such as the cleaning and meaningful organization of the data, in particular those related to key pedagogical constructions such as orchestration and collaborative learning. Methods for simplifying the graphical user interfaces are also being studied.

- In the field of vocational training, there is interest in "smart workplaces", based on tracking data related to tasks, time, results, and the emotional and social culture. Such data are collected, classified, aggregated and finally sent to workers and managers to support workplace learning processes (Ruiz-Calleja et al., 2017). These concepts are especially important in specific professional fields, such as medical training, where the data collected support adaptive learning processes for complex technical tasks, such as training or urgent surgical interventions such as cardiopulmonary resuscitation (Di Mitri, 2018). The difficulties associated with the use of multimodal data tracking devices, such as wearable technologies, are becoming ever more apparent. Developers are finding workers are highly resistant to systems that could be invasive in terms of their autonomy and ability to manage their own time and work breaks.

- Higher Education Institutions (HEIs) have focused on developing the kind of systems discussed in the section above, bearing in mind that at university level students are continuously online in much greater numbers and more intensively than at any other level or in any other learning situation, both via the LMS (Learning Management System) platforms that form the basis of virtual campuses and via digital text and video repositories. Students' personal data are also collected throughout their courses for administrative purposes. Nevertheless, the current state of development shows little progress with regard to the adoption of analytics, giving rise to concern about the real validity and scalability of technologies such as predictive learning analytics and dashboards for learning (Viberg et al., 2018). In addition, the ethical issues attached to the use of data are not considered serious enough for the construction of institutional policies that treat learning analytics as part of models of quality education (Vuorikari et al., 2016).

The examples presented to date exhibit certain common features. In particular, the theoretical and empirical reliability of the various technologies being explored continues to be an issue. Although it is true that the lack of authentic contexts for validating data leads to a problem related to empirical consistency, of perhaps even greater concern are problems related to the theoretical, political and ethical validity of the constructs underlying data aggregation, modelling and visualizing. In addition, data are collected in contexts where students are not always aware of the type of data published, raising ethical questions about those forms of surveillance that require balances to be found between personal privacy, the personal data needed for the quantified self, and the institutional uses of big data (Raffaghelli & Stewart, 2020).

This all suggests that analytics is still a niche development: innovation has not yet moved beyond the experimental to be turned into a service used by the educational community in HEIs. This means that no large-scale assessments of its efficacy have been performed (Vuorikari et al., 2016). So it is even less likely that we will find research focusing on aspects of quality involving equity and social justice: not only is the technology not yet sufficiently developed to the point where it can easily be applied to day-to-day teaching, but there are still so many ethical, social and political aspects to be examined that analytics remains a dark area for now.

Despite these observations, Siemens, Dawson and Lynch (2014) noted early on that the implementation of learning analytics should be considered within the framework of quality. Figure 5 illustrates the authors' vision of institutions' learning analytics sophistication, comprising five stages: awareness of learning analytics, experimentation, the training and professional development of teachers and students in its use, organizational transformation (constructing an IT-based system of institutional practices), and culminating in the transformation of the research sector, teaching information and data-based academic management. This, according to the authors, will make it possible to reflect on the quality of learning analytics, at least from the perspective of linear progress and productivity.

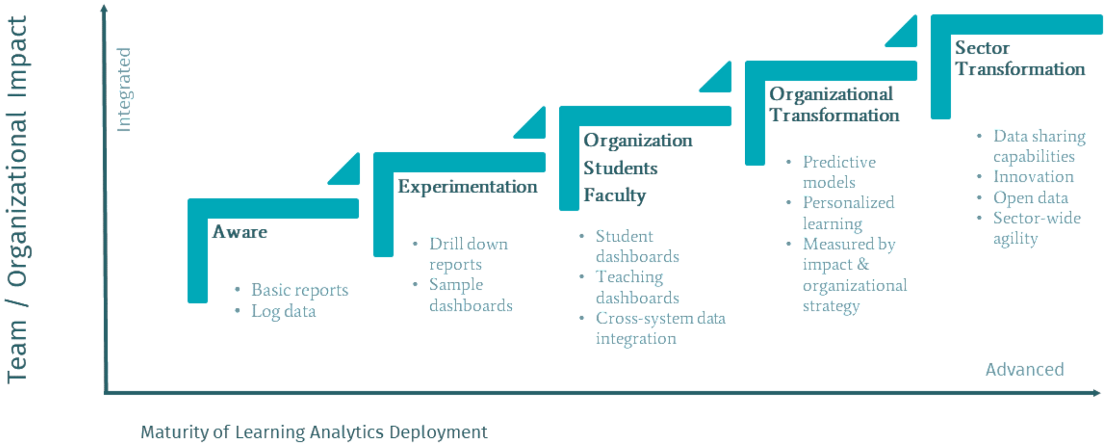


Figure 5 - Siemens, G., S. Dawson, Lynch, G, (2014) Improving the Quality and Productivity of the Higher Education Sector. White Paper for the Australian Government Office for Learning and Teaching. Retrieved from: http://bit.ly/Policy_Strategy_Analytics

Major advances are taking place, however, on two fronts.

The first is related to the development of the technology itself, with increasing levels of *in situ* experimentation to test the efficacy and impact of the instruments made available to users.

The second, more disruptive, advance, comes from the rigorous critique emerging from the social sciences. These studies indicate the need for a research and policy-making agenda for learning analytics based on a practical, contextualized and critical perspective (Prinsloo, 2017). It is extremely important to put students at the centre of a participative design process that balances decisions about privacy and the utility of instruments based on the continuous tracking of data (Broughan & Prinsloo, 2020).

Although these two lines of thought are not related to the discussion on quality, they do represent an embryonic debate about what could at a later stage be converted into instruments and education quality strategies for higher education.

• Further thoughts •

According to Broughan & Prinsloo (2020, p. 618)

"Central to much of the research on student success and retention in higher education is a normative acceptance that student dropout and failure are linked to deficits in students' educational background, attitude, commitment, and ability (Kahu & Nelson, 2018). Deficit models of understanding student ability in higher education often underpin institutional responses to students who do not correspond to the norm of often white, first-language English-speaking students (e.g. Banks & Dohy, 2019; Trent, 2019). As higher education institutions increasingly process student data in learning analytics, these deficit understandings of student learning have the potential to determine not only what data matters and are collected, but also how they are used (Macgilchrist, 2019; Vytasek, Patzak, & Winne, 2020)*. As always, the methods deployed, and the ontological stance taken will inevitably shape the evidence produced."*

** Cited in the original*

• In a nutshell •

- Over time, technological advances (growing processing capacity, advances in research into algorithms and the testing of interfaces for human-computer interaction for visualizing data) would be expected to provide increasing support for vital tasks such as pedagogical guidance for teachers, supporting at-risk students, empowerment, personalization and self-regulation.
- The focus of learning analytics has expanded rapidly to encompass all levels of education (school, higher education and vocational training) and types of learning (formal, informal and non-formal).
- This all suggests that analytics is still a niche development: innovation has not yet moved beyond the experimental to be turned into a service used by the educational community in HEIs.
- Two new lines of thought have now emerged in the debate on the use of data in the pedagogical process, concerning the experience of the user and the technical-pedagogical interface (experimentation in real teaching situations).

5 • 3 • The necessary (but insufficient) ethical discourse on the use of students' data •

Thanks to efforts to go beyond mere enthusiasm for "development", thinking on the ethics of using learning analytics has moved on to ensuring that a focus on the use of data in the teaching process is built into institutional policies.

For example, some European and Latin American initiatives have incorporated open and advanced discussions on the issues to be taken into account when "mainstreaming" learning analytics (building them into daily practice), including ethical aspects as well as design.

These include transnational projects with European funding: "LACE" (http://www.laceproject.eu/, 2014-2016) "SHEILA" (http://sheilaproject.eu/, 2015-2018) and "LALA" (https://www.lalaproject.org/, 2018-2020). The specific aim of the first of these, developed from 2015 to 2018 and led by the Open University of the Netherlands (PI Hendrik Draschler) was to develop a quality framework for analytics (Scheffel et al., 2015). This framework was called "DELICATE" (as handling students' data is a delicate matter). Each letter of the word refers to a dimension of the analysis of policies for implementing analytics in an HEI, i.e.: (D) Determination of why you want to apply learning analytics, (E) Explain it to stakeholders, (L) Legitimate, (I) Involve stakeholders in experiencing and assessing the system (C) Consent to the use of the data, (A) Anonymize data, (T) Technical/technology used to develop and perform the analytics, (E) External providers that come into contact with sensitive data must also fulfil the rules. The aim of the second project, led by the University of Edinburgh (PI

Dragan Gasevic) was to help European universities to become more mature users and custodians of digital data about their students as they learn online. It built a policy development framework that promotes formative assessment and personalized learning, by taking advantage of direct engagement of stakeholders in the development process. The framework provides pointers for an institution to self-assess whether it is correctly organizing the implementation of analytics systems, taking into account in particular the participation of its students (Tsai & Gasevic, 2017). A MOOC was also developed to aid the professional development of teachers, helping them to understand the nature and problems of analytics. The third and final project, led by Carlos III University in Madrid (PI Pedro Muñoz-Merino) expanded on the work of the SHEILA project in partnership with major Latin American universities (in Ecuador and Chile), to explore the possibilities for implementing analytics in Latin American HEIs. The project worked with an extensive network of affiliated associations that took part in research activities. In fact, in Latin America, critical thought about taking privacy into account as part of the design is at an advanced stage, factoring in all the infrastructure and organization issues affecting national and transnational projects for standardizing and harmonizing practice (Cechinel et al., 2020).

In 2018, working at Edul@b UOC, the author of this study produced a summarized map of analytics policies, referring to the ways in which said policies are applied, taking into account the DELICATE framework. A number of university websites in Europe and Latin America were sampled:

- GROUP A – 7 European cases + 3 Latin American "pioneers", participants in the LACE and LALA projects
- GROUP B – 20 "Top Performers" (10 EU and 10 LA) taken from the rankings [1] (top ten universities in said regions)
- GROUP C – 30 EU and 20 LA cases selected at random from the ranking.

The portals of these 80 universities were analysed using internal search engines, using the keywords (Learn*) AND (Analytics) OR (educational) AND (data), or (Apren*) AND

(Analític*) OR (educacional), in Spanish. Manual reviews were also performed on some specialized eLearning centres and of policy-making documents, such as institutional policy regulations.

The aspects analysed were:

- Identification of the uses of learning analytics: dropout prevention, pedagogical decision-making, pedagogical process, feedback for self-regulation
- Application of "DELICATE" criteria*: Determination, Explain, Legitimate, Involve, Consent, Anonymize, Technical, External

Two researchers allocated points from 0 (complete absence of the analysed aspect in the documentation reviewed) to 2 (full presence). The results, presented in table 2, were not very satisfactory: in general it was found that, except for those institutions closely involved in research into analytics, HEIs do not yet have policies that set usage and service standards based on learning analytics, so there is clearly no space there for a debate about ethics as a quality parameter.

Aspects analysed		**EU-A [7]**	**EU-B [10]**	**EU-C [30]**	**AL-A [3]**	**AL-B [10]**	**AL-C [20]**
Use	Dropout prevention	1.43	0	**0.03**	**0**	**0**	**0**
	Pedagogical decision-making	1.43	0.4	0.19	1	**0**	**0**
	Pedagogical process	1.71	0.2	0.19	1	**0**	**0**
	Feedback for self-regulation	**1**	0.2	0.19	**0**	**0**	**0**

DELICATE Framework	Determination	1.71	0.2	0.22	2	**0**	**0**
	Explain	1.71	**0.1**	0.16	1	**0**	**0**
	Legitimate	1.43	**0.1**	0.22	2	**0**	**0**
	Involve	**0.57**	**0.1**	**0.09**	1	**0**	**0**
	Consent	1.43	0.2	**0.06**	**0**	**0**	**0**
	Anonymize	1.43	0.2	0.18	**0**	**0**	**0**
	Technical	1.28	0.2	**0.12**	2	**0**	**0**
	External parties	**0.14**	0.2	**0.09**	2	**0**	**0**

Table 2 – Monitoring analytics policies in 80 HEIs in Europe and Latin America

In line with these findings, one of the most recent reviews of the literature available at the time this resource was being prepared (Pargman & McGrath, 2021) identified 21 works published between 2014 and 2019 concerning the ethical debate around the implementation of learning analytics systems. Nevertheless, the authors also note that the perceptions, perspectives, attitudes and views on the subject were more representative of the institutions' vision than that of the students. The areas where the most research has taken place are transparency, privacy and informed consent. There has, however, been far less exploration of the themes of justice, equity, algorithmic bias and intellectual freedom.

Griffiths (2020) went beyond this, noting the need to place the ethical discourse within a historical context. He argues that an ethical discourse is needed in the light of the exponential growth of data and the ease with which they can be used, and of the simplified approach to the transfer of the data handling tools that have emerged from the research to the processing of students' data for their use in analytics systems. He argues that the ethical discourse has viewed learning analytics as a discrete field at the expense of its connections with the wider social and institutional context, giving rise to contradictions between the use of analytics for improving quality and its use by academic management to strengthen control. This all occurs in a context of coercive extraction of data that students cannot opt out of.

Apart from these specific efforts to devise policies for implementing learning analytics, we note that the ethical debate surrounding data-based technologies has moved in the same direction as that related to the development of artificial intelligence systems. In fact, learning analytics are a special case within AI.

For example, in their review of the field, Tzimas and Demetriadis (2021) linked the ethical issues associated with learning analytics more closely with the debate on AI, linking technological development with the teaching and academic management aspects of the debate, using concepts such as labelling, algorithmic bias, and privacy by design, terms already in use and applied to AI. Figure 6 contains a map of the key concepts codified by the authors based on 53 articles examining ethical matters in learning analytics. The authors identified an initial structural level within institutions (the technological, pedagogical and institutional management dimensions) which they then linked to ethical aspects (privacy, transparency, labelling, data ownership, algorithmic fairness and the obligation to act) and their constituent elements. On the map, there are areas where the elements and concepts are more densely clustered, reflected in a greater number of articles covering those areas.

The question of privacy has received the greatest amount of attention, in general, containing lines of work including security, legal systems, anonymity, privacy by design and respect for cultural differences, based on actions such as consent, and teaching/learning about the mechanisms of the system to generate trust and methods for controlling the data. Labelling, which is necessary for the construction of systems based on machine learning, is a recurring theme in the articles reviewed, expressing concern for the autonomy of the individuals labelled and subsequently classified, with clear impacts on their behaviour. This is conceptually related to a context of paternalism and surveillance, a deterministic technological perspective and the trend towards the monetization/industrial use of the results. The areas where there are fewer concepts, and less coverage in the literature, probably because these are emerging issues, include algorithmic fairness, with a potential focus on algorithmic democracy, or "algocracy", which is closely related to institutions' obligation to act and teachers' and students' right to know.

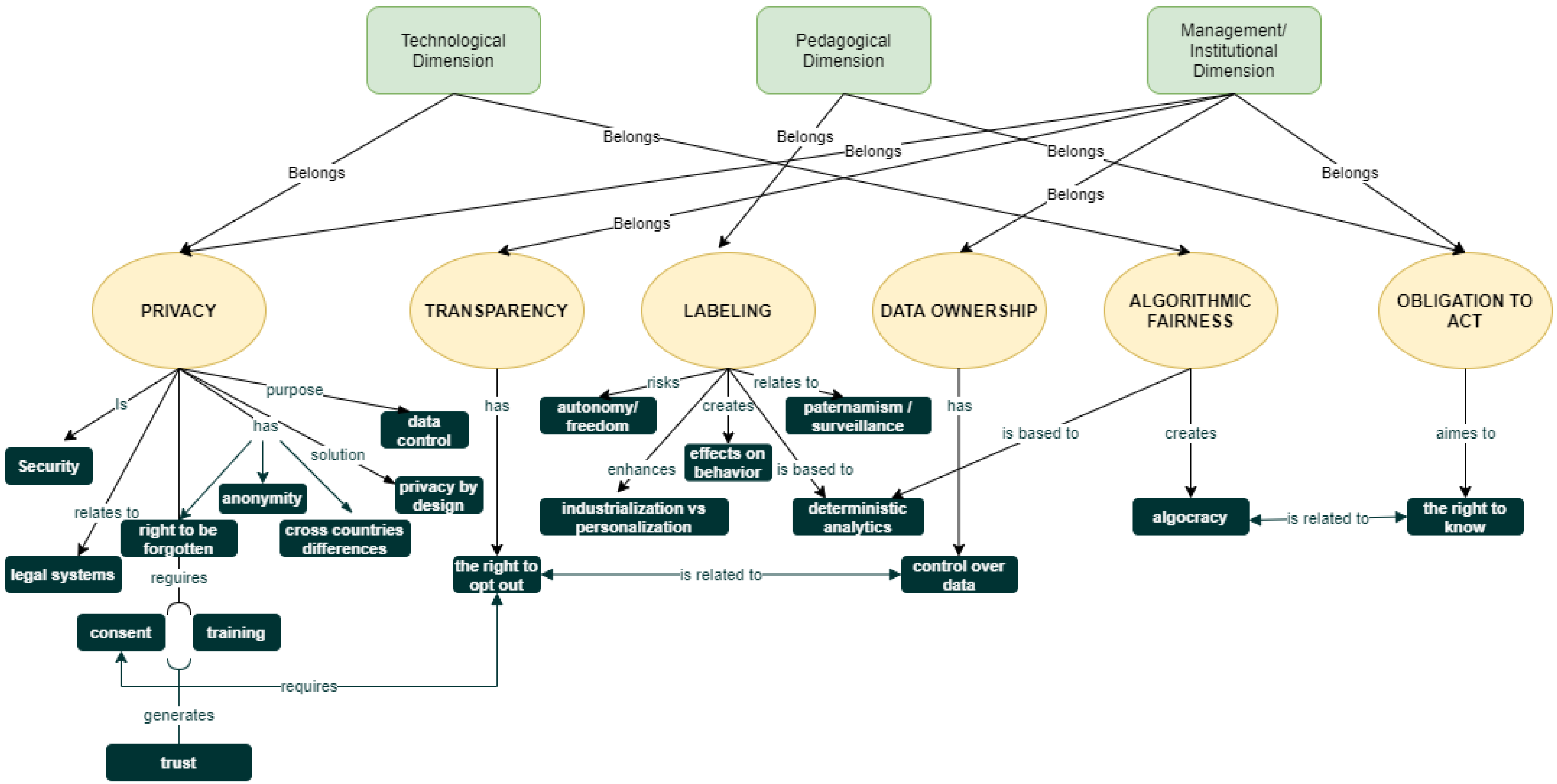


Figure 6 - Map of key concepts in the discourse on ethical issues in learning analytics (Prepared in-house based on the map by Tzimas & Demetriadis, with minor modifications)

A recently published set of guidelines on ethics in the development of learning analytics by Slade & Tait (2019, p. 2) uses the following headings:

Transparency	The purpose of a learning analytics system must be made clear to stakeholders, in particular students. Although it is fair to say that the institution may be pursuing general aims (that may not be of immediate interest to the individual, such as understanding why students drop out), how student data are collected, analysed and presented should be explained and accessible.
Data ownership and control	According to the European Union's 2018 General Data Protection Regulation, students should approve the purposes for which their data are used, and they must not be ceded to third parties without their permission. They must also have the right to access their data files and ask for them to be deleted if they so wish. The institution does not own the student data that it holds, but has temporary stewardship for purposes that must be agreed with the stakeholder.
Accessibility of data	Accessibility of data can relate to both the determination of who has access to raw and analysed data, and to the ability of students to access and correct their own data (as the owners thereof). The student should be able to send feedback requesting clarification or better information on what types of data may be used in an application. While the general focus of this work is at the institutional level, some aspects may be agreed with local, regional or national authorities.

Validity and reliability of data	Data must be valid and reliable to ensure that the reports, estimates and guidance generated from them have a sound, accurate and fair basis. Raw data does not provide any information. The operations used to define the variables and indicators (e.g. probability of dropping out) associated with the metrics and data collected (e.g. failure to log into the virtual campus in the last two weeks of the course) could be problematic (e.g. if the student did not have access to Wi-Fi and worked mainly offline). Proxy measures, variables that come close to defining a phenomenon but do not exactly match it, should also be treated with caution and should be constantly reviewed (e.g. using the number of downloads of a video to measure student engagement). The limitations of statistical calculations must also be made explicit. Certain processes involve progressive calculations that can drift substantially from their starting point (e.g. a regression model of student satisfaction based on the voluntary completion of a questionnaire). Finally, the algorithms used to process data must be very carefully defined to avoid biases that lead to groups of students or features thereof being under-represented or misrepresented (e.g. algorithms that associate race or gender with academic performance).
Institutional responsibility and obligation to act	The institution has a moral obligation to act in relation to the data collected. This is not just about a process of collecting data, it refers to information that could significantly improve (or worsen) the student's life. For example, if a specific group is observed to be at risk of dropping out, the institution must, at the very least, create a space for consulting and working with said group.

Communications	Care should be taken when communicating with students about situations of risk or conflicts detected on the basis of their analytics. Analytics that trigger communications must use appropriate language, so that the student understands it is not a personal message but an automated one, and there must always be an option for human communication to clear up disagreements and errors.
Cultural values	In multicultural contexts, extreme, unclassifiable or unusual cases (outliers) may occur more frequently and may not correlate with analytics systems generated using algorithms based on a more typical student body. Special care and attention must be paid in such cases, in particular if purchasing pre-configured analytics packages associated with LMS platforms.
Inclusion	Ensuring inclusion calls for an approach that considers more than just the goals of the institution, which can lead to students and teachers failing to identify with the technological media used. Worse still, these may be perceived as sources of control. In addition, the use of analytics by institutions, combined with national policies imposed on them (e.g. Global South) could drive behaviours and choices which do not reflect the interests of the communities in which these institutions are located, leading to even greater exclusion.

Consent	This is not about asking permission to use data, especially in circumstances where the student could feel obliged to give consent. Consent implies an act in which there is full understanding of the actions involved and their implications, with freedom to opt out of or halt processes that do not feel secure, and to request more information or results. This is particularly important in the case of sensitive data while generic data can be reported more generally.
Student agency and responsibility	Where feasible, it is recommended that institutions seek to engage students in the design, implementation and monitoring of learning analytics systems. It is important that students understand that they have a responsibility towards the university (and therefore ceding their data could be vital for the common good), both in terms of care regarding their own personal data (not revealing unnecessary information) and in their handling of the materials of third parties (not sharing materials, messages or other information obtained from teachers on social media, for example).

Along these lines, Selwyn (2019) noted some of the key issues that could arise from the misuse of learning analytics. These revisit and broaden the points discussed above.

The consequences of misusing analytics could include:

- A reduced understanding of education. The phenomena measured by the data collected in the analytics necessarily minimize the complexity of the learning process.

- Ignoring the broader contexts of education. Learning analytics suffers from a lack of understanding of the social dynamics that can make an educational issue important, while detecting and guiding irrelevant micro-behaviour.

- Reducing students' and teachers' capacity for informed decision-making. Systems that provide diagnoses and recommendations run the risk of diminishing users' ability to understand their own cognitive processes and interactions.

- A means of surveillance rather than support. When analytics are used to observe if users' behaviours align with the interests of the business.

- A source of performativity. When measuring systems are invented, users learn to act in ways that "please" the indicators, i.e. they perform for the system.

- Disadvantaging those excluded from the system. When an assessment and recommendation model is based on behaviours seen as desirable for the elite group responsible for programming the system, there is a risk of excluding minorities who do not fit this pattern.

- Serving institutional (rather than individual) interests. When an institution collects mass volumes of data using systems it has developed itself, it has unlimited scope for acting in its own interests following its own models of ethics and professional duty.

Selwyn's proposals to remedy these issues include:

- Giving users the right to inspect. The design of analytics applications that are more open and accessible, giving users genuine control and supervision, better reflecting their real lives.

- Giving users more control over their data. Designing learning analytics systems to inform users of how their data are being used in research and in institutional business models linked to education.

- Rethinking the governance and economy of the learning analytics industry. All the services for visualizing data and recommendation systems linked to learning platforms have the potential for monetizing students' data to produce new dashboards and recommendation services.

One final point that cannot be ignored is the impact of the COVID-19 pandemic, which forced the widespread use of digital platforms and tools, initially generating a naive enthusiasm for what was considered a global experiment in the use of educational technologies. Williamson et al. (2020) termed this phenomenon "pandemic pedagogy". The economic policy behind what appeared to be a heroic response from "Big Tech" companies such as Google, Amazon, Microsoft, Apple and Facebook, later became an opportunity for the massive extraction of student data which could then be monetized in digital educational products and services. In fact, said companies (especially Google and Microsoft) immediately offered free training services and the use of their platforms and cloud-based storage, representing a fast and easy solution for many governments. In the early months of the pandemic, many countries opted to support or legalize this use by purchasing private services to provide public education (Bozkurt et al., 2020). According to Williamson et al. (2020), these and other actors in the EdTech industry treated "the crisis as a business opportunity" (op.cit., p.108) with "potentially long-term consequences for how public education is perceived and practised long after the coronavirus has been brought under control" (p.108). This mechanism, which was studied in detail in a report on higher education institutions by Williamson & Hogan (2021), was used by many welfare states as a subterfuge for privatizing a formerly public asset, bringing their policies pragmatically and "by default" into line with neoliberal thinking. One of the concerns expressed by Williamson & Hogan was how the analytics services business has been built up by training, predicting and fine tuning algorithms using mass volumes of data harvested from universities that had no other resources to pay for these services except in the form of their students' data, especially universities in developing countries, or in city outskirts or community networks. This is linked to "long-standing pressures of HE marketisation, privatisation and commercialisation" which "are now instantiated in and enacted by educational digital technologies and data systems weaving educational aims together with political aspirations to regulate HE in terms of its performance on multiple metrics and private sector ambitions to capitalise on emerging market opportunities" (the commodification of data) (p.17).

This criticism of the principles underlying products based on harvesting students' data brings into question the very existence of the products (such as learning analytics) that they generate. These products are themselves constructed on a failed premise, that of appropriation and commercialization, so it is pointless to debate whether data have been collected with or without consent or participation, if they are later transformed for the benefit of a few. And it must be remembered that all ethical approaches can be criticized as having a fatal flaw: they encourage "whitewashing" practices by businesses, who use recommendations, declarations of adherence to international standards, lists and guidelines to paint a superficial portrait of ethical behaviour (Green, 2021).

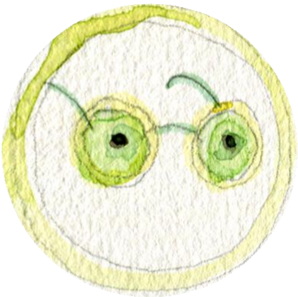
• Further thoughts I •

In the race to develop analytics systems, the ease with which data can be collected was initially highlighted as an opportunity.

A critical movement later emerged based on aspects of how people interact with analytics and issues of educational and social fairness.

Why do you think analytics has developed along these lines?

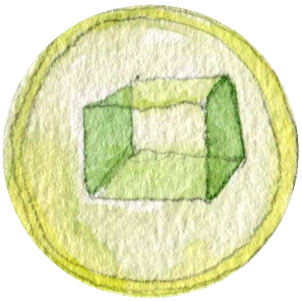
• Further thoughts II •



According to the report coordinated by Vuorikari et al. (2016), all the signs are that analytics is still a niche development: innovation has not yet moved beyond the experimental to be turned into a service used by the educational community in HEIs. This means that no large-scale assessments of its efficacy have been performed.

Do you know of any mass data applications used in the university? Think about why you would give a negative or positive response.

• Further thoughts III •



Open and advanced discussions are taking place in Europe and Latin America on the issues to be taken into account when "mainstreaming" learning analytics (building them into daily practice), including ethical aspects as well as design.

Are you aware of any debates around the use of students' data in your university? Think about why you would give a negative or positive response.

• In a nutshell •

- Reviews of the literature identify a number of key works on the ethical debate surrounding the implementation of learning analytics systems. Nevertheless, the perceptions, perspectives, attitudes and views on the subject were more representative of the institutions' vision than that of the students.
- The areas where the most research has taken place are transparency, privacy and informed consent.
- There has, however, been far less exploration of the themes of justice, equity, algorithmic bias and intellectual freedom.
- Other studies focus on the failure of analytics systems to take into account historical or cultural contexts.
- International proposals and recommendations have emerged from the research. In general they relate to issues such as giving users control, the right to be forgotten and the right to know, together with institutions' obligation to act.
- Two new lines of thought have now emerged in the debate on the use of data in the pedagogical process, concerning the experience of the user and the technical-pedagogical interface (experimentation in real teaching situations).

5 • 4 • Data activism as a scholarly commitment: building fair data cultures in higher education •

Discussion of the development of and innovations in learning analytics seems much more advanced than considerations about the educational quality cultivated and embedded in systems based on student data. While technical, social, educational and ethical issues are under review, the question remains as to how useful, inclusive and "fair" analytics are. The notion of encouraging participative design and taking into account the ethical issues inherent in the use of data should not be raised after the system is implemented, but before it is developed. We must also appreciate that, the more recent a techno-pedagogical innovation is, the less discussion concerning quality we will find, even more so concerning the associated socio-ethical issues: these normally emerge later, when cases arise that generate public debate. The problems that emerge from social and technological research still form the base of what will go on to be the focus of studies of quality. There is still, therefore, a long way to go.

• Why do we want to focus on "Data Activism"? •

Data activism emerged as a response to the surveillance inequalities identified by José van Dijck (2014) and subsequently explored by other authors who pointed out the differences in activists' approaches to preventing the worst aspects of datafication (Gutiérrez, 2018; Lehtiniemi & Ruckenstein, 2019; Milan & van der Velden, 2016). Milan & van der Velden (2016) postulated that some activists fall on the side of seeing data as a common good, for opening up science and government, while others engage in resistance, attempting to remove themselves from surveillance devices or protesting against their existence. In *Critical Data Futures*, Neil Selwyn (2021) returned to the idea that a range of future scenarios could arise with regard to our attitude, understanding and use of data, and it is therefore necessary to work actively, using these futures to determine how to act in the present.

We must not forget at this point the important work done by communities promoting open software, linked today to what we understand as forms of digital, technological infrastructure and, consequently, data sovereignty. For example, using the DECIDIM en Barcelona platform (https://www.decidim.barcelona/), Francesca Bria (coordinator of the European DECODE project behind said platform) introduced an activist approach based on the idea that data should be accessible to all, whether the data are generated by the public or private sector (Graham, 2018). Several Latin American universities use open-source software as a basis for ensuring they control how data are used (Cechinel et al., 2020) and are calling for educational policies that take into account the potential loss of control to foreign platforms (Lim & Tinio, 2018). Another interesting example is the Huayra scheme to distribute Linux operating systems for installation in PCs issued to teachers and students by the Argentine government until 2015 (Ceballos et al., 2020).

There is an Universitat Oberta de Catalunya initiative along these lines: the Folio tool (https://folio.uoc.edu/es/).

The tool was the idea of Prof. Quelic Berga, who describes it as follows on the Folio home page:

Folio is a reinterpretation of the portfolio concept that allows users to work collaboratively, to develop a digital image, to build an identity as a student and make this identity visible in the professional world, among other functions that you will discover in this document and while you are using the tool. Folio has been developed using WordPress technology. As you may know, WordPress is open source software developed by hundreds of collaborators. It is currently one of the most popular platforms for creating blogs and all types of website.

This short presentation highlighted two key aspects: that the tool will digitally capture, through a voluntary act by the student, central elements of their professional identity, and that it does so using non-private software.

Folio is based (as pointed out on its home page) on the transversal publication of students' achievements during their courses, with graphics and an aesthetic chosen by the students themselves, allowing them to connect transversally with other members of the university community who may be interested in work published in an individual Folio. The idea is clearly intended to move away from the traditional way of recording achievements (a course-based degree), with achievements presented as selected items based on a decision involving both content and aesthetic structure. The project includes students' data, which they are free to select. These data are linked to databases "stewarded" by the university. The visibility and representative nature of the tool give students a sense of ownership, personal development and usage.

Figure 7 – Quelic Berga presents Folio as part of the "Data Praxis" project https://datapraxis.net/taller-2-datos-en-el-proceso-pedagogico-en-busca-del-equilibrio/

This view of how Folio embeds the UOC's learning model in the graphical interface of its virtual campus is one example of how student data can be used to create spaces that give students greater creative and expressive freedom rather than for tracking, profiling and controlling their behaviour. The design of Folio's technological interfaces and infrastructures is underpinned by political, cultural and social postulations that affect how students relate as a community, a special kind of community that never meets in person (the university is entirely online). This model allows students to create a personal online space for working and presenting their work, thereby empowering both the student and the community by facilitating the circulation of data that have been consciously chosen and shared. Berga's intention is to encourage a culture of data governance, technological sovereignty and free software.

The development of Folio has led to an additional reflection: data, when collected in accordance with principles of equity and fairness, as described in previous sections, can be transformed in many ways, including as graphics or as information associated with the activities of the participants. Nevertheless, it must never be forgotten that these representations are cultural artefacts, an assemblage of processes, practices and ideas that are material (they exist in the world) before they are converted into digital representations. If, therefore, they are taken away from the end user, they end up representing the desire of a power group, which implies control and a focus on productive goals, the efficacy of the system, etc.

The harvesting of student data and closely related developments such as analytics have no power in themselves, unless they are a product of a cultural system, a fair data culture (see the glossary for this module) that shapes them. They are only useful if they are recognized as such, and made part of the life of the class or the learning community in order to enrich their discussions and narratives. For the authors, therefore, no data harvested from the pedagogical process and transformed and reorganized as learning analytics can lead to "success", "efficacy", "productivity" or "self-regulation". Instead, a creative use of data, balanced within a system of resources, can inform the decisions and/or discussions that this group of humans can (and wish to) engage in, as part of their pedagogical relationship.

It is clear that an activist approach seems necessary in a context where the interrelations between technological development, economic interests and the policies that inform institutional strategies leave teachers little room for free agency. Resistance, opposition and drawing attention to violations of the ethical mechanisms discussed previously cannot always take place in an institutional framework. Academics can often be found acting alone, or in groups which are of increasing interest, trying to oppose or delay actions, derecognize devices or even block them when technology is being used coercively in scenarios where they suspect data are being monetized. This may even extend to "civil disobedience" (García González, 2006): a striving for justice that sometimes, occasionally, means breaking rules or standards that form part of the system established to ensure justice, but which is revealed as unjust by the act of civil disobedience. For example, a data system that profiles students to predict enrolment patterns and thus regulate the university's cash flows, in order to maintain certain staffing levels, could be the object of resistance or obfuscation by groups of academics who seek to protect their classes and their pedagogical relationship with their students.

Alternatively, academics may take a proactive approach, using open-source software or setting up work groups that use said software as the basis for technologically mediated educational innovation, as demonstrated by the Folio initiative.

In line with the cases studied by Miren Guitérrez in her work on data activism as a source of social change (2018), the teacher thus uses their intellectual autonomy to become a node in a network of transformation, or at least of resistance to scenarios involving a loss of transparency, where negotiation is not possible and technological sovereignty is therefore removed from the teacher's relationship with their students.

• Further thoughts •

To what extent is "disobedience" an option for teachers? Is it desirable or viable to oppose technological innovation in your area of work? If we embrace these innovations, should we ask ourselves what values (axiologically or ethically speaking) we are fostering?

• In a nutshell •

- The more recent a techno-pedagogical innovation is, the less discussion concerning quality we will find, even more so concerning the associated socio-ethical issues: these normally emerge later, when cases arise that generate public debate.
- Data activism emerged as a response to surveillance inequalities. Later studies explored the differences in activists' approaches to preventing the worst aspects of datafication.
- Activists are working on the basis of future data use scenarios, constructing in the present small spaces and actions that lead towards these futures.
- We already have some good examples (including in education) of current projections, with data activism pushing for technological and data sovereignty and the need to open and share the richness of data wherever possible.

• Module References •

Adell, J. (n.d.). *Seminar 'Analíticas del aprendizaje: Una perspectiva crítica' | CENT*. Retrieved 26 September 2021, from https://cent.uji.es/pub/jordi-adell-analitica-aprendizaje

Baker, R. S., Gašević, D., & Karumbaiah, S. (2021). Four paradigms in learning analytics: Why paradigm convergence matters. *Computers and Education: Artificial Intelligence*, 2, 100021. https://doi.org/10.1016/j.caeai.2021.100021

Blikstein, P., & Worsley, M. (2016). Multimodal Learning Analytics and Education Data Mining: Using Computational Technologies to Measure Complex Learning Tasks. *Journal of Learning Analytics*, *3*(2), 220–238. https://doi.org/10.18608/jla.2016.32.11

Bozkurt, A., Jung, I., Xiao, J., Vladimirschi, V., Schuwer, R., Egorov, G., Lambert, S. R., Al-Freih, M., Pete, J., Olcott, D., Rodes, V., Aranciaga, I., Bali, M., Alvarez, A. V., Roberts, J., Pazurek, A., Raffaghelli, J. E., Panagiotou, N., De Coëtlogon, P., … Paskevicius, M. (2020). A global outlook to the interruption of education due to COVID-19 Pandemic: Navigating in a time of uncertainty and crisis. *Asian Journal of Distance Education*, *15*(1), 1–126. https://doi.org/10.5281/zenodo.3878572

Broughan, C., & Prinsloo, P. (2020). (Re)centring students in learning analytics: In conversation with Paulo Freire. *Assessment and Evaluation in Higher Education*, *45*(4), 617–628. https://doi.org/10.1080/02602938.2019.1679716

Ceballos, L. D., Maisonnave, M. A., & Londoño, C. R. B. (2020). Soberanía tecnológica digital en Latinoamérica. *Propuestas para el Desarrollo*, *IV*, 151–167.

Cechinel, C., Ochoa, X., Lemos dos Santos, H., Carvalho Nunes, J. B., Rodés, V., & Marques Queiroga, E. (2020). Mapping Learning Analytics initiatives in Latin America. *British Journal of Educational Technology*, *51*(4), 892–914. https://doi.org/10.1111/bjet.12941

Chaudron, S., Gioia, R. Di, Gemo, M., Holloway, D., Marsh, J., Mascheroni, G., & Peter, J. (2017). *Kaleidoscope on the Internet of Toys Safety, security, privacy and societal insights*. https://doi.org/10.2788/05383

Colmenarejo Fernández, R. (2018a). Ética aplicada a la gestión de datos masivos. *Ética Aplicada a La Gestión de Datos Masivos*, *52*(52), 113–129. https://doi.org/10.30827/acfs.v52i0.6553

Colmenarejo Fernández, R. (2018b). *Una ética para big data*. UOC Editorial. https://www.editorialuoc.cat/una-etica-para-big-data

Di Mitri, D. (2018). *Multimodal Tutor for CPR* (pp. 513–516). Springer, Cham. https://doi.org/10.1007/978-3-319-93846-2_96

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6), 304–317.

Ferguson, R., Brasher, A., Clow, D., Cooper, Adam., Hillaire, Garron., Mittelmeier, J., Rienties, B., Ullmann, T., & Vuorikari, R. (2017). *Research Evidence on the Use of Learning Analytics Implications for*

Education Policy. - R. Vuorikari, J. Castaño Muñoz (Eds.). Joint Research Centre Science for Policy Report; EUR 28294 EN; doi: 10.2791/955210.https://intef.es/wp-content/uploads/2017/05/Learning-Analytics_JRC_INTEF_Abri2017.pdf

García González, D. E. (2006). La desobediencia civil como recurso de la sociedad civil para el alcance de la justicia. *Signos filosóficos*, *8*(15), 25–64.

Graham, T. (2018, May 18). Barcelona is leading the fightback against smart city surveillance. *Wired UK*. https://www.wired.co.uk/article/barcelona-decidim-ada-colau-francesca-bria-decode

Green, B. (2021). *The Contestation of Tech Ethics: A Sociotechnical Approach to Ethics and Technology in Action*. http://arxiv.org/abs/2106.01784

Griffiths, D. (2020). The Ethical Issues of Learning Analytics in Their Historical Context. In D. Burgos (Ed.), *Radical Solutions and Open Science: An Open Approach to Boost Higher Education* (pp. 39–55). Springer. https://doi.org/10.1007/978-981-15-4276-3_3

Gutiérrez, M. (2018). *Data Activism and Social Change*. Palgrave Pivot. https://doi.org/10.1007/978-3-319-78319-2

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., & Hlosta, M. (2019). A large-scale implementation of predictive learning analytics in higher education: The teachers' role and perspective. *Educational Technology Research and Development*, *67*(5), 1273–1306. https://doi.org/10.1007/s11423-019-09685-0

Holloway, D., & Green, L. (2016). The Internet of toys. *Communication Research and Practice*, *2*(4), 506–519. https://doi.org/10.1080/22041451.2016.1266124

Knight, S., Buckingham Shum, S., & Littleton, K. (2014). Epistemology, Assessment, Pedagogy: Where Learning Meets Analytics in the Middle Space. *Journal of Learning Analytics*, *1*(2), 23–47.

Lehtiniemi, T., & Ruckenstein, M. (2019). The social imaginaries of data activism. *Big Data & Society*, *6*(1), 205395171882114. https://doi.org/10.1177/2053951718821146

Lim, C., & Tinio, V. L. (2018). Analíticas de aprendizaje para el sur global. *Fundación para la Formación en Tecnología de la Información y el Desarrollo*. https://prep-digital.fundacionceibal.edu.uy/jspui/handle/123456789/279

Long, P., & Siemens, G. (2011). Penetrating the Fog: Analytics in Learning and Education | EDUCAUSE. EDUCAUSE Review, 31–40.

Milan, S., & van der Velden, L. (2016). *The Alternative Epistemologies of Data Activism*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2850470

Noroozi, O., Alikhani, I., Järvelä, S., Kirschner, P. A., Seppänen, T., & Juuso, I. (2018). Multimodal Data to Design Visual Learning Analytics for Understanding Regulation of Learning. *Computers in Human Behavior*. https://doi.org/10.1016/J.CHB.2018.12.019

Pargman, T. C., & McGrath, C. (2021). Mapping the Ethics of Learning Analytics in Higher Education: A Systematic Literature Review of Empirical Research. *Journal of Learning Analytics*, *8*(2), 123–139. https://doi.org/10.18608/jla.2021.1

Prieto, L. P., Sharma, K., Kidzinski, Ł., Rodríguez-Triana, M. J., & Dillenbourg, P. (2018). Multimodal teaching analytics: Automated extraction of orchestration graphs from wearable sensor data. *Journal of Computer Assisted Learning*, *34*(2), 193–203. https://doi.org/10.1111/jcal.12232

Prinsloo, P. (2017). Fleeing from Frankenstein's monster and meeting Kafka on the way: Algorithmic decision-making in higher education. *E-Learning and Digital Media*, *14*(3), 138–163. https://doi.org/10.1177/2042753017731355

Raffaghelli, J. E. (2020). *Analíticas de Aprendizaje ¿Un continente oscuro?* Universitat Oberta de Catalunya.

Raffaghelli, J. E., & Stewart, B. (2020). Centering complexity in 'educators' data literacy' to support future practices in faculty development: A systematic review of the literature. *Teaching in Higher Education*, *25*(4), 435–455. https://doi.org/10.1080/13562517.2019.1696301

Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action Evaluation Framework: A Review of Evidence-Based Learning Analytics Interventions at the Open University UK. *Journal of Interactive Media in Education*, *2016*(1). https://doi.org/10.5334/jime.394

Ruipérez-Valiente, J. A. (2020). El Proceso de Implementación de Analíticas de Aprendizaje. *RIED. Revista Iberoamericana de Educación a Distancia*, *23*(2), 85–101. https://doi.org/10.5944/ried.23.2.26283

Ruiz-Calleja, A., Prieto, L. P., Ley, T., Rodríguez-Triana, M. J., & Dennerlein, S. (2017). *Learning Analytics for Professional and Workplace Learning: A Literature Review* (pp. 164–178). Springer Verlag Heidelberg. https://doi.org/10.1007/978-3-319-66610-5_13

Scheffel, M., Drachsler, H., & Specht, M. (2015). Developing an evaluation framework of quality indicators for learning analytics. *ACM International Conference Proceeding Series*, *16-20-March-2015*, 16–20. https://doi.org/10.1145/2723576.2723629

Selwyn, N. (2019). What's the problem with learning analytics? *Journal of Learning Analytics*, *6*(3), 11–19. https://doi.org/10.18608/jla.2019.63.3

Selwyn, N. (2021). *Critical data futures*. https://doi.org/10.26180/15122448.v1

Siemens, G., Dawson, S., & Lynch, G. (2014). *Improving the Quality and Productivity of the Higher Education Sector. White Paper for the Australian Government Office for Learning and Teaching*.

Siemens, G., & Gasevic, D. (2012). Guest Editorial—Learning and Knowledge Analytics. *Journal of Educational Technology & Society*, *15*(3), 1–2.

Slade, S., & Prinsloo, P. (2013). Learning Analytics, Ethical Issues and Dilemmas. *American Behavioral Scientist*, *57*(10), 1510–1529. https://doi.org/10.1177/0002764213479366

Slade, S., & Tait, A. (2019). *Global guidelines: Ethics in Learning Analytics*. ICDE. https://www.icde.org/knowledge-hub/the-aim-of-the-guidelines-is-to-identify-which-core-principles-relating-to-ethics-are-core-to-all-and-where-there-is-legitimate-differentiation-due-to-separate-legal-or-more-broadly-cultural-env-5mppk

Tsai, Y.-S., & Gasevic, D. (2017). Learning analytics in higher education—Challenges and policies. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference on - LAK '17*, 233–242. https://doi.org/10.1145/3027385.3027400

Tzimas, D., & Demetriadis, S. (2021). Ethical issues in learning analytics: A review of the field. *Educational Technology Research and Development*, *69*(2), 1101–1133. https://doi.org/10.1007/s11423-021-09977-4

Van Dijck, J. (2014). Datafication, dataism and dataveillance: Big data between scientific paradigm and ideology. *Surveillance and Society*, *12*(2), 197–208. https://doi.org/10.24908/ss.v12i2.4776

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. In *Computers in Human Behavior* (Vol. 89, pp. 98–110). Pergamon. https://doi.org/10.1016/j.chb.2018.07.027

Vuorikari, R., Ferguson, Rebecca., Brasher, Andrew., Clow, Doug., Cooper, Adam., Hillaire, Garron., Mittelmeier, J., & Rienties, Bart. (2016). *Research Evidence on the Use of Learning Analytics*. https://doi.org/10.2791/955210

Williamson, B. (2016). Coding the biodigital child: The biopolitics and pedagogic strategies of educational data science. Pedagogy, Culture & Society, 24(3), 401–416. https://doi.org/10.1080/14681366.2016.1175499

Williamson, B., Eynon, R., & Potter, J. (2020). Pandemic politics, pedagogies and practices: Digital technologies and distance education during the coronavirus emergency. In *Learning, Media and Technology* (Vol. 45, Issue 2, pp. 107–114). Routledge. https://doi.org/10.1080/17439884.2020.1761641

Williamson, B., & Hogan, A. (2021). *Education International Research Pandemic Privatisation in Higher Education: Edtech & University Reform*. Education International.

• Recommended Activity •

If you are engaged in academic development and coordination, organize a space for reflection with your colleagues to explore your own data culture:

- What types of data are we using in our teaching activity?
- How do the data relate to or form part of the development policies of our university?
- How do we feel about the data-driven images used in quality systems, academic policy-making, or to inform teaching practice and that involve us directly?
- How are students informed about the use of data obtained from educational processes?
- What channels for dialogue with technological development groups exist in relation to the innovations applied in the virtual campus?

Use these results to:

- Generate a permanent working group that supports interdisciplinary dialogue to foster a fair data culture.
- Raise the issue in activities connected to organizational development such as meetings, open sessions, workshops, etc.
- Participate via a scholarship of teaching and learning approach that focuses on issues of data use. Produce scholarly literature drawn from your teaching practice that helps to widen current thought and debate, especially that linked to techno-enthusiastic narratives.

If you are a teacher who works in university teaching and research, make room in your courses to discuss the following questions with your students:

- What types of data are we using in the teaching process and what meaning do we attribute to them?
- How do we feel about the data-driven images used to assess students' work, to evaluate students within a quality system and to project an image of ourselves to the outside world on the basis of these indicators?
- How can we gain more "control" over the use of learning analytics and other metrics in higher education?

 Back to Understanding Data: Praxis+Politics

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