Learning Analytics as a tool in academic learning contexts: Possible impacts on social inclusion

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Abstract
In the field of teaching and learning processes, the potential of Learning Analytics is one of the topics that is attracting most interest in the scientific community. However, it would be important to place L.A. within a historical perspective, able to focus on the scientific, cultural and social roots of this approach. This would also allow us to address a question that cannot be overlooked, namely whether Learning Analytics is one of the teaching technologies or, rather, should be understood as a new global approach to learning processes. In our opinion, L.A. are placed at the crossroads between the formal and informal dimensions of learning and are part of the behaviorist tradition, with the aim of identifying the behavioural clusters that recur most frequently and which are considered to adhere to predefined performance standards. The search for the performative standard typical of L.A., not considering the differences, the peculiarities and the specific personal abilities as of the resources, seems, moreover, to refer to the system/model of the integration that, in a homologating perspective more than inclusive, sets objectives on the basis of a presumed normality, ignoring Specific Learning Disorder (SLD) and Special Educational Needs and Disability (SEND).

Keywords: Learning Analytics, Inclusion, Behavior, Education, Technology, MOOC.

Introduction

Until a few decades ago it was quite easy to draw the line between formal, informal and non-formal education. Formal education was an intentional, normalised and largely compulsory education given in organised training contexts, the aim of which was to lead to the attainment of a qualification. The

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school was the privileged place to provide formal knowledge and the teachers were the depositaries of this. Non-formal education, on the other hand, was the result of attending sports, musical, artistic and religious clubs. These learnings - even if structured - were highly personal, as they were not compulsory, not always programmatic and closely linked to the contexts of life of the individual subjects. Finally, informal education, unstructured in terms of objectives, times and methods, included all those lessons deriving from social relations: family, friendships and peers (Galliani, 2012).

Since the advent of the Web, the possibilities and places of learning have multiplied. The Web, as we know it today, in fact, allows both the acquisition of formal learning (from academic sites, online newspapers, e-learning platforms and MOOC), non-formal learning (thanks to apps we can have in our pockets, for free or at low cost, "laboratories" with which to exercise, for example, our musical or photographic skills) and informal learning (social networks still convey knowledge and skills of various kinds and prefigure complex forms of collective intelligence). Starting a few years ago, didactics has been measuring itself with this multiform universe, in search of innovation strategies that allow it to keep up with the times.

Learning Analytics' behaviorist roots?

The potential of Learning Analytics in the field of teaching and learning processes is one of the topics that is attracting most interest in the scientific community. In fact, in the face of a growing number of experiments and a fairly intense conference activity, there are still few studies produced on L.A. at international level. We do not know whether this is an indication of a theoretical reflection activity still in an embryonic phase or, rather, of an attitude of the "experts"mainly oriented towards "doing" and field experimentation. In our opinion, however, it would be important to place L.A. within a historical perspective, able to focus on the scientific, cultural and social roots of this approach, which certainly refer us to the experiments carried out from the early '900 onwards. This would also allow us to address a question that cannot be overlooked and that is whether – also in academic field – Learning Analytics are part of the didactic technologies or, rather, should be understood as a new global approach to learning processes. In the first case, we would be faced with a technological and methodological innovation while, in the second case, many theories and didactic strategies used up to now should certainly be rethought.

Technically, L.A. are placed at the crossroads between the formal and informal dimensions of learning and, in our opinion, are part of behaviorist tradition. If L.A. are inscribed, for example, in the list of Education

Technology, it's necessary to mention the pioneering experiments of Sidney Pressey in the 20s and 30s of the last century. This American scholar designed the first "teaching machines", rather rudimentary but certainly ingenious devices whereby it was possible to submit multiple-choice items to the student: if, by pressing a button, he gave the right answer, the machine allowed him to move on to the next question; if, on the other hand, the answer was wrong, the student was blocked by the machine until he identified the exact one among the alternative options. It is clear that, in case of error, it was possible to draw little information on the behavior and strategies adopted by the student to solve the problem because it was inevitable the temptation to proceed by "trials and errors", selecting without reflecting the other answers until you find the right one. Pressey, however, thought when an exam is corrected and made known to the student several hours or days late, the student's behavior did not change significantly. The immediate report, on the other hand, provides a way of self-assessment through the score reported, which can have an important didactic effect. In 1954, B. F. Skinner paid tribute to Pressey's inventiveness in an essay in which he emphasized, on the one hand, the great limits that the Pressey's machines presented in terms of teaching (Skinner called them "testing machines", as they only recorded the skills possessed) but, on the other, the enormous potential that could be developed within the programmed teaching. Skinner's basic thesis was that the school environment could be compared to a laboratory, where students learned complex behavioral sequences suitably reinforced by the machine, which replaced the teacher. Skinnerian teaching machines used open-ended questions and not multiple-choice questions, as the student only had to use discriminatory stimuli to increase the likelihood of success and not likely but wrong alternatives. For Skinner, in fact, the progression of the knowledge to be learned must be very gradual and of increasing difficulty, so that the student is in a position to make no mistakes or to do so only rarely.

Pupils received immediate information reinforcement – in the form of feedback – for each question to which he gave the exact answer and could also take advantage of various cues, very numerous in the initial frames and less frequent in subsequent ones, until they disappeared near the final item. Skinnerian programming, in fact, is linear and divided into frames or items, each of which includes a unit of information and a question to which the student can easily answer.

If Pressey's machines were never made, Skinner's machines were more successful, probably due to the concomitant effect of two factors: on the one hand, the explosion, in the 1960s, of the large-scale production and consumer society, which called for the training of workers with a set of standard knowledges and skills, and, on the other hand, the expansion of public school, whose aim was to reach as many people as possible – especially the white middle class – through agile and simplified curricula.

This demand for training could not be satisfied only through the construction of more schools and the introduction into the school circuit of more teachers but needed an in-depth review of the philosophy underlying formal education and an updating of teaching tools. Moreover, in any other field, an increase in demand would have led to the design of tools to save work and increase productivity and, in Skinner's view, teaching machines would have allowed this latter objective to be achieved because they would have allowed a programmer to get in touch with an indefinite number of students and, although this could recall the idea of mass production, according to the American psychologist the effect on each individual student would have been surprisingly similar to that of a private tutor, thanks to the possibility of customizing learning processes.

A further step forward in the planned education was finally taken with the IBM 1500 computer teaching system, designed to implement Computer Assisted Instruction (CAI) and introduced by the American multinational on March 31, 1966. The system involved the use of IBM 1130 and IBM 1800 minicomputers and supported up to 32 student workstations, each with various audiovisual features available. Pennsylvania State University, Alberta University (Canada) and Stanford University were among the first to experiment with the 1500 system, which was used until the 1980s by lower and higher education institutions.

Can Learning Analytics really predict students' success?

L.A. probably are inscribed in the wake of the experiments mentioned above. According to the definition of the Society for Learning Analytics Research (SoLAR), Learning Analytics refers to 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" (Ferguson, 2012). Learning Analytics, therefore, by systematically monitoring student behavior in their learning environments - both the physical and digital classes - aim to build exploratory-descriptive learning models (de Waal, 2017).

To achieve this, therefore, data is needed. In this regard, the UNESCO Policy Brief on Learning Analytics (2012) states that: "Learning analytics promise is to transform educational research into a data-driven science, and educational institutions into organisations that make evidence-based decisions", resulting from the study of behaviors. The data that determine these evidences, therefore, come from the constant monitoring of the students' way of acting (of their moving heads, orienting their eyes, changing their posture) that should be predictive of future performance. To this end, L.A., to focus, record and encode data, use information technologies that utilizes an algorithmic logic – such as eye tracking systems, facial recognition software, Computer Vision techniques – because the volume and complexity of the data obtained can escape the observation, even the most systematic, of the teacher.

The teacher, on the other hand, has the task of analysing, interpreting and evaluating these data, with the aim of identifying the behavioural clusters that recur most frequently and are considered to adhere to predefined performance standards. In our opinion, these behaviours are provided in the form of a response to a stimulus elaborated by the teacher himself (the words used during a frontal lesson, a video lesson, etc.). Through Learning Analytics, therefore, we aim to "represent the status quo of specific teaching and learning processes, in specific contexts, which can be described at the level of a single person, but also as clusters of people represented by patterns or similar "cases", classes or groups of classes represented by patterns or "similar cases", or as entire populations of students and teachers of a school, a type of school, a region or a country" (de Waal, 2017). In our view, Learning Analytics are not aimed at identifying cognitive profiles of students and customizing, on the basis of these, the teaching-learning process, but rather at identifying homogeneous patterns of behavior to be used to distinguish, for example, attentive from inattentive students (Raca, 2015), or "Struggling passive" students from "Nitpicking active" students and "Actively understanding" students (Harrak et al., 2019). Since Learning Analytics examine the behaviours that students manifest in the various learning environments and the data that derive from them, we think that L.A. refer to the behavioural approach. For example, in the teacher's eyes, the orientation of the gaze – the behavior acted on – becomes not only predictive of the skills and performance objectives achieved by the individual student, but also reason to profess him as a "good" or "poor" student (Sharma et al., 2015). The same authors use an eye-tracking system to monitor the eyes of students watching a video lesson, consisting of a series of slides that follow one another with the background of the teacher's voice intent on presenting them.

In the first phase of the study, students receive a textual (T) or schematic (S) priming and complete a pretest, they are then asked to watch two videos without time limits. At this point, the experimenters are pairs of students TT, SS, TS, depending on the priming received, who are asked to create a concept map with IHMC CMap Tools. Among the process, variables considered are gaze similarity and with-me-ness. The gaze similarity is a measure of the "coherence of gaze" of a couple, it indicates how much the two components dwell on the same element at the same time. The with-me-ness (Sharma et al., 2014), on the other hand, measures the student's attention during a video lesson and is divided into perceptual and conceptual. The perceptual with-me-ness, closely anchored to a temporal discourse, is in turn constituted by an entry time (temporal lack between the focusing of elements appearing on the screen and the time that the student takes to stop the gaze on a precise point the first time it appears), by a first fixation duration (the total time the gaze dwells on a new element that appeared for the first time) and by the numbers of revisits (the number of times a student returns to gaze at a point previously indicated by the teacher). Conceptual with-me-ness, on the other hand, is the measure of the frequency with which the student looks at the objective indicated to him by the teacher. In the opinion of Sharma et alii, the results show that there is a positive correlation between priming received, levels of with-me-ness, gaze similarity and improvement in learning. The authors conclude that the "good learner follows the teacher in both the perceptual and conceptual spaces of teacher-student interaction. More-over, a good learner is also well synchronized with his/her partner during a collaborative task" (Sharma et al., 2015). The good student, therefore, is the "looking through" one, who undertakes to collaborate with the teacher and with peers by focusing his or her gaze on the elements indicated by the teacher during the explanation and, consequently, establishes a relationship with them – albeit mediated by the screen – while the poor student is the one who "looking at", who relates exclusively with the learning material. It is not clear to us, however, how a good student can interact with the teacher, since his behaviour appears to be the answer to a series of stimuli and not a real interaction.

The difference between "good" and "poor" students is, therefore, quantitative and the aim seems to be to standardize their performance; the with-me-ness, for example, is the time standard to which the student should conform to understand the contents of the video lesson. It is for this reason that, even if students can watch the video several times, this does not lead to better learning outcomes. Another element on which we would like to focus is the distinction between "textual" and "schematic" that is made between students and that becomes a discriminating parameter in the construction of pairs of equals, but also predictor of learning outcomes. First of all, the distinction between "textual" and "schematic" is not made on the basis of the individual cognitive profile and, therefore, of the preferential learning channel, but established by a priming. It should also be noted that both the video – in which the teacher's words indicate the points on which the gaze should focus and, consequently, the student's attention – and the conceptual map, which has a propositional nature, benefit those who have had a textual type of priming.

Raca (2015) also argues that "attentive students have a common pattern of behavior" and that the position of the head and gaze have predictive power over attention levels. The author analyzes attention predictor behaviors by monitoring entire classes – and not individual subjects – during frontal lessons. This choice was made because the attention of many individuals focuses simultaneously on a single subject (the teacher), who, in turn, while doing class, must realize how he is managing the thresholds of attention of the students. To identify the behavioural patterns of an "attentive" student, Raca uses computer vision algorithms. One of the parameters monitored is synchronization, which is divided into "direct" and "indirect". Direct synchronization is, on the one hand, the reaction of those who receive the message to a change in the signal and, on the other hand, an adjustment to receive it better (nod, move the head to look at what the teacher indicates); indirect synchronization, however, is defined by the author as follows: "if the receptors are "tuned-in" to the same source, they should react in a similar way" (Raca, 2015). We are very puzzled to think that within a class group the reactions of students to the same stimulus can determine the same response in all, because we believe that the cognitive profiles and learning channels are different and that this also affects interest, attention and individual participation.

Raca's "end goal is not to build a detailed interpretation of a single person's behaviour [...], but to allow the teacher to perceive the "thermodynamic" entropy of the whole classroom as a system" (Raca, 2015). In this case also, however, it is the teacher who – receiving the data encoded by the algorithm – interprets and evaluates the appropriate patterns of behavior and, therefore, defines the standard.

Also in the context of L.A., the research of Harrak, Bouchet and Luengo (2019) investigates the profiles of students by analyzing the questions they ask following the viewing of video lectures provided by the flipped approach. Number, popularity and type of questions asked become predictive of learning outcomes that, according to the authors, will be below or average for students formulating popular questions and above average for students making unpopular requests. This type of profiling could, therefore, even be a predictor of school success and failure. While Learning Analytics are proposed as a resource to be spent on analyzing the behavior of students engaged in a process of teaching-learning and predicting performance produced in response to stimuli provided by the teacher, the possibility that L.A. can also be used to predict success at school seems to us risky. The fact that the final stages of the observation sequence (evaluation and interpretation) are the responsibility of the teacher could represent, in our opinion, a danger as it could lead him to prophesy the profiles without relying on objective data. Among the main risks of systematic observation – which could also be transferred in the interpretation of data collected and analyzed with algorithmic techniques – is the halo effect (who formulates the judgment tends to be influenced by a single trait, positive or negative, of the evaluated subject) and the self-fulfilling prophecy

(Rosenthal, Jacobson, 1972). In conclusion, at present, L.A. can be considered as a systematic observation tool, a behavioral educational technology, which has, therefore, the sole objective of predicting - in protected, formal and closed environments - the behavior of the monitored students.

Conclusion

The platforms of e-learning and MOOC, privileged settings of application of L.A., even if on the one hand they allow to socialize formal contents to participants connected by different geographical areas, seem to us not able to exploit at best the potentialities of the Net. The data of the students, in fact, are traced in digital classrooms, which, for the access systems (login) and for the closed structure, recall the "real" classrooms, with the further disadvantage of being, often, frequented by students who do not know each other and who are enrolled mainly for practical purposes (pass an exam, find materials). These factors could, therefore, negatively affect the number and quality of social interactions, making, in fact, the learner isolated in learning.

The focus, on the other hand, seems to be on the teacher rather than on the learner, who receives and adapts to the expectations of the teacher. The mechanism put in place by such a process seems to be aimed at flattening interpersonal differences, which are no longer perceived as a resource, but as an obstacle to achieving clustered objectives. The model resulting from the application of L.A. in the school environment does not seem to take into account the parameters of inclusiveness, which should allow not only to take into account all students who have difficulties (Special Educational Needs), but above all to produce a "systemic change, a transformative process of the education system (school, university, professional, etc..) aimed at identifying (culturally, politically and in practice) and removing all barriers and obstacles that determine all forms of exclusion, marginalization or discrimination" (Bocci et al., 2016). The search for the performative standard typical of L.A., not considering the differences, the peculiarities and the specific personal skills as resources, seems, instead, to refer to the system/model of integration that, in a homologating rather than inclusive perspective, sets objectives on the basis of a presumed normality, ignoring Specific Learning Disorder (SLD) and Special Educational Needs and Disability (SEND).

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