

Artificial Intelligence in Education: Big Data, Black Boxes, and Technological Solutionism

Xavier Giró Gràcia

University of Barcelona
xaviergiro@ub.edu

Juana Sancho-Gil

University of Barcelona
jmsancho@ub.edu

Abstract

The use of digital technology is constantly permeating and transforming all social systems, and education is not an exception. In the last decade, the development of Artificial Intelligence has given a new push to the hope of providing educational systems with 'effective' and more personalized solutions for teaching and learning. Educators, educational researchers, and policymakers, in general, lack the knowledge and expertise to understand the underlying logic of these new systems, and there is insufficient research-based evidence to fully understand the consequences for learners' development of both the extensive use of screens and the increasing reliance on algorithms in educational settings. This article, geared towards educators, academics in the field of Education, and policymakers, first introduces the concepts of 'Big Data', Artificial Intelligence, Machine Learning algorithms and how they are presented and deployed as 'black boxes', and the possible impact on education these new software solutions can have. Then, it focuses on the underlying educational discourses that historically have seen information and communication technologies as a panacea for solving educational problems, pointing out the need to analyse not only their advantages, but also their possible negative effects. It finishes with a short exploration of possible future scenarios and conclusions.

Keywords: Technology-enhanced learning, artificial intelligence, learning analytics, persuasive technologies, educational contexts.

Introduction

We construct our technologies, and our technologies construct us and our times. Our times make us, we make our machines, our machines make our times. We become the object we look upon but they become what we make of them (Turkle 1995, p. 46).

The history of education cannot be disentangled from the development of information and communication technologies. According to McClintock (1993) the use of printed texts had a dramatic impact on the way formal education was conceived and implemented in the Modern Age. The paperback revolution was touted as a way of freeing teachers and students from textbooks, lectures, and recitation (Cohen, 1988). Cinema, radio, television, computers, and an ever-growing collection of digital devices have periodically been announced as the new panacea for solving educational problems (Cuban, 1986; Saettler, 1990; Papert, 1993; Perelman, 1992; Gates, 1996; Sancho, 1998; Sancho-Gil, 2020; Sancho-Gil et al., 2020).

Disregarding the fact that these technologies have not been intended or developed in or for the educational context (Noble, 1991), schools and universities have been trying for decades to implement and use new information and communication tools in the teaching and learning processes, with the explicit aim of finding simpler, cheaper, and less time-consuming ways of communicating, transferring, or delivering knowledge. Alfred North Whitehead's idea that "the best education is to be found in gaining the utmost information from the simplest apparatus" (Cuban 1986, p. 3) seems more alive than ever, in spite of all the evidence challenging it, and the growing concerns around "the folly of technological solutionism" (Morozov, 2013). Moreover, for many practitioners and scholars, the hidden agenda behind the adoption of new technologies lies in the urge of industry to find new customers ready to adopt the last version of their new gadget and keep the idea of 'endless progress' alive (MacDonald, 1993).

The dawn of the third decade of the 21st century is witnessing the unstoppable influence of large digital corporations in education. An area that has become for them an endless pool of data and money, and therefore power. Power to shape and mould the notions of knowledge, teaching and learning, and the roles of teachers and learners. More and more educators are becoming aware of the key social role played by a few non-elected people and the power they exercise through algorithms and Big Data (Lupton & Williamson, 2017, Williamson, 2017). A tendency that led Buchanan and McPherson (2019, para. 2) to argue that "Australia may be heading towards an educational future designed by Silicon Valley not by educators and school communities".

This article, geared towards educators, academics in the field of Education, and policymakers, aims to shed light on the many aspects of Artificial Intelligence that are not widely known. Presented in two main parts, it first introduces the notions behind what Big Data means in contemporary society, how data is fuelling the use of algorithms in all areas of our lives, and specifically in the field of Artificial Intelligence, and the concept of 'black boxes'. Then it focuses on the educational discourse underlying the idea that technology is the panacea for solving persistent problems in education and finishes with a short exploration of possible future scenarios and conclusions.

The era of Big Data

Human societies have relied on data gathering for thousands of years. The first census we have evidence of was taken by the Babylonians in 3800 BCE and it counted the number of people, and livestock, as well as quantities of butter, honey, milk, wool, and vegetables available (Lennon, 2016). Human beings have always used data to try to better understand the world around them, and to develop models that allow them to make predictions about the future. Will we have enough food stored to survive the winter? How many hospitals do we need in a county, or a big city? Are people able to live comfortably with the jobs and salaries available? But, around the turn of the millennium, the way we look at data changed greatly. The evolution of computer systems, both in terms of raw processing power and data storage, together with the exponential growth in the use of digital technologies, created the perfect storm that coalesced in what we now call Big Data.

Data is now produced, processed, stored, and transformed at rates never seen before (Hilbert & López, 2011), and that is transforming our lives. The invention of the Internet, and its pairing with the widespread use of traditional computers first, and mobile technologies later, have not only revolutionized the ways we access information, with their political, economic, and cultural consequences (Castells, 1996), but the way data is collected and exploited in massive quantities. We are now surrounded by computer agents, as predicted by Negroponte in the nineties (Negroponte, 1995) —Siri, Alexa, Google, the most well-known, and a myriad others— and, in order for these digital agents to work, to adapt, and to offer us the best answer to our queries, they need to know everything about us; our appointments, our musical preferences, where we live, how we commute, what we like to do in our free time... But the massive use of data is not only contributing to changing our relationship with information and the way we process it; it is also at the root of a new economic paradigm, in which the currency is our digital footprint, the breadcrumb trail of small interactions we leave behind every time we use a digital device (Muhammad, et al., 2018). Social networks, search engines, or branded apps use all this data to build our bespoke digital profiles, that then are repurposed, transformed, and sold to marketers for advertisement, sometimes with little regard for privacy or ethics, as seen in cases like the Cambridge Analytics and Facebook scandal (Isaak & Hanna, 2018). If you

are a Google user, you only have to visit your profile and look at the ‘Ad Settings’ page¹ to see (if you have not manually turned ‘Ad personalization’ off) how much Google knows about you: age, gender, children, education, employer, or interests, to name a few. Google offers, like other big data gatherers, the option to opt out of some or most of the tracking they do, but the burden is always on the user, and some of the tracking is considered integral to the way the services work, and thus cannot be avoided.

Learning Analytics and Artificial Intelligence

When it comes to education, data analytics have been used regularly to assess the well-being of educational systems, as exemplified by the OECD’s Programme for International Student Assessment, commonly known as PISA². But the data gathered in this kind of studies is geared towards giving a global and, at the same time, limited view of educational systems as big monolithic institutions, and one that contains inherent unsolved issues (Goldstein, 2018). Inspired by the explosion of Big Data, the new fields of Learning Analytics and Educational Data Mining try to take advantage of our new capabilities of gathering data to create new models to foster student learning. Through algorithmic (software based) processes (prediction, clustering, relationship mining, distillation of data for human judgement, social network analysis, among others), these methodologies take advantage of the vast amount of data that can be collected in online e-Learning platforms like Canvas, Moodle, Sakai, or Blackboard. “In addition to student’s background and performance data, each action carried out (reading files, participating in forums, sending messages, or visiting recommended links, for example) leaves a digital fingerprint” (Calvet Liñán & Juan Pérez, 2015). As more schools adopt e-Learning platforms and the use of mobile technologies in their everyday teaching, this digital footprint can be harvested and processed to build individualized learning profiles for every student (just like Google does), and these profiles can be used to predict student performance, offer personalized learning content, and assess students’ learning (Ray & Saeed, 2018). And to effectively process all the data and create the models that can drive this personalization, the proposed solution is Artificial Intelligence, which is already being used in many other sectors, from finance to justice.

The field of Artificial Intelligence (AI) goes back to the origins of computer science. The English mathematician Alan Turing, famous for his work on deciphering the Enigma machine used by the Nazis to encode their messages during World War II, is regarded as one of its fathers. He proposed the Turing Test as a replacement for the question “Can machines think?” in his 1950 article ‘Computing Machinery and Intelligence’ (Saygin et al., 2000). The term is rooted in cybernetics and the belief of humans, and the universe itself,

1 <https://adssettings.google.com/>

2 <http://www.oecd.org/pisa/>

being what Finn (2017) calls ‘effectively computable’ in which “cognitive faculties could be abstracted from the supporting physical operations of the brain” (Dick, 2019, n.p.). Contemporary computer science however regards AI as a field that encompasses multiple disciplines related to developing machines with human-like abilities: machine learning, computer vision, image recognition, self-driving cars, natural language processing and generation, etc. AI relies on algorithms that can recognize patterns, which is an essential characteristic of the human brain. While traditionally the approaches to AI relied on the construction of very complex algorithms that could imitate rational processes, like Weizenbaum’s ELIZA (Weizenbaum, 1966), modern approaches rely on machine learning, which is the process by which the algorithm imitates a network of neurons, and by trial and error, through repeated generations of results based on training datasets, reaches a state where it is capable of producing human-like (correct) results for any arbitrary input. When you reach a very complex set of artificial neurons that model a multitude of layers of thinking and are capable of self-assessing their assumptions and adapting them accordingly, computer scientists use the term Deep Learning (Dickson, 2021). These Deep Learning algorithms are at the heart of automatic image classification, voice to text transcription or stock price prediction.

Machine learning systems have been penetrating businesses around the world during the last decade and are seen as a big catalyst of growth in many industries, from retail to manufacturing and everything in between. They have also started making inroads in the public sector, being applied in the justice system to determine sentence duration, or in the education system to process college admissions (O’Neil, 2016). These systems are presented as objective and neutral, since the models are developed by machines with limited human input, and as sophisticated tools that are too complex to be explained to the general population, so they can’t be challenged (O’Neil, 2016).

Black box algorithms

When you have an algorithm that is too complex to understand by a human being, but you trust that, given a certain input, it will produce a correct answer, that is called a black box. As Cathy O’Neil states in her book *Weapons of Math Destruction*, “Verdicts from WMDs land like dictates from the algorithmic gods. The model itself is a black box, its contents a fiercely guarded corporate secret.” (O’Neil, 2016, p. 8). You know what goes in, and what comes out, but not what the process of converting the input to the output entails. And even when we analyse what we could agree are successful models of black box algorithms, like Google Search, Netflix suggestions, or Apple’s Siri, what we might find is that, at least in part, the algorithm is an illusion that requires constant human intervention to keep it working. Ian Bogost describes it as:

Once you adopt scepticism toward the algorithmic- and the data-divine, you can no longer construe any computational system as merely algorithmic. Think about

Google Maps, for example. It's not just mapping software running via computer—it also involves geographical information systems, geolocation satellites and transponders, human-driven auto mobiles, roof-mounted panoramic optical recording systems, international recording and privacy law, physical- and data-network routing systems, and web/mobile presentational apparatuses. That's not algorithmic culture—it's just, well, culture. (2015, n.p.).

A good example of this is YouTube's Content ID system, which is described in the report *How Google Fights Piracy* as such: "With advancements in machine learning, Content ID can now detect copyrighted melodies, video, and audio, helping identify cover performances, remixes, or reuploads they may want to claim, track, or remove from YouTube" (Google, 2018, p. 27).

Built to appease the big media conglomerates and keep Google (or Alphabet) out of legal trouble, the system requires content creators to register their creations, and to enter them into a database of copyrighted material. Drawing from this ever-growing database, Content ID determines automatically if a video uploaded by a user contains copyrighted content and flags the video. This flagging can lead, depending on the copyright holder's wishes, to the video being blocked, or monetization being redirected to the claimant³. Solomon describes the results of the algorithm like this:

Content ID is a great system for YouTube and for copyright holders, but it is not so great for YouTube users because it not only fails to protect them, but also effectively deprives them of their rights under copyright law. The system is incapable of recognizing fair use, which means that a lot of videos are flagged as infringing even when they are not. Furthermore, when these videos are flagged, most users fail to dispute the claims made against them. (2015, p. 255)

One could argue that the algorithm is very successful in fulfilling the role that Google has devised for it. It quickly and quite accurately (according to Google) identifies copyrighted content in user uploaded videos. But it also can be argued that being YouTube the dominant platform to distribute video online, the algorithm has an immense power to decide what can be published and how, even though it cannot understand the laws that govern copyright, and fair use (or fair dealing, or its equivalents in different countries) is not part of its concerns. Also, the algorithm can be used as an indirect weapon to silence unwanted critique or analysis, since they might require showing the original material in the process, as pointed out by the Electronic Frontier Foundation (Trendacosta, 2020).

When dealing with machine learning algorithms, we must keep in mind that data is, despite what it may seem, never objective or complete. Datasets used to train these algorithms are created on the basis of available data and the expected outcomes, which

³ Google maintains a Help Center page about Content ID, how it works, and frequently asked questions at <https://support.google.com/youtube/answer/2797370>

partially reproduce ‘reality’, with its biases and dysfunctions. These datasets may fail to include relevant information that is crucial to produce what a human being would accept as correct results, or they can rely on historical information that reproduces undesirable socio-economic trends. As O’Neil puts it: “The question, however, is whether we’ve eliminated human bias or simply camouflaged it with technology. The new recidivism models are complicated and mathematical. But embedded within these models are a host of assumptions, some of them prejudicial” (2016, p. 25). The impact of the use of black box algorithms in education is still limited, but they are already in use in teacher performance assessment (e.g., the IMPACT programme in Washington, DC’s public schools started in 2009, that used machine learning and AI to measure teachers’ performance) (O’Neil, 2016) and a growing number of voices are pushing for the introduction of learning analytics and data mining models, smart assistants, and recommendation engines in the classroom, especially in e-Learning settings. We have to therefore ask ourselves what role can AI have in education, what problems can it provide solutions for, and what are the underlying imaginaries on educational discourses pushing for the use of these technologies.

The need to meeting students’ learning needs

The idea of going beyond the uniform way of approaching institutional teaching and learning builds somehow on two contradictory perspectives, one progressive, and one technological.

At the beginning of the 20th century, John Dewey, the Progressive Education (in the USA) and the New School (in Europe) argued the need to consider children and young people not as empty vessels to be filled with books and teachers’ knowledge. It was proclaimed that students, regardless of their biological, socio-economic, and cultural background, came to school with their backpack of experience, knowledge, and their ability to learn. They were an essential part of the teaching and learning process that should consider their peculiarities. However, in 1970, Basil Bernstein was still pointing out that many dropped out children and young people did not feel recognised, respected, or valued by schools. Fifty years later, the “persistence of inequitable education” (Pigot et al., 2021, p. vii) remains the greatest educational, social, and political challenge to meet students’ needs.

On the other hand, in the 1950s, the need to improve learning outputs and an increasing interest in technology, led behaviourist psychologist Burrhous Frederic Skinner to build a machine that would automatically apply his principles of learning to teaching. For him, new advances in the experimental analysis of behaviour suggested that for the first time it was possible to develop a true technology of education. This technology, in the form of a teaching machine, following the practice of the experimental laboratory, would use instrumentation to equip learners with extensive repertoires of verbal and non-verbal behaviours. Moreover, the equipment would be able to create enthusiasm for further study (Skinner, 1961).

These two views seem to coexist in the current interest for personalising learning (OECD-CERI, 2006) and the push for introducing learning systems based on persuasive technologies, algorithms, and Big Data into formal education. Persuasive technologies were developed by Fogg at Stanford University to design machines to change what people think and do (Fogg, 2003; 2009). “He talked about helping people stay fit, quit smoking, manage their finances and study for exams. Two decades later, his methods are world-famous for generating billions of dollars for several dozen companies, but not for helping anyone quit” (Peirano, 2019, p. 28). As made evident by different studies (Alter, 2017; Desmurget, 2020; Williams, 2018) among others.

Nevertheless, as it has been the case with successive waves of technological developments, Artificial Intelligence has raised new expectations as a ‘solution’ to educational problems. For international organizations such as UNESCO (Chakroun, et al., 2019), “AI offers a diverse range of solutions, apps and techniques for use by the education sector to enhance teaching and learning” (p. 7). They seem particularly enthusiastic about how “Big Data can be leveraged to track book performance and automate processes to build predictive machine-learning models” (p. 12), to enhance readers’ engagement analysis in projects such as World reader, aimed to help people to “achieve better educational success, improve their earning potential, and lead healthier, happier lives”⁴. They also believe that:

Increasingly, service and application providers collect, save and utilize large amounts of people’s data. Algorithms, produced on the basis of these data, effectively reinforce human biases and propagate ‘filter bubbles’ – states of intellectual isolation that can result from personalized searches when a website algorithm selectively guesses information that a user would like to see, based on the user’s own information, such as location and past click behaviour. (p. 52)

Even if they do not disregard that “Historical prejudice can also be amplified by AI when its development is based on historical datasets. These considerations must be taken into account in any discussion around the use of Big Data” (p. 59).

All these statements come for the Discussions at 2019’s Mobile Learning Week (MLW) centred on the challenges of reducing barriers to education, improving learning outcomes for all, and the possibilities afforded by AI, which was supported by UNESCO. The economic power of MLW is well known, as it is the UNESCO’s power to create discourses and guide educational policies in many countries. Hence the importance of pointing out the lack of complexity in its analyses and the inordinate enthusiasm, in this case, for AI as a solution to education problems. However, discourses and ‘solutions’ to teaching and learning in formal contexts based on the almost ‘miraculous’ role of technology systematically ignore the complexity involved in any social systems.

⁴ <https://www.worldreader.org/>

Reductionist solutions to wicked problems

For every complex problem there is an answer that is clear, simple, and wrong.
(H. L. Mencken, 1880-1956)

As suggested earlier, the idea of reducing the complexity of education and learning to effective ways of processing pre-packed information has a long history with its more important roots in the United States in the 1950s (Saettler, 1990). As discussed in previous writings (Sancho, 1995; Sancho, 2020), education and learning are one of the best examples of what Rittel and Webber (1984) coined as ‘wicked problems’. According to Sancho (2020), this kind of problems are:

[...] poorly formulated. The information needed to understand them depends on the ideas of those trying to solve them. Require a comprehensive inventory of all possible solutions previously proposed. It is practically impossible to understand the problem without knowing its context, nor to search for information without looking at the possible solution. They are not considered solved for reasons inherent to the logic of the problem (true-false), but because of what those who try to solve them find an adequate degree of “satisfaction”. Any intervention in a “wicked” problem has consequences, leaving traces that cannot be erased by a “reparative” action of its unwanted effects, which in turn will generate other problems. They have specific characteristics that make them “unique” and act as symptoms of other issues (Buchanan, 1992; Rittel & Webber, 1984) (p. 198).

One of the main problems of converting education to information processes for designers, machines and learners is the ontological reductionism involved. For Searle (1992, p. 15), ontological reduction consists in “the way in which objects of certain kinds are shown to consist of nothing but objects of another kind”. For example, if learning is only about ‘retaining information’, all aspects of intentionality, context, meaning making... disappear or are rejected as not ‘objectionable’ or measurable. So, they are converted into their approximate substitute values, something that can be particularly controversial, even dangerous, when modelling students’ learning (O’Neil, 2018). As Searle (1992, p. 15) points out, “in general in the history of science, successful causal reductions tend to entail ontological reductions”.

Discussions related to the role of algorithms and Big Data to improve education and learning cannot be abstracted from contexts. We cannot disregard that:

Learning is a phenomenon that involves real people who live in real, complex social contexts from which they cannot be abstracted in any meaningful way. [...] learners are contextualized. They do have a gender, a sexual orientation, a socioeconomic status, an ethnicity, a home culture; they have interests—and things that bore them; they have or have not consumed breakfast; and they live in neighbourhoods with or without frequent gun violence or earthquakes, they are attracted by (or clash with)

the personality of their teacher, and so on. (Phillips, 2014, p. 10).

Human beings are lifelong, life-wide, and life-deep learners (Banks et al, 2007), even in moments and contexts where they are not explicitly taught. This feature of learning is what makes the process of teaching and learning so intricate, so ‘wicked’. We must be aware of what we mean by teaching and learning. Today it seems crucial to enlarge and complexify the notion of teaching, to go beyond the idea that “teaching is telling [by a teacher or an algorithm], learning is listening [or following algorithm’s directions] and knowledge is what is in books [or a digital application]” (Cuban, 1993, p. 27 — our additions in brackets).

But not only that. We need to consider how people make sense of information, of situations they go through, of the world that surrounds them, that can be restricted or amplified by different means (social and cultural capital, access to digital technologies). This means we need to consider all learning processes in social settings (school, family, community) or in artificially created ones. In *The Age of Surveillance Capitalism* (Zuboff, 2019), any corporation can have access to massive volumes of data about practically all students, particularly those who use digital platforms the most, both in and out of school. This is one of the most powerful arguments for using Big Data in education today, but this data is loosely contextualized, and is often gathered without considering its collateral effects.

Nevertheless, these arguments are confronted with several significant issues. First, the increasing identification of children goes against children’s digital rights. “An issue that has begun to intersect with existing children’s rights instruments such as the United Nations Convention on the Rights of the Child (UN CRC) (1989)” (Lupton, & Williamson, 2017, p. 782). As these authors argue:

The data generated by these technologies are often used for dataveillance, or the monitoring and evaluation of children by themselves or others that may include recording and assessing details of their appearance, growth, development, health, social relationships, moods, behaviour, educational achievements and other features” (p. 781).

The second relates to the ways of converting this data into algorithms to guide students’ learning. Thomas Popkewitz (2018) warns of the perverse effects that educational research can have, especially for vulnerable children and youth, when they are confronted with labels such as lack of motivation, attention deficit, lack of concentration, health problems, etc. As it has been discussed, algorithms developed and trained by human beings are not ‘objective’ and unbiased. Besides, most people do not possess the expertise needed to understand them as they work as black boxes. We can identify the ideological positioning and interests of an educational bill, a curriculum, a school, a university planning, or a textbook or a ‘simple’ educational app. However, most of us can hardly understand the

underlying views that algorithms hold about teaching, learning, knowledge, learners, and teachers, beyond the marketing discourse of the corporation selling them.

The third has to do with the ongoing transformation of education by the frenzied data collection activity taking place in many countries. For Buchanan and McPherson (2019):

Australia may be heading towards an educational future designed by Silicon Valley not by educators and school communities. The developers of educational technologies have a growing influence in our classrooms, and we are witnessing a shift of public education from a democratic controlled system to one designed and run by corporations (n.p.)

For them, replacing the teacher's expertise with the pattern detection abilities of learning analytics algorithms can reduce students' opportunities by the assumptions encoded in algorithmic logic. A situation that opens many intricate and related issues, the discussion of which would require a separate article.

Apparently, this can be said of many other countries. People's progression, not only in institutional settings, can be tracked along with actions such as physical activity, use of digital devices, participation in social media, etc. Information that can be matched with data provided by students and teachers through learning platforms and personalised learning apps used in classrooms or at home (Thompson, 2017), most of them designed with persuasive technologies driven by algorithms based on student data to foster progression and motivation, as well as surveillance (Knox et al., 2020; Warzel, 2019). Without disregarding the fact that educational algorithms can directly influence the practices of educational agents and determine students' learning. These are important aspects to consider since, as it has been pointed out earlier, their development incurs in cognitive and cultural biases, and issues related to users' abilities (Hartong & Förschler, 2019).

Only learning or education?

All these considerations raise fundamental questions about the present and future of education. We must decide what we mean by education. Is education only about teaching and learning at school, information transmission, and filling learners with facts, concepts, procedures to solve already solved problems, or skills to respond in exams to what is expected from them? Or is it about learning to know, learning to do (in formal and informal settings), learning to live together, learning to live with others, discovering others (not only virtually, but also face to face), working towards common objectives, learning to be, and learning through life? (Delors, 1998).

We cannot disregard the development of children and young people in all their dimensions. That not only 'the brain' needs to be trained. That the whole body needs all

kinds of experiences (intellectual, affective, physical, tactile, olfactory, visual, auditory, gustatory). That an excessive use of screens, that systematically trump physical exercise and many fundamental human experiences, can definitively damage people's harmonic development.

We cannot deny the importance of acquiring digital skills nowadays. However, according to neuroscientist Desmurget (2020, p. 231), we should not confuse "learning about 'the' digital with learning 'through' the digital". Several studies have found that "the more we leave an important part of our cognitive activities in the hands of the machine, the less material our neurons find to structure, organise and connect themselves" (Ibid, 232). Probably for this reason, the promoters and main beneficiaries of these technological applications try to preserve their children from their influence by sending them to schools with little or no use of digital devices, but with experiences of nature, art, and philosophy (Lahitou, 2018; Weller, 2018).

To this regard, we must consider that different studies are showing that despite the huge investment in digital technologies in educational systems, learning results are terribly disappointing, giving the impression that the expenditure may not only have been futile, but even harmful (Desmurget, 2020, p. 145). The OECD (2015) study about the use of computers and PISA results highlighted that "Despite considerable investments in computers, Internet connections and software for educational use, there is little solid evidence that greater computer use among students leads to better scores in mathematics and reading" (p. 145). And even more: "PISA data show that for a given level of per capita GDP and after accounting for initial levels of performance, countries that have invested less in introducing computers in school have improved faster, on average, than countries that have invested more" (p. 149). These results point out the need to decentralise the focus of learning from a single device, to develop comprehensive teaching projects capable of taking advantage of all available technology and to improve both the conditions of learning environments and teacher training.

All the above discussions have led us to two main reflections. (a) Whether all this expenditure in digital technology would not have been more effective if it had been invested in the many shortcomings of education systems. (b) What is the role and responsibility of teachers, school principals, counsellors, inspectors, researchers, and policymakers in deciding where and how to invest scarce resources in education?

Future scenarios and conclusions

Artificial Intelligence has been recognized as a key asset for future growth by most developed countries. The OECD's *Principles on Artificial Intelligence*, that state that "AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and they should include appropriate safeguards –for

example, enabling human intervention where necessary– to ensure a fair and just society” (OECD, 2019, The OECD AI Principles), have been adopted by 42 countries. The European Commission has recently published their *Regulatory framework proposal on Artificial Intelligence* where it has classified the use of AI in “Educational or vocational training, that may determine the access to education and professional course of someone’s life (e.g. scoring of exams)” as high-risk, which requires that AI “systems will be subject to strict obligations before they can be put on the market” (EC, 2021, A risk-based approach). The growing amount of political and social scrutiny in the use of AI-based technologies, especially when it concerns basic human rights, indicate that new regulations will probably be adopted in the short or medium term, and the lead of the European Union could be a big factor in defining the boundaries of what is acceptable and what is not around the world, since international companies have to abide to European Law if they want to operate in Europe. How these regulations will affect the use of AI in education remains to be seen since it is still very limited, but a strict policy framework could have a big impact in the feasibility of certain practices, and make some uses, like delegating learning assessment to AI, forbidden or requiring human supervision.

The main promise of embracing Big Data and Artificial Intelligence in education is that they will provide us with insights that will help us personalize education for every learner, so they can be better served in schools and be more engaged with their educational voyage. The old model of learning analytics (subject marks being the most salient) are limited in scope and fall short in telling us what the learner is struggling with, so they only serve as a coarse way of classifying students into achievers or failures. The promise of a new model that solves all these problems is greatly appealing. However, educational systems have proven very refractory to big sweeping changes, and even if new policies regarding the use of AI may take time to be put in place, the widespread adoption of AI decision systems, especially in public schools, seems unlikely, and the impact of this adoption may be very limited.

AI algorithms are becoming ubiquitous in our modern society, but they are often offered as black boxes, too complex to comprehend, or as trade secrets, intellectual property of big corporations, too valuable to openly discuss. Also, the models that govern them are often based on biased assumptions, and datasets gathered from a ‘reality’ that is far from ideal. AI can be useful, especially to complement human instruction or in situations where human contact is limited, like on e-Learning environments. However, the use of algorithms in education requires supervision, informed teachers that understand what the limits of the algorithms are, and transparency in their implementation and the data they collect. It also hinges on a high level of maturity from both the learner and the teacher, to critically approach the assessments, predictions, or materials that the algorithm offers. Teachers cannot abdicate from their role, and the results of the algorithms must be challenged when they are flawed.

There are also important ethical questions surrounding the gathering of student data and the creation of models around it. Data is a very valuable currency nowadays, and it is essential to acquire students' consent and treat data properly, in terms of acquisition, storage, sharing, anonymization, and destruction. Legislation will have to catch up with the data economy to protect users' privacy, and to put limits in what algorithm developers can acquire from us, and what they can do with it, and that will also impact their use in education.

Smartphones, computers, and the Internet are an integral part of our lives in the 21st century, and algorithms are a part of this reality. We live our lives in an online/offline duality, where it is not always obvious where one ends and the other begins. Educators cannot be oblivious to that fact and must be aware of the advantages and pitfalls that the algorithmic era presents. Policymakers, educators, and educational researchers not only have to find the best use of these technologies in education, maximizing their effects for the benefit of all individuals and social groups, and avoiding their pitfalls, but they also must educate students in what algorithms are and the impact they can have in our lives.

Finally, we cannot forget the physical, intellectual, and emotional development of students and must be aware that spending too much time in front of screens could be to the detriment of vital experiences for the growth of human beings. We urgently need a broad and in-depth interdisciplinary research initiative that can provide a clear picture of the benefits and harms of the development and use of newer digital technologies in education.

References

- Alter, A. (2017). *Irresistible: The Rise of Addictive Technology and the Business of Keeping*. Penguin Press
- Banks, J. A., Au, K. H., Ball, A.F., Bell, P., Gordon, E. W., Gutiérrez, K. D., Heath, S. B., Lee, C. D., Lee, Y., Mahiri, J., Nasir, N. S., Valdés, G., Zhou, M. (2007). *Learning in and out of school in diverse environments. Life-long, Life-wide, Life-deep*. The LIFE Center for Multicultural Education, University of Washington. http://life-slc.org/docs/Banks_etal-LIFE-Diversity-Report.pdf
- Bernstein, B. (1970). Education cannot compensate for society. *New society*, 26, 344-345.
- Bogost, I. (2015, January 15). The Cathedral of Computation. *The Atlantic*. <http://www.theatlantic.com/technology/archive/2015/01/the-cathedral-of-computation/384300/>
- Buchanan, R., & McPherson, A. (2019, July 8). Education shaped by big data and Silicon Valley. Is this what we want for Australia? *EduResearch Matters*, <https://www.aare.edu.au/blog/?p=4182>

- Calvet Liñán, L., & Juan Pérez, Á. A. (2015). Educational Data Mining and Learning Analytics: differences, similarities, and time evolution. *RUSC. Universities and Knowledge Society Journal*, 12(3), 98-112.
<http://dx.doi.org/10.7238/rusc.v12i3.2515>
- Castells, M. (1996). *The Rise of the Network Society* (Information Age), vol. 1. 2nd ed. Blackwell Publishers.
- Chakroun, B., Miao, F., Mendes, V., Domiter, A., Fan, H., Kharkova, I., Holmes, W., Orr, D., Jermol, M., Issroff, K., Park, J., Holmes, K., Crompton, H., Portales, P., Orlic, D., & Rodriguez, S. (2019). *Artificial Intelligence for Sustainable Development: Synthesis Report, Mobile Learning Week 2019*. UNESCO
- Cohen, D. K. (1988). Educational Technology and School Organization. In R. S. Nickerson & P. P. Zodhiates (Eds.), *Technology in Education: Looking Toward 2020* (pp. 231-264). Hillsdale, NJ: Lawrence Erlbaum Associates, Pu.
- Cuban, L. (1986). *Teachers and Machines: The Classroom Use of Technology Since 1920*. Teachers College.
- Cuban, L. (1993). *How teachers taught: constancy and change in American classrooms, 1890-1990*. Teachers College Press.
- Delors, J. (1998). *Learning: The treasure within*. Unesco.
- Desmurget, M. (2020). *La fábrica de cretinos digitales*. Península.
- Dick, S. (2019). Artificial Intelligence. *Harvard Data Science Review*, 1(1).
<https://doi.org/10.1162/99608f92.92fe150c>
- Dickson, B. (2021, January 28). Demystifying deep learning. *Techtalks*.
<https://bdtechtalks.com/2021/01/28/deep-learning-explainer/>
- European Commission (2021). *Regulatory framework proposal on Artificial Intelligence*.
<https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai>
- Finn, E. (2017). *What Algorithms Want. Imagination in the Age of Computing*. The MIT Press. <https://doi.org/10.7551/mitpress/9780262035927.001.0001>
- Fogg, B. J. (2003). *Persuasive Technology: Using Computers to Change what We Think and Do*. Morgan Kaufmann Publishers.
- Fogg, B. J. (2009). A Behavior Model for Persuasive Design. *Persuasive'09*, April 26-29. Claremont, CA. <https://doi.org/10.1145/1541948.1541999>

Gates, B. (1996). *The road ahead*. Viking.

Goldstein, H. (2018). Measurement and Evaluation Issues with PISA. In L. Volante (Ed.), *The PISA Effect on Global Educational Governance* (pp. 49-58). Routledge.

Google (2018). *How Google Fights Piracy*.

https://www.blog.google/documents/25/GO806_Google_FightsPiracy_eReader_fi nal.pdf

Hartong, S., & Förschler, A. (2019). Opening the black box of data-based school monitoring: Data infrastructures, flows and practices in state education agencies. *Big Data & Society*. <https://doi.org/10.1177/2053951719853311>

Hilbert, M., & López, P. (2011). The World's Technological Capacity to Store, Communicate, and Compute Information. *Science*, 332(6025), 60-65. <https://doi.org/10.1126/science.1200970>

Isaak, J., & Hanna, M. J. (2018). User Data Privacy: Facebook, Cambridge Analytica, and Privacy Protection. *Computer*, 51(8), 56-59. <https://doi.org/10.1109/MC.2018.3191268>.

Knox, J., Williamson, B., & Bayne, S. (2020). Machine behaviourism: Future visions of 'learnification' and 'datafication' across humans and digital technologies. *Learning, Media and Technology*, 45(1), 31-45. <https://doi.org/10.1080/17439884.2019.1623251>

Lahitou, J. (2018, August 18). Silicon Valley Parents Choose Low & No Tech Schools. What About Your Kid's School? *The Good Man Project*. <https://goodmenproject.com/uncategorized/silicon-valley-parents-choose-low-no-tech-schools-thats-probably-not-the-tech-policy-at-your-kids-school/>

Lennon, T. (2016, August 11). Babylon's ancient clay tablets made more census than today's computers. *The Daily Telegraph*. <https://www.dailytelegraph.com.au/news/babylons-ancient-clay-tablets-made-more-census-than-todays-computers/news-story/3f76510db70c6bfd1185192a2e90badc>

Lupton, D., & Williamson, B. (2017). The datafied child: The dataveillance of children and implications for their rights. *New Media & Society*, 19(5), 780-794. <https://doi.org/10.1177/1461444816686328>

MacDonald, B. (1993). Micromundos y mundos reales. Una agenda para la evaluación. *Comunicación y Pedagogía-Infodidac*. October, 31-41.

- McClintock, R. O. (1993). El alcance de las posibilidades pedagógicas. In R. O. McClintock, G. Vázquez, M. J. Streibel (Coord.), *Comunicación, tecnología y diseños de instrucción: la construcción del conocimiento escolar y el uso de los ordenadores* (pp. 104-125). CIDE-MEC.
- Morozov, E. (2013). *To save everything, click here: The folly of technological solutionism*. Public Affairs.
- Muhammad, S.S., Dey, B.L., & Weerakkody, V. (2018). Analysis of Factors that Influence Customers' Willingness to Leave Big Data Digital Footprints on Social Media: A Systematic Review of Literature. *Information Systems Frontiers*, 20(3), 559-576. <https://doi.org/10.1007/s10796-017-9802-y>
- Negroponte, N. (1995). *Being Digital*. Alfred A. Knopf.
- Noble, D. D. (1991). *The Classroom Arsenal: Military Research, Information Technology, and Public Education*. The Falmer Press.
- O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Crown Publishing Group, USA.
- OECD-CERI (2006). *Personalising Education*. OECD. <http://dx.doi.org/10.1787/9789264036604-en>
- OECD (2015). *Students, Computers and Learning: Making the Connection, PISA*. OECD Publishing. <http://dx.doi.org/10.1787/9789264239555-en>
- OECD (2019). *OECD Principles on Artificial Intelligence*. <https://www.oecd.org/going-digital/ai/principles/>
- Papert, S. (1993). *The Children's machine*. Basic Books.
- Peirano, M. (2019). *El enemigo conoce el sistema. Manipulación de ideas, personas, influencias después de la economía de la atención*. Debate.
- Perelman, L. J. (1992). *Schools Out. Hyperlearning, the New Technology, and the end of Education*. William Morrow and Company, Inc.
- Phillips, D. C. (2014). Research in the Hard Sciences, and in Very Hard "Softer" Domains. *Educational Researcher*, 43(1), 9-11. <https://doi.org/10.3102/0013189X13520293>
- Pigott, T. D., Tocci, C., Ryan, A. M., & Galliher, A. (2021). Quality of Research Evidence in Education: How Do We Know? *Review of Research in Education*, 45(1), vii-xii. <https://doi.org/10.3102/0091732X211001824>

- Pinar Saygin, A., Cicekli, I. & Akman, V. (2000). Turing Test: 50 Years Later. *Minds and Machines* 10, 463-518. <https://doi.org/10.1023/A:1011288000451>
- Popkewitz, T. (2018, September 6). *The Paradox of Research: The Good Intentions of Inclusion that Excludes and Abjects*. ECER 2018. Bolzano, Italy. <https://cutt.ly/pk6dwqQ>
- Ray S., & Saeed M. (2018). Applications of Educational Data Mining and Learning Analytics Tools in Handling Big Data in Higher Education. In M. Alani, H. Tawfik., M. Saeed & O. Anya (eds), *Applications of Big Data Analytics*. Springer, Cham. https://doi.org/10.1007/978-3-319-76472-6_7
- Rittel, H. W. J., & Webber, M. M. (1984). Planning Problems are Wicked Problems. Developments. In N. Gross (ed.), *Design Methodology* (pp. 135-144). John Wiley and Sons.
- Saettler, P. (1990). *The Evolution of American Educational Technology*. Libraries Unlimited, Inc.
- Sancho-Gil, J. M. (1995). Looking for the 'Right' Answers or Raising the 'Right' Questions? A Dialogical Approach to Automating Instructional Design. In R. D. Tennyson & A. E. Barron (Ed.), *Automating Instructional Design: Computer-Based Development and Delivery Tools* (pp. 79-99). Springer-Verlag. NATO ASI Series F: Computer and Systems Sciences, Vol. 140.
- Sancho, J. M. (1998). Enfoques y funciones de las nuevas tecnologías para la información y la educación: lo que es no es lo que parece. In J. de Pablos & J. Jiménez (Eds), *Nuevas Tecnologías, Comunicación Audiovisual y Educación* (pp. 71-102). Cedecs.
- Sancho-Gil, J. M. (2020). Digital technology as a trigger for learning promises and realities. *Digital Education Review*, 37, 195-207. <https://doi.org/10.1344/der.2020.37.191-203>
- Sancho-Gil, J. M., Rivera-Vargas, P. & Miño-Puigcercós, R (2020). Moving beyond the predictable failure of Ed-Tech initiatives. *Learning, Media and Technology*, 45(1), 61-75. <https://doi.org/10.1080/17439884.2019.1666873>
- Searle, J. R. (1992). *The Rediscovery of the Mind*. The MIT Press.
- Skinner, B. F. (1961). *Teaching machines*. Freeman. <https://doi.org/10.1037/11324-011>
- Solomon, L. (2015). Fair Users or Content Abusers? The Automatic Flagging of Non-Infringing Videos by Content ID on YouTube. *Hofstra L. Rev.*, 44(1) 237-268.
- Thompson, G. (2017). Computer adaptive testing, big data and algorithmic approaches to

education. *British Journal of Sociology of Education*, (38)6, 827-840,
<https://doi.org/10.1080/01425692.2016.1158640>

Trendacosta, K. (2020, December 10). Unfiltered: How YouTube's Content ID Discourages Fair Use and Dictates What We See Online. *Electronic Frontier Foundation*.
<https://www.eff.org/wp/unfiltered-how-youtubes-content-id-discourages-fair-use-and-dictates-what-we-see-online>

Turkle, S. (1995). *Life on the Screen: Identity in the Age of the Internet*. Shuster and Shuster.

Warzel, Ch. (2019, July 2). Welcome to the K-12 Surveillance State. Is tech really the solution to student safety? *New York Times*.
<https://www.nytimes.com/2019/07/02/opinion/surveillance-state-schools.html>

Weizenbaum, J. (1966). ELIZA--A Computer Program for the Study of Natural Language Communication Between Man and Machine. *Communications of the ACM*, 9(1), 36-45. <https://doi.org/10.1145/365153.365168>

Weller, C. (2018, February 18). Silicon Valley parents are raising their kids tech-free — and it should be a red flag. *Buisness Insider*. <https://www.businessinsider.com/silicon-valley-parents-raising-their-kids-tech-free-red-flag-2018-2>

Williamson, B. (2017). *Big Data in Education: The Digital Future of Learning, Policy and Practice*. SAGE Publications. <https://doi.org/10.4135/9781529714920>

Williams, J. (2018). *Stand out of our Light: Freedom and Resistance in the Attention Economy*. Cambridge University Press. <https://doi.org/10.1017/9781108453004>

Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new frontier of power: Barack Obama's books of 2019*. Profile books.