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Digital education governance: data visualization, predictive analytics, and 'real-time' policy instruments

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Educational institutions and governing practices are increasingly augmented with digital database technologies that function as new kinds of policy instruments. This article surveys and maps the landscape of digital policy instrumentation in education and provides two detailed case studies of new digital data systems. The Learning Curve is a massive online data bank, produced by Pearson Education, which deploys highly sophisticated digital interactive data visualizations to construct knowledge about education systems. The second case considers 'learning analytics' platforms that enable the tracking and predicting of students' performances through their digital data traces. These digital policy instruments are evidence of how digital database instruments and infrastructures are now at the centre of efforts to know, govern and manage education both nationally and globally. The governing of education, augmented by techniques of *digital education governance*, is being distributed and displaced to new digitized 'centres of calculation', such as Pearson and Knewton, with the technical expertise to calculate and visualize the data, plus the predictive analytics capacities to anticipate and pre-empt educational futures. As part of a data-driven style of governing, these emerging digital policy instruments prefigure the emergence of 'real-time' and 'future-tense' techniques of digital education governance.

Keywords: big data; database; governance; infrastructure; policy instruments; predictive analytics; visualization

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Digital database technologies facilitate the generation, calculation and circulation of the data required to govern education. Seemingly objective statistical data are now being integrated into much educational policy-making, with schools and classrooms configured as 'data platforms' linked to vast global data collection programmes, and the 'reality' of education rearticulated in numerical practices that are enacted by new software developments, data companies and data analysis instruments (Lawn 2013). The influence of digital technologies in such practices is complementing existing uses of data with methods of *digital education governance*, whereby digital technologies, software packages and their underlying standards, code and algorithmic procedures are increasingly being inserted into the administrative infrastructure of education systems. Education governance is being enacted through new kinds of digital 'policy instruments' that allow educational 'policy to be made material and operational' (Lascoumes and le Gales 2007, 4), and that are also situated in a wider 'data infrastructure' (Kitchin and Lauriault 2014). The aim of this article specifically

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is to contribute to interpreting the role of digital technologies in enacting education governance, focusing on the schools sector, and more generally to contribute to debates about data in contemporary educational governing practices.

While data as a form of 'governing knowledge' have become a key focus in studies of educational policy at national and global scales (e.g. Fenwick, Mangez, and Ozga 2014; Lawn and Grek 2012; Ozga et al. 2011; Rizvi and Lingard 2010), little research has focused on the digital technologies that facilitate its collection and analysis (Edwards 2014; Williamson 2015). This is despite the fact that 'digital data work' has been normalized within education, as evidenced by proliferating database-related technologies of governance (such as those associated with global testing instruments), and that education is increasingly treated as a 'computational' project, characterized by:

> algorithmically driven 'systems thinking' – where complex (and unsolvable) social problems associated with education can be seen as complex (but solvable) statistical problems. … This leads to a recursive state where data analysis begins to produce educational settings, as much as educational settings producing data. (Selwyn 2015, 72)

Such recursion means that digital database technologies not only represent educational settings and subjects as data-sets, but also that the data actively change them. Of course, making things 'seeable' and observable, and thus governable, always alters the observed (Lawn 2013); only now the recursivity of data is being accelerated, automated and transformed into a 'real-time' process. It is taking place in a context in which 'datafication' – the objective quantification of all kinds of human behaviour and sociality to enable real-time tracking, monitoring and predictive analysis – has become a new paradigm in science and society (Van Dijck 2014, 198). The policy instruments detailed below provide concrete examples of how real-time techniques of datafication are increasingly being normalized and enacted in the governing of education.

This article surveys the digital data policy instruments, organizations, actors and database technologies facilitating the archiving, flow and analysis of educational data. In particular, two case studies detail the technical principles of functioning of some emerging digital policy instruments and the social contexts framing them. Methodologically, the approach combines aspects of an 'instruments'-focused policy analysis (e.g. Lascoumes and le Gales 2007) with a sociological 'software studies' approach (e.g. Beer 2013) to educational technologies. Both approaches adopt a sociotechnical perspective from science and technology studies that acknowledges how specific devices are inseparable from both their social, cultural, political and economic processes of *production* and their socially, culturally, politically and economically *productive* effects. Practically, adopting such an approach has involved collecting and examining documentary materials produced to promote, justify and naturalize the use of such devices in education, such as websites, published interviews and blog posts by the actors who brought the devices into being; and producing descriptions of the functional principles of these devices, not in order to specify their technical operations but 'to be able to understand some of the logics or principles of their functioning in order to critically engage with the ways in which systems work on a theoretical level' (Bucher 2012, 1177).

Drawing on this combination of documentary and software analysis to the study of digital policy instruments, the first case study is the Learning Curve Data Bank, produced by the commercial company Pearson Education. The focus is on its digital interactive visualizations and on how these graphical forms of display invite particular forms of social action from its audiences. The Learning Curve brings a

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popular logic to the data from the domain of social media, soliciting audiences as 'prosumers' of educational data – not just consumers of its archive, but also producers who interact with the data co-creatively (the term 'prosumer' originates with the futurist Alvin Toffler and is discussed in relation to digital data by Beer [2013]). The second case study is of emerging 'learning analytics' platforms. Learning analytics enable individual students to be tracked through their digital data traces in real-time and to provide automated predictions of future progress (Siemens 2013). Learning analytics constitutes an emerging form of policy instrumentation in educational governance privileging techniques of prediction and pre-emption. Such 'big data' practices are distinct from the large-scale data-sets used in contemporary techniques of governance (such as international assessment). The point is that big data are positioned to short-circuit existing educational data practices, enabling data and feedback to flow synchronously and recursively within the pedagogic apparatus of the classroom itself. Thus, while large-scale statistical data systems acting 'at a distance' (Miller and Rose 2008) continue to influence national systems of education governance at temporal intervals, new digital data analytics complements them by providing automated feedback intended to govern 'up close' through recursive interaction with the individual student in real time. The governing of education is becoming increasingly organized through such digital policy instruments and the data infrastructure in which they are located.

Digital policy instruments and data infrastructures

Education governance is always at least partly technical. It is subject to what Lascoumes and le Gales (2007, 4) articulate as 'public policy instrumentation,' the techniques, methods of operation and devices that 'allow government policy to be made material and operational … [and] the effects produced by these choices'. The idea of 'public policy instrumentation' needs to be understood in two key ways. First, public policy instruments constitute 'a condensed form of knowledge about social control and ways of exercising it'; and second, 'instruments at work are not neutral devices: they produce specific effects, independently of the objective pursued (the aims ascribed to them), which structure public policy according to their own logic' (Lascoumes and le Gales 2007, 3). As such, instruments are bearers of values and interpretations of the social world that are materialized and operationalized by particular concrete techniques and tools, and that as a result have the capacity to partly structure policies, determine how actors behave and privilege certain representations of problems to be addressed. That is to say, the choice of instruments structures capacities for action, the process and its results. Operationalized by particular techniques and tools, policy instruments enable shared representations to be stabilized and debates preformatted around particular social issues.

Drawing on this framework in the educational context, Carvalho (2014) argues that the governing of education depends on public policy instruments (such as international assessments, quality criteria and comparative benchmarks) that carry values, worldviews, interpretations and political aspirations to coordinate and control education. Such instruments are combined of both technical components and social components. This article emphasizes how the technical aspects of public policy instruments (the software, its code, algorithms and database architectures) and their social aspects (the organizations and actors producing them, their representations about education, their values and the discursive regimes framing them) combine to 'organize social relations between administrative and administered subjects' (Carvalho 2014, 59). Digital public policy instruments, in this context, are becoming increasingly legitimized and naturalized in educational governance.

Digital policy instruments also need to be understood in the wider context of 'data infrastructures'. Building on a relational view of infrastructure from science and technology studies, Bowker and Star (1999) describe a dense infrastructural apparatus that consists of technical and social components. Technically, infrastructures consist of database architectures, platforms, packages and the thickets of code, algorithms, ontologies and standards on which they depend for their functioning; while socially, they are peopled by new kinds of experts in digital data analysis, knowledge production, presentation and communication, and are located in particular institutions, organizations and communities with their own ways of doing things, knowledge practices, expert methodologies, styles of thinking, professional subjectivities, and objectives and aspirations. An infrastructure is a hybrid 'data assemblage' of technical systems, human actors and institutions all located in social, political and economic contexts (Kitchin and Lauriault 2014). All of these entangled sociotechnical elements are articulated in the digital software that enables an infrastructure to function. As one such emerging infrastructure of digital data and knowledge production in which policy instruments do their work, education is increasingly the site for an array of digital data collection and analysis practices. The promotion by international, governmental and commercial organizations of new database instruments is reconfiguring the educational landscape as a 'virtual world of data' (Lawn 2013), one that is continuous with emerging governing techniques utilizing digital databases for the purposes of knowing and intervening in social worlds.

Machine readability

Database technologies have expanded in reach and influence significantly in recent years. The sociotechnical constitution of many aspects of the contemporary world now increasingly depends on various infrastructural database architectures and database technologies, and the processes of archiving, ordering, sorting, counting and classification they enact (Mackenzie 2012). With the emergence of 'big data', there has been a rush by businesses, governments, research and civil society organizations alike to make powerful use of data sources and techniques of analysis. Big data refer to data-sets that are huge in volume, highly diverse, exhaustive in scope, combinable, flexible and scalable (Kitchin 2014, 1–2). Big data are also generated continuously and analysed in or near real time (often through automated analytics functions), meaning that data can provide not just static snapshots of discrete temporal events but dynamic and continuously updated forms of intelligence and insight. Of course, large-scale data archiving and statistical analysis have a very long history across governmental, commercial and academic sectors, for example, in national censuses, consumer loyalty schemes and the production of massive scientific knowledge databases; big data itself can be traced through the complex histories of computerization, military funding, commercialization, academic research agendas and changing forms of government regulation (Barnes and Wilson 2014). While large-scale data archiving concentrates on the planned and sequenced collection of data at

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temporal intervals, the promise of big data is a massive acceleration in the velocity of data collection and analysis and a scaling-up in the volume of its accumulation. In this historical sense, big data need to be seen in terms of its continuities with past and existing forms of data collection and analysis, but also to be distinguished in terms of its current particularities.

With the rise of big data, databases are increasingly responsible for ordering, managing and augmenting vast parts of our everyday lives, from online finances and networked sociality to consumer practices and cultural participation. Familiar online services such as Amazon, Google, Netflix, Spotify and Facebook all rely on database systems that are able to archive people's everyday activities, then sort and classify individuals on the basis of their tastes, judgements and choices in order to generate results and recommendations (Beer 2013). Beyond the data infrastructures of popular cultural participation, databases are becoming governmentalized, as 'open data' on citizens' activities contribute to 'digital governance' (Williamson 2014) and data-driven surveillance (Lyon 2014), while scholarly research is increasingly operationalized through dense 'knowledge infrastructures' of database technologies and big data techniques too (Edwards et al. 2013). Digital data are interweaving constitutively with how the cultural, political and economic dimensions of contemporary existence are known and navigated.

Ultimately, databases function by capturing people and things as quantifiable, encodable and machine-readable characteristics which enable them to be identified, classified, ordered or sorted through data processing algorithms. They do not simply represent people mimetically, but interact with people by continually identifying them, classifying them, and delegating and automating choices and decision-making. What databases accomplish is a recursive interaction with people that subtly changes how they act. This is what Ruppert (2012) terms 'database government' – the collection and counting of vast data-sets for the purposes of measuring, monitoring and governing people's behaviour. Database government is predicated on the assumption that it is possible to construct computational theories of human behaviour out of data that can then be used to model and predict how people act, in order to facilitate pre-emptive interventions. The possible implications of such a computational theory of human behaviour for government are clear. Davies (2012, 774) describes an emerging 'style of government' in which a 'constant audit of behaviour' is undertaken, through techniques of data mining, sentiment analysis and social network analysis, in order to measure and manage the conduct of individuals and thus maintain the social order as a whole. Such a style of government depends for its enactment on the utilization of digital databases as policy instruments. As Bowker (2005, 30) notes, the governmental operations of the state and the functional logics of databases are symmetrical, and 'a good citizen of the modern state is a citizen who can well be counted – along numerous dimensions, on demand'. Such a style of governing is not just concerned with record keeping but gives rise to new kinds of material effects, especially as the world with which one engages 'becomes more and more closely tied to the world that can be represented by one's theories in one's databases; and this world is ever more readily recognized as the real world' (Bowker 2005, 152).

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The virtual world of educational data

In the field of education governance, digital policy instruments and data infrastructures are playing an increasingly influential role in representing the social ‘reality’ of education, as will be illustrated below, and in enabling techniques of governing education to be operationalized in new ways. Of course, the numerical manipulation of educational systems has a long history. As Lawn (2013) argues in a recent history of the rise of data systems in education, numerical data were long ago mobilized in nineteenth-century Europe and the United States as part of the spectacular exhibitionary practices of the international expositions, world’s fairs and scientific congresses. Many previous studies have documented the processes of ‘policy by numbers’ and ‘governing through data’ that increasingly dominate contemporary attempts to govern education (e.g. Grek 2009; Ozga et al. 2011). Today, however, the cascade of educational data, with its underlying ‘logic of enumeration’ (Hardy 2014), is increasingly being augmented by digital devices that make the power of the numbers even more visible, reproducible and persuasive. Lawn (2013) argues that database software packages and data companies are the ‘hidden’ new managers of the virtual educational landscape. Educational systems are mirrored by a digitally rendered, graphical landscape in which the data have been mediated into a variety of diagrams, charts, tables, infographics and other forms of representation that make education intelligible to a wide variety of audiences. Educational governance remains to a large extent a statistical project, but increasingly materialized and operationalized by a vast infrastructure of database software, digital policy instruments and expert computational techniques of data analysis and visualization. While there are distinct continuities with existing efforts to govern education through enumeration, the digital aspect of such efforts is less well documented.

Recent educational research on digital data and educational governance has begun to map out some emerging issues. For example, Decuypere, Ceulemens, and Simons (2014) focus on the ways ‘governing by evidence’ is increasingly achieved through ‘publicly available instruments’ such as school websites that act as ‘active platforms’ to enact and stage data as authoritative evidence, and which make it possible to act upon schools (Decuypere, Ceulemens, and Simons 2014, 618–619). Ultimately, they argue that educational data make different ‘school realities’ available as objects of thought and action. Likewise, Piattoeva (2014) argues that ‘governance by numbers’ is a ‘technology of government’ that functions by rendering schools visible and calculable to both the public and central government. In particular, she highlights how new ‘transparent and user-friendly’ database technologies and online data portals act as a form of ‘public social statistics’ that enable ‘media-assisted government from afar’, whereby authorities are enabled to act upon schools through indirect forms of control, by guiding users to make rational evidence-informed decisions (Piattoeva 2014, 8). In the Australian context, the *My School* website, argues Gorur (2013), serves as a technology for making ‘like-school’ comparisons possible (between schools with ‘statistically similar’ populations) by standardizing and homogenizing school performance metrics nationally. In these examples, the governing and managing of education are attached to the large-scale infrastructural capacities of data servers, database software developments, data mining and visual data presentation techniques, as well as to new forms of technical, methodological and graphical design expertise that are materialized in particular policy instruments.

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What, then, are the major policy instruments and techniques operationalizing contemporary education systems? One of the most well-known and established educational databases in UK education is the National Pupil Database. The NPD demonstrates some longer lines and continuities in the mobilization of digital data in education governance that anticipate more recent 'big data' developments and practices discussed later. Established in 2002 by the UK Government, the NPD features extensive data-sets on the educational progress of children and young people from the early years through to higher education and contains detailed information on over 7 million pupils currently matched over a period of 12 years. The NPD captures students at regular intervals throughout their schooling. It collects information on their progress through the educational system as traces of data that can be standardized, joined together and aggregated with a national population data-set. The NPD pages on the gov.uk website enable interested parties to request access to the data, which are presented in Excel spreadsheet files as thousands upon thousands of rows of numbers that can be searched and analysed in myriad ways, and used to generate graphical displays such as charts, tables, plots and graphs. Such spreadsheets are a highly mundane form of database technology, but have also become, since their invention at the end of the 1970s, highly influential in the organization and presentation of data across commercial and governmental sectors. The spreadsheet enables a particular view of reality as enumerable and calculable by its in-built statistical formulas and models. As a data source that is enacted through Excel spreadsheets, the NPD has become a central policy instrument of educational governance in the UK. For example, in 2015, the Education DataLab was launched as 'the UK's centre of excellence for quantitative research in education, providing independent, cutting-edge research to support those leading education policy and practice', a task largely to be accomplished by conducting secondary analyses of the NPD in order to 'improve education policy by analysing large education data-sets' (Education DataLab 2015). The Education DataLab is indicative of how education governance is being displaced to new centres of technical expertise, such as 'policy labs', that are able to translate the massive data resources of the NPD into actionable policy insights through advanced data analysis methods (Williamson forthcoming).

Educational data also have to be packaged to be made accessible to a growing audience of policy-makers, the media and the public. To this end, the Department for Education produces 'school performance tables' that allow the performance of individual schools across England to be searched. The data are visually mapped with a graphic representation of England that breaks down the data by region or local authority; by school name or town; by postcode; and by type of school/college. The school performance tables translate data-sets on pupil test scores and school funding into easily searchable, representable and intelligible forms that make meaning out of the data for its various audiences. The digital functions of the performance tables enable greater accessibility to the statistics, translating the numbers into publicly accessible formats. Despite the simplicity of the interface and the software running behind it, these public statistics and performance tables are an expert technical and presentational accomplishment, and represent the increasing hybridity of policy work with digital data analysis and public presentation in the accomplishment of educational policy.

Fulfilling a similar function, the Office for Standards in Education (Ofsted), which has overall responsibility for inspecting and assessing schools in England, has produced its own 'School Data Dashboard' package. The data dashboards consist of graphically presented accounts of school data including exam results, progress, attendance and other contextual factors. The data dashboards are promoted as an objective and data-led augmentation to the conventional school inspection by expert inspectors embodied in their various codes of evaluation and judgement. Promoted primarily for use by school governors, Ofsted claims the data dashboards provide ‘an analysis of performance over a three year period and comparisons to other schools or providers’. As such, school inspection is being performed through data technologies that have been crafted through the technical expertise of data software developers whose very existence is hidden behind the apparently objective surfaces and interfaces of the data itself. The school data used in the process of inspection, evaluation and judgement are organized and coded by the dashboards before the embodied inspector even arrives at the school, and to a certain extent, the apparently objective data displace informed professional judgement (Ozga 2014).

Likewise designed to appeal to wider demands about data transparency, the commercial producer of educational technology Research Machines (RM) has produced a ‘School Finder’ website for use by parents. Through simple drop down menus, it allows parents to search schools in specific geographical areas, to compare those schools according to various data and then to shortlist their preferred school choices. School Finder aggregates and combines data from school performance tables, the School Census, Ofsted data, Ordnance Survey data and information from schools’ own promotional and marketing materials. It ultimately remaps the landscape of UK schooling in terms of geotagged data collected from traces of children’s activities in schools. The data presented by School Finder are also augmented with an extensive set of promoted materials from RM’s commercial catalogue, configuring the parent-user as a consumer and active chooser of the data. As a policy instrument, School Finder is structured according to the principles of online consumer services such as MoneySupermarket and GoCompare, and thus, combines the popular appeal of the wider online media environment with the expert judgement associated with statistical data comparison.

The most globally well known of all educational data systems is the Programme for International Student Assessment (PISA) administered and managed by the Organization for Economic Cooperation and Development (OECD). The subject of extensive scholarly critique (e.g. Meyer and Benavot 2013), PISA is a set of triennial standardized tests administered across OECD nations. In May 2014, the OECD launched its Education GPS site. Publicly available on the web, Education GPS specifically enables the user to access interactive data in order to compare countries on a ‘wide range of indicators’. Through a simplified menu system, it allows the user to compile the data held by the OECD from its extensive PISA data-sets in order to ‘create your own, customized country reports, highlighting the facts, developments and outcomes of your choice’, and to compare and review different countries’ educational policies. The user can generate extensive customized datasets, and the Education GPS tools can generate maps overlaid with data representations, charts and scatterplots. Education GPS is a data-based policy instrument that demonstrates how powerful the OECD has become as a ‘centre of calculation’ in global education. ‘Centres of calculation’ are those spaces described by Latour (1986) that accumulate and aggregate numbers in order to affect things somewhere else. Historically, government education departments were key centres of calculation that were able to collect and aggregate data on schools. These ‘distant’ data from schools could then be transported back to a central locale, and represented in order

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to render it ‘seeable’, intelligible and amenable to deliberation and decision-making – what Miller and Rose (2008) have termed ‘government at a distance’. With the rise of digital forms of data collection in education by other non-state agencies and organizations, however, the centres of calculation in education have become more dispersed and distributed. The calculative techniques of a newer centre of calculation like the OECD make it capable of collecting vast quantities of educational data from across states and countries in order to produce a global grid of visibility in which national performance is made comparable and, importantly, public through seemingly scientific and non-political modes of technical expertise in statistical measurement and graphical presentation.

The various data sheets and dashboards described above, then, are the hybrid product of political aspirations to manage and orchestrate the flow of school data with the capacity of software to provide an apparently neutral, non-political interface. As with data dashboards more generally, they are configured according to a ‘realist epistemology’ that the world can be represented as ‘visualized facts’ (Kitchin, Lauriault, and McArdle 2015). These dashboards perform a double function, in that they render invisible the underlying data and the various algorithmic and statistical techniques performed on it, while rendering visible particular representations of that data. The structure of the software interface of the policy instrument in this sense structures the data, and is intended to structure the user’s interaction with that data as a means to facilitate social action. The next sections provide a closer examination of two emerging issues in policy instrumentation: the roles of data visualization and of predictive analytics in new techniques of governance.

Centres of visualization

A key technique of database governance in education is data visualization. The turn to visualization in education is part of a wider trend where data are increasingly visualized and mobilized graphically in a ‘cascade of representations’ (Gitelman and Jackson 2013, 12). Researchers are now pointing to the political significance of data visualization both in terms of its representational power and its techniques of production. The visualization of data is no neutral accomplishment but amplifies the rhetorical or persuasive function of data, allowing it to be employed to create arguments and generate explanations about the world and to produce conviction in others that such representations, explanations and arguments depict the world as it really appears (Gitelman and Jackson 2013). Thus, Beer (2013, 118–119) argues that researchers need to examine the actors involved in producing visualizations, ask what data they are using, how those data have been formed, as well as interrogating ‘what software is used in the analysis, what code or algorithms shape the data and the visualization’, in order to ‘treat these visuals seriously as they come to envision the social world’. As Rose, Degen, and Melhuish (2014) have identified, any visualization produced using software and digital data is ultimately assembled as it circulates around a network of offices and computer screens, as it is worked on by a variety of designers, visualizers, project managers, programmers and data analysts, and as it encounters various software programmes and hardware devices. A visualization is an ‘interfacial site’ created through networks of human bodies at work with various kinds of software and hardware, facilitated by vast repositories of code and databases of fine-grained information. The visualization and diagrammatization

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of the world described in such accounts constitute a complex sociotechnical act involving a variety of actors and technologies with the persuasive power to shape people's engagement and interaction with the world itself.

A notable producer of data visualizations in education is the global educational publisher Pearson Education. Pearson's Learning Curve Data Bank combines 60 global data-sets into one place in order to 'enable researchers and policymakers to correlate education outcomes with wider social and economic outcomes'. The Learning Curve includes national performance data (sourced from, for example, the National Pupil Database) along with PISA data from the OECD and other sources such as UNESCO, in order to produce a 'Global Index' of nations that is ranked in terms of 'educational attainment' and 'cognitive skills'. The Learning Curve is highly relational, enabling the conjoining of multiple data-sets, as well as scalable in that it can expand rapidly – new data are added frequently as new data-sets from Pearson's various sources become available. The Learning Curve was designed by the Economist Intelligence Unit, a development of the Economist Group of which Pearson itself owns a 50% stake. Unsurprisingly, the Economist Intelligence Unit is peopled by economics and statistics experts, and its methods tend to be largely quantitative and data based. It specializes particularly in country analysis and profiling, and on regional forecasting for the global economy. As such, the EIU is responsible for operationalizing the Learning Curve as a predominantly statistical project premised on the presupposition that educational performance, like economic performance, can be monitored in terms of statistical fluctuations, risks and country comparisons. This means that while quantitative data are included in its analyses, thicker forms of qualitative data are excluded.

As a public-facing policy instrument, the Learning Curve is especially notable for its data visualization tools. It features a suite of dynamic and user-friendly mapping and time series tools that allow countries to be compared and evaluated both spatially and temporally. Countries' educational performance in terms of educational attainment and cognitive skills is represented on the site as semantically resonant 'heat maps'. It also permits the user to generate 'country profiles' that visually compare multiple 'education input indicators' (such as public educational expenditure, pupil:teacher ratio, educational 'life expectancy') with 'education output indicators' (PISA scores, graduation rates, labour market productivity), as well as 'socio-economic indicators' (such as GDP and crime statistics). The Learning Curve, like Education GPS, is a powerful technique of political visualization for envisioning the educational landscape, operationalizing the presentation and representation of numbers for a variety of purposes, users and audiences.

Perhaps most interesting about the Learning Curve is how it 'configures the user' (Woolgar 1991) as an interactive participant. The user of the Learning Curve is solicited to perform independent analyses by tweaking variables, adjusting statistical weightings and generating new visualizations. As a result, the user is solicited not quite as the consumer figure of school comparison websites described earlier, but more as a 'prosumer' who does not only consume content, but also produces it. A term originally coined by the futurist Alvin Toffler, the prosumer is the ideal figure of the social media era, who 'plays' with data by creating and uploading multimedia content, updating profiles and participating in diverse online activities (Beer 2013). These logics of 'prosumption' elide distinctions between popular and expert knowledge practices. As a consequence, the Learning Curve functions as a particular kind of policy instrument that Lascoumes and le Gales (2007, 13–14) have termed

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'communication-based and information-based instruments' that privilege 'audience democracy', whereby public authorities are obliged to provide citizens with rights of access to the information they hold and citizens are required to play an active role. In this vein, Michael Barber, the Chief Education Adviser to Pearson who launched the Learning Curve (and formerly the leading government advisor behind the National Pupil Database), has described it as an act of 'co-creation' that allows the public to 'connect those bits together' in a way that is more 'fun' than preformatted policy reports (Barber and Ozga 2014, 84).

Even so, as an interactive and co-creative policy instrument, the Learning Curve is no neutral device. The choice of the instrumentation materializes the forms of analysis that are possible. It constitutes a condensed knowledge of social control, whereby its users are attracted to participate in its logics of global comparison. Users' own analyses are in effect preformatted by the design of the interface as a form of user-generated comparative analysis. This is consonant with the approach of the Economist Intelligence Unit with its emphasis on statistical country comparison and economic forecasting. Global comparison and forecasting, including the values and methodological preferences that underpin such approaches, are structured into the software in such a way to shape interpretation, make visible particular educational realities and encourage particular kinds of responses. The Learning Curve as a policy instrument therefore reveals a particular theorization of the relationship between the governing and the governed – as co-creators of the data required to know and act upon educational institutions and systems – and it functions concretely as an intermediary device to orient those relations. In so doing, it reinforces a view of education as made up of elements that can be compared and correlated through statistical analyses. Its interactive visualizations function as a form of 'soft governance' that works through techniques of persuasion, attraction and seduction, rather than 'hard' regulation, to nurture and secure assent, affinity and consensus among both policy-maker and wider publics around particular identified problems and worldviews (Lawn and Grek 2012).

Moreover, by eliding the distinction between expert and popular knowledges, the Learning Curve reconfigures the kind of 'governing knowledge' that is valued and acted upon. The social media logic of prosumption enables governing knowledge to appear as the product of co-creation rather than an expert technical and methodological accomplishment. It appears to normalize, neutralize and depoliticize statistical analysis and comparison as a mundane act, akin to monitoring one's own social media profile, personal analytics or contributing user-generated content to a website. Additionally, it appears to make educational judgement consonant with everyday social media practices of online rating, 'liking' and comparing consumer products. The Learning Curve therefore reconfigures governing knowledge as a form of 'play' and 'fun' that is consonant with the logics of social media participation and audience democracy in the popular domain, but at the same time preformats the possible results of such activities through the methodological preferences built-in to its interface. It incites the wider publics of education to see themselves as comparative analysts, and as participatory actors in the flow of comparative data. This exacerbates what Carvalho (2014) has termed the 'plasticity' of governing knowledge. With the Learning Curve, publics, rather than experts, are incited to become responsible for multiplying the analyses that take place, visualizing the data for different possible uses, and circulating it in different contexts. The Learning Curve promotes the public or popular plasticity of governing knowledge, simultaneously soliciting the

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democratic participation of its audiences while shaping the possible analyses they can conduct. It is in this sense a technology for the 'conduct of conduct' (Foucault 2007), one that functions by governing its users' capacities for action both by enabling and delimiting what they can do with the data and what can then be said about it.

As such, the dominant global centres of calculation such as the OECD and Pearson are now increasingly becoming *centres of visualization* with the technologies and techniques to render dynamic educational data visualizations and to mobilize the interactivity of users to secure their consensus. Their visualizations act as surfaces on which millions of educational performances and measurements are inscribed and made visible for inspection, analysis, evaluation and comparison. As a form of public policy instrumentation, these visualizations act as 'interfacial sites' through which different views and visions of education are constantly being composed and compared, altered and modified, developed and designed in order to render certain kinds of meanings and arguments possible. Such techniques of inscription turn schools into 'particular realities' that can be invested with meanings that 'make sense' and can be acted upon in different ways (Decuypere, Ceulemens, and Simons 2014). They guide user interpretation and produce conviction through the ways they flatten and compress extraordinary complexity into simplified and seductive visual presentations. Educational data visualization does not simply provide a mimetic representation built upon the accumulation of data from individual pupil performances, but makes education actionable through the production and stabilization of specific kinds of views of what education and learning should be. Particularly, through new technical capacities for interactivity, policy instruments such as the Learning Curve also make users active in the co-creation of data, its comparison and its visualization – making educational problems 'seeable', traceable and therefore amenable to being acted upon.

Centres of anticipation

While the governing experts at places like the OECD are increasingly contributing to global governance through vast digital systems of data collection and analysis, newer technologies and their promoters are promising to accelerate the data collection, analysis and feedback cycle, shifting the emphasis from large-scale governance of national education systems to real-time governance of the individual. According to emerging approaches, the governing of education is to be achieved through technical practices often associated with 'big data', particularly its capacity for the analysis of massive data-sets that allow fine-grained knowledge to be generated at the level of both the individual and the masses (Ruppert 2013). These are based on the notion that individuals, not just large populations, can be made viewable, enumerable and calculable in terms of numbers and visualizations. Big data thus appear to make it possible to pinpoint and trace individuals through their data trails continuously, rather than focusing on national systems or 'like-school' comparisons (Gorur 2013).

The emergence of big data in education means that data can now, increasingly, be collected and analysed in real time and automatically, short-circuiting the need for its transportation to expert centres of calculation. Pearson, for example, has established a Center for Digital Data, Analytics, and Adaptive Learning, which has produced a report on how 'big data' are set to transform education. It envisions

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education systems where 'teaching and learning becomes digital' and 'data will be available not just from once-a-year tests, but also from the wide-ranging daily activities of individual students' (DiCerbo and Behrens 2014). The report highlights the possibilities of data tracking, learner profiling, real-time feedback, individualization and personalization of the educational experience, and probabilistic predictions to optimize what students learn. These approaches combine real-time problematization of the individual with synchronous feedback and pedagogic recommendation. The vision associated with Pearson's Centre for Digital Data, Analytics and Adaptive Learning is consistent with imagery of school as a 'data platform', the 'cornerstone of a big-data ecosystem' in which 'educational materials will be algorithmically customized' and 'constantly improved', all accomplished via educational 'algorithmists' and other data experts (Meyer-Schönberger and Cukier 2014, n.p.). Developments emerging from new sites of digital expertise such as Pearson's Center for Digital Data, Analytics and Adaptive Learning provide evidence of aspirations to reorganize education through a sociotechnical infrastructure of big data technologies and expert techniques of data collection, analysis and presentation performed by 'educational data scientists' (Pea 2014).

The production of such educational big data signals the emergence of some new digital governing practices exemplified by the field of 'learning analytics'. Sometimes also known as 'educational data mining', learning analytics platforms capture data from children's educational activities in order to track, monitor and assess their development, their attainment and their dispositions to learning, in order to then algorithmically optimize and individually customize their future educational experiences (Siemens 2013). The learning analytics platform Knewton, for example, collects a variety of different educational attainment data, combined with psychometric information and social media traces, to produce a kind of 'cloud' of data on each individual. Knewton provides much of the back-end learning analytics software support to Pearson's e-textbooks. According to its chief executive, Ferreira (2013, n.p.), Knewton is based on a combination of 'low-cost algorithmic assessment norming at scale' along with 'sophisticated database architecture and tagging infrastructure, complex taxonomic systems, and groundbreaking machine learning algorithms'. The ostensible promise of absolute techno-scientific objectivity, free from human bias or pre-determined theories of learning, lies at the centre of the algorithm-led Knewton approach. These algorithmic techniques, inscrutable to all but technical specialists, are intended to generate 'inferred student data', or data that identify (by inference from comparative analysis of a huge number of data points) why students are able to progress on certain tasks rather than others. This inferred student data can then be used for personalizing or customizing pedagogic intervention. The Knewton approach, then, constructs student 'data doubles' (Raley 2013), constituted through the dynamic composition and recomposition of countless distributed data points (Ruppert 2013), all of it mediated by highly technical algorithmic processes constructed by Knewton's programmers and data science experts.

Notably, the construction of student data doubles enables individuals to be compared with much larger population datasets. While much has been written on comparison in educational governance, as noted earlier, much of it has focused on the global comparability facilitated by the collection and analysis of international assessment data. Learning analytics transforms comparison by enabling the individual student to be compared with global data-sets in a recursive fashion. As the individual's performance on a particular task is monitored, it is continually compared

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with norms algorithmically inferred from a global database, and then used for customizing future instruction. The 'big data' logics of social media are firmly articulated into the governing practices of education through such instruments. Learning analytics functions through the same principles of 'recommender systems' such as those found in consumer/prosumer spaces such as Facebook and Trip Advisor. In this way, the governing logic of global comparison becomes a real-time event concentrated to the scale of the individual among the global masses.

Equally significantly, learning analytics platforms such as Knewton are programmed with the capacity to anticipate or predict pupils' probable future progress. 'Predictive analytics' techniques form the basis of many contemporary social media and consumer 'recommender systems' (e.g. Amazon, Spotify), and again here the basic functional principles of emerging big data technologies can be seen to be beginning to structure public policy devices. This kind of predictive profiling provides institutions with actionable intelligence that can be used to determine appropriate pre-emptive pedagogic interventions. Learning analytics platforms act as anticipatory devices that are embedded within the pedagogic routines of the classroom, and are based on technical developments in 'machine learning'. The importance of machine learning algorithms is that they exhibit some tendencies of emergence, adaptivity, anticipation and prediction. Machine learning and predictive analytics software are part of a world in which 'probabilistic outcomes' and predictions about the future now prevail, with significant implications for how individuals think about and anticipate their own futures (Mackenzie 2013). In addition to the predictive analytics functions, some learning analytics platforms also feature 'prescriptive analytics' capacities. Prescriptive analytics can automate actions in a feedback loop that might modify, optimize or pre-empt outcomes. Understood as a kind of instrument, machine learning thus configures action according to its own logics of predictivity and anticipation.

Predictive and prescriptive learning analytics have the potential to shape students' possibilities for action – they create 'actionable insights' as it says on the Knewton website. Such practices embed in the classroom pre-emptive practices of prediction and 'future-tense' anticipation based on 'human-algorithm relations' where there is 'a deliberate intention to reduce someone's range of options' through 'future-oriented preventative measures' (Lyon 2014, 5). The 'robotic algorithms' of learning analytics platforms are able to access spreadsheets of learner data, calculate odds and make probabilistic predictions, and automate decisions about pedagogical intervention in a few milliseconds, with 'the risk that our predictions may, in the guise of tailoring education to individual learning, actually narrow a person's educational opportunities to those predetermined by some algorithm' (Mayer-Schönberger and Cukier 2014, n.p.).

Although learning analytics has yet to combine with national or global systems of governance, clear ambitions in this direction can be detected. Notably, Knewton already has a partnership with Pearson, and it is not hard to speculate how this might lead to greater joined-up use of data between Knewton, Pearson and the OECD. Moreover, in a recent presentation to the US Department of Education, Knewton's chief executive Jose Ferreira claimed that the system is able to collect and mine millions of data points on students, and that it holds more data on students than Google has on its users. This is a potentially tantalizing prospect for policy-makers, promising to provide the kind of fine-grained 'governing knowledge' that is required to formulate decisions and solutions to identified problems, but also to

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speed up the solution to such problems by automating the prescription of remedial pedagogic solutions. Indeed, late in 2014, Pearson Education published a report (co-authored by Michael Barber) calling for an 'educational revolution' using 'intelligent software and a range of devices that facilitate unobtrusive classroom data collection in real time', and to 'track learning and teaching at the individual student and lesson level every day in order to personalise and thus optimise learning' (Hill and Barber 2014, 55). In particular, Pearson promotes 'the application of data analytics and the adoption of new metrics to generate deeper insights into and richer information on learning and teaching', as well as 'online intelligent learning systems', and the use of data analytics and automated artificial intelligence systems to provide 'ongoing feedback to personalise instruction and improve learning and teaching' (Hill and Barber 2014, 58). Moreover, it argues for a revolution in education policy, shifting the focus from the governance of education through the institution of the school to 'the student as the focus of educational policy and concerted attention to personalising learning' (Hill and Barber 2014, 23). The report clearly represents an emerging educational imaginary where intelligent analytics devices are taken to be key policy instruments – and where policy is to concentrate on the real-time tracking of the individual, rather than the planned and sequenced longitudinal measurement of the institution or system. Pearson's own Center for Digital Data, Analytics, and Adaptive Learning is intended as the organizational setting for the development and advancement of such instruments.

Ultimately, the analytics being developed by Knewton and Pearson anticipate a new form of 'up-close' and 'future-tense' educational governance. Learning analytics makes every individual learner into a *micro-centre of anticipation* – the focus for a constant and recursive accumulation, analysis and presentation of data, real-time feedback, probabilistic predictions and future-tense prescriptions for pedagogic action. These analytics capacities complement existing large-scale database techniques of governance such as those of the OECD. But they also, to some extent, short-circuit those techniques. The deployment of big data practices in schools is intended to accelerate the temporalities of governing by numbers, making the collection of enumerable educational data, its processes of calculation and its consequences into an automated, real-time and recursive process materialized and operationalized 'up close' from within the classroom rather than 'at a distance' by expert centres of calculation. While OECD data influence the conduct of national policy-makers over distinct long-term temporal intervals, for example, Knewton and Pearson aspire to target the conduct of the individual student in real time and automatically, shaping performance and progress in class in ways that sculpt their conduct according to norms inferred from a growing global database. As big data developments increasingly join disparate data-sets, it is feasible to speculate that the linking of global international assessment data with individualized learning analytics data by companies such as Pearson would produce a vast and powerful data infrastructure in which student data could be collected continuously, analysed in real time and fed back not just into national profiles and global league tables but directly into the pedagogic apparatus of the classroom. With both The Learning Curve Databank and its Center for Digital Data, Analytics, and Adaptive Learning, Pearson would be well placed to provide the data infrastructure for both global comparison and personalized pedagogic intervention combined. Along these lines, notably, the OECD itself is moving towards new forms of machine learning in its international assessments technologies, with a proposal to assess collaborative problem-solving as part of PISA 2015 through ‘a fully computer-based assessment in which a student interacts with a simulated collaborator or ‘avatar’ in order to solve a complex problem’ (Hill and Barber 2014, 49). Rather than governing at a distance through expert centres of calculation, with learning analytics, the centre of calculation and the governing knowledge it generates is in the algorithmic machine itself.

Conclusion

Educational digital data are not novel in themselves. The collection and digitization of massive educational data-sets have a relatively long history, and data collection in education goes back well over a century. However, emerging digital data practices of data analysis, visualization, prediction and prescription enabled by emerging public policy instruments – many based on functional principles and discursive logics derived from social media and big data – are becoming powerful sources of contemporary digital educational governance. Digitally rendered as a vast surface of machine-readable data traces through data companies such as Pearson and Knewton, education is increasingly amenable to being effortlessly and endlessly crawled, scraped and mined for insights. While this is not all new, then, it does indicate the emergence of a relatively distinctive style of education governance in which digital data-based policy instruments are employed to perform a constant audit of student actions in order to make them visible and thus amenable to pedagogic intervention. As a consequence, to examine educational governance increasingly requires exploration of the sociotechnical data infrastructures framing it and the digital policy instruments making it operational.

The new managers of the virtual world of educational data are the technical, statistical, methodological and graphical experts – both human and non-human – at the OECD, Pearson and Knewton who are able to inscribe schools and the learners within them in enumerable, visible and anticipatory data, and to address their audiences as particular users. New kinds of data careers have been made possible, both for leading policy advisors such as Michael Barber and entrepreneurs like Jose Ferreira, but also for the educational data scientists, experts and algorithmists required to do the data work, construct the database architectures and design the analytics. The techniques produced and promoted by such data experts appear at the very least to accelerate the temporalities of digital data collection and use in education – complementing the massive, longitudinal data-sets such as those held by national governments or by the OECD with more dynamic, automated, real time and recursive systems such as those being developed by Knewton and Pearson.

The digital datafication of education is part of a wider methodological shift in commercial and governmental settings to utilize big data as a statistical source for developing computational models, theories and understandings of human behaviour (Kitchin 2014). In a statistical regime of datafication, the state seeks to shape its citizens into an enumerable form in order to fit them to classificatory schemes, undertake constant and real-time audits of their behaviours, make probabilistic predictions and allocate services that might reshape the ways that they act and conduct themselves – a process of ‘database government’ that is increasingly being delegated to automated algorithmic systems (Ruppert 2012). The ways statistical digital data technologies are being deployed as policy instruments are part of an emerging style of data-based digital education governance which sees individual learners subjected to continuous tracking, visualization and anticipation to facilitate real-time

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pre-emptive pedagogic practices. These methods are designed according to the values and assumptions about learning and pedagogy held by technical experts such as data scientists, graphics designers and software developers, thus displacing the pedagogic expertise of educators while valorizing technocratic models of the pedagogic interaction as measurable and modifiable events. Understood in terms of policy instrumentation, data visualization and big data analytics methods hybridize techniques of 'governing through data' with techniques of 'governing through pedagogy' (Pykett 2012), where there is an intention to activate the capacities of learners through the pedagogic apparatus of the classroom. This is a fully recursive arrangement where learners produce data to be calculated, compared and used for prediction; the result is that differential feedback then flows directly into the classroom in the shape of pedagogic prescriptions intended to sculpt learners' conduct to fit algorithmically inferred global norms, leading to a situation where the data produce the learner as much as the learner produces the data.

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