Digital policy sociology

Citation for published version:
Williamson, B 2019, 'Digital policy sociology: Software and science in data-intensive precision education', *Critical Studies in Education*, pp. 1-17. https://doi.org/10.1080/17508487.2019.1691030

Digital Object Identifier (DOI):
10.1080/17508487.2019.1691030

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Critical Studies in Education

Digital policy sociology: software and science in data-intensive precision education

Ben Williamson, University of Edinburgh

[Manuscript version of paper published in *Critical Studies in Education*, special issue on 'Revisiting Policy Sociology': https://doi.org/10.1080/17508487.2019.1691030]

Abstract Software code, algorithms, data analytics and infrastructures have become inseparable from policy processes and modes of governance. This article introduces 'digital policy sociology' as a way of studying the role and influence of digital technologies in education policy. Building on existing 'policy sociology' approaches combined with emerging insights rom 'digital sociology', digital policy sociology extends the analytical gaze to new technical actors—nonhuman software and hardware, as well as human experts, technology companies, and promotional organizations. As a case study exemplar, the analysis focuses on an emerging domain of data-intensive science and technology with significant implications for education policy in the future. 'Precision education' is an emerging combination of psychological, neuroscientific and genetic expertise, with a particular emphasis on using advanced computational technologies to produce 'intimate data' about students' bodies and biological associations with learning. These intimate data have potential to become new sources of biological policy knowledge, raising significant methodological and analytical challenges for policy sociology.

Keywords *biology, data, genetics, neuroscience, precision education, psychology*

Computer software and data are increasingly integral to many areas of social and public policy. This article presents an approach to 'policy sociology' that focuses on the role of digital software in education policy specifically. The term 'digital policy sociology' signifies emerging attention to how policy processes have become entangled with digitally coded software, databases, algorithms, infrastructures, and analytics. In this sense, it combines 'policy sociology' with 'digital sociology' and cognate social scientific approaches to the analysis of digital technologies. In order to highlight policy sociology approaches to digital technologies in emerging policy approaches, the article presents a case study of the capture and analysis of 'intimate data' from students as an exemplar of a 'data-intensive' and 'life-sensitive' form of educational governance. A new interdisciplinary educational science focused on the quantification of students' affects, bodies and brains, captured in the term 'precision education', has emerged as a priority among scientists, foundation funders, philanthropic donors, and commercial entities. Set in the context of intensive scientific advances in the biological sciences, including psychophysiology and biometrics, neuroscience and genomics, precision education raises fresh questions about the intersections of biology with society, politics and governance. The aims of this paper are, specifically, to interrogate how data-intensive digital technologies participate in the production of policy-relevant knowledge, and, more generally, to contribute to emerging research foregrounding the role of digital technologies in educational governance.

The shift to capturing 'intimate data' from students' bodies represents a step-change in the quantification of education. International large-scale assessment data such as those generated by the OECD (Organization of Economic Cooperation and Development), and their subsequent impact on education policies globally, have become a core concern of education policy sociology over the last decade (Grek, 2009; Sellar & Lingard, 2014), reflecting the social, organizational and political effects of the use of numbers in transnational governance (Hansen & Porter 2012). Digital technologies, infrastructures, 'big data', analytics, and algorithms have become significant in such analyses as they introduce new capacities for production of policy-relevant knowledge and insights for governing education (Williamson, 2017). However, mining 'intimate data' from students enhances the optical powers of digital data systems considerably, bringing 'life itself' into the purview of education policy through the digitally-filtered lenses of the biological sciences (Gulson & Webb, 2018).

Specific precision education initiatives are part of a rising uptake of new scientific knowledge in education policy twinned with growing enthusiasm and advocacy for data-led policymaking (Webb & Gulson, 2015; Gulson & Webb, 2017). The OECD's Andreas Schleicher (2018) claims effective use of educational data brings 'the rigours of scientific research to education policy,' and allows 'digital exhaust' to be transformed into 'digital fuel,' 'using data as a catalyst for educational practice'. A subsequent OECD report on the 'science of learning' explores 'the interplay of the biological, physiological, cognitive and behavioural processes supporting the learner', and advocates:

> large-scale, convergent and interdisciplinary efforts that integrate across levels of analysis and disciplinary perspectives—from molecular/cellular mechanisms of circuits and brain systems that underlie cognitive and behavioural processes, to social/cultural influences that affect learning—in individuals and in groups … taking advantage of technological advances, particularly in neuroscience, engineering, and computer and information sciences. (Kuhl et al, 2019, p.16).

The OECD identifies new scientific knowledge from psychology, neuroscience, and biomedicine, twinned with computer science, machine learning, and software engineering, as relevant sources for education policy, and supports 'global networking around a more integrative and interdisciplinary science of learning' (p.14) plus 'investment in socio-technical infrastructure to facilitate knowledge convergence and collaboration among research, educator and policymaker communities' (p.19). Simultaneously, the Chan-Zuckerberg Initiative, the 'for-profit philanthropy' of Facebook founder Mark Zuckerberg, has begun significant investment in 'learning science' as a way of rapidly intervening in school practices and shaping policy trajectories through psychological, neuroscientific and biomedical evidence and expertise (https://chanzuckerberg.com/education/learning-science/).

These catalytic calls for new sciences of learning are important levers in efforts to embed scientific, data-driven and evidence-based approaches in education policy and practice, signifying the emergence of data-intensive and life-sensitive learning sciences as sites of policy-relevant knowledge production and potential sources of transnational governance. The term precision education is used in this article to capture the sociotechnical ensembles of scientific expertise, data-intensive technologies, research labs, business interests, philanthropic support and policy advocacy that constitute the new data-intensive learning sciences.

As such, there is a pressing need for studies of how digital software and scientific expertise are mobilized together in the new sciences of learning, and their implications for educational practices and policies. As a way of opening up these issues, this article consists of a digital policy sociology analysis of precision education, examining the sociotechnical networks of organizations, technologies, and forms of scientific expertise and knowledge involved in data-intensive biological approaches to education. The task here is to interrogate how digital technologies and computational experts participate in the production of new kinds of educational knowledge that are rooted in biological conceptions of learning, and to query the emerging implications for knowledge-based policy and governance. The analysis reveals a persistent ontological commitment to scientific realism in these data-intensive and life-sensitive forms of precision education, based on objectively measured scientific knowledge of the biological substrates of student learning. Precision education raises the prospects of data-driven and biologically-informed policy which recasts students as calculable objects composed from traces in datasets, whose 'traceability' makes them amenable to practices of 'learning engineering'.

Doing digital policy sociology

'Policy sociology' grew out of frustration in the late 1980s and 90s with reductivist, deterministic and atheoretical accounts of straightforward, linear policy 'implementations', and a rejection of positivist 'policy science' scholarship which sought to solve policy 'delivery' problems and contribute to policy formation and improvement (Bowe, Ball & Gold, 1992). Instead, critical policy sociology approaches sought to engage with the complex and contested *production* of education policy, including the 'macro' politics in which it was embedded, and with the uneven, often unpredictable *effects* of policy in the micro-spaces and practices of educational institutions, by investigating 'the source, scope and pattern of any education policy, the operation of the state apparatus, its internal contradictions and conflicts, the historical antecedents of policy structure, content and culture' (Ozga, 1990, p.361). Policy sociology research would 'trace through the development, formation and realization of those policies from the context of influence, through policy text production, to practices and outcomes', and then follow 'the ways in which policies evolve, change and decay through time and space and their incoherence' (Ball, 1997, p.266).

Policy sociology analyses in education have advanced in the last decade to pay concerted attention to cross-border 'network governance' (Ozga et al, 2011), geographically dispersed and fast moving 'policy mobilities' (Ball, Junemann & Santori, 2017), and 'policy assemblages' that consist of nonhuman material objects and devices (Savage, 2019). As policy sociology has shown, contemporary education policy is the accomplishment of webs of government agencies, transnational governance organizations, private sector companies, think tanks, consultancies, material things and discourses (Fontdevila, Verger & Avelar, 2019). One important thrust of policy sociology and policy mobilities research has drawn attention to the 'knowledge-based technologies' used to make policy and enact governance over education systems, institutions and individuals, and to the technical and statistical experts who bring new skills to policy processes (Fenwick, Mangez & Ozga, 2014). This emphasis on new forms of 'epistemic governance'

> highlights the importance of knowledge as a resource for governing, knowledge that is now available in mobile, global forms, produced and translated by experts, and collected and distributed through knowledge-based technologies. Adopting an epistemic governance perspective highlights the importance of policy actors' values and beliefs, while also drawing attention to the networks of professional scientists and experts who claim policy-relevant knowledge, but who often share a set of normative beliefs that guide their knowledge production activities. (Ozga, 2019, p.730)

A crucial aspect of epistemic governance and 'governing through knowledge' is the historical rise and contemporary proliferation of systems of data collection, analysis and dissemination (Lawn, 2013), including the 'data infrastructures' of technologies, human actors, software companies and policies involved in enabling data to flow at national and international scales (Gulson & Sellar, 2018; Hartong, 2018). Such studies interrogate the nonhuman hardware, software, code, algorithms and data analytics programs, as well as the human technical experts, data scientists, software developers, algorithm designers, analysts, visualization artists and intermediaries involved in different aspects of policy work, and includes analyses of the databases, infrastructures, web portals, apps, platforms, companies and actors that participate in education policy processes, as well as the political, economic and social contexts that frame them. Instruments designed by informaticians, data scientists and software engineers have become integral to the formation, enactment and effects of education policy (Williamson, 2017; Landri, 2018). Such studies indicate the emerging centrality of the 'digital' in policy sociology, and highlight the possibilities of 'digital policy sociology' analyses of contemporary and emerging practices and techniques of education policy and governance.

Digital policy sociology expands the resources available to critical policy researchers by engaging with theory, concepts and methods from STS, the sociology of statistics, software studies, and critical data studies, recently brought together as 'digital sociology' (Lupton, 2015). 'Digital sociology' signifies a social scientific attention to 'the relations between knowledge, technology and society', highlighting the role of digital technologies in making it possible to 'see' the social world through 'traceable' data (Marres, 2017, p.3). As such, digital sociology and related research trains the analytical gaze on the very digital methods of knowledge production through which institutions, individuals, events, or patterns and trends may be traced, known and intervened on. Recent social scientific studies of data of a broadly digital sociology style have drawn attention to how digital infrastructures, algorithms, software and analytics participate in societies and forms of governance (Beer, 2016). In 'an algorithmic age' the practices of 'mathematics and computer science are coming together in powerful ways to influence, shape and guide our behaviour and the governance of our societies' (Danaher et al, 2017, p.1). Beer (2019) exemplifies a broadly conceived digital sociology approach, forensically unpacking the infrastructures and practices of the data analytics industry in order to understand how such companies generate data, produce knowledge, and influence societies through specific sociotechnical practices and methods of analysis.

Big data is already transforming the human sciences too, with sociologists of fields such as biomedicine increasingly turning their attention to the work of digital infrastructures and analytics in scientific knowledge production. Through infrastructural advances in 'bioinformatics' and 'biodata' storage, for example, research biologists and consumer companies can project the data gaze into human DNA (Parry & Greenhough, 2018). Neuroscientific practices of brain imaging have made neural structures, functions and processes legible under scientific lenses and amenable to being modelled and simulated computationally (Rose, 2016). Psychological and emotional life, too, has been rendered 'machine-readable' by emerging technologies of 'algorithmic psychometrics' and 'emotional artificial intelligence' (Stark, 2018). Wearable biometrics and facial detection technologies that can 'read' autonomic biological signals from the surface of the human body—as biophysiological proxies for psychological states—also open it up to being controlled, engineered and reshaped (McStay, 2018). The emerging data-intensive and life-sensitive sciences of the body rely on the data infrastructures that make biological, neural and psychological data available to the gaze of the analyst. In turn, those intimate data can then be made available for the inspection of those authorities that seek to govern human conduct.

These approaches rely on an ontology of 'metrological realism', or 'the dream of the statistician', which assumes 'reality is independent of the observation apparatus' (Desrosieres, 2001, p.341). Metrological realism emerged from nineteenth century natural sciences and was developed through statisticians' pursuit of large numbers, based on the assumption that 'computed moments (averages, variances, correlations) have a substance *that reflects an underlying macrosocial reality, revealed by those computations*' (p.348, original emphasis). This metrological realism of a computable macrosocial reality persists into positivist twenty-first century 'social physics' based on big data analytics (Marres, 2017). From a critical sociological perspective, however, biologically intimate data are rather the products of sociotechnical networks of actors and technologies that selected and shaped them (Leonelli, 2018). The objectivity and precision of data is always in fact a practical, situated and value-laden accomplishment, involving such processes as the standardization of working practices, the demarcation of categories for classifying and organizing data, the design of analytical instruments, and choices about which data to present and how (Beer, 2019).

This point about the fabrication of objectivity is especially crucial in relation to the datafication of human subjects in contemporary scientific and commercial domains, as physical bodies have become technically augmented and digitally rendered as 'data traces' in 'inexhaustible datasets' (Pickersgill et al, 2019). Through combining data-intensive technologies and the life-sensitive gaze of the human sciences, the body is first constructed as data, and then integrated into systems that are designed to monitor, engineer and reshape embodied life processes (Stevens, 2017). These 'data bodies' are not precise digital shadows or representational mirrors of embodied subjects, but, because data can be endlessly linked or taken apart, combined and recombined, analysed and reanalysed, data subjects are constantly composed and recomposed from their digital traces (Prainsack, 2017). The digital data body is only ever a temporarily stabilized accomplishment, and could always be remade in multiple different forms at different times, by different scientists working in different disciplinary conditions under different objectives, funding schemes and research questions (Parry & Greenhough, 2018). Moreover, computational metaphors of human bodies in biology—as genetic 'codes', neural ‘networks’ and psychological ‘software’ that may be decoded—means bodies have been rendered ‘machine-readable’ and data-minable as corporeal containers of biological information (Stevens, 2013). Making bodies machine readable as digital data means that biology has been translated into the language of computation, raising the prospect that bodies may then also become as ‘machine-writable’ as silicon, and de-bugged, optimized and engineered through software codes and algorithms (Rose, 2016).

These points alert us to the potential consequences of ‘metrological realist’ approaches which seek to precisely and objectively measure and monitor the intimate corporeality of the human body. Biological machine-readability implies multiple translations of fleshly, material bodies into standardized, stabilized data formats that are intelligible to computers, and focuses the biological data gaze on measurable data bodies. As such, the research challenge is to unpack how these intimate data are produced, the forms of expert scientific knowledge and software techniques employed to do so, and to inquire into the ways such knowledge, software and data may then be promoted as resources for policymaking and governance. ‘Digital policy sociology’ is a tentative category for studies combining policy sociology analysis of the production of policy-relevant knowledge with digital sociology studies on the role of digital methods in producing new forms of knowledge. It highlights the changing conditions of knowledge production made possible by advanced digital technologies, especially as education policy and governance become increasingly data-intensive and life-sensitive.

Precision education

‘Personalized learning’ has become a key contemporary imaginary of data-driven education. Emergent ideas and practices of ‘precision education’ build on techniques of personalized learning, such as learning analytics and adaptive learning software, but also encompass ideals associated with ‘precision medicine’ and ‘personalized healthcare’, the biomedical ‘effort to collect, integrate, and analyze multiple sources of genetic and nongenetic data, harnessing methods of big data analysis and machine learning, in order to develop insights about health and disease that are tailored to the individual’ (Ferryman & Pitcan, 2018, p.3). Precision medicine is a major site of biomedical innovation uniting high-tech Silicon Valley businesses, healthcare providers, bioscientists, and venture capital (Reardon, 2017). It has been criticized for promoting a neoliberal imaginary of the ‘empowered,’ self-responsible individual; shifting attention from social determinants of health to technological fixes for health problems; privileging computable evidence over subjective experience; and treating ‘patients as continuous data transmitters’ who accept digital surveillance as the price of personalized healthcare (Prainsack, 2017, p.12).

Discursively symmetrical with precision medicine, precision education research asks 'What intervention worked for whom and how did it work?' in order to 'tailor interventions' to individual needs' (Cook, Kilgus & Burns, 2018, p.5). While precision education does not (yet) have the massive infrastructural capacity of precision medicine, it is similarly based on scientific practices of collecting multiple sources of data about psychological states, genetic identities and brain activity through advanced scientific methods and digital data-processing technologies, led and promoted by researchers in educational psychology, genomics and neuroscience. The OECD 'science of learning' agenda highlights how 'significant insights have been achieved into the complex, dynamic processes and mechanisms that underlie how people learn' from disciplinary experts including 'neuroscientists, social, behavioural and cognitive scientists, mathematicians, computer scientists, engineers and education researchers' (Kuhl et al, 2019, p.13). It further advocates 'the use of Big Data, Artificial Intelligence algorithms, education data mining and learning analytics … to improve learning and education', and proposes 'science-based actions' to enhance 'real-world education practice and policy' (p.14). As this OECD emphasis on learning sciences and data-driven personalized education indicates, 'life-sensitive' and 'data-intensive' digital technologies are enabling the production of novel policy-relevant scientific knowledge about the 'intimate' details of students' behaviours, bodies and brains.

Some programmes bearing the term precision education or precision learning are emerging already. One is the Precision Learning Center (PLC) at the University of California (http://www.precisionlearningcenter.org/). The PLC approaches education as an applied science, and suggests that 'learning engineering' can be made possible through better scientific understanding of the psychological, neurological and genetic substrates involved in learning. In Europe, the philanthropic Jacobs Foundation is promoting precision education too. It focuses on the science of learning and supports research and advocacy on educational psychology, neuroscience and genetics, drawing attention especially to its multidisciplinarity and large-scale computational requirements, and by funding international 'interdisciplinary work on individual development and learning' that combines 'genetic, epigenetic, neurobiological, behavioral and social levels of analysis' (https://jacobsfoundation.org/en/activity/jacobs-foundation-research-fellowship-program/). These specific precision education programmes are actively seeking policy influence through the digital generation of new scientific data and knowledge, though their aspirations are shared by other stakeholders in the data-intensive psychological, neuroscientific and genomic fields. The following sections identify key actors, technologies and activities in each of these fields, revealing how new kinds of policy-relevant knowledge are being produced through data-intensive and life-sensitive scientific methods and practices.

Psychodata

Psychology and psychometrics played a large part in transposing human bodies, characteristics and mental life into atomistic data points as long ago as the late nineteenth and early twentieth centuries, though the availability of digital big data in the twenty-first century has made it possible to capture, quantify and calculate about the human condition with unprecedented fidelity, granularity and precision, as the human sciences have become increasingly data-intensive (Armstrong, 2019). Across the commercial social media sector, companies have adopted new psychological techniques of 'algorithmic psychometrics' and 'digital phenotyping' (Stark, 2018). Techniques such as 'emotion AI'—wearable biometric sensors, facial recognition, voice tone analysis, and natural language processing—constitute a new mode of 'automated industrial psychology' which views human subjects as 'leaky bodies' emitting autonomic biological signals that indicate an emotional state (McStay, 2018). As a consequence, human psychological states have become 'machine readable' as the biological materiality of the human body has become 'traceable' as digital data.

Students' psychological traits are increasingly being enumerated as objective data and made machine readable in the emerging field of 'social-emotional learning' (SEL), with educational psychologists beginning to argue for 'precision education' initiatives 'mirroring precision medicine' (Cook et al, 2018). With the emergence of algorithmic psychometrics, emotion AI and SEL policy agendas as context, organizations including transnational governance institutions, startup technology companies, and psychology labs alike have begun to pursue the production of policy-relevant 'psychodata' through advanced digital infrastructures and devices. For example, the OECD has positioned itself as a key site of SEL measurement and development as part of its long-term Education 2030 programme to reimagine the future of education (Schleicher, 2018) and its turn to new 'sciences of learning' (Kuhl et al, 2019). It has established the Study on Social and Emotional Skills (SSES) as an international assessment instrument to measure and compare the noncognitive dimensions of learning across different countries, combining an online test and keyboard biometrics with a personality profiling index and econometric methods of 'human capital' calculation (Williamson, 2019). Likewise, the World Economic Forum exemplifies the move toward automated industrial psychology in SEL by promoting facial recognition and wearable biometric emotion sensors (WEF 2016). Across both the OECD and WEF is evidence of advocacy for the assessment of students' social-emotional skills through a mixture of facial action coding, personality profiling and biometric arousal sensing, in ways that indicate the potential for new biological big data methods to become integral to the production of policy knowledge.

Emotion detection is a form of 'psychometric realism' which assumes subjective emotional experiences, psychological traits and personalities can be captured accurately and quantitatively (Michell, 2008), and that these measures can be read precisely from biological signals that are traceable in skin, facial expression, and bodily comportment (McStay, 2018). The data gaze of automated psychology concentrates on autonomic biological processes rather than subjectively embodied and articulated experiences, as enumerated and known through webs of standardized classifications, technologies, and scientific knowledge. The student-subject of SEL is a data body constituted by the psychological categories in-built to personality profiling models, the biometrics of wearable devices, and the affect categories and scales of facial action coding systems. Stark (2018) argues that 'scalable subjects' are formed from the constant collation of psychometric and behavioural data traces—not stable data bodies or 'data doubles' but constantly mutating models that may be called up on-demand as data become available to add, combine and aggregate with existing datasets. Specifically, these scalable data bodies are made possible by a reconceptualization of bodies as 'leaky' containers of biological signals (McStay, 2018). As the OECD's turn to SEL measurement and the learning sciences now demonstrate, students' scalable data bodies are now becoming a potential source of governing knowledge.

Digital SEL measurement technologies, then, are based on standardized models and instruments for precisely recording, measuring and classifying human affects and traits from autonomic biological processes in ways that may be presented as quantifiably objective, unambiguous and precise. The psychological data produced may be effective in animating policy interest through the advocacy of international policy-influencers such as the OECD and WEF. These organizations are already establishing a precision science of the psychological traits, personalities and noncognitive capacities of students. They also potentially open up the body, moods, and behaviours of students to new forms of policy influence. As an OECD report on SEL indicates, data about noncognitive skills is understood to have increasing 'policy relevance' as it can be used to determine priorities for intervention (Kankaras, 2017).

Brain data

The human brain is the current focus of intensifying interest among scientists, governments, businesses, the media and various publics as 'neurotechnology' developments have made it possible to gaze upon the brain's structure, functions and plasticity through scientific lenses (Ienca & Andorno, 2017). Educational researchers and policymakers have increasingly turned to neuroscience for insights into the brain-based aspects of students' learning (Youdell & Lindley, 2018). New neurotechnologies appear to open up the 'learning brain' not just for inspection and inscription, however, but to new forms of prescriptive policy intervention and even direct modification (Williamson, 2018).

Neuroscience is one of the key sources of knowledge and expertise cited by advocates of precision education. The Precision Learning Center has direct partnerships with a dedicated neuroimaging centre at UCSF, BrainLENS (Laboratory for Educational NeuroScience), which integrates 'the latest brain imaging techniques, genetic analysis, and computational approaches to examine processes of learning' (http://brainlens.org/). It is dedicated both to shaping educational practices around neuroscientific insights and to influencing policymakers through the deployment of neuroscientific knowledge and evidence. Another partner, Neuroscape, uses 'sophisticated neuroimaging, adaptive cognitive assessments' to investigate 'real-world learning and mechanisms that influence academic achievement and overall cognitive health' (https://neuroscape.ucsf.edu/education/). Its main application is a 'precision cognitive assessment tool—ACE (Adaptive Cognitive Evaluation)—that incorporates adaptive algorithms to rapidly assess and longitudinally track the multidimensional profile of cognitive control over time'. These partners demonstrate how neuroscience-based technologies are centrally positioned in precision education, treating the brain as a 'leaky' neural network of electrical signals that can be translated into new educational knowledge.

What is the key technology underpinning the production of new neuro knowledge in education? A key area of neurotechnology development in education is electroencephalogram (EEG) recording of neural activity and neuroimaging. EEG has a long history supporting neuroscientific claims that the brain has been made 'legible' (Rose, 2016). It remains a key neurotechnology in brain science research, and is integral to big data brain initiatives (Yuste et al, 2017). In particular, EEG data has become the subject of machine learning-based analyses using brain-computer interfaces (BCIs):

> BCI systems can be trained to recognize the brain signatures associated to specific tasks and decode the current mental task of a user in real-time. … The capacity to decode mental states in real-time and modify the feedback to the subject accordingly opens unprecedented opportunities in neuroscience. (Biasiucci, Franceschiello & Murray, 2019, R84)

Significant infrastructural development is underway to construct the institutions, technical systems, and professional expertise necessary to undertake intensive EEG studies in education. These include new research centres and labs, innovative startup companies, and partnerships between researchers, developers and educators. One notable example is the Brainwave Learning Center, a partnership between Stanford University and a 'lab school' in Silicon Valley with its own on-site ‘brainwave recording studio’ featuring sophisticated wearable EEG headnets and BCIs for real-time analyses of the neural correlates of learning and cognition (https://www.synapseschool.org/about-us/blc). Another example is the FocusEDU neuroheadset produced by the Harvard-incubated startup company BrainCo, which ‘can quantify real-time student engagement in the classroom’ through brainwave-detecting headbands and a software platform which gives teachers access to real-time student brain data (https://www.brainco.tech/product/focusedu). BrainCo’s FocusEDU package also comes with neurofeedback software offering ‘brain priming exercises’ for improved ‘self-regulation’, and in partnership with another education technology company it announced a ‘neuro-optimized education platform’ to deliver personalized learning based on machine learning analysis of students’ brainwaves during ‘microlearning routines’ (https://www.brainco.tech/use-cases-new/). As such, FocusEDU reads the material brain for proxy signals of learning processes, actively primes the brain for enhanced performance, and informs adaptive platforms to personalize the digital learning experience.

EEG is opening opportunities for educational neuroscientists to render the ‘learning brain’ legible, particularly as insights about the brain’s ‘plasticity’ have inspired efforts to sculpt its cognitive and affective capacities (Costandi, 2016). From a digital policy sociology analysis, these emerging neurotechnologies present the prospect of new forms of ‘neurogovernance’ that are concerned with the measurement and reshaping of malleable brain processes (Pitts-Taylor, 2016). Pitts-Taylor (2016, p.35) argues that phenomena such as ‘neuroplasticity’ are the products of a ‘specific configuration’ of ‘knowledge systems, tools, researchers, research subjects, bodies, [and] institutions’:

> A phenomenon includes the entities under investigation, the scientific tools and practices that touch them, the knowledges that inform them, and the material changes the measures make. Neural plasticity can be understood this way. To make sense of the plasticity of the brain, scientists, scholars, and policymakers call forth particular configurations of bodies, brain matter, measurements and other practices. (Pitts-Taylor, 2016, pp. 35-36)

Neurotechnologies such as EEG headsets are key sociotechnical parts of the configuration of brain plasticity. They provide the measurement techniques by which to scan and quantify the brain and its malleability, and they introduce neurofeedback to then materially sculpt that measured brain to perform in optimized ways. In this sense, neurotechnologies are ‘materially performative’ (Pitts-Taylor, 2016), actively targeting regions and processes of the brain for priming and activation in order to improve or sculpt its measured qualities. As the brain has been made machine-readable by neurotechnologies, it may become increasingly ‘machine-writable’ as it becomes possible not just to decode mental processes but directly manipulate the brain mechanisms underlying people's physical and mental abilities (Yuste et al, 2017).

As neuroscience and neurotechnologies are taken up in precision education initiatives, they too raise the possibility of materially performative effects, as measures and 'readings' of brain activity generated through the digitally-filtered gaze of neuroscience become knowledge for use in brain-based policy interventions and pedagogic practices. The scientific groundwork for brain-based policy is already being laid. Policy-influencing organizations including the OECD are increasingly turning to data from the brain sciences as knowledge of how young people learn as a way of recommending policy interventions, for example investing in early years programs to stimulate brain development (Kuhl et al, 2019). These brain data need to be understood as complex sociotechnical accomplishments that are inseparable from the infrastructures of people, technologies and methods that produced them. As such, further unpacking of the computational structures and functions of neurotechnologies would illuminate the novel ways in which student brain data are now able to be created, and further contribute to analyses foregrounding the role of digital technologies in producing the new neuro-knowledge that transnational governance organizations such as the OECD support as sources of policymaking.

Biodata

The third thread of precision education is human genomics. Again, the crucial question here is about how the turn to data-intensive technology in human genomics is changing the ways knowledge is produced, and what implications this raises for the use of genomic knowledge in epistemic governance. Human genomics is integral to the precision education initiatives at the PLC and Jacobs Foundation, and to the wider development of a field of 'educational genomics' which aims to enable educational organizations to create tailor-made curriculum programmes based on a student's DNA profile (Gaysina, 2016).

The emergence of a data-intensive educational genomics depends on the historically-situated creation of standardized measurement practices that determine what 'biodata' can and cannot be subjected to the analytical gaze, the design of the bioinformatic infrastructures for moving biological data, the production of biotechnologies for analysis, and the varied data practices of biologists, bioinformaticians and biotechnology companies, such as ordering, combining, organizing, correlating and clustering genetic data (Leonelli, 2016). The infrastructures, statistical practices and technologies underpinning genetic sciences are highly consequential to the forms of analysis and knowledge production that can take place (Stevens, 2013). From this perspective, digitally-stored 'biodata' or 'bioinformation' is the current instantiation of long-standing scientific concerns with recording human biology in standardized statistics (Porter, 2018). Human genetic science has now advanced to aggregate individual level genomic data into vast 'biobanks' that are amenable to analysis through machine learning and predictive analytics (Prainsack, 2017).

Within education specifically, the work of behavioural geneticist Plomin (2018) on 'polygenic scores' is significant since he has cultivated a strong media presence and become an especially forceful advocate for the use of genetic data in education practice and policy. He explicitly advocates the ideal of 'precision education' to 'customize education, analogous to "precision medicine"' (Plomin & von Stumm, 2018, p.155). Plomin's advocacy for genetics in precision education depends on massive biotechnological advances in recent years. At the core of his research is a 'fortune telling device' capable of predicting an individual's psychological traits from DNA traces, such as school attainment, achievement and intelligence. This device is a 'polygenic score' based on a single nucleotide polymorphism (SNP) microarray analysis. SNPs are tiny genetic variants that, if added together, can produce a polygenic score for various traits. Underlying polygenic scoring are SNP microarrays, or 'SNP chips'. Genetic microarray SNP chips combine genomics, silicon chip manufacturing, signal and image processing, statistics, software skills and bioinformatics. They are, ultimately, highly standardized bioinformatics technologies for the automated analysis of genomic information, which exist in material form as credit card-sized silicon glass membranes imprinted with prepared biodata. Within education, Plomin (2018, p.181) argues that 'polygenic scores are key for personalized learning, as they predict pupils' profiles of strengths and weaknesses, which offers the possibility to intervene early to prevent problems and promote promise'. SNP microarray chips are thus changing the very conditions of knowledge production in education, and raising the prospect for precision education based on polygenic scores. Moreover, Plomin's SNP chips are manufactured by Illumina, one of the world's largest biotechnology companies, which situates his research in a global industrial genomics infrastructure, and illustrates how the production of policy-relevant genetics knowledge is inseparable from the market logics of the biotechnology industry (Leonelli, 2016).

One key way that data-intensive genetics projects create novel conceptualizations of education and implications for policy is illustrated by the largest educational genomics study ever undertaken. The study is approvingly referenced by Plomin (2018) as an exemplar of how polygenic scoring will up-end existing theories of genetics in education. In 2018 the Social Science Genetic Association Consortium (SSGAC) published a huge genetic analysis of the educational attainment of a sample of a million people (Lee et al, 2018). The sample included data from two large-scale 'biobanks', including that of the private consumer genetic ancestry company 23andMe, which also contributed research staff and resources to the analysis. The results found genetic patterns associated with educational attainment across over a thousand genetic variants, demonstrating strong polygenic evidence for genetic influence on educational outcomes. But the million-sample study also links genetics and education to other outcomes with significant policy implications. The SSGAC is not merely a genetics consortium, but is co-directed by a 'genoeconomist' (Benjamin et al, 2012). 'Genoeconomics' is interested in the application of genetic data to economics, and focuses on polygenic scoring because it is partly predictive of socio-economic outcomes—with school attainment, as the SSGAC study concluded, strongly associated with longer-term economic outcomes such as labour market 'success' (Ward, 2018). As such, the SSGAC study instantiates the use of genetics data as a predictor of socio-economic outcomes, such as human capital, labour market productivity, and public spending. Although the SSGAC is careful not to generate specific policy implications from the study, it is clear that data linking genes to educational attainment and long-term economic outcomes could be valuable evidence for policymakers seeking to enhance human resources according to various 'success' metrics. Research on the 'genetics of success' modelled on precision medicine shares the 'ultimate goal' of a 'treatment target', though instead of a drug, the treatments would include 'policies and programs—interventions that change children's environments rather than their physiologies' (Belsky, 2016).

An ontological commitment to bio-objective realism, derived from standardized biodata imprinted on silicon, infuses educational genomics, which is now producing highly policy-relevant knowledge about the associations between DNA, education, and socio-economic outcomes. The key critical point is that educational genomics depends on educational processes being captured as 'biodata' in biobanks, imprinted on to bioinformatic SNP chips, and calculated into polygenic scores to predict socio-economic outcomes. Such genetics studies treat these technologies as mere 'tools' of scientific discovery, rather than instruments that participate actively in what and how knowledge is produced. Critical researchers of bioinformatics, however, contend the human subjects of genetic analysis are in fact 'networked and calculable bodies' conjured from interoperable datasets (van Baren-Nawrocka, Consoli & Zwart, 2019), or 'bioinformation' translated from fleshly matter into standardized and portable formats for inclusion in datasets and biobanks (Parry & Greenhough, 2018). Furthermore, Stevens (2017) argues biological science has adapted to the computational capacities of big data systems, with biologists tailoring their work to the capacities, constraints and quantitative logics of technological infrastructure. In particular, he notes how big data-based biological studies are modelled on the very same algorithmic techniques of 'searching' and 'pattern detection' that were developed by commercial web companies. From this view, the uptake of bioinformatics and big data is not simply a rescaling of biological sciences. Rather than seeing bioinformatics as a passive portal to the secrets of the human body, how human biology is understood is actively shaped by the apparatus of the bioinformatics lab. It bears consequences for the kinds of biological knowledge and conceptualizations generated as a result, which tend to foreground a 'cybernetic' view of human biology as consisting of codes, information and data that can read, transcribed, scripted and analysed (Parry & Greenhough, 2018). These computational bio-objects are the constructs of new relations between biology, digitalization and business, as 'bioinformatic infrastructures are built around the values of business: speed, efficiency, growth.... In this new world, business and biology unite forces' (Reardon, 2017, p.177). Genoeconomics further mobilizes these bioinformatics infrastructures to advance scientific understanding of the connections between DNA and economic outcomes.

Bioinformatic education studies therefore produce novel knowledge about education that is only attainable through automated big data methods of searching and detecting patterns across huge biobanks. This raises significant methodological challenges for policy sociology analyses, since if we are seeking to understand how policy-relevant knowledge is produced then we need to understand how complex bioinformatics instruments and infrastructures perform this work. The expertise of epistemic governance now resides in robotized machines and in the computational expertise of the professional bioinformaticians and biotechnology engineers who inhabit the digital laboratories of contemporary biology.

Conclusion

Precision education demonstrates the importance of attending to the role of the digital in contemporary forms of policy sociology. With the emergence of intimate data based on psychology, neuroscience and genomics, the biological body is being presented as explanatory evidence for learning processes, school attainment, and other socio-economic outcomes, and then mobilized as an evidence base for the promotion of an applied, multidisciplinary precision science of education. The OECD is now firmly advocating new 'science of learning' insights from computationally data-intensive advances in psychology, neuroscience and biomedicine in order to 'transmit scientific evidence into education policy and practice' (Kuhl et al, 2019, p.3). Variations of precision education are being presented as potential sources of policy knowledge and of transnational governance. This article represents an initial attempt to open up precision education for policy sociology analysis in the 2020s.

Data-intensive and life-sensitive sciences represent an emerging, next-generation iteration on the logics of transnational, comparative modes of 'governing by numbers' (Grek, 2009). Hansen and Porter (2012, p.410) argue that numbers are integral to transnational governance because of their properties of 'order, mobility, stability, combinability, and precision'. Through the data-intensive production of numbers and calculations about the 'machine-readable' student bodies, precision education 'stabilizes' and 'orders' the body according to psychological, neurological and biological categories; it renders the body 'mobile' across instruments, infrastructures, and scientific settings, and 'combinable' through the networked interlinking of datasets; and it presents the body as precisely knowable by dint of its technical traceability. To this list, 'predictability' may also be added, as precision education aims to calculate corporeal measures into predictions of future states and trajectories of learning. Precision education in this scientific context exemplifies a 'metrological realist' (Desrosieres, 2001) ontology, rooted in the natural sciences, that students' emotions, personalities, behaviours, neural activities, and genetic traits can be made objectively and precisely machine-readable as biological codes and numbers contained in the body, and from there potentially machine-writable as targets of learning engineering, policy intervention and governance.

From a policy sociology perspective, precision education illustrates the increasingly integral work of digital technologies in the production of knowledge and evidence for policymaking and governance. A key contribution of policy sociology over the last decade has been to the understanding of 'epistemic governance' and the use of large-scale comparative data as 'governing knowledge' (Fenwick et al, 2014). While international large-scale assessments and comparative data have produced important governing knowledge for decades, the shift to real-time big data analytics has opened up new opportunities for evidence production and policy influence. The use of digital technologies in new forms of scientific educational research and evidence creation is reconfiguring the conditions for knowledge production, and reconfiguring understandings of the human beings that are the subjects of education policy and governance. However, forensic understanding of the technologies of knowledge production such as those of digital psychometrics, biometrics, neurotechnology, and bioinformatics remains lacking. This paper has presented some initial coordinates for future studies in digital policy sociology. Unanswered questions persist about the specific ways in which computational structures, hardware, infrastructures, software algorithms, analytics and machine learning participate in data-intensive forms of psychology, brain science and genetics, and how they shape the knowledge that may then be deployed in policy production and governance. Policy sociology in the coming decade will need to attend to these very specific digital ways of knowing and intervening in education.

References

Armstrong, D. (2019). The social life of data points: Antecedents of digital technologies. *Social Studies of Science* 49(1), 102-117.

Ball, S. 1997. Policy Sociology and Critical Social Research: A Personal Review of Recent Education Policy. *British Educational Research Journal* 23(3): 257-274

Ball, S., Junemann, C. & Santori, D. (2017) *Edu.net: Globalisation and education policy mobility*. London: Routledge.

Beer, D. (2016). *Metric Power*. London: Palgrave Macmillan.

Beer, D. (2019). *The Data Gaze*. London: Sage.

Belsky, D.W. (2016). Why should we study the genetics of success? Blog on Learning & Development, 23 November: https://bold.expert/why-should-we-study-the-genetics-of-success/

Benjamin, D.J., Cesarini, D., Chabris, C.F. et al. (2012). The Promises and Pitfalls of Genoeconomics. *Annual Review of Economics* 4, 627–662.

Biassiucci, A., Franceschiello, B. & Murray, M.M. (2019). Primer: Electronencephalography. *Current Biology* 29, R71–R85.

Bowe, R., Ball, S. & Gold, A. (1992). *Reforming Education and Changing Schools: Case studies in policy sociology*. London: Routledge.

Costandi, M. (2016). *Neuroplasticity*. London: MIT Press.

Danaher, J., Hogan, M.J., Noone, C. et al. (2017). Algorithmic governance: Developing a research agenda through the power of collective intelligence. *Big Data and Society*: https://doi.org/10.1177%2F2053951717726554

Desrosieres, A. (2001). How real are statistics? Four possible attitudes. *Social Research* 68(2), pp. 339-355.

Fenwick, T. Mangez, E. & Ozga, J. (eds). (2014). *Governing Knowledge: Comparison, knowledge-based technologies and expertise in the regulation of education*. London: Routledge.

Ferryman, K. & Pitcan, M. (2018). Fairness in precision medicine. *Data & Society*, 26 Feb: https://datasociety.net/output/fairness-in-precision-medicine/.

Fontdevila, C., Verger, A. & Avelar, M. (2019) The business of policy: a review of the corporate sector's emerging strategies in the promotion of education reform. *Critical Studies in Education*: https://doi.org/10.1080/17508487.2019.1573749

Gaysina, D. (2016). How genetics could help future learners unlock hidden potential. *The Conversation*, 15 November: https://theconversation.com/how-genetics-could-help-future-learners-unlock-hidden-potential-68254

Grek, S. (2009). Governing by numbers: the PISA 'effect' in Europe. *Journal of Education Policy* 24(1), 23-37.

Gulson, K. & Webb, P.T. (2017) Mapping an emergent field of 'computational education policy': policy rationalities, prediction and data in the age of artificial intelligence. *Research in Education* 98(1), 14–26.

Gulson, K. & Webb, P.T. (2018). 'Life' and education policy: intervention, augmentation and computation. *Discourse: Studies in the cultural politics of education* 39(2), 276–291.

Gulson, K. & Sellar, S. (2018). Emerging data infrastructures and the new topologies of education policy. *Environment and Planning D: Society and Space*: https://doi.org/10.1177/0263775818813144

Hansen, H.K. & Porter, T. (2012). What do numbers do in transnational governance? *International Political Sociology* 6, 409-426.

Hartong, S. (2018). Towards a topological re-assemblage of education policy? Observing the implementation of performance data infrastructures and 'centers of calculation' in Germany. *Globalisation, Societies and Education* 16(1), 134-150.

Ienca, M. & Andorno, R. (2017). Towards new human rights in the age of neuroscience and neurotechnology. *Life Sciences, Society and Policy* 13(5), 1-27.

Kankaraš, M. (2017). *Personality matters: Relevance and assessment of personality characteristics.* OECD Education Working Papers, No. 157. Paris: OECD Publishing,

Kuhl, P.K., Lim, S.-S., Guerriero, S. & van Damme, D. (2019). *Developing Minds in the Digital Age: Towards a science of learning for 21st century education*. Paris: OECD.

Landri, P. (2018). *Digital Governance of Education: Technology, standards and Europeanization of education*. London: Bloomsbury.

Lawn, M. (ed) (2013). *The Rise of Data in Education Systems: Collection, visualisation and use*. Oxford: Symposium.

Lee, J.J., Wedow, R., Okbay, A., et al. (2018). Gene discovery and polygenic prediction from a genome-wide association study of educational attainment in 1.1 million individuals. *Nature Genetics 50*, 1112–1121.

Leonelli, S. (2016). *Data-Centric Biology: A philosophical study*. London: University of Chicago Press.

Leonelli, S. (2018). Assembling biomedical big data. In Meloni, M., Cromby, J., Fitzgerald, D. & Lloyd, S. (eds). *The Palgrave Handbook of Biology and Society* (317-337). London: Palgrave Macmillan.

Lupton, D. (2015). *Digital Sociology*. London: Routledge.

Marres, N. (2017). *Digital Sociology.: The reinvention of social research*. Cambridge: Polity.

McStay, A. (2018). *Emotional AI: The rise of empathic media*. London: Sage.

Michell, J. (2008). Is Psychometrics Pathological Science? *Measurement* 6(1-2), 7-24.

OECD. (2017). *Social and Emotional Skills: Well-being, connectedness and success*. Paris: OECD.

Ozga, J. (1987) Studying education through the lives of policy-makers: an attempt to close the micro-macro gap. In Barton, L. and Walker, S. (eds). *Changing Policies, Changing Teachers*. Lewis: Falmer Press.

Ozga, J. (1990). Policy Research and Policy Theory: a comment on Fitz and Halpin. *Journal of Education Policy* 5(4), 359-362.

Ozga, J. (2019) Governing and Knowledge: theorising the relationship. In Langer, R. & Brüsemeister, T. (eds). *Handbuch Educational Governance Theorien. Educational Governance* 43. Wiesbaden: Springer.

Ozga, J., Dahler-Larsen, P., Segerholm, C. & Simola, H. (eds). (2011). *Fabricating Quality in Education: Data and governance in Europe*. London: Routledge.

Parry, B. & Greenhough, B. (2018). *Bioinformation*. Cambridge: Polity.

Pickersgill, M., Chan, S., Haddow, G. et al. (2019). Biomedicine, self and society: An agenda for collaboration and engagement. *Wellcome Open Research* 4(9): https://doi.org/10.12688/wellcomeopenres.15043.1

Pitts-Taylor, V. (2016). *The Brain's Body: Neuroscience and corporeal politics*. London: Duke University Press.

Plomin, R. & von Stumm, S. (2018). The new genetics of intelligence. *Nature Reviews Genetics*. doi:10.1038/nrg.2017.104

Plomin, R. (2018). *Blueprint: How DNA makes us who we are*. London: Allan Lane.

Porter, T. (2018). *Genetics in the Madhouse: The unknown history of human heredity*. Oxford: Princeton University Press.

Prainsack, B. (2017). *Personalized Medicine: Empowered patients in the 21st century?* New York: New York University Press.

Reardon, J. (2017). *The postgenomic condition: Ethics, justice, and knowledge after the genome*. Chicago: University of Chicago Press.

Rose, N. (2016). Reading the human brain: How the mind became legible. *Body and Society* 22(2), 140-177.

Savage, G.C. (2019). What is policy assemblage? *Territory, Politics, Governance*: https://doi.org/10.1080/21622671.2018.1559760

Schleicher, A. (2018). *World Class: How to Build a 21st-Century School System*. Paris: OECD.

Sellar, S. & Lingard, B. (2014). The OECD and the expansion of PISA: new global modes of governance in education. *British Educational Research Journal* 40(6), 917-936.

Stark, L. (2018). Algorithmic psychometrics and the scalable subject. *Social Studies of Science* 48(2), 204-231.

Stevens, H. (2013). *Life Out of Sequence: A data-driven history of bioinformatics*. London: University of Chicago Press.

Stevens, H. (2017). A Feeling for the algorithm: Working knowledge and big data in biology. *Osiris* 32, 151-174.

Van Baren-Nawrocka, J., Consoli, L. & Zwart, H. (2019). Calculable bodies: Analysing the enactment of bodies in bioinformatics. *BioSocieties*: https://doi.org/10.1057/s41292-019-00143-x

Ward, J. (2018). The 'geno-economists' say DNA can predict our chances of success. *New York Times Magazine*, 16 November: https://www.nytimes.com/interactive/2018/11/16/magazine/tech-design-economics-genes.html

Webb, P.T. & Gulson, K.N. (2015). Policy scientificity 3.0: theory and policy analysis in-and-for this world and other-worlds. *Critical Studies in Education* 56(1), 161-174.

WEF (World Economic Forum). (2016). New Vision for Education: Fostering Social and Emotional Learning through Technology. WEF: http://www3.weforum.org/docs/WEF_New_Vision_for_Education.pdf

Williamson, B. (2018). Brain Data: Scanning, scraping and sculpting the plastic learning brain through neurotechnologies in education. *Postdigital Science & Education* 1(1), 65-86.

Williamson, B. (2019). Psychodata: Disassembling the psychological, statistical and economic infrastructure of social-emotional learning. *Journal of Education Policy* https://doi.org/10.1080/02680939.2019.1672895.

Youdell, D. & Lindley, M. (2018). *Biosocial Education: The social and biological entanglements of learning.* London: Routledge.

Yuste, R., Goering, S., Arcas, A. et al. (2017). Four ethical priorities for neurotechnologies and AI. *Nature* 551(7679), 159-163.