CRITICAL SOCIAL THOUGHT

DIGITAL DISRUPTION IN TEACHING AND TESTING

ASSESSMENTS, BIG DATA, AND THE TRANSFORMATION OF SCHOOLING

Edited by
CLAIRE WYATT-SMITH, BOB LINGARD, AND ELIZABETH HECK

ROUTLEDGE

DIGITAL DISRUPTION IN TEACHING AND TESTING

This book provides a significant contribution to the increasing conversation concerning the place of big data in education. Offering a multidisciplinary approach with a diversity of perspectives from international scholars and industry experts, chapter authors engage in both research- and industry-informed discussions and analyses on the place of big data in education, particularly as it pertains to large-scale and ongoing assessment practices moving into the digital space. This volume offers an innovative, practical, and international view of the future of current opportunities and challenges in education and the place of assessment in this context.

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FOREWORD

I am writing this Introduction in the midst of the COVID-19 crisis. Truly major changes in how formal schooling is (or is not) being carried out are visible all around us. Deep-seated inequalities in access and resources are distressingly evident. Teachers are being called upon to engage with technologies for which they have had little preparation and experience at the same time as they struggle to maintain personal connections with students. Models of curriculum and pedagogy that depend on a substantive understanding of and responsiveness to student and community knowledge and realities are being lost as physical, emotional, and epistemological distance is maintained. At the same time, there are calls to suspend all testing of students given the realities of hybrid forms of mostly distance education that have been put in place. As a result of these and other conditions, a significant number of students are moving from public schools to private schools, to for-profit schools, or to homeschooling. Schools are facing a looming fiscal crisis that threatens to make their already difficult financial status even worse. Many more aspects of what has been happening in education could be listed. All of this makes the book you are about to read even more significant.

There are times when I read a book that opens up new and insightful ways of thinking about crucial issues in education that deserve our close attention. Digital Disruption in Teaching and Testing: Assessments, Big Data, and the Transformation of Schooling is definitely one of these books. I personally have weighed on the debates over digital technologies in education, on the over reliance on particular kinds of evaluation and testing, and on the ways in which surveillance creates differential identities for students and teachers. And I have documented how such policies and practices often work to reproduce inequalities and impose quite reductive assumptions about "legitimate" knowledge, "real" learning, "good teaching," "good students," and "good schools" (Apple, 2006; Apple, 2014).

After reading the volume that Bob Lingard, Claire Wyatt-Smith, and Elizabeth Heck have produced, and the debates they provide us entry into, I now realize that even if the COVID-19 crisis finally passes, there is an even broader range of issues that are at stake when schools are increasingly deeply connected to the world of digital forms and practices, to the accumulation of massive amounts of data, and to the reliance on an ever expanding arsenal of managerial and evaluative expertise and procedures. The issues are complicated, but ignoring them simply increases the possibility that our often unreflective moves in this direction will produce unfortunate results.

At the outset, let me emphasize that Digital Disruption in Teaching and Testing is not simply an analysis of what is wrong and what the dangers of these tendencies are. It is instead a very thoughtful and detailed assessment of the limits and possibilities of digital technologies and the sense-making processes that accompany them, of the rapidly growing influence of "big data" in educational decisions, and of changes in what counts as evidence in educational policy and practice. While this alone makes the book a valuable contribution, the fact that it is truly international in its analyses helps us better understand that context matters in understanding these limits and possibilities. The ambitious aims of the book can be seen in the following description.

This book provides research-informed accounts of the multiple various ways digital disruption and data use are beginning to profoundly reshape education systems, policymaking practices, and the work of schools and teachers. This reshaping comes with implications for young people's learning, identities, and experiences of schooling with significance for their futures. Such analyses…are necessary to begin constructive dialogues across knowledge domains and groups with legitimate interests in education policy and the future of schooling. These include students, teachers, teacher unions, parents/carers, the wider community, school leaders, system leaders, policymakers, and researchers…[The book opens] up these necessary conversations about educative and democratic uses of data and digital for policymaking and how these might amplify and augment the new teacher professionalism requiring new knowledges and expanded evaluative expertise.

Given these emphases, the volume also adds to the growing tradition of critical analyses of the influences of neoliberalism on education and the increasing transformation of schools into sites of profit (Burch, in press). It also provides insightful weight to the arguments surrounding the role of schooling in what might be called an "epistemological war." What is important is that which is measureable.

In addition, the book makes a substantive contribution to the debates about the role both inside education and the larger society of the uses of algorithms. Algorithms are now used to predict and at times change tests scores on assessments that have a truly major impact on students' futures. The results have been quite controversial, to say the least. Yet educators need to be much more cognizant that the uses of algorithms in society at large have been challenged by many people. For example, one of the largest uses is in predicting which communities and which people will supposedly engage in "criminal acts." This has all too often resulted in very damaging and racializing effects. As Noble states, such effects should make us deeply concerned about accepting "the benign instrumentality of technologies" such as these (Noble, 2018, p. 230; see also, O'Neil, 2016).

These are of course extremely complicated issues. They raise ethical and political as well as practical questions. Do "big data" and digital resources in education actually pay off in practice? What are their connections to neoliberal agendas? Does education increasingly get turned into one more site for the creation of profit? What are the issues of student and parent privacy? What are the effects of all of this on teacher autonomy and professionalism? Does it change what counts as crucial teacher skills and dispositions from more substantive and nuanced culturally responsive interpersonal practices into those that largely emphasize managerial impulses? What can we do to make it more likely that progressive possibilities for schools, students, teachers, and communities are the results? What does this mean for teacher education? The list of questions goes on and on. Dealing with them requires that everyone who can be affected by these "reforms" have a substantive voice in them.

Digital Disruption in Teaching and Testing helps us deal honestly with these and other questions and provides us with significant insights into how they might be answered. It also provides us with a wide range of conceptual, empirical, and policy-related tools both to raise important questions about what we too often think of as "technical" solutions and to provide paths to create more thoughtful answers to these questions. Some of these questions and answers will require that we step back from our preconceptions about many of the things we too easily take for granted. In the process, it asks us to think deeply about what we are doing, why we are doing it, and what the results might actually be.

In a number of places, I have argued that schools can be and at times are sites of important social transformation and of the movements that support them (Apple, 2013; Apple et al. 2018). This is a time when schools have become testing grounds for a number of such changes. But such transformations can often have contradictory results. They can be a "yes" and "no" at the same time. This book documents that reality; it is both a cautionary tale and a way forward.

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LIST OF ABBREVIATIONS

ACARA	Australian Curriculum, Assessment, and Reporting Authority
AI	Artificial intelligence
AIEd	Artificial intelligence in education
AITSL	Australian Institute for Teaching and School Leadership
ANNs	Artificial neural networks
AR	Augmented reality
BMBF	Federal Ministry of Education (Germany)
CAT	Computer adaptive testing
CBA	Cost-benefit analysis
CBT	Computer-based testing
DfID	Department for International Development (United Kingdom)
DL	Deep learning (in ML)
EdTech	Educational technology
EEG	Electroencephalography
ESA	Education Services Australia
ESSA	Every Student Succeeds Act (United States)
ETIN	Education Technology Industry Network
EVAAS	Education Value-Added Assessment System
GDP	Gross domestic product
GDPR	European General Data Protection Regulation

GEI	Global education industry
GEPD	Global Education Policy Dashboard
GPS	Global positioning systems
IA	Immersive assessments
ICICLE	IEEE Industry Consortium on Learning Engineering
IEA	International Association for the Evaluation of Educational Achievement
IEEE	Institute of Electrical and Electronics Engineers
ILSAs	International large-scale assessments
IoT	Internet of Things
ITSs	Intelligent tutoring systems
KMK	Standing Conference of the Education Ministers of the German States
LA	Learning analytics
LAK	Learning Analytics and Knowledge
LINK	Learning Innovation and Networked Knowledge
LMS	Learning management systems
LP	Learning personalization
MELQO	Measuring Early Learning and Quality Outcome
ML	Machine learning
MR	Mixed reality
NAPLAN	National Assessment Program – Literacy and Numeracy
NCLB	No Child Left Behind Act (United States)
NIET	National Institute for Excellence in Teaching
NPM	New public management
NSIP	National schools interoperability program
OECD	Organization for Economic Cooperation and Development
OFAI	Online Formative Assessment Initiative
PA	Predictive analytics
PAs	Pedagogical agents
PIRLS	Progress in International Reading Literacy Study
PISA	Program for International Student Assessment
PLEs	Personalized learning environments
PPPs	Public-private partnerships
RL	Reinforcement learning (in ML)

ROI	Return on investment
RTTT	Race to the top initiative
SABER	Systems Approach for Better Results
SAGE	Scientific Advisory Group for Emergencies (United Kingdom)
SDG	Sustainable Development Goals
SDI	Service Delivery Indicators
SIF	Schools interoperability framework
SIIA	Software and Information Industry Association
SLOs	Student learning objects
SoLAR	Society of Learning Analytics Research
SSO	Single sign-on
T-TESS	Texas Teacher Evaluation Support System
TEA	Texas Education Agency
TIMSS	Trends in International Mathematics and Science Study
UIS	UNESCO Institute for Statistics
UL	Unsupervised learning (in ML)
UN	United Nations
UNESCO	United Nations Educational, Scientific, and Cultural Organization
UNICEF	United Nations Children's Fund
VAM	Value-added measurement
VR	Virtual reality
XR	Extended reality

1

TRANSFORMING SCHOOLING THROUGH DIGITAL DISRUPTION

Big Data, Policy, Teaching, and Assessment[1]

Bob Lingard, Claire Wyatt-Smith and Elizabeth Heck

> Big data and digital learning assessments… are part of the broader digital disruption brought about by enhanced computational and digital capacities, in terms of the volume, variety, and velocity of data that now circulate within countries and globally… Data are not inherently disruptive. It is the datafication of experience and the digitalization of data that are the source of disruption.
>
> *(Wyatt-Smith et al., 2019, p. 2)*

Introduction

This introductory chapter highlights the major issues concerning digital disruption in teaching and learning in schooling, and implicitly in other educational institutions. We want to do more than simply document how digital disruption is playing out in contemporary schooling. The chapters in the collection provide insightful accounts of these matters and as such contribute to contemplating improved social futures. Our aim in this chapter, drawing on our different expertise, is to open up some normative questions about how the digital might productively be used to construct better and more equitable schooling for all. Of special interest is how the digital is reshaping what it now means to be learners, teachers, school leaders, and policymakers, with impact on the place and the roles of parents, caregivers, and communities. Related are significant issues around the rights of the child, privacy and confidentiality, ethics, and legal issues associated with data use and ownership, storage, curation, and purpose. These matters also have high relevance to teachers, parents/carers, and communities.

In editing this book, we conjoin our collective academic expertise in assessment and testing, education policy and governance, and the influence of the

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digital on how learning occurs. Bringing together these domains is a potent mix: policy shapes the possibilities for school and teacher practices and is currently being heavily affected by digital disruption. Within policy frames, educational assessment and testing decisions always affect the work of teachers, learners, and school communities. This is a reality that has been intensified by digital disruption. Adding to this are rapidly evolving digitally-based opportunities for young people's learning, both in and out of school. Assessment has a particular salience in the work of schools as it is the main technology through which sorting and selection, linked to the provision of the opportunity function of modern schooling, are manifested. In these ways, assessment is intensely value-laden, and to ensure its perceived legitimacy, it must be seen to be valid, reliable, and fair.

Sometime ago, Bernstein (1971) wrote about the three message systems of schooling: curriculum, pedagogy, and evaluation (including assessment and testing). We assert that today, given the predominance of test-based accountability in many systems throughout the globe, the "evaluation message system" steers schooling systems as meta-policy. Schooling systems today have invested heavily in data infrastructures to manage huge volumes of data, including about school and individual student performance. The restructuring of schooling systems through new public management, and subsequently through network governance, have enabled new non-state actors to be involved in the work of the state. In education, this has opened the space for edu-business, particularly EdTech companies, to be influential players in policy, the provision of data infrastructures, testing, and even curriculum (Ball, 2012). This involvement is driven by an overriding concern for profit, while it putatively offers the advantages of efficiency and dependability of testing, and a rapid return of results for use by "clients" in schools. These matters have been amplified in the context of the global COVID-19 pandemic.

It is in this context and from our cross-disciplinary approach that we seek to precipitate ideas and challenges, looking to raise possibilities for more productive and educative uses of the affordances of digital technologies and data for policy, teaching, assessment, and learning. We thus seek to take stock of where these matters are at, while acknowledging that they defy stabilization. The book addresses the actual and appropriate affordances of digital technology in public policy, including education policy, and in relation to teacher professional practices. We problematize: *appropriate* human+machine relationships in the construction and production of data; *appropriate* policymaker and teacher interpretations and uses of data; and *appropriate* design and development of data infrastructures, including data interoperability. These are very important considerations as the digital is restructuring contemporary schooling systems and is radically reforming teaching and learning.

In what follows, we first briefly outline the broader backdrop and contexts to the concerns of the collection, followed by a brief account of the policy context that has enabled digital disruption in education, and then address the changing terrain of educational assessment. We then deal with digital disruption in and through evaluation, followed by consideration of this disruption in relation to big data. The subsequent section explores digital disruption in teaching. Summaries of the chapters in the collection, including a suite of provocations, are then presented prior to the summative conclusion of the chapter. The collection, in effect, offers the reader a contemporary pause and a moment to reflect at a critical juncture in human history on the future trans/formation of schooling and learning in respect of the affordances of the digital and of data.

Backdrop and Contexts

We are at a critical juncture in human and societal history. Some of the tried and tested approaches of the past may no longer be relevant. This also appears to be the case in schooling. Yet, while new technologies can offer potentially new and very positive opportunities for education, we argue strongly that schooling and teacher professional practices are intrinsically relational, contextual, and cultural in nature and work with an ethics of care (Noddings, 2003). Further, we argue that this ought to remain the case in the context of digital disruption. However, a thorough reconceptualization of the broadest purposes of education in schools and the wider society, including academic and social purposes, needs to be addressed and adopted. In this reconceptualized frame, new technologies should play a vital positive role in the future of schooling. In and of themselves, however, they are not the panacea. We are arguing here that the affordances of digital technologies ought to complement a new teacher professionalism. This involves inter alia reconceptualizing teacher evaluative expertise for discerning what data are useful and how they can be used to inform teaching and improve learning.

New thinking is required about the appropriate place of the range of new technologies, data infrastructures, new computational capacities, and software (for example, big data, virtual reality, artificial intelligence, predictive analytics, machine learning, and individualization and personalization of learning trajectories). This is an acute need in respect of systemic policy and steering, educational leadership, teacher professional practice, including professional judgement, and student learning. These matters are undoubtedly not new in deserving attention, although they have come to the fore in the context of the COVID-19 pandemic. These are the core considerations of this collection, *Digital disruption in teaching and testing*.

We note that these matters are pressing at a time of substantial social, political, and economic changes. They play out as growing inequality, political divides, economic uncertainty, mass global movements of people, greater population diversity, race riots, civic unrest, environmental risks and climate crises, health risks, rise of new nationalisms, and ethno-nationalism. These are all too familiar on our daily news platforms and show no signs of abating. Arguably they are intensifying. Perhaps paradoxically, the era is also characterized by "post-truth," "fake news," and "anti-science" tendencies (McIntyre, 2018) in the context of a seemingly new positivism in data-based public policymaking (Lather, 2013). All of this is occurring at a time of weakening of social cohesion and significant loss of public confidence in civic institutions and political processes, and even of democracy.

On the one hand, the new technologies could be deployed to ameliorate these conditions; on the other, they could exacerbate them. At the core of how these human futures will emerge is the key issue of appropriate human+machine interactions. We emphasize this point as we recognize that a technological and data juggernaut has been unleashed, is gaining significant power and influence, and is inexorably creating futures for us (rather than with us). In compiling this book, we adopt the position that, on a meta level, human ethics and values will be central to determining what sort of futures we create and the place of technologies in that future. These matters will affect the broad societal arrangement, but will also play out in education policy, curriculum choices, assessment, student learning, and in the work of schools and teachers.

For some time now the digital has been disrupting many aspects of contemporary social life. Many of these disruptive effects have been positive. Consider, for example, the affordances of new communication technologies (e.g., mobile phones), digital platforms (e.g., aspects of social media and virtual meeting spaces), and digital applications (generally referred to as "apps"). We also include much expanded computational capacity that enables the collection of unprecedented volumes of data, expanded analytic and predictive power, and the speed and efficiency of presenting new "useable" knowledge. In the early stages of digital disruption, there was a hope and aspiration that the new communication technologies would enable more democratic and inclusive participation and engagement in public and social life (Carpentier, 2009, 2011; Jenkins, 2006, 2009; Jenkins et al., 2013; Jenkins & Deuze, 2008; Zuboff, 2019). There is ample evidence that digital disruption has changed social interactions, in some cases profoundly. Yet there are downsides to these developments and less evidence of the democratic benefits.

Recent thinking has alerted us to how all of our online activity has been controlled by mega technology companies, and this datafication of human experience enables these companies to use this human data as a commodity to be traded and from which new profit is generated. This is what Zuboff (2019) refers to as "surveillance capitalism."[2] We would also make the point that such surveillance techniques are utilized in market socialist countries, including the People's Republic of China. Here the Social Credit System, introduced in 2020, utilizes the online participation of citizens to construct individual profiles, which are used then by both government and business to determine what citizens will be able to receive, and what opportunities will be opened up or closed down for them. This is a manifestation of what Deleuze (1992) called "control societies," in which we are always subject to evaluations. The emergence of these societies might also be seen as part of what the German sociologist Mau (2019) called the "metric society" based on the quantification of the social. We would note that data from such surveillance have been "weaponized" and have become central to security concerns and potential risks to national governments.

While commercialization and profit are at play in digital disruption in the business sector, they are also evident today in education from the earliest years, and are equally applicable to privatizing (outsourcing, public–private partnerships) and network governed schooling systems. Network governance sees non-state actors involved in the policy work and delivery of the state, and these non-state actors include national and multinational edu-businesses, individual edupreneurs, and philanthropic organizations (Ball & Junemann, 2012). This, in turn, involves the provision of costly data infrastructures, hardware and software, evidence bases, and systems and processes for storing and analysis of a wide range of data. To this we add the design of computer adaptive testing (CAT); test data analysis at national, sub-national, regional, and international levels; and the publication of reports to governments, schools, teachers, parents, and students. The private sector has seen in digital developments a new opportunity to remake education as a site for profit making. It is clear that edu-businesses are flourishing in both Global North and Global South contexts (Ball et al., 2017; Riep, 2014, 2019; Verger et al., 2016). Edu-business involvement across all stages of the policy cycle in education and in respect of all aspects of schooling (curriculum, pedagogy, and evaluation; Ball, 2012) raises matters to do with who ought to determine the broader purposes of schooling and the way it is delivered in societies. This involvement of edu-business is certainly the case in the nations of the Global North and is increasingly the case in the Global South as well (Junemann & Ball, 2015).

In this book, we adopt the concept of a "socio-technical education data imaginary." We acknowledge Jasanoff and Kim's science and technology studies-based definition of "sociotechnical imaginaries" as referring to "collectively imagined forms of social life and social order" (Jasanoff & Kim, 2009, p. 120). Here, as a point of difference, we hyphenate "socio-technical" so as to emphasize the social construction of new technologies, knowledge, and human involvement. At the same time, we acknowledge the ways in which the new technologies help constitute the new social and indeed spatial realities in ways that elide distance. Put simply, for us, hyphenating socio-technical stresses that the social and the technical are products of each other and that the social is constituted by human activities. Our usage then is also a normative one of how human/technology relationships ought to function, rather than be only an analytical approach; specifically, how they ought to function in education and, more specifically, in relation to data.

We also focus explicitly on education and education data as they contribute to learning. We take such data to have primacy in reconstituting the work of education systems and teachers, and as having very profound effects on young people's learning, their futures, and the future of social arrangements, locally, nationally, and globally. Here we are picking up on the datafication of schooling, of teachers, and of students (see Grek et al., 2021). Our use here of "imaginary" is also derived from the work of Charles Taylor (2004), who argues that a social imaginary is a world view that underpins the understandings and actions of large social groups, and helps constitute the present and influences possible futures. This means that the social remains in a state of constant flux and that the future is in some ways immanent, that is, in a state of becoming. While Taylor acknowledges that social imaginaries may have links to social theory, they are different from social theories in their quotidian everyday character, broader adoption among the population, and serve to keep the social working. In effect, they have a normalizing function. Thus, for us, a socio-technical education data imaginary is about appropriate human-data relationships for shaping desirable future systems and practices of schooling.

In focusing on education data, we also acknowledge there is a broader digital revolution going on, which some refer to as the "Fourth Industrial Revolution" (Pfeiffer, 2017; Schwab, 2017). This is where the new technologies are already having profound impacts on production, consumption, and the experiences of place, space, and time (Avis, 2018). In this moment in human history, we have the concurrent effects of a global pandemic intertwined with this Revolution in something of a symbiotic relationship with the two together now having an impact on all spheres of life. This impact is evident in education. The provocations in this collection in Chapter 12 address the various effects of the COVID-19 pandemic on the place of the digital in education. They collectively stress that the pandemic has accelerated trends already underway.

Against this backdrop, we focus on schooling, teaching and testing, and big data. This provides an opening to consider what is and what ought to be continuous and discontinuous in relation to the workings of schooling systems, the practices of teachers, and the role and functions of new technologies. As noted already, these new technologies are reconstituting schooling systems in both the Global North and Global South. For example, data infrastructures, as subjects of significant investment in many countries, created and managed by edu-business in many systems, are helping to constitute these systems through interoperable data flows (Anagnostopoulos et al., 2013; Lingard, 2019; Sellar, 2017; Sellar & Gulson, 2019). The reach of these can be national, cross-national, and global. In respect of the global, they are important in the work of International Large Scale Assessments (ILSAs), such as the Organization for Economic Cooperation and Development's (OECD) Program for International Student Assessment (PISA), and the International Association for the Evaluation of Educational Achievement's (IEA) Trends in International Mathematics and Science Study (TIMSS), and the Program for Reading Literacy Study (PIRLS). These in turn help constitute a commensurate global space of measurement with policy effects in nations (Breakspear, 2012). Data infrastructures are also important in enabling national testing regimes such as Australia's National Assessment Program – Literacy and Numeracy (NAPLAN; Lingard et al., 2016; McGaw et al., 2020).

There is ample evidence that in most schooling systems, the appetite for more and more data is insatiable. Schools and systems today are awash with data, much of which is underutilized for policy and learning purposes. This is the playing out of a technical imaginary of what current and future schooling should look like and is one very much encouraged by large and small edu-businesses and some influential philanthropic organizations. There is also evidence to suggest an emerging cargo cult mentality among some politicians and some senior policy-makers that there are easy technological fixes to tame "wicked problems" in education (Rittel & Webber, 1973). Thus, for example, the Governor of New York State, Andrew Cuomo, in the context of the COVID-19 pandemic will work with the Bill and Melinda Gates Foundation to look at the possibility of schools being remade through the new technologies (see Tompkins-Stange, 2016 on the role of philanthropy in education reform). Cuomo stated, "The old model of everybody goes and sits in the classroom, and the teacher is in front of that classroom, and teaches that class… all these buildings, all these physical classrooms – why, with all the technology you have?" (Strauss, 2020, para 3). We see this view that technology and digital innovations will solve education problems and provide a utopian future for schooling as exceedingly naïve. We also need to ask, "Who would benefit from such changes?"

In this book, we are working with the concept of a socio-technical education data imaginary as enabling a different way of thinking about contemporary schooling and its futures, in the context of digital disruption. We reject a technologically determinist view. Instead, we argue strongly for human leadership in the construction of policy, particularly in respect of the role of new technologies and data, and in relation to the appropriate role of data in the professional practices of teachers and their judgements. Hotly contested here is the desired relationship between humans+machines. For example, consider the work of algorithms, artificial intelligence (AI), machine learning (ML), learning analytics (LA), predictive analytics (PA), and virtual reality (VR).

Algorithms are mathematical processes that help to solve problems. They are not a new development, though their everyday influence has grown exponentially through their centrality to computing. They permeate every aspect of everyday life including our use of social media, shopping, and even dating. Algorithms work in different ways. They remain, however, invisible to us. Algorithms of various kinds are necessary elements for ML and AI, but they are not the same thing. Both ML and AI are prevalent in discussions of big data. ML drives AI. Here computers bring algorithms to big data analysis and surface patterns in the data. This is a "learning process" that sets computers up for dealing with increasing volumes of data, and in this way ML functions as the vehicle driving AI. Given the current lack of big data in education, there is limited use of AI, but certainly future opportunities (see Gulson et al., 2018).

Taken together, ML, AI, and algorithms have inherent potential to *black box* decision-making in a non-transparent way unprecedented in human history.

Black boxing, according to Rose (1999), renders "invisible and hence incontestable – the complex array of judgements and decisions that go into a measurement, a scale, a number" (p. 214).[3] This black boxing is already well underway in some data uses, and potentially denies the agentic role of humans in decision-making in systems and schools. It seemingly offers the lure of efficiency, transparency, and objectivity in policy and professional decision-making, while neglecting and omitting human decision-making and values in the construction of these algorithms. Researchers such as Rose (1999) who have written about black boxing in relation to governance by numbers have been referring to the technical work that goes into the construction of statistical numbers, literally state numbers and the like. We would suggest that the black boxing associated with algorithms hides in even deeper ways the multiple processes they utilize so as to provide insights from large data sets and those that are longitudinal and linked with other data sets. Those who have written about the black box phenomenon in assessment have focused on assessment for learning, which could be considered as part of the secret garden of teachers' work (Black & Wiliam, 1998). Some assessment theorists have called for the lifting of the lid on the black box of teacher judgement in assessment practices to give greater transparency to this element of teacher expertise (Wyatt-Smith & Adie, 2019). In this chapter, we advocate for the important place of human judgement and expertise in relation to the construction and production of data and the related use of algorithms.

Within this frame, the affordances of the new technologies need to be acknowledged, along with the place of fit-for-purpose data in good curriculum design, rich pedagogies, and assessment practices. However, there are significant issues in how we move from the present to a future that will be even more technologically mediated. Among these issues, perhaps the most pressing, is what should be held onto from the past and present, and what should be made entirely new for the future. Currently, humankind does not have a clear line of sight to the future. Writing about the effects of the end of the Cold War and related intellectual challenges to Enlightenment values, Laidi (1998) argued that "the need to project ourselves into the future" has never been greater, but "we have never been so poorly armed on the conceptual front to conceive this future" (p. 1). Thirty years after the end of the Cold War and in the context of digital disruption and the negative contemporary political realities alluded to earlier, this observation appears even more applicable now than when Laidi made his observation more than 20 years ago.

Yet we acknowledge that technologies and data will play an even greater role in how we live, work, and what counts as meaningful civic contributions in the context of digital governance. In that context, we would still argue that teaching, like medicine, is an inherently relational practice, and this ought to continue, whatever the technological future holds. At issue, therefore, are the knowledge, skills, expertise, and dispositions that will be necessary for a productive future teaching profession.

Policy and Assessment Frames

Education Policy

The digital disruption in education that is the focus of this collection has been aided and abetted over the last three decades by new practices of statecraft and a restructured (post)bureaucratic state. Following the end of the Cold War and the rapid globalization of the economy, the bureaucratic state in most nations was restructured to accompany the neoliberal framing of the global economy. State restructuring and neoliberalism were not the same thing; they had different rationales, but the new state structure sat comfortably with the neoliberal frame of the global economy, which resulted from nations breaking down tariff barriers and encouraging global free trade. The restructured state, first under New Public Management and subsequently through network governance, occurred against the back drop of the neoliberal prioritizing of the market over the state, individual responsibility over state welfare, and a seeming view that the private sector was more efficient and effective at achieving its policy goals, than was the bureaucratic state, which was hierarchical in character and framed by technical-rationalist rule following. The classical Weberian bureaucratic state structure was deemed to be too sclerotic for the fast character of global capitalism and economy and also in respect of "fast policymaking" (Peck & Theodore, 2015). This witnessed the use by the restructured state of public-private partnerships as a way of delivering state services and the opening up of other opportunities for the involvement of edu-businesses and profit making in education (Ball, 2007).

New Public Management (NPM) sought to thin out the bureaucracy and steer through outcome measures rather than through input measures. Here we can see the move from the Keynesian policy frame of extensive state spending and steering to a more frugal state and thinned-out bureaucracy, emphasizing outcomes through the creation of performance indicators and the like. It is in that context that the digital disruption and enhanced computational capacities enabled a new governing by numbers, with data becoming more important in state policy steering and in top-down modes of accountability. This saw the bureaucratic center setting broad goals, steering at a distance, with the frontline, street-level deliverers of these policies held to account through outcome measures.

We need to acknowledge that numbers as statistics, literally state numbers, have long been central to the functioning of modern bureaucracy and democracy (Desrosieres, 1998). What is different now is the enhanced computational capacities and the greater ability and desire to "datafy" and quantify the social (Mau, 2019; Zuboff, 2019). Large amounts of state data required data infrastructures, which were often provided by the private sector, as were the standards according to which they operated (Sellar, 2017). Indeed, the restructured state opened up many opportunities for the private sector to work with and for the state for profit-making in relation to data work, which became more important. The place of data in the governance of education has moved beyond the initial creation of "infrastructures of accountability" (Anagnostopoulos et al., 2013) created to manage test-data towards "digital education governance" (Williamson, 2017, p. 94) with data playing an enhanced role in the functioning of school systems.

This state restructuring affected education systems, as did neoliberal ideology. There was an attempt to create quasi-markets in schooling. These markets were instantiated through the implementation of top-down, test-based forms of accountability, with comparative test scores putatively enabling parental choice of schooling. In many nations, census national testing was introduced and functioned as a complement to international large-scale assessments (ILSAs). Numbers and data became ever more important in the work of systems and schooling. Comparison of performance was now central to governance; here Mau (2019) has observed that "data create a comparative panopticon with diverse visual axes of numeric comparison" (p. 159). Regarding this mode of accountability, Ranson (2003) argued that this mode, with schools (and systems) being held to account for a range of test scores and performance measures, was actually becoming the system. Related, Ozga (2009) has argued persuasively that schooling is now governed through data.

NPM subsequently transitioned to network governance (Ball & Junemann, 2012). With network governance, private sector actors (edu-businesses and EdTech companies, also philanthropists) entered the state, its structures and practices, and had influence across all aspects of the policy cycle in education. These included agenda setting, through policy production, to policy implementation and evaluation, with potential impact on curriculum, pedagogy, assessment, and reporting (Ball, 2012). State restructuring also saw one-line budgets devolved to schools with school autonomy enabling school-level purchase of education apps and other digital technologies from the private sector. The recent rise of nationalist backlashes against globalization have begun to have an impact in politics and policies, but the state restructurings in education outlined here have remained in place (Lingard, 2021).

Educational assessment

In this section, we consider debates in educational assessment and the opportunities the digital opens in relation to these debates. The debates are far from new but take on new salience in the current digital era, noting Delandshere's (2002) point that there the field lacks a general theoretical position that connects assessment to "meaning making." Over the 20th century and to the present, assessment writers have continued to concentrate on issues of validity[4], reliability[5], standards, and accountability, while human judgement, decision-making, and evaluative expertise have received less sustained attention (Cooksey et al., 2007). Limited attention has been paid to the affordances of digital technologies beyond the focus on data infrastructures, standardized testing, scoring, and reporting, largely driven by systems and private testing companies.

Historically, assessment has served two main purposes with distinct goals; first, summative assessment serving the goals of measurement and reporting, and second, formative assessment serving the goals of learning improvement (Harlen, 2005a; Sadler, 1989; Wiliam & Black, 1996). Summative assessment typically occurs at the end of a designated phase of study, say at the end of a term or semester, or at the exit from a course of study. It is primarily concerned with measuring individual achievement or competence and securing high reliability. Examinations have been the primary mode for summative assessment. The tasks included in examinations are necessarily limited, being subject to the conditions of restricted time for student completion. Examinations also prioritize rater- and inter-rater reliability with less emphasis on claims to validity and authenticity of assessments.

Formative assessment and the evidence of learning that it produces are most commonly collected by the classroom teacher (Black & Wiliam, 1998). Formative assessment and feedback are intended to occur as part of teaching and to serve the goals of improving learning (Black & Wiliam, 1998; Shepherd, 2000). Formative assessment is concerned with evidence for informing decisions about the student's current level of performance; the desired and realistically attainable next level of performance; and the strategies necessary to close the gap between the two (Ramaprasad, 1983; Sadler, 1989, 1998). In short, it serves to inform next steps teaching and learning, whereas summative assessment is not intended, generally speaking, to have a future application.

In formative assessment, validity and authenticity have been priorities. The alignment of curriculum, pedagogy, and assessment is also a feature along with clarity about expectations of quality. However, one issue for enhancing the status of formative assessment has been the reported problems of the dependability of teacher judgement. Human judgement in assessment practices has continued to be construed as largely subject to the influence of random error, bias, and even whimsy. Interestingly, teacher judgement has not been widely trusted by systems, though research shows that when calibrated, teacher judgement can be rendered reliable (Harlen, 2005b). Research also shows that dependability of teacher judgement can be achieved through explicitly stated criteria and standards, and moderation practices where teachers come together to share samples and apply standards supported by "cognitive commentaries" (Wyatt-Smith et al., 2010) in which the deep structures of judgement are revealed. The commentaries serve to reveal the appraisal processes used by teachers to arrive at an overall grade, including complexities of trade-offs that they considered in combining both the stronger and weaker aspects of performance. These research insights into judgement have informed initiatives in feedback, including voice recorded feedback on the application of criteria in the course of scoring and commentary to inform future learning. However, despite these developments, examinations have retained the highest status as producing trusted and fair measures typically regarded as objective assessment.

Historical boundaries between formative and summative assessment are well established. The teacher has been the primary agent in the former, and in the latter, the state and education jurisdictions have prescribed requirements for examinations, scoring, and reporting. The boundary has served to ensure that examinations for summative purposes have been the province of examination boards and testing companies at system level, committed to demonstrating system and sector accountability. The formative-summative boundary has held in most countries. This became crystal clear in the turbulence caused by the pandemic when terminal examinations could not be scheduled; systems needed to maintain a pipeline of students through to graduation from schooling and to develop radically different means for assessing and reporting student achievement.

In recent times, there has been a laser-like focus on improved learning with schools coming under the concerted gaze (panopticon) of the state and testing companies. Formative assessment has now moved to be the new domain of software developers and testing companies. Discourse has shifted to assessments online, at the point of need, serving to guide teacher decision-making, and customizing monitoring of learning and learner growth. This has been fueled in part by the appeal of digital technologies to enable easy delivery of assessments on a continuing basis, fulfilling the purposes of formative assessment as mentioned earlier. There is already the imperative in some countries to collect such monitoring data online and in this way, extend the gaze directly into schools and classrooms. In the digital disruption era, the boundary between formative and summative has blurred and accountability is being reconceived as extending to collecting and storing online point-in-time data on student learning, teaching quality, and school and system performance. Added to this is the formative use of national and international testing data, even though by design, the tests are not constructed for these purposes.

This raises the key question of where change in education in general and assessment specifically comes from. The answer seems to be clear: change is coming to education from agents with expertise outside schooling. These include edu-businesses, philanthropic organizations, private entrepreneurs with capital investment in schooling (e.g., charter schools), testing companies, and more recently, EdTech companies, systems designers, and data analysts. Their collective incursions reflect that education is now a prized marketplace and how assessment for both formative and summative purposes has become big business. Somewhat ironically, these moves occurred at a point when education research confirmed the value of formative assessment in teachers' hands (Black & Wiliam, 1998; Earle, 2003), but at the same time, revealed that formative assessment had not worked in schools (Baird et al., 2017; Booth, 2017). This possibly reflects the historical dominance of external examinations and the failure to develop evaluative expertise among teachers, especially regarding teacher judgement and the use of standards (Wyatt-Smith & Adie, 2019).

Working Together – Policy and Assessment Frames in the Digital

To circle back, the new practices of statecraft, along with exponentially evolving dependence on numbers and data, in education policy, and in the work of systems and schools, have opened the space for for-profit edu-businesses and EdTech companies to take on ever increasing roles in them. What we have seen are moves towards an emergent mode of "digital education governance," a concept that "registers the displacement of educational governance to new digitized sites of expertise in data collection and analysis" (Williamson, 2017, p. 94). This form of governance "also acknowledges the role of digital software, code, algorithms in governing and guiding the conduct of diverse educational actors and institutions" (p. 94). Digital governance has serious implications for education budgets, the economics of education, and democracy more generally.

We assert that much of the digital development in the fields of assessment and testing, driven by testing companies, often in partnership with governments, has prioritized the psychometric properties and efficiencies of testing and scoring over a fulsome engagement with the scholarly corpus of literatures on assessment and evaluation, which we have succinctly traversed in the subsection above. Overcoming this divide would demand collaborations and a sharing of expertise across numerous fields, including digital architects; learning engineers; systems designers; psychometricians; education data scientists; and curriculum, pedagogy, and assessment experts including teacher practitioners. We next consider the impact of the digital on assessment and testing.

Digital Disruption in and through Assessment and Testing

Globally, in relation to digital disruption, most current debates in education are concerned with the role of tests and test data, and how this will assist teachers and policymakers. Put simply, digital learning assessments involve the design of standardized tests in an online format. For this to occur, optimally, they are "born digital" (McGaw et al., 2020, p. 126). Additionally, they are structured in a way to enable rapid computer scoring, a quick turnaround of results and feedback, and subsequent analysis at system and local levels. Here we make a distinction between *digitizing* tests and *digitalizing* them, with the former simply the reproduction of the paper and pencil test online. In stark contrast, with the digitalization of standardized tests, the online format recontextualizes and rearticulates the test. This means the test appears differently, students engage with the test differently, and the opportunities are there for multimodal design of items. Moving to digitalized assessments requires much more than simply reproducing a print text in an online environment. Such learning assessments are thus freed from the constraints of paper and pencil tests and framed by the affordances of the technology.

Computer Adaptive Testing (CAT) is the contemporary manifestation of assessments born digital. To date, CATs have been developed utilizing a detailed item bank. CATs are designed so as to adapt the test to the abilities of those taking the test, so that not all test takers answer the same sets of items. This is called "branching": test takers' engagement with the test is tailored to their performance on the items at predetermined junctures in the test design. This is where algorithms are important; it is an algorithm that selects the items for test takers in response to their success or not in answering initial or subsequent questions. Figure 1.1 presents an example of how branching works in computer adaptive testing, and Figure 1.2 represents how branching manifests in the national testing of literacy and numeracy in Australia for those students who take the test online.

There is no doubt that the development of digitalized assessments brings new challenges for test design, analytic capacity, scoring, and reporting mechanisms for systems, schools, and teachers. We note that a move from paper and pencil to online testing requires a new time series and the selection of new anchor items. Anchor items are important for tracking performance over time. The fiscal capacity, expertise, and professional competence to meet these challenges vary widely, even within a country. In a context in which governments are both demanding and dependent on a supply of education data for accountability purposes, these capacity shortfalls have opened the space for the outsourcing to for-profit edu-businesses to provide their costly services. These costs can include those associated

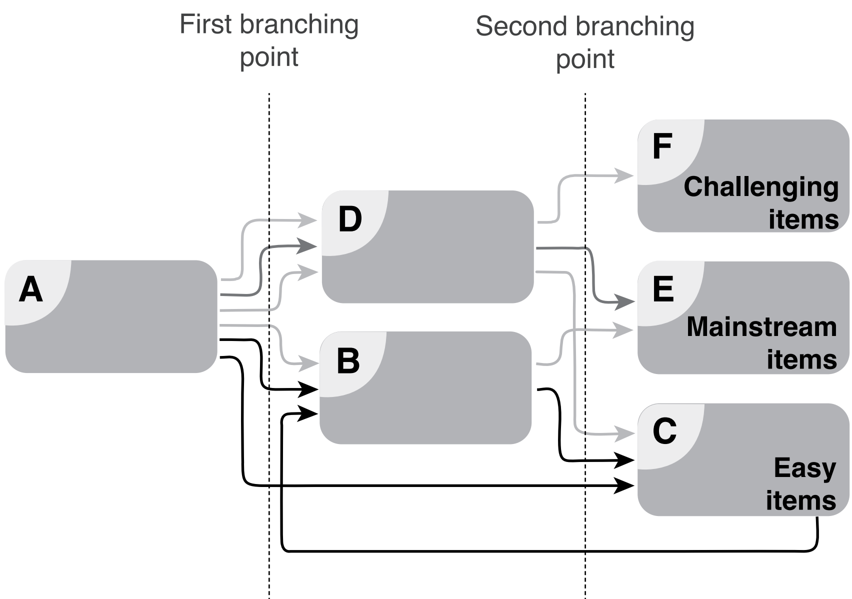

FIGURE 1.1 Test tailored design with branching
Source: Australian Curriculum, Assessment, and Reporting Authority (ACARA; 2014). Reproduced with permission.[6]

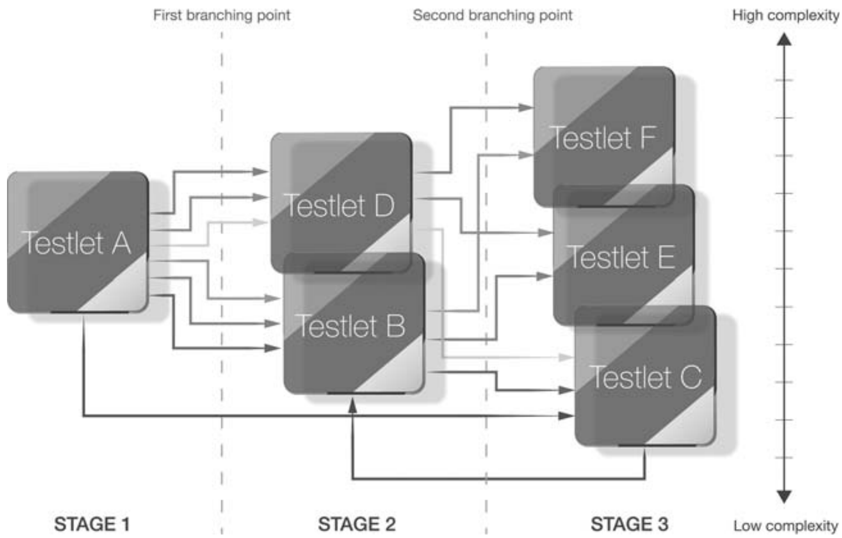

FIGURE 1.2 Branching structure of NAPLAN online literacy and numeracy tests
Source: Australian Curriculum, Assessment, and Reporting Authority (ACARA; 2020). Reproduced with permission.[7]

with item development for online delivery, administration of the test, secure test data storage, security of test items for use in subsequent tests to potentially enable longitudinal analysis, and the application of predictive analytics.

Here we recognize that this set of issues has serious implications for tests and test items, and for the provision of feedback and reporting on the performance of cohorts, special at-risk groups, and individuals. We also note that there is very little published cost-benefit analysis undertaken by governments to examine the costs and benefits of census and sample standardized testing. Cost-benefit analysis is common practice in other domains of government activities.

Within this set of complex issues, writing assessment is well recognized to be perhaps the most difficult domain in designing standardized assessments, with these issues intensified in attempts to digitalize such assessments, including the scoring of them. To illustrate, in their current forms, PISA, PIRLS, and TIMMS are among the high-status international large-scale testing programs that do not include tests of writing. Assessing writing in domain areas lies generally beyond large-scale learning assessments, and inter-country assessment of writing is recognized to be in its infancy (McGaw et al., 2020; United Nations Educational Scientific and Cultural Organization (UNESCO, 2019). At the point of moving writing to online testing, it is interesting to note how few countries have installed this to date (see McGaw et al., 2020, p. 163).

There are numerous issues with the testing of writing, whether it is completed online or with traditional technologies. This is the case for a range of reasons.

There are, for instance, decisions to be taken about the forms/genres of writing to be assessed, the related curriculum areas in which the writing is situated, the conditions under which the students undertake the test, and provision of time for planning, drafting, and revising. Added to this is how to develop digital stimuli to engage young people in an authentic writing test. There are also complex questions regarding assessment criteria for scoring, the potential influence of co-dependencies among criteria and how these can affect scoring, and the means by which reliability can be demonstrated. Additionally, there are questions to do with assessment standards and moderation across participating jurisdictions and importantly, considerations of the role of the profession in test design, implementation, including scoring and moderation, and reporting.

Among these is perhaps the biggest question of all: "Is machine scoring equivalent to human scoring of writing assessment?" At its core, this question calls for careful research into the validity of automated scoring systems related to the validity of test content and response processes (Bridgeman & Ramineni, 2017; Shermis, 2014). Moves to machine scoring of writing have triggered deep skepticism among citizens and the teaching profession regarding the prospects for fair and informed assessment of writing by machines. The press for online testing of writing is nevertheless evident in at least some contexts. The Australian Government is one example, calling for all states to move to national numeracy and literacy testing online, including writing, as soon as possible. This brings to the fore priorities concerning moving tests online or improving the quality of the tests.

Going beyond writing, the scope of testing is a further important consideration in the management and delivery of computer adaptive testing. In census testing, whole cohorts participate, as distinct from sample testing, where a purposive cohort is drawn. We note that these two types of testing serve different purposes, and in census testing in particular, resource implications are significant. Such testing is dependent on an important set of conditions for effective implementation. These include: the necessary digital infrastructure at school and site levels, necessary bandwidth and stability of online delivery, essential provision of hardware and software, and student keyboarding fluency and typing competence. The last of these cannot be under-estimated; such competence reduces the cognitive demands of responding in online test environments. Additionally, we note the challenges of ensuring sustained Internet connections and secure supply of power in some nations, particularly in the Global South.

The next generation of digitalized assessment testing has been characterized as "immersive assessments" (Wyatt-Smith et al., 2019). Figure 1.3 shows that these are an evolution from Computer-based Testing (CBT), through Computer Adaptive Testing (CAT), to Immersive Assessments (IA). The features of these digitally mediated assessments are identified in Figure 1.3. Immersive assessments rely on augmented reality (AR), virtual reality (VR), mixed reality (MR), and extended reality (XR). Immersive assessments also rely on artificial intelligence and 3D developments that focus sharply on the cognitive, experiential, and

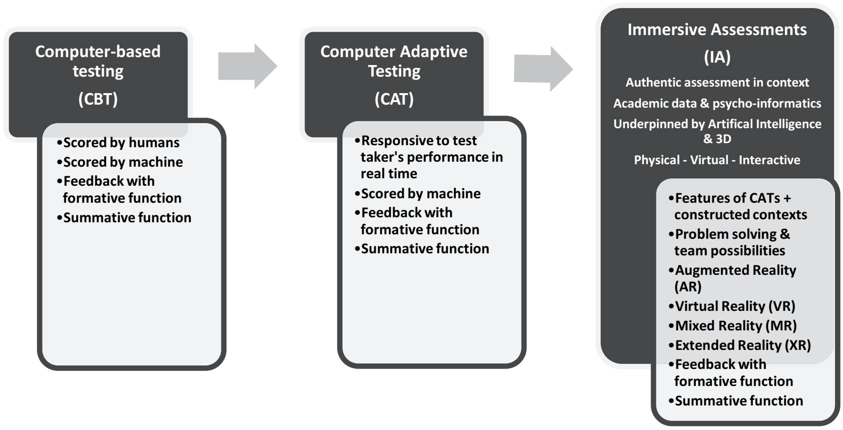

FIGURE 1.3 The evolution of digitally-mediated ways to assess student progress authentically in context

Source: Wyatt-Smith, C., Lingard, B., & Heck, E. (2019). Digital learning assessments and big data: Implications for teacher professionalism. Education Research and Foresight Working Paper. 25. Paris, UNESCO (p. 6).

sensory potential of digital learning assessments that include psycho-informatics. Williamson (2019) suggests that, "Psycho-informatics is based on the application of computer science techniques to psychological tracking, measurement and analysis of behaviors, emotions, personality traits, attitudes, cognition and abilities" (p. 66). He goes on to suggest that psycho-informatics "makes use of behavioral data sources and analytical platforms employing techniques from data mining and machine learning to detect, characterize and classify behavioral patterns and trends" (p. 66).

To succinctly define the constituent parts of immersive assessments, augmented reality (AR) uses the real world environment augmented by computer-generated input (e.g., sounds, global positioning systems (GPS), touch); virtual reality (VR) immerses participants in completely virtual environments (for VR in curriculum and pedagogy, see Southgate, 2020); and mixed reality (MR), sometimes called hybrid reality, merges real and virtual worlds where the physical and the digital co-exist and interact in real time. Extended reality (XR) is where real and virtual environments are combined, and human+machine interactions are generated by computer technology and wearables. XR is an umbrella concept that brings AR, VR, and MR together.

Immersive assessments have the benefits of computer-based assessment of scoring efficiency and prompt feedback. However, they have potential additional benefits of creating virtual realities that enable an authenticity in assessment in ways not previously possible. We are not suggesting, though, that all knowledge forms lend themselves equally well to these immersive assessments. Elsewhere we have argued that the evolution, represented in Figure 1.3, is not intended to suggest a linear progression, and is also not intended to imply that all schooling systems around the globe should be moving to immersive assessments at this time (Wyatt-Smith et al., 2019). Readers will be well aware, however, that simulated reality is central to computer gaming with which many young people are familiar. However, while simulations have also been utilized in some instructional domains, such as the training of pilots, military personnel, dentists, surgeons, and other health care professionals, simulated reality has had limited systematic use in schooling to date. We note that there are multiple potential positive uses of simulated reality in classrooms across multiple subject areas, stretching from Science through the Arts and Physical Education. There is also work underway developing virtual reality classrooms in which students are immersed in the virtual realities of what they are studying (Southgate, 2020). The lack of uptake of simulated reality is even more the case in respect of assessment. Rich immersive assessments are costly to design and costly to implement. There is thus the inevitable situation of the haves and have nots in relation to these developments: those who have opportunities to access such advanced assessment practices, and the knowledge and expertise needed to complete them, and those vulnerable populations with no such access, resulting in a widening of the gap in opportunities and learning. This discussion suggests that digitalized assessments have the potential to exacerbate inequalities in the experience of schooling across different populations and across nations.

For most readers, the experience of assessment has involved undertaking a prescribed, non-negotiable task, alone and unaided, under time restricted non-negotiable conditions, with limited or no access to human or material resources. What we have been considering here in relation to the evolution and disruption of assessment and learning are challenges to the traditional, taken for granted assumptions about assessment. Moreover, this exogenous pressure to change due to digital disruption demands new ways of assessing and new ways of demonstrating accountability.

The COVID-19 phenomenon has taught us that the tried and trusted ways of bringing young people together to sit terminal examinations in large halls, with invigilators patrolling the desks, are not the only ways. In this context, systems and leaders have been forced to find new ways to assess and rank students. There is a deep irony here in the context of COVID-19 and schooling from home; at least in some countries, there has emerged a new respect for teachers and their professional judgements and also the recognition of the complexities of teachers' work. Yet we note the fiasco in 2020 in England in relation to results generated by algorithms for GCSE and A-level students who were not able to sit their examinations due to the pandemic. The fiasco was caused by deep concern reported by parents, students, and the broader community about the veracity and fairness of the algorithmically derived results based on historical data. The Prime Minister blamed the fiasco on a "mutant algorithm" (Poole, 2020, para. 1). Of interest in this book is how this example illustrates the way in which past history of performance became hard wired into the algorithm, which had the effect of reproducing structural inequalities, thereby disadvantaging high performing students in schools that had historically performed poorly. This brought into clear sight the ways in which schooling systems, especially through assessment, have tended to reproduce, rather than ameliorate, structural inequalities. Interestingly, some activists have argued that algorithms used for public policy purposes should be subject to extant anti-discrimination policy.

Digital Disruption in and through Big Data

We begin this section by offering a working definition of big data and then unpack it. Big data is one of those concepts with "terminological simplicity that marks highly contested territory" with "data" recognized as "the most elusive term of all" (Borgman, 2019, p. 1). While acknowledging the elusive nature of the concept of data, we are taking it here to refer to "numerical information in digital formats" (Sellar, 2017, p. 341). Attempts have been made to define the combination of data + big, including by Williamson (2017), who formulated the following technical definition of big data drawing on the cognate literature:

> In technical terms, big data refers to data sets that are huge in volume (at the scale of petabytes, exabytes and zettabytes); highly diverse in type and nature; generated continuously at great velocity in or near real-time; exhaustive in scope (enabling the capture of entire populations – or "n = all" – rather than sampled selections); fine-grained in resolution at the level of indexing individual units; combinable with other networks of datasets; and flexible and scalable enough for new fields to be added and to expand in size rapidly. (p. 32)

This extract captures the commonly referred to characteristics of big data as volume (necessitating cloud storage), variety, and velocity. Drawing on the literature, De Mauro et al. (2016) also defined big data in a way that highlights that it is an asset. In so doing, they suggest its potential for transformation and in turn, value-added status and monetization. These authors wrote that "big data is the information asset characterised by such High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value" (p. 131). This later point relates to the usage of big data analytics "for intelligent decision-making" (Hilbert, 2016, p. 139), involving predictive analytics. There are interesting considerations here in respect of how these matters construct the temporal, particularly relationships between the past, present, and predicted futures and on what basis (see Webb et al., 2019).

Such definitions provide an opening to consider various matters relating to data that are distinguishable in nature and kind from data themselves. These include, for example, the necessary computational and infrastructural capacity to collect and store large volumes of data. These preconditions for working with data routinely involve substantial costs. Dependent on the scale and nature of the data, these preconditions open up issues of network governance and related opportunities for the private sector to bring profit-making motives to how the data are processed and even on-selling opportunities.

According to Sellar (2017), a data infrastructure "can be understood as an active and changing platform for storing, sharing and consuming data across networked technologies" (p. 345). Such infrastructures rely on technical, software, and hardware capacities to facilitate system and data interoperability. Sellar also identified that a number of interoperability standards have been developed, an example being Microsoft's Schools Interoperability Framework (SIF), which was developed in conjunction with 18 other software companies and the US Software and Information Industry Association (Sellar, 2017). From 2003, the US Federal Department of Education became involved in these developments. In Australia, governments, in conjunction with the EdTech industry in 2009, moved to develop the National Schools Interoperability Program (NSIP) to ensure the interoperability of all data from all systems and all schools across Australia.

Analytical capacity to design algorithms, applied to multiple data sets, is yet another issue, together with the ways in which the algorithms are used in policymaking. For example, the continuous collection of data and how big data are constituted over time also raise questions of privacy, confidentiality, and rights of students, teachers, and carers. As boyd and Crawford (2012) have argued, while big data can provide solutions to problems, they pose issues about privacy. These issues have been referred to as "dataveillance," a concept taken to denote the collection and monitoring of personal data (i.e., data of a range of types relating to individual identity and group membership, and even health records). These privacy issues become even more significant when EdTech companies are involved in the collection, storage, and analysis of data, with the potential to on-sell to third parties. Usually, such uses occur without the consent of those whose data have been collected. This is an example of network governance at work with private, non-state actors involved with the state in developing policy.

There is growing concern, even cynicism, about government and system use of data. Lingard et al. (2017) identified that Australian teachers were deeply concerned about student data being in private hands. Further, in the USA, there was the collapse of the *InBloom* initiative in a group of Eastern states, which had been supported by philanthropic money. In response to then President Obama's Race to the Top Initiative (RTTT), the aim was to create data infrastructures and interoperability between multiple data sets, across government portfolios and across states. The collapse reportedly occurred as a result of organized parental opposition to the involvement of private companies, data privacy issues, and the potential for student data to be on-sold to third parties for profit (Bulger et al., 2017; Lingard, 2019). In Japan, data privacy has also been a concern to the point where legislation ensures data collected by governments can only be used for the explicitly defined purposes for which they were collected (Takayama & Lingard, 2019).

With big data, using data linkage, various extant data sets can be integrated, and algorithms used to produce "patterns" and other insights can make visible solutions to seemingly intractable problems. Drawing on Mayer-Schonberger and Cukier (2013, 2014), this means reducing emphasis on causality and a turn to correlations. This focus on correlations raises the prospect that we will know *what* has occurred, but not *why*. This has implications for subsequent stages of decision-making. We stress yet again that human decision-making is the necessary element to interpret such meaning from data and what it may mean for future actions. This is certainly the case in relation to education and student learning.

So, how do data and specifically big data apply and work in education? Cope and Kalantzis (2016) define these concepts in the following ways:

> (a) The purposeful or incidental recording of interactions in digitally-mediated, cloud-interconnected learning environments; (b) the large, varied, immediately available and persistent datasets generated; (c) the analysis and presentation of data generated for the purposes of learner and teacher feedback, institutional accountability, educational software design, learning resource development, and educational research. (p. 197)

The above definition opens wide the vista of students individually and in small groups working continuously on computer-based curricula, pedagogy, and assessment. This is the individualization, personalization, and customization aspect of big data as it comes into, and attempts to service the classroom, be it in schools or universities. There is the real prospect of schooling to be recast to prioritize what can be produced and presented online. Here we acknowledge that such data have the potential to "recreate the world," rather than simply represent it (Espeland & Sauder, 2007). Rose (1999) suggests that while numbers and data represent reality, they are also simultaneously "inscription devices" that help constitute that reality.

When this occurs, the broader social and citizenship goals of schooling could be considerably downplayed and recast. The risk is that the message systems (curriculum, pedagogy, and evaluation; Bernstein, 1971) in online format become standardized and reductive and come to redefine schooling. In turn, we see here the possibility of the message systems being constituted and controlled by edu-businesses and for profit. Sellar and Hogan (2019) point to the possibility that personalized online schooling might elide considerations of the social purposes of schooling, including for example, learning to collaborate and work in teams. We note that there has been parental opposition to these developments as evidenced in the opt-out movement in the USA, which, while mainly focused on high-stakes testing, has also been concerned over edu-business control of the message systems and of schooling reduced to students working all day on computers (Lingard & Hursh, 2019).

All this points to pressing new questions for our times: Who ought to develop curricula in schools in democratic societies? What should be the role of the teacher (or knowledgeable other) in relation to computer-based scripted curriculum, pedagogy, and evaluation? Do the answers change in low-income countries, when it may not be possible to produce professionally educated teachers in the necessary numbers?

There are very few national and cross-national large-scale learning assessments that might be defined as big data. The case of Australia's National Assessment Program Literacy and Numeracy (NAPLAN) illustrates how little big data there might actually be in extant school assessments. This is despite the fact that NAPLAN is a census test involving full cohorts in Years 3, 5, 7, and 9 at the time of writing. Similarly, international large-scale assessments including PISA, TIMMS, and PIRLS are sample tests and do not currently generate big data.

Edu-businesses have been among the main advocates of a big data approach to reforming schooling systems and schools (Hill & Barber, 2014; Hursh, 2017; Sellar & Hogan, 2019; Williamson, 2017). Perhaps it is therefore not surprising to see the upswing of engagement by edu-businesses in what has previously been the domain of the classroom teacher, namely learning assessments (sometimes called assessment for enabling learning or formative assessment). The primary purposes of such formative assessments have been to assist with teachers' instructional decisions. Has the child learned the concept? Is the child ready to proceed to next-step learning and teaching? What is the child's current level of performance; what is the desired level, and importantly, what are the necessary actions to close the gap across the zone of proximal development (between the current and desired levels) (Ramaprasad, 1983; Sadler, 1989; Vygotsky, 1997).

To date, learning assessments have been the domain where the teacher's curriculum, pedagogical and evaluative expertise have been the source of their professional decision-making and judgement. In contemporary times, however, in high-income countries, this is a relatively new space for schools and parents/carers to purchase formative assessment apps and intelligent tutoring systems for online learning (e.g., Reading Eggs, Mathseeds, Mathletics, and Quizlet), as well as apps for behavior management (e.g., Class Dojo[8]). There are also some of these in middle-income countries such as India (e.g., BYJU's – The Learning App[9]). These formative assessment apps are effectively creating new markets and, in turn, catalyze a big data disposition: insights from built-in analytics can be readily deployed by private companies to improve the apps to increase their effectiveness and attractiveness for purchase. Far less overt are questions of ownership of data collected about teachers and students, and further, how these relate to bigger questions about data ethics, matters of consent, and issues of data privacy.

Whether and how consent is given to the collection of such data and who owns it are significant and complex issues. We argue that this is particularly the case when the mode of assessment is conducted by private actors, and done within, and sometimes contracted by governments, schooling systems or schools, and other administrative agencies relating to the teaching workforce. The implications of this commercial arrangement, supported by hardware and software, can be significant when they manifest as achievement targets and track performances of students in ways that are not formally authorized by the students and in some cases, even school leadership: surveillance schooling has potentially arrived.

A report prepared for the European Commission explored issues to do with data privacy in relation to big data (Berendt et al., 2017). The report recommended that data protection and data privacy both be explicitly incorporated into the design of big data systems. Agreement on such measures, however, especially as they relate to ethics and integrity protocols, remains a work in progress. Zuboff (2019) has made a similar point about the potential taming of big data through legislative and legal frameworks in relation to privacy.

The research on schooling systems and leadership suggests that schools in several countries are awash with data (Landri, 2018; Williamson, 2017). The problem therefore is not that schools, teachers, and school leaders do not have sufficient data to inform their practices and decision-making. On the contrary, they have such a constant deluge of data that the onerous task is to discern fitness-for-purpose of the data they have. Adding to these demands are what Polonetsky and Jerome (2014) have identified in their US report as ethical and privacy issues associated with the rapidly expanding data in US schools. They explored legislative frameworks and suggested that these appear inadequate to the task at this point, especially with the enhanced involvement of EdTech companies and other edu-businesses in respect of data work. Undoubtedly, there are complex legal and ethical issues here concerning data ownership. The US report exposed the intricacies of consent by students and parents in respect of various data sets. These matters remain in their infancy in relation to legislation in education and the rights of the child. These issues are undoubtedly becoming more significant to the public and legislators, indicated by privacy and usage concerns about the data that citizens readily surrender to social media (e.g., Facebook, Twitter, Instagram; Zuboff, 2019). According to Williamson (2017), "considerable unresolved concerns remain about the adequacy of contemporary student privacy and data protection policies and frameworks in relation to the rise of educational data science practices of big data analytics and data mining" (p. 121), including the local use of data dashboards. The era of data walls (as material artifacts) has been replaced by digital displays, including on the big screens in schools, with little systematic research on how they are being used, and with what educative effects (Adie et al., 2020; Harris et al., 2020). We suggest exactly the same about issues of data ownership and the rights of the child/student/parents in the current moment of digital disruption to schooling.

Digital Disruption in Teaching

Elsewhere we have identified that digital disruption may precipitate a rapid deprofessionalization of teachers in low-, middle-, and high-income countries

(Wyatt-Smith et al., 2019). In some low-income countries, schooling is provided by unqualified teachers and machines, using scripted curriculum, pedagogy, and assessment provided by for-profit edu-businesses (Junemann & Ball, 2015; Riep, 2015, 2017). In some middle- to high-income countries, teacher e-readers can be readily connected to smartphones with resultant data moving from teacher computers to storage in the cloud to frame next step teaching. At the very core of efforts to maximize educative potentials of digital technologies is teacher expertise. In addition to the necessary teacher expertise, policy also needs to be cognizant of digital divides within and across nations, so as to avoid further entrenching inequalities in and through schooling, which have been growing across the past two decades (Chmielewski, 2019).

Digital Literacy and Data Literacy for Teachers

Teacher professionalism encompasses various professional knowledges and practices (e.g., in relation to curriculum, pedagogy, and evaluation) that are paramount to the development of learning for all students (see Hattie, 2008; Hayes et al., 2006; Iivari et al., 2020; OECD, 2005, 2011). In the digital age, as we have been arguing in this chapter, there is a clear need for rethinking teachers' professional knowledges and practices, given the affordances of the new technologies. These new knowledges and skills include: technical proficiency in the use of hardware and software; pedagogical know-how in the design and implementation of teaching sequences, using these digital materials; deep knowledge of the curriculum and evaluation practices; acute evaluative capacities; abilities to discern the value of digital technologies and data as fit-for-purpose; and capacities to collect, interpret, and discern the meaning of data so as to inform professional practices.

On this point, Cope and Kalantzis (2016) comment astutely, "to teach and learn in such environments requires new professional and pedagogical sensibilities. Everyone becomes to some extent a data analyst" (p. 8). Data have become critical to teachers' daily work and a significant focus of and complement to teaching (Hardy & Lewis, 2017; Lewis & Holloway, 2019; Takayama & Lingard, 2019). Importantly, educational data can come from multiple sources, including the digital. While the very definition of data literacy is currently undergoing transformation, given these new and rapidly emerging digital contexts, teachers are well aware of the need for clarity about the characteristics of quality digital resourcing. Pangrazio and Sefton-Green (2019) note that data literacy "involves both critical understandings of the technological infrastructure and the political economy of digital platforms, as well as strategies and tactics to manage and protect privacy and resist being profiled and tracked" (p. 7). This draws us to the nexus between data literacy and digital literacy and the new capacities for using both to promote learner growth and track performance in meaningful and productive ways. The risk is that the easily measured can come to dominate what counts as valued performances in learning. This is where human judgement remains so important. Applying Zuboff (2019) to schooling, there are two questions here: "Can all the important elements of classroom practices and student learning be datafied?" and the additional normative one, "Should all such experiences be datafied?"

Building capacity in effective educational data usage involves the understanding of multiple sources, purposes, and aims of data. Skills involve analyzing and turning data into instructional actions, beliefs, sensemaking, and working collaboratively with data in school teams (Ikemoto & Marsh, 2007; Van Gasse et al., 2016). This is the context in which data dashboards provide a way to catalogue data for access and use by teachers and school leaders, seeking information about how well their schools are tracking against themselves over time and against other like schools (see also Gorur & Arnold, Chapter 10). The dashboards provide the means for making the data accessible and useable. However, they bring with them the demand for new forms of teacher expertise, what is usually included in the concept of data literacy. As teachers and school leaders work with digital data, a key aspect of professionalism is how to transform such data into action in the classroom and at the whole school level. Teacher expertise is necessarily processing data so that the data then become information and evidence for considering appropriate pedagogical practices. Here we see the important distinction between data and information, and data and evidence, with information and evidence referencing the processing and evaluation of data. Increasingly, systems and schools are looking to use digital architecture in productive ways for informing policy and practice and for monitoring and reporting on student learning.

Systemic data can trigger tensions between system and school site validity in various types of academic assessment. This tends to occur when priority is given to systemic data as the source of truth and typically works with standardization, in contrast to site validity, which works with the idiosyncratic specificities of students in classrooms (Freebody & Wyatt-Smith, 2004). Bourdieu (1998) makes a related point that the logics of practice of the state work with the universal and are manifested in public policy, which is then applied for example universally in schooling systems to the this-ness of individual schools, thus always ensuring some infidelity in the enactment of policy in different schools situated in variable contexts. Related, Thomson (2020) talks about the separation in schooling systems between "systemic data related to equity and effectiveness" and "school-based evaluations necessary for diagnostic and improvement work" (p. 216). This tension between system and site validity (Freebody & Wyatt-Smith, 2004) raises the question of who should control the field of judgement in schooling (Ball, 2003). It also raises the contemporary issue of the impact of the emerging shift to increased control in the digital space of psychometricians, test constructors, data and learning analysts, and policymakers (Nichols & Berliner, 2007; Popham, 2014). It is in that context that we stress the significance of teacher judgement and their evaluative expertise.

Chapters in the Collection

Ben Williamson in Chapter 2 uses science and technology studies to provide a partial genealogy of developments in education data science, specifically the emergence of the learning engineer from the earlier construction of the education data scientist. The focus is on what Williamson refers to as the "big data imaginary," how this is materialized in specific infrastructural arrangements and embodied in the practices of data scientists. In his analysis, Williamson problematizes the current fixation on big data in education, as learning sciences and engineering developments enable "automated knowledge discovery." He demonstrates how the concept of the learning engineer is based on a mix of cognitive science, psychology, and neuroscience and involves a move from organizational data-based analytics to individual learner analytics that open up to data analysis the internal substrates of learning (emotions, brain activity/reactions, eye/iris movements, etc.). The heavy involvement of EdTech companies such as Pearson, and philanthropists, such as the Chan Zuckerberg Institute and the Bill and Melinda Gates Foundation, in these developments is also demonstrated. Williamson's genealogy provides stunning exemplification of digital disruption in education and its potential ramifications for the work of teachers, teacher professional judgement, student learning and school experiences, and the constitution of democratic public schooling systems. We note how Williamson has demonstrated the ways external developments outside of the education policy community are affecting the work of schools and teachers.

Erica Southgate, in Chapter 3, seeks to translate and interpret the technical, mathematical, statistical, ethical, and legal/regulatory issues associated with artificial intelligence (AI) and machine learning (ML) for teachers and education policymakers. This is necessary knowledge so that both groups can have informed professional conversations about AI and machine learning. Such conversations are necessary so that professional teachers are not merely the objects of EdTech and system developed AI based reforms. The main focus is on the ethico-governance matters raised by these developments, produced by both large and small EdTech companies, and their take-up in education systems and schools. Clear explanations are provided of different types of AI and related ML and their usage in schools – Artificial Intelligence in Education (AIEd), while noting the often-anthropomorphic construction of AI and ML and exaggerated expectations currently about what they can or might be able to do. The chapter concludes by considering the ethico-governance issues that these matters precipitate. A number of issues are raised for teachers, schools, and systems in respect of AI in education in relation to its design, use, and governance. These are: the need for necessary foundational knowledge for teachers and policymakers, explainability of AI, fairness, transparency (difficult given the at times opaque character of algorithmic decision-making that underpins both AI and ML), and accountability, while recognizing that AI and ML developments have outpaced contemporary governance structures and regulatory frameworks.

In Chapter 4, Brian Lee-Archer begins with what he refers to as a challenging paradox: societies' increasing use of digital data to help address serious problems facing the planet, and citizens' growing lack of trust in their governments and public institutions. Within this frame, the chapter focuses on the emerging relationships between humans and machines (often referred to as "human+machines"), in a phase of human history increasingly dominated by artificial intelligence (AI) and the use of big data (Daugherty & Wilson, 2018). Lee-Archer explores how the use of digital data is a significant contributing factor in declining trust and presents the strong case that the way humans work with machines is vital to arresting this decline, and more positively, building public trust. He argues that stronger societies and better educational outcomes for children are dependent, in part, on the human element in decision-making. He proposes that stronger societies use existing assets including data, and promote citizen-led initiatives, to achieve the necessary balance between managing societal risk and rewards. He argues that such balance can be achieved through innovation from within the human dimension, guided by a dynamic base of digital data. While Lee-Archer recognizes that trust in public institutions and government is constantly challenged, a counter-balancing move would be for policymakers to adopt what he refers to as a structured process driven approach to AI and big data to provide a basis for building public confidence in digital initiatives. Finally, Lee-Archer asserts that a key issue in this approach is how policy promotes citizen-led initiatives so that people control their affairs in a democratic and inclusive way.

In Chapter 5, Kalervo Gulson, Andrew Murphie, and Kevin Witzenberger use the idea of Amazon Go as an intellectual springboard for education and open wide "the intensifying and disruptive capacities of AI in education." The authors put to readers the unsettling idea that: "for the first time in history we have no idea what to teach in schools." They propose the use of speculative approaches as ways of thinking through the implications of the future, as it involves artificial intelligence (AI), disruption, and intensification. They imagine the implications of a kind of Amazon Go for education. The chapter presents scenarios of changed roles of schools, universities, teachers, and forms of organizations that develop as AI is introduced. The authors have based the chapter on secondary evidence and acknowledge inherent limitations in how we can predict and plan for the future of education and schooling. They challenge readers to focus on what they refer to as "preparedness in relation to the unexpected." They locate the chapter within the conceptual resources from critical technology studies in education, new media studies, and science and technology studies. The chapter is presented in four parts. They first outline what they refer to as their "conceptual apparatus and methodological concerns," based on a future yet to be born, a future that invites speculation and the challenge for educational research of examining conditions which are yet to appear. The second part of the chapter provides a review of literature, and speculations about the intensification and disruptive possibilities of AI in education. With the continuing focus on AI, the authors posit that the current organization of education may shape the ways new AI technologies are adopted. This is a future where the influence of corporate interests and technological advances also shape the adoption of AI and, in turn, the nature and function of education. They then turn to consider possible substantive disruptions to education, addressing issues of provision and knowledge. They conclude the chapter by attempting to provide a sense of the issues or questions that they think require further examination. Drawing on Ross (2017), the authors recognize the limitations of speculative methods and also highlight that digital education research currently lacks what they refer to as "an imaginative resource to take a strong position at the edges of educational change."

Anna Hogan and Sam Sellar in Chapter 6 investigate the impact of the for-profit edu-business Pearson and the company's subsequent role in public education as they extend their corporate strategy. Through a review and discussion of the digital transformation of the Global Education Industry (GEI) and followed by a scoping review of Pearson's commissioned reports in education, Hogan and Sellar critically analyze Pearson's priorities and broader corporate strategy. Key points include the digital transformation of teaching, curriculum, and assessment, and the disruption of schools and schooling. Pearson's influence on the role of the teaching profession is a key concern, in addition to the company's collection of digital data and the subsequent issues that surround privacy, ownership, transparency, bias, and openness. Of particular note, Hogan and Sellar argue that consent is not always explicitly sought, and as a result, this complicates questions around responsibility and data ownership. These are significant concerns in regard to the impacts and the place of such private for-profit edu-business, particularly in poorer nations. There are further risks of deprofessionalization of teachers, as the teacher is reimagined as a "facilitator," and the consequent transformation and disruption of public education.

Laura Engel and David Rutkowski in Chapter 7 focus on the costs of participation in ILSAs, specifically the costs of the US's participation in both PISA and TIMSS. Here they build on their earlier work (Engel & Rutkowski, 2020). They argue that this focus on costs is important in terms of the educational benefits or otherwise of such participation and given the reality that ILSAs both drive the datafication of educational governance and are an effect of it. The costs fall into two categories: the overhead costs paid to the OECD and IEA for participation, and the costs of implementation of the tests inside the US, including the direct and indirect costs in each area. Using publicly available data, some of which is quite difficult to access, they document the amounts expended, which are very substantial. In various cycles of both PISA (every three years) and TIMSS (every four years), some states (sub-national units) have participated as individual entities in addition to the national sample. There are further state-level costs involved here. Engel and Rutkowski then consider potential costs/benefits of participation in these two ILSAs. In so doing, they review the cost/benefit methodology and point out the futility of trying to put a monetary amount on the benefits, which are both direct and indirect. In considering costs/benefit analysis in respect of ILSAs, they point out the lack of clarity of the US's rationale for participating in them, which limits accountability. They recommend broader educational community involvement in the establishment of this rationale and call for more research on evaluating the benefits of participating in ILSAs in the USA and in other nations.

Sigrid Hartong, Annina Förschler, and Vito Dabisch in Chapter 8 investigate data infrastructures and the (ambivalent) effects of increasing data interoperability in German schooling. This case study explores the very different political contexts for digital datafication and disruption of education in Germany, against the backdrop of German federalism. They note that although Germany, compared with other nations, has been a latecomer to datafication and digitalization in education, there has been a transformation and expansion of centralized performance data in school systems, and since 2012, a growth of digital learning tools. Yet, this has also been met with much greater caution in local sites of decision-making and implementation. They explore the emergence of datafication in German schooling via the transformation of standardized testing in state school monitoring and provide examples of school platforms and learning management systems. This chapter demonstrates the significance of the specificities of national contexts to understanding emerging datafication in and across national school systems. This is the broad point that digital disruption plays out in path-dependent ways in different nations and in different schooling systems.

In Chapter 9, Jessica Holloway and Steven Lewis use the concepts of "datafication" and "surveillance capitalism" in the context of schooling in Texas, USA. They lift the lid on a new type of "black boxing" in education data and assessment, revealing how schooling is being fundamentally reconceptualized by a mix of new partnerships, digital data, new technologies, technicians, and statisticians. They identify the influence of public-private partnerships involving Texas public schools and three organizations: SAS Institute Inc., Responsive Learning, and the National Institute for Excellence in Teaching (NIET). They discuss how these groups have worked in collaboration with the Texas Education Agency to build the Texas Teacher Evaluation Support System (T-TESS) as the new data that serve to manage schooling processes. Holloway and Lewis reveal how value is ascribed to the work teachers do – teacher effectiveness – and more fundamentally, how teacher identity is being changed and reconstituted as data. More than this, the authors shine the spotlight on how new actors in schooling with expertise in digital data, technicians, computational processing, prediction, and statistical calculation are contributing to partnerships with schools in Texas, changing how benefit is understood in relation to such partnerships. In opening up the black box of datafication in this case, they present for readers a stark picture of data in a mix of private, business-oriented purposes in education, with impacts on teacher professionalism including professional judgement. This is a cautionary tale!

In Chapter 10, Radhika Gorur and Ben Arnold explore the sociotechnical imaginary of "governance by dashboard" in education. The authors argue that although the concept of digital data dashboards is seemingly transparent, these dashboards also perform their own invisibilities. As such, there are concerns for the goals of accessibility, reform, governance, quality, and equity in education provision. Empirically, Gorur and Arnold focus on the Global Education Policy Dashboard (GEPD), currently in development by the World Bank in conjunction with DfID (the United Kingdom's Department for International Development, now being restructured) and the Bill and Melinda Gates Foundation. Through an analysis of various documentation, themes explored in this chapter include "The Imagined System," "The Imagined Classroom," "The Imagined User," and discussion about the contradictions, challenges, and the various complexities of such a sociotechnical imaginary of education. This is significant, as the presentation, visualization, and curation of data via digital data dashboards can affect the ways in which problems are understood, and the ways in which policymakers from low-income nations are viewed – as unsophisticated and requiring external expertise. Importantly, as the authors note, this is also concerning particularly for nations in the Global South, where there is the risk of neo-colonial policy directions from the Global North and from edu-businesses located there.

In Chapter 11, Greg Thompson examines the evolving nature of digital assessment or what he refers to as "next generation assessment." He notes that standardized testing has been problematic as it is often linked to a top-down form of accountability. To investigate "next generation assessment," he delves into the Australian Online Formative Assessment Initiative (OFAI), with a focus on learning progressions. A key concern in this regard is the place of teachers in this context and their potential displacement in such automated and algorithmic systems. To frame his chapter, Thompson first examines the educational and policy contexts in Australia, followed by consideration of the implementation of NAPLAN, and the emerging debates around digital technology in this assessment space, before discussing concerns about the OFAI. As a result, he explores a solution to adopt a technical and more democratic focus, or a "technical democracy" (drawing on Callon et al., 2009; Thompson et al., 2019), which considers the roles of decision makers and stakeholders in these emerging assessment systems.

The suite of Provocations, collectively structured as Chapter 12, deals with the very real impact of the COVID-19 pandemic on digital disruption in education. We decided these provocations were needed as recognition that the social, which is the focus of our research, continues to change. In the pandemic crisis, some problems are made more visible, which are usually hidden from view and from political consideration. The pandemic has brought to the fore, for example, matters of inequality in relation to access and participation in the digital revolution (e.g., the digital divide) and in the provision of schooling and related opportunities for learning. With the move to so much online schooling from home, the reality of the digital divide has become very apparent. Many young people from poor families do not have laptops or access to the Internet. The pandemic has raised the issue of whether these matters should be universally provided by the state. A positive move in some parts of Australia has seen the state step in to ensure everyone has laptops and connectivity. The pandemic has also witnessed the EdTech industry use the crisis to intervene further in many aspects of school provision, with some suggesting schooling at home during the pandemic, using all of the new technologies, has offered a glimpse of the future, a sort of online driven deschooled society (Illich, 1973). The pandemic has foregrounded these matters and potentially increased the speed and extent of digital disruption in education. It is this set of matters that these provocations so effectively and concerningly address.

Neil Selwyn, author of *What is digital sociology?* (2019) and *Should robots replace teachers?* (2019), argues persuasively that COVID-19 means that we need to see the digitalization of education through the lens of the pandemic. He makes two important points: 1) COVID-19 is being used as a cover for accelerating an EdTech framed future of schooling, the dismantling of established schooling (cf Hursh, 2017), and 2) in that context, there is a pressing need for critical education scholars to articulate a counter and alternative policy narrative and imagined future for socially just public schooling. One purpose of the *Digital disruption in teaching and testing* collection is to form a basis for such counter narratives.

Nick Couldry, co-author with Ulises Mejias of *The costs of connection* (2019), which documents the ways data is colonizing human life, makes two significant points about the impact of the pandemic on education in his provocation. The first relates to the possibilities of more intense governing of teachers and students as school systems move to online teaching and learning. The second is the danger of substituting the deep inequalities of different home lives of students for the "common resource" of schools and classrooms. The latter, of course, still remains an aspiration, given inequalities between schools and in relation to funding, but it is at least an aspiration and focus of political mobilization and policy interventions. It is the former that Couldry focuses on, while noting that the present moment of home schooling is in some ways akin to Ivan Illich's (1973) "deschooled society," while pointing out that Illich always saw potential dangers in such deschooling in ushering in other axes of power. As with Selwyn, Couldry suggests that what we are seeing is the acceleration of trends already underway and the use of this crisis as an opportunity for edu-businesses to intervene further in schooling and classrooms. Specifically, he evocatively suggests that the management of the classroom by the eye and voice of the teacher will be replaced by surveillance via online resources, continuous assessment practices, and data collection.

Anna Hogan and Ben Williamson, drawing on their report for Education International, *Commercialization and privatization in/of education in the context of COVID-19* (2020), suggest that the pandemic has enabled the EdTech companies to characterize themselves as emergency responders as 1.6 billion children moved to remote online learning across the globe. Utilizing Naomi Klein's (2007) concept of "disaster capitalism," they argue that the EdTechs will use this opportunity for further privatization of schooling to their long-term benefit and profit. They document the global network of policy actors (international organizations, philanthropies, and EdTech companies) driving these changes and also note the significance of private infrastructures that manage online learning.

Sotiria Grek in her provocation documents another continuity pre- and post-pandemic, namely the distrust of teachers in policy terms, particularly in England. She documents how the health pandemic has produced a new epidemic of "linguistic signifiers," which represent quantitative measures of both everyday life and politics; think of the infamous R measure of the potential impact of COVID-19 infection rates. She suggests, rightly in our view, that the pandemic has also enhanced the standing of science. It is, however, the new moral discourses that have arisen in the context of the pandemic that she is concerned with. She shows how key or essential workers have become heroes, yet in England teachers as front-line workers, have been constituted in government discourses as anti-heroes, not worthy of trust. What is interesting in Grek's provocation is this long-term demonizing of teachers. What we see is the path dependent ways the pandemic plays out discursively in different national contexts. In Australia, in sharp contrast, teachers have been included in the category of essential workers and it seems that public recognition of their work and professionalism has been enhanced during remote schooling as a result of the pandemic. The situation in England, Grek notes, has also provided a further business opportunity for the EdTech companies.

Sam Sellar, in his provocation, draws on the work of Zuboff (2019) on "surveillance capitalism" to suggest three strategies that might enable us to resist its forages into schooling and its further privatization. He notes how the pandemic has opened a space for EdTech companies seeking to profit from the temporary shutdown of schools and the move to online learning from home. Using Zuboff, he talks of the ways in which, under surveillance capitalism, all human experience is being rapidly datafied as we use multiple digital online platforms in our lives. This datafication is then used as a commodity to profit from. This rendering is accompanied by a surrendering of our privacy and experiences to tech companies, as Zuboff insightfully puts it. Yet, it is strategies of opposition to surveillance capitalism and its playing out in schooling that Sellar is concerned with and in the context of the pandemic.

The three strategies of resistance Zuboff developed are taming, hiding, and indignation. The first works in relation to demands for legal and legislative protections of our data privacy – a difficult to achieve outcome given the power and influence of the huge tech companies. The second strategy is hiding, whereby we mask our identities and activities from digital platforms. However, as Sellar argues, such a strategy leaves surveillance capitalism intact. The final strategy is the one he holds most hope for: indignation. As Zuboff argues, the current situation of surveillance capitalism "teaches us how we do not want to live." It is in such indignation that Sellar argues there are political possibilities for repairing the infrastructure of public schooling and recognizing the importance of the collective experiences there, as opposed to the individualization that accompanies online modes of curriculum, pedagogy, and assessment. Sellar argues that the experiences of home schooling and online learning during the pandemic have driven home the significance of schooling as a centrally important social infrastructure. He asserts, rightly in our view, that schools are very important "public things."

Conclusion

Change is a characteristic of the human condition and human societies. The current moment of digital disruption provides striking evidence that confirms this observation, demonstrating accelerated change in relation to the formation and functioning of societies and human identities. Digital technology and computational power and capacity have advanced exponentially since the 1960s. Compare the computational capacity and processing speed of the smart phone today with those of the mainframe computers of the 1960s and 1970s. The impact of digital disruption is often referred to as ushering in a Fourth Industrial Revolution. This references *inter alia* the ways the digital revolution has reshaped production and consumption practices in the economy, and the nature and provision of employment opportunities and the skills needed for work and civic contributions. More than this, however, the digital revolution is having an impact on the broader social fabric and human identities. We acknowledge, however, this is manifested differently in the nations of the Global North and the Global South, with the potential for the digital divide to exacerbate inequalities that have been growing over past decades (Piketty, 2014) and also in relation to schooling (Chmielewski, 2019).

The digital has enabled new opportunities for human connections, locally, nationally, and globally and at speed. It has given ready access to knowledge in unprecedented ways and has also enabled knowledge generation to solve a whole range of human problems, across health, well-being, business, and tracking of economies and finance systems. We have now at our fingertips opportunities to follow and track (surveil) individuals, groups, and wider populations. Education has been slower in relation to other domains in taking up the digital.

The digital revolution has occurred in a changing context of a post-Cold War world that saw the emergence of a global economy, the dominance of neo-liberal ideology, the rejection of Keynesian welfare states, and restructured state bureaucracies, first through new public management and subsequently through network governance. This context has seen the digital revolution, driven by the interests of huge tech companies with profit motives, assert an unprecedented authority over governance and decision-making at system, and in turn, local levels as nations have moved to digital governance (see Grek et al., 2021), including digital governance of education (Williamson, 2017).

Added to this mix is the potency of big data, which have become central to public policymaking and government steering of the social that has become increasingly quantified and datafied (Mau, 2019; Zuboff, 2019). In education, it is widely reported that governments have an insatiable appetite for data. These data are now constituting and remaking education systems (Lawn, 2013), through accountability systems of a range of kinds used to track the performance of schools, teachers, and students. These performance-based modes of accountability hold schools and teachers to account. There has been heavy edu-business and EdTech involvement in these developments, as many chapters in this collection document. The transparency of these, and the ways in which they are remaking the social fabric of schooling, however, are less apparent. It was the big EdTech companies that created the standards for data infrastructures in education. The schooling of young people at home during COVID-19 has revealed a range of benefits of the digital in education, but also a range of shortcomings. These are well documented in the provocations in the collection.

In this chapter, we have documented the affordances of technology in education, noting that the social remains in a state of constant flux. We have adumbrated how the digital revolution is moving to provide *big* data at global and national levels, and education is potentially poised to use this for policymaking and educative purposes. Education data are valuable assets, a phenomenon already well recognized by the EdTech companies.

The digital revolution has already had some impact on teachers and teaching. We would stress here again that teaching is a relational and cultural activity. In so recognizing, we are aware that the digital revolution might continue without recourse to the profession, and in doing so, accelerate rapid deprofessionalization. In that concerning context, we argue the need for teachers' professional knowledge and judgement to be utilized in conjunction with the affordances of the digital. This will demand new collaborations and networks, along with new knowledges and expertise in digital and data literacies. As we argued earlier, the integrating of expertise across fields and the collaboration of individuals and groups with this expertise are critical in optimizing human+machine interactions for better futures. This is much more than "technical know-how."

We have also documented positives that might arise from the conjoining of digital change and new approaches in assessment practices. There are real opportunities, for example, for new designs in assessment eliciting a wider range of knowledge and skills, and greater flexibility for "assessment to be less time critical and location specific." There are also opportunities for addressing the desirable authenticity of assessment, enabling young people to work collaboratively in teams, focusing on creativity and problem-solving. Digital technologies "can make it possible to vary the location, timing, and length of assessments to suit the individual needs and preferences" (Timmis et al., 2016, p. 7).

In the context of this rapid change, we present some value propositions. First and foremost, we argue that humans should knowingly drive the digital revolution broadly and in education specifically. Put succinctly, the institutional provision of education is central to the production and shape of human futures. We use "knowingly" here to refer to the social justice position that the affordances of the digital revolution be utilized to benefit all and be geared towards strengthening education as and for the common good (UNESCO, 2020) to focus on the place of the human. Schooling is central to the socially just provision of opportunities for all, irrespective of social class background, race, ethnicity, gender, or ability. The affordances of the digital and data must be used to enable these aspirations to become reality. We note here Piketty's (2014) telling observation that, "refusing to deal with numbers rarely serves the interests of the least well-off" (p. 577). Here, drawing on Mau (2019), we make the cautionary observation that the datafication and quantification of the social might very well reinforce a competitive individualism where "people no longer fight collectively" for "a fair distribution of wealth" (Mau, 2019, p. 169), but simply pursue their own interests, reinforcing a central premise of neoliberalism. Further, Mau characterizes that "the metric society is a mass of individuals in competition with each other, not a solidary or cooperative community" (p. 169).

Second is the proposition that teacher professional judgement and evaluative expertise are core in decision-making for realizing the potential of the digital in schooling. It is here we note the reported "remarkable innovation in the responses of education in the COVID-19 crisis, with those systems most engaged with families and communities showing the most resilience" (UNESCO, 2020, p. 5). This observation points to the critical need for new partnerships and collaborations in advancing education. It also acknowledges the centrality of professional teachers and quality teaching to the provision of quality schooling for all.

Third, we propose that a new knowingness is necessary across social and policy actors in relation to the utilization of the data, the use of algorithms and the uptake of the affordances of virtual reality in curriculum, pedagogy, and assessment. There needs to be a real mindfulness that, as the digital change plays out in education, the gap between the "haves and have nots" does not broaden (students, schools, systems, and sectors), both within and across nations. Here we return to our concept of "socio-technical education data imaginary," highlighting appropriate human+digital and human+data relationships (subsets of human +machine considerations) for determining the appropriate place of the digital and of data, for shaping possible futures of education systems, schools, and young people's learning.

We well recognize the lure and the attractiveness of the customization and personalization of learning for growth as promoted by digital interventions. However, positive connotations here can mask the underlying standardization necessary to deliver such personalization. There is a deep irony in the interweaving of personalization and standardization: the former offers the promise of individually designed learning pathways and progressions, whereas the latter operates on the assumption that individual performance is to be tracked using a predetermined underpinning scale. We stress here with digital assessments that personalization and standardization are inextricably conjoined. We would also point out that edu-businesses desire standardization of testing and curriculum materials and reporting to broaden their market opportunities and make products at scale (Verger et al., 2017).

Countering the lure are other risks in digital and data disruption, including the digital rights of the child (see Livingstone et al., 2019) and also those of parents and teachers. There have been some moves to counteract this by organizations like UNICEF. As we have noted, digital disruption can bring both benefits and disadvantages. Regarding the critical issue of children's rights, Livingstone identifies how digital environments facilitate,

> the rapid spread and extensive networking of information and communication in ways that can be aggregated and analyzed on a global scale, which can be both beneficial and harmful. Today, all our digital interactions generate data that can be shared, searched, altered or exploited by third parties, and the consequences may be exciting or unwanted, and are often unintended and unpredictable.
>
> *(Livingstone, 2019, para 3)*

More broadly, there are important questions about the privacy and security of the massive amounts of data collected and stored by both governments and private sector actors. These concerns apply to the collection and storage of data in education and the further risks of hacking. Added to this, are numerous questions about data ownership and transfer. These questions are evident in concerns globally, about data security, invasion of privacy, and potential on-selling of data to third parties for profit. Governments around the world and inter- and supranational organizations (e.g., the UN, UNESCO, and EU) are undertaking the critical work of developing appropriate legislative frameworks to deal with these complex and rapidly evolving matters. The technology, however, has already run well ahead of these developments. Most of humankind is in a consequential game of catch-up.

This book provides research-informed accounts of the multiple ways digital disruption and data use are beginning to profoundly reshape education systems, policymaking practices, and the work of schools and teachers. This reshaping comes with implications for young people's learning, identities, and their experiences of schooling with significance for their futures. Such analyses as provided are necessary to begin constructive dialogues across knowledge domains and groups with legitimate interests in education policy and the future of schooling. These include students, teachers, teacher unions, parents/carers, the wider community, school leaders, system leaders, policymakers, and researchers. What we have attempted in this introductory chapter is to set the scene to the chapters included as a way of opening up these necessary conversations about educative and democratic uses of data and the digital for policymaking and how these might amplify and augment the new teacher professionalism requiring new knowledges and expanded evaluative expertise.

Beyond this, we invite readers to think about how this kind of reshaping of schooling links to desirable imagined futures, where considerations of the common good are openly debated and transparently frame policymaking and professional practices in education. How can we re-imagine schooling for a more democratic and socially just future (Apple, 2013)? It is now imperative to go beyond the lure of the efficiencies and effectiveness of technologies and turn to how they should serve humankind and its advancement. In education, these matters clearly play out in data usage, policymaking, and new forms of digitalized testing and assessment. It is already abundantly clear that education is a new marketplace; data are valuable commodities and assessment remains among the highest of education policy priorities. In that limiting social imaginary, there is also a very real prospect of teachers and students becoming datafied objects of policymakers and EdTech companies. There is the added danger of such changes being imperceptible. However, this is not inevitable and is why we offer our alternative normative concept of a "socio-technical education data imaginary." While many questions remain, of one thing we are sure: we are at the very beginning of addressing profound educative, ethical, legal, privacy, and technical complexities, along with aporias of human+data interactions in general, in education, and machine learning in particular. We offer this collection as a step towards opening up these matters as part of the necessary ongoing conversations of humanity.

Notes

1 In writing this chapter, we have drawn on our earlier Education Research and Foresight Working Paper: Wyatt-Smith et al. (2019). Digital learning assessments and big data: Implications for teacher professionalism. *Education Research and Foresight Working Paper 25*. UNESCO.
2 The docudrama "The Social Dilemma" (Coome et al., 2020) deals with these matters, as does David Eggers' (2014) novel and related film, The Circle.
3 In this chapter, we have used "black boxing" to refer to a number of different processes in governance, assessment practices, and teacher judgement and decision making.
4 The term validity is taken to refer to what is assessed and the extent to which the assessment or test is measuring what it claims to measure.
5 The term reliability is taken to refer to rater- and inter-rater consistency or agreement.
6 ACARA does not endorse any product that uses its material or make any representations as to the quality of such products.
7 ACARA does not endorse any product that uses its material or make any representations as to the quality of such products.
8 See Manolev et al. (2019), for an overview, analysis, and concerns of Class Dojo and its potential for surveillance and performative classroom culture. A parental Class Dojo app has been developed to complement the data collected at school.
9 See India Education Diary Bureau Admin. (2019).

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2

AUTOMATED KNOWLEDGE DISCOVERY

Tracing the Frontiers, Infrastructures, and Practices of Education and Data Science

Ben Williamson

Introduction

The emergence of "big data" and "artificial intelligence" (AI) in education are closely associated with developments in assessment and testing, such as learning analytics, adaptive tests, and personalized learning platforms. Less visibly, however, big data and AI practices are now being used as the basis for new scientific approaches to the understanding of learning and educational processes. Data-intensive forms of scientific discovery and knowledge production are being promoted extensively by "education data scientists," "learning scientists," and "learning engineers," with support from influential institutions including the Organization for Economic Cooperation and Development (OECD) and the Chan Zuckerberg Initiative. Drawing extensively on technical engineering and data analytics advances in knowledge discovery – from disciplines including psychology, cognitive science, neuroscience, and genomics – these developments exemplify the emergence of a new science of policy-relevant research and development in education.

This chapter adopts the science and technology studies method of unpacking the expert practices and material apparatuses by which science makes its objects legible for intervention. It provides an analysis of "automated knowledge discovery" as an emerging epistemology and a set of expert data practices in educational research, tracing the implications of applying learning science and engineering insights to the tasks of educational policy and practice. As such, this chapter represents a partial genealogy of the formation and evolution of education data science as a site of expert practice and knowledge production. As a method,

> genealogical analysis traces how contemporary practices and institutions emerged out of specific struggles, conflicts, alliances, and exercises of power…

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> its intent is to problematize the present by revealing the power relations upon which it depends and the contingent processes that have brought it into being.
> *(Garland, 2014, p. 372)*

Genealogies seek to trace out the historical processes and conditions out of which contemporary practices emerged and upon which present-day practices depend. As Gehl (2015) has shown in his "partial genealogy of the data scientist," multiple historical threads, conflicts, bifurcations, con- and dis-junctures have produced the expert practices, subjects, and apparatuses of data science. These include disciplinary conflicts and encounters, technological developments, methodological advances, and in large part, sectoral encounters between academic research and commercial imperatives.

Taking up this genealogical method, this chapter represents an attempt to problematize the current fixation on the use of "big data" in education, in general, and more specifically to interrogate how the subject that mines and analyses it – the education data scientist – has come to be. The focus is on three particular interrelated aspects of this genealogy of education data science. First is the "big data imaginary" that has come to animate much education research, policy, and practice. Secondly, this imaginary is argued to be materialized and instantiated in specific infrastructural arrangements of technologies, methods, and organizations, all framed by particular social, economic, and political concerns and contexts. Thirdly, the imaginary is embodied in the particular practices of education data scientists. The presentation of some of these genealogical threads problematizes the idea of education data science as an objective science of learning, and instead highlights the messy convergences and contingencies across sectors, institutions, and practices that have enabled data science to become authoritative in educational knowledge production. The central argument of this chapter is that a series of genealogical combinations have enabled education data science to push back the boundaries of data-informed knowledge discovery beyond the exterior boundary limits of the human body, and to open up intimate interior functions and mechanisms of students' bodies, affects, and brains to increasingly automated forms of data collection, analysis, and knowledge discovery.

Data Science Frontiers

Data science has been defined as "an umbrella term to describe the entire complex and multistep processes used to extract value from data" (Irizarry, 2020, para 5, drawing on Wing 2019) and involves various practices of data generation, collection, organization, processing, analysis, and interpretation. As an academic discipline, data science first emerged in the 1960s as research scientists sought to accommodate technical practices of data analysis and computing within the wider field of statistics. As a profession, data science was popularized only in the 2000s as "a new type of project was becoming more and more common in the tech industry: extracting value from messy, complex, and large datasets" (Irizarry, 2020, para. 3). It is, however, not an entirely coherent field formed around a consistent or coordinated professional set of practices and epistemologies, but rather a complex ecosystem that includes computer science, statistics, engineering, information and library sciences, law and philosophy, mathematics, data visualization, and social and behavioral sciences, as well as innumerable areas of application (Meng, 2019). Crucially, it has been enabled by significant advances in computational capacity and processing power. "Data science is characterized more by modern technical resources and opportunities than by a set of methods or even specific applications" (Garber, 2019, para. 11).

Although data science is clearly associated with developments in computing, algorithms, and analysis over the last half century, it is also located in a longer genealogy of the rise of statistical technologies and practices going back two hundred years (Bigo et al., 2019). Contemporary data science, especially in its industrialized and commercialized forms, remains animated by a particular realist epistemology that is rooted in empiricist 19th-century natural sciences and statistics. It maintains that data represent reality as they appear in the world, as if separate from the modes and apparatus of computation that brought the data into being (Kitchin, 2014). From the perspective of the humanities and social sciences, however, data are understood not simply as objective numbers or facts to be computed, but as the constructs of knowledge or data infrastructures that govern how they are created, managed, used, and interpreted (Edwards et al., 2013). Many practices of data science involve complex arrangements of computational processes such as data analytics, machine learning, recurrent neural networks, cognitive computing, and deep learning, as the "datafication" of natural and social worlds is defined by both material infrastructures and expert practices of knowledge production. "Data are selected, collected, organized, and generated by humans, using the knowledge infrastructures available to them at the time" (Borgman, 2019, para. 14).

As the practices, epistemology, and profession of data science have expanded their authority, value, and legitimacy, a new data analytics industry has formed to spread analytic processes, and the technologies they rely upon, into an increasing range of sectors and institutions. Beer (2019) describes the data analytics industry as an amalgamation of imaginaries, infrastructures and practices, which together push "data frontiers" into "previously uncharted and new territories" (p. 19). Data frontiers are boundary lines where data-informed processes reach their limits. The data analytics industry is constantly trying to push these boundaries back by deploying persuasive visions of the power of data analytics. Beer states, "they are active in ushering in the expansion and intensification of data within organizational and social structures. These visions of data analytics persuade, enact and produce notions and ideals that are designed to force back those frontiers" (Beer, 2019, p. 19). Beer further asserts for understanding, "the expansion and intensification of data as an active component of the social world" necessitates a turn to look at "the work that is being done at these data frontiers" (p. 19).

For Beer (2019), the work done at data frontiers is characterized by the production of imaginaries, the construction of infrastructures, and the enactment of practices. The concept of data imaginaries captures the "visions" projected by the data analytics industry, "the promises, futures, potentials and possibilities that are associated with data" (p. 9) and its embedded rationalizing discourses that shape the integration of data analytics into different settings. These imaginaries pave the way, Beer argues, for the engineering or expansion of data infrastructures that consist of software packages, data processing algorithms, AI techniques, and human operatives, which are required for analysis to take place. Data practices refer to the various sorts of labor involved in data analysis. These are practices that are embodied by figures, such as data engineers and data analysts, but are performed through hybrid configurations of humans and computers to discover knowledge from the identification of patterns in databases. With the development of "smart" analytics powered by machine learning, such data practices are becoming increasingly automated in "thinking infrastructures" (Bowker et al., 2019). Data analysts are required to work within automated structures, while also constructing and managing them, ultimately "to mesh with machine learning and automated systems" (Beer, 2019, p. 101) in the process of automated knowledge discovery.

Within education, the boundaries of datafication are also being pushed back by the burgeoning field of education data science. Perrotta and Selwyn (2019) suggest that automated knowledge discovery in education data science is not merely a technical or methodological accomplishment, but emerges from a complex set of relations and tensions between competing definitions of "learning," disciplinary perspectives and practices, models and datasets, technical platforms and infrastructures, academic and commercial entities, and epistemic cultures and economic interests. In this chapter, the focus is on two ways in which work is being done at data frontiers and on the genealogical threads that enabled such practices in the present.

First, data analytics are being envisioned and put to work as powerful technologies for knowledge discovery in educational research. Education data science has increasingly sought new ways of generating, collecting, analyzing, and interpreting evidence of learning, and has proceeded from relatively limited and static datasets available from large-scale tests and assessments to "real-time" digital traces available from digital learning platforms. As such, a data frontier is being pushed back into processes and practices of knowledge production in the field of education, which is being accomplished through the construction and management of new analytic infrastructures and the development of new human-machine practices.

Second, education data science is itself seeking to push a new data frontier further into the cognitive, psychological, neurological, and even biological mechanisms that underpin human learning. In some cases, and as this chapter illustrates, education data science has even begun to deploy sensor-based technologies, facial recognition, neurotechnologies, wearable devices, or bioinformatics infrastructures to generate data from learners' bodies and physical movements. The data frontier of education data science has begun, its advocates claim, to penetrate through to the internally embodied substrates of learning. The work being performed at this data frontier, however, is genealogically related to longer-term encounters between education, technology, and data science over the last three decades.

Education Data Science

A distinctive form of education data science began to emerge in the first decade of the 21st century through a series of convergences between technical developments, educational agendas, and scientific research and development (R&D) in data science and data mining. From the 1990s, concerns with educational accountability and evidence-based policy drove the implementation of data systems that could be used to record progress towards performance targets and improvement goals (Lingard et al., 2013). The use of accountability data as a key source of education policy and governance was enabled by large-scale information infrastructures for collecting and processing the data (Anagnostopoulos et al., 2013), with interest growing over the subsequent decades in analytics packages and data dashboards for analyzing, interpreting, and displaying up-to-date data. Lockyer et al. (2013) state,

> shrinking fiscal resources and the expansion of a global competitive education market have fueled this increasing pressure for educational accountability. The offshoot of these economic drivers has been the development in the education sector of standardized scalable, real-time indicators of teaching and learning outcomes.
>
> *(p. 1439)*

A key enabling technology in this context was business intelligence systems developed for use by commercial enterprises to analyze their organizational performance through internal data mining, which were adopted by the nascent field of Educational Data Mining around 2005 for systematic quantitative analysis in the field of education (Agasisti & Bowers, 2017). Specifically, in higher education, new forms of institutional or academic analytics were developed to understand and improve organizational processes (such as admissions, finances, management, and administration procedures; Piety et al., 2014). "Learning analytics" emerged at the same time as the analysis of data from learning management systems and massive online courses, later expanding to individual-level learner analytics and adaptive "personalized learning" software (Siemens, 2013).

These genealogical points of convergence – between education administration; management and business intelligence; accountability agendas; and data science, analytics, and data mining – were supported and advanced considerably by a growing number of powerful R&D centers located both in academic and commercial settings. Stanford University's Lytics Lab, the Connected Intelligence Centre at the University of Technology Sydney, the Educational Institute of Technology at the Open University in the U.K., and the Learning Innovation and Networked Knowledge (LINK) Research Lab at the University of Texas at Arlington, among others, have become leading global centers of a growing international network of learning analytics researchers, developers, and advocates. The Society of Learning Analytics Research (SoLAR), a global members association of learning analytics researchers and developers, launched its own journals and an annual conference, Learning Analytics and Knowledge (LAK) to define, consolidate, and advance the field.

These labs, centers, and networks have combined disciplinary expertise and defined the "skillset" and "mindset" of the figure of the educational data scientist (Buckingham Shum et al., 2013). The skillset and mindset of educational data science include computer science techniques of computational statistics, data mining, machine learning, network analysis, semantic web, knowledge modelling, natural language processing, and human-computer interaction, as well as drawing from psychometrics, cognitive neuroscience, and bioinformatics (Cope & Kalantzis, 2016; Piety et al., 2014). A 2014 Stanford University report proposed a new "specialized" field, combining the sciences of digital data and learning to consist of a "big data infrastructure" for analyzing large volumes of educational and learning data, plus a "professional infrastructure in the field of learning analytics and education data mining, made up of data scientists (straddling statistics and computer science) who are also learning scientists and education researchers" (Pea, 2014, p. 17). The Stanford report clearly illustrates how an imaginary of educational data science was put to work in pushing back new data frontiers in educational knowledge production, and in animating the development of both infrastructural and professional development to realize that vision.

These genealogical developments in educational data science, in addition, were buttressed and fortified by a growing education technology (EdTech) industry. Global edu-businesses such as Pearson were early adopters of learning analytics and related forms of educational data science. Pearson (in particular) began a "digital transformation" of its entire business around 2012, embedding data analytics across its portfolio of e-learning and courseware products, partnering with both established and start-up analytics companies, and developing its own in-house capacity for data analytics, adaptive "personalized learning" platform development, and even the creation of AI-based student assistants (Sellar & Hogan, 2019). Wealthy venture philanthropic funders including the Bill and Melinda Gates Foundation and the Chan Zuckerberg Initiative became high-profile supporters of data-driven education, especially "personalized learning" based on the real-time tracking and profiling of students. Zuckerberg even seconded a Facebook team to build an adaptive personalized learning platform for the Summit Charter School chain in 2014–15, a platform now used by hundreds of schools across the United States.

The imaginary of educational data science has been further strengthened by advocacy from think tanks, consultancies, and international organizations. Think tanks such as the Center for American Progress, the Brookings Institution, and the Center for Data Innovation; consultancies including KPMG and McKinsey; and international organizations including the OECD, World Bank, and the World Economic Forum have become highly influential supporters of EdTech generally and data-intensive education specifically. These organizations have sought to make such forms of education technology policy-relevant to government ministries and departments by linking the capacities of real-time analytics-based personalized learning platforms to longer-term agendas of accountability, performance monitoring, improvement in educational outcomes, and large-scale school and university reform. They have, in other words, sought to legitimize data analytics as an authoritative source of governance over education.

As this brief genealogical survey of the formation of educational data science shows, as an emergent field of social, technical, economic, and political relations, it has gradually but perpetually pushed back the limits and boundaries of datafication in education. Education data science began to challenge those boundaries through the application of business intelligence and data mining to organizational analysis, but also incorporated increasingly sophisticated analytics based on algorithmic processing and adaptive machine learning to advocate personalized learning as a reformatory vision for whole education systems. Along the way, educational data science has assembled both the vast infrastructural capacity and enlisted an international network of expert brainpower from across both the academic and commercial technology sectors as educational data practitioners and professionals. These infrastructures and expert practices are now key to knowledge discovery in the field of education, with education data scientists increasingly rewarded with prestigious research grants or commercial positions to address complex questions through computational machinery.

Precision Learning Engineering

The previous section showed how educational data science has pushed the frontier of datafication further into the field of education, from organizational analytics to individual-level learner analytics and adaptive learning platforms. Educational data science is also advancing an additional data frontier across the very boundaries of the human body of the student. As already indicated, educational data science draws its expertise not only from computational or statistical disciplines, but from psychological, cognitive, neurological, and even biological fields. Within education research, the transdisciplinary combination of cognitive science, psychology, and neuroscience is known as "learning science," a field that emerged in the 1990s and "marked by collaborations among instructional technologists, educational psychologists, content area educators, anthropologists, computer scientists, linguists, philosophers, and many more" (Evans et al., 2016, p. 1).

Originally associated with the established field of AI in education, the learning sciences have rapidly gained scientific legitimacy over the past decade (Pea, 2016). Learning science approaches based on various aspects of cognitive, neuro-, and psy-sciences are being advocated in emerging centers and departments in research-intensive universities such as Harvard, Massachusetts Institute of Technology, the University of California, Carnegie Mellon, and Stanford, as well as by venture philanthropies including the Bill and Melinda Gates Foundation and the Chan Zuckerberg Initiative. The OECD has begun to invest significant institutional resources and advocacy into "the science of learning." Focusing on "the interplay of the biological, physiological, cognitive, and behavioral processes supporting the learner," it advocates for "technological advances, particularly in neuroscience, engineering, and computer and information sciences" to be put to the task of policy-relevant knowledge production in education (Kuhl et al., 2019, p. 16).

Learning science has also converged genealogically with learning analytics research and development, both of which are taken to be key sources of expertise in the wider interdisciplinary space of educational data science (Piety et al., 2014). One of the key figures in the development of both the learning sciences and learning analytics fields clearly marked out this convergence in his Stanford University report on building the field of learning analytics. Learning analytics specialists, Pea (2014) argued, would require skills in "computational and statistical tools," including "traditional statistics skills" as well as "newer techniques like machine learning, network analysis, natural language processing, and agent-based modelling," alongside "general educational, cognitive science, and sociocultural principles in the sciences of learning" (p. 17). This report also gave an early indication of how a learning analytics-mediated version of learning science would seek to gather data from students' bodily movements and facial expressions. Pea proposed using data science methods to engage with "non-cognitive factors" in learning and the "emotional state" of learners by collecting "proximal indicators that relate to learning" through such techniques as "facial expressions detected by a computer webcam while learning" (p. 32), plus other data sources like "video, eye tracking, and skin temperature and conductivity" (p. 46).

This turn to capturing autonomic biological signals as "proximal indicators" of learning is related to the subfield of emotional learning analytics, and to the broader development of "emotional AI" infrastructures and practices in education. Emotional AI, or "empathic media," is a form of "automated industrial psychology" that utilizes biosensing and analytics to monitor signs of emotional behavior. McStay (2018) states,

> artificial emotional intelligence is achieved by the capacity to see, read, listen, feel, classify and learn about emotional life… this involves reading words and images, seeing and sensing facial expressions, gaze direction, gesture and voice. It also encompasses machines feeling our heart rate, body temperature,

> respiration and the electrical properties of our skin, among other bodily behaviors. Together, bodies and emotions have become machine-readable.
>
> *(p. 3)*

The incorporation of emotional AI into learning sciences and analytics has instantiated automated industrial psychology as a mode of knowledge discovery in the field of education, rendering students' bodies, voices, faces, and affects seemingly machine-readable as autonomic proximal signals of the emotional substrata of learning.

The combination of learning science and learning analytics has been captured in the emerging figure of the "learning engineer." This term, first coined by Carnegie Mellon University's AI pioneer Herb Simon in the 1960s, has been embraced by major technology-intensive universities in the US, engineering societies, technology-based philanthropies, and education-focused think tanks and consultancies (Lieberman, 2018). The Learning Agency, a startup consultancy supported by the Chan Zuckerberg Initiative, the Bill and Melinda Gates Foundation, and Schmidt Futures, approaches learning engineering as a "revolutionary" combination of learning science and "the new and powerful tools of computer science – rich computation, nascent AI, natural language processing" to "promise the same benefits for education research and development" (The Learning Agency, 2019, para. 15). The agency adds,

> learning engineers must, then, have a broad knowledge of learning science, data science, and computer science. They must be able to understand different aspects of engineering processes, including everything from pedagogy to artificial intelligence. The main aim is to use data to improve learning and teaching. Learning engineers use technologies, standards, and science to propose, test, and implement solutions.
>
> *(para. 22–23)*

Learning engineering is also undergoing a process of standardization and professionalization as a scientific discipline and practice. The Institute of Electrical and Electronics Engineers (IEEE), the world's largest and most influential organization for standards-setting in computer technologies and engineering, has established the IEEE Industry Consortium on Learning Engineering (ICICLE) as a "professional organization committed to the development of Learning Engineering as a profession and as an academic discipline" (IEEE Industry Consortium on Learning Engineering, n.d., para. 2). They define learning engineering as "a process and practice that applies the learning sciences using human-centered engineering design methodologies and data-informed decision-making to support learners and their development" (IEEE Industry Consortium on Learning Engineering, n.d., para. 1). With membership including more than 60 organizations representing industry, academia, and government (including Google, HP, and IBM), ICICLE has established special interest groups to undertake projects in AI and adaptive learning technologies, learning analytics, competency frameworks, learning data standards, learning data governance, and learning experience design, plus teams exploring routes to growth of learning engineering both in industry and academia (Wagner & Lis, 2018).

The Chan Zuckerberg Initiative has become perhaps the most influential organization to promote learning engineering, with its director of learning science a high-profile advocate of learning engineering as a multidisciplinary blend of the learning sciences and learning analytics. Saxberg (2018) states,

> getting the most from learning analytics has to be an interdisciplinary effort: computer science, linguistics, education, measurement science, cognitive science, motivational and social psychology, machine learning, cognitive neuroscience among others. These different domains will need to be combined to build out an effective evidence-grounded "learning engineering" version of learning analytics.
>
> *(p. viii)*

In this imaginary, learning engineers gather and analyze evidence "at multiple levels, from clickstreams, motion position data, speech streams, gaze data, biometric and brain sensing, to more abstracted feature sets from all this evidence" (Saxberg, 2018, p. viii). The use of this evidence across "multiple dimensions" would also allow for the identification of "new opportunities for targeted intervention" and "precise action" analogous to data-scientific "precision medicine" (p. x). The Chan Zuckerberg Initiative, along with Schmidt Future and the Bill and Melinda Gates Foundation, has begun awarding grants and investments for R&D programs and initiatives to support this vision. They include neuroscience-based technologies for tracking cognitive processes and brain function, as well as adaptive personalized learning platforms based on real-time cognitive and performance assessments.

The figure of the learning engineer represents an evolution of the image of the education data scientist, an expert embedded not just in the infrastructure of software, algorithms, and analytics of data science but in the laboratory apparatus of the cognitive, neuro-, and psy-sciences too. This configuration of the education data scientist as a learning engineer embodies a particular imaginary in which data scientific practices can penetrate human bodies with the precision of neurotechnologies such as brain-scanners, body-worn biometric and psychophysiological sensors, and bioinformatics technologies for reading molecular genomic codes. This biomedicalized version of the education data scientist possesses not only the infrastructural apparatus for making bodies machine-readable, but also the engineering prowess and design methodologies for programming precision-targeted interventions. The precision learning engineer forces the data frontier back beyond skin, into the interior psychological, neurological, and biological substrates of student learning, affect, and cognition.

Inscribed Bodies

The overarching imaginary of education data science is one of automated knowledge discovery, whereby computational and analytics infrastructures are given key tasks to identify patterns in large and complex datasets under the skilled supervision of expert practitioners. Automated knowledge discovery is undergirded by a particular rationality and an epistemology rooted in statistical science, natural science, and data science styles of thinking and working. This realist or empiricist epistemology assumes data provide accurate and objective representations of underlying physical or social realities. However, this perspective neglects the powerful ways in which infrastructures of data analysis, and the practices of those experts embedded in such infrastructures, co-produce and configure the data themselves (Borgman, 2019).

Automated knowledge discovery does not so much discover or reveal facts as objective quantitative data but partakes in their construction.

> Choices about methods of producing data… produce and reproduce the very objects that they ostensibly reflect. In this sense they are performative in that they do not involve the discovery of truths about objects but simultaneously represent and enact, that is, bring into being the very objects they are meant to describe and represent.
>
> *(Ruppert, 2018, p. 19)*

In the specific context of education data science, Perrotta and Selwyn (2019) claim that methods of automated knowledge discovery "superimpose multiple layers of algorithmic complexity on stripped-down (and highly contentious) understandings of human learning" (p. 4). From this performative epistemology, the infrastructures and practices of education data science bring into being new understandings of human learning that would not be the same without the algorithms, analytics, and automated systems that produced them.

A consequence of approaching education data science in this performative way is to see the data frontier not just as being pushed back into the biological substrates of human learning, but to see the frontier as changing the very objects it passes across and through. Automated industrial forms of educational data science render bodies computable in ways that make them amenable to various forms of intervention or even "engineering." The analogy with precision medicine proposed by the Chan Zuckerberg Initiative's director of learning science is suggestive in this sense. It suggests a biomedical desire to precisely profile individual bodies through the collection and analysis of quantified bioinformation, and then to design personalized, targeted "precision education" interventions that might modify, improve, or otherwise transform how those bodies function, behave, feel, or think (Williamson, 2020).

Understood in this way, education data science is not simply a new scientific field, but is invested with a particular politics, or a biopolitics of control over human life. Whitehead et al. (2017) conceptualize a novel biopolitics centered on the governance of human bodies, minds, brains, emotions, and behaviors. "Neuroliberalism," as they term it, mobilizes insights from the psychological, behavioral, neurological, cognitive, and biological sciences "to deliberately shape and govern human conduct within free societies" (p. 1). Further, it recognizes the role of emotional responses, habits, social norms, and "the automatic, unconscious and involuntary within human action, and an ability to be able to predict, respond, regulate, enhance and exploit these behavioral vectors" (p. 2).

With its emphasis on the hidden biological and autonomic signals that indicate learning, education data science instantiates neuroliberal strategies of behavior change within the field of education. A neuroliberal education data science seeks to render the autonomic, unconscious, embodied, and automatic signals that indicate learning amenable to being machine-read and analyzed through methods of automated knowledge discovery, and from there potentially opened up to enhancement and engineering.

The human subject and body of neuroliberal forms of data science is, in this sense, an "inscribed surface of events" understood in genealogical terms, as "genealogies are also concerned with the body which is conceptualized as a material surface, as a flesh upon which the micro-physics of power leave their mark" (Garland, 2014, p. 373). The diverse historical threads that have produced education data science as a discipline made up of expert practices and infrastructural arrangements in this sense can be understood as imprinted on the bodies of its laboratory subjects. Not only are the human subjects of neuroliberal forms of education data science inscribed numerically from their data traces and embodied signals – as the result of long-term genealogical convergences between data science, education, and learning science – but their analysis also catalyzes practical efforts to change the actions, affects, and behaviors of the bodies from which those signals and traces were captured.

Conclusion

The aim of this chapter was to offer a partial genealogy of education data science. By focusing on its imaginaries, infrastructures, and practices, it has illustrated some key convergences over the last two decades in the evolving field of education data science, from its origins in educational data mining and business intelligence, its combination with learning analytics and machine learning-based adaptive platforms, through to current convergences with the learning sciences. Education data science, like its parent discipline of data science itself, is not a fixed and monolithic field, but one that remains in motion as a science in the making. By projecting powerful imaginaries of the power of data analytics, education data science has expanded and intensified its influence over knowledge production across the past decade. It has constructed infrastructures of data collection, calculation, and presentation to this end, and developed programs for upskilling and socializing new kinds of multidisciplinary experts who can move across the computer, data, and learning sciences.

Tracing out education data science genealogically reveals the contingency of claims to objective knowledge discovery through data analytics infrastructures and practices. Instead, education data science constructs the very objects it purports to merely measure or reflect. The infrastructures and practices of education data science shape processes of learning, as well as learning subjects and bodies, to fit into databases and to be made amenable to data analytic inspection. Education data science is also imprinted with strong political imperatives regarding performance-based accountability, and in many cases with the market-making concern of commercial EdTech businesses for whom data analytics are a source of value creation. As with all techno-scientific infrastructures and practices, education data science is imbued with politics, economics, values, and disciplinary epistemologies. These factors are all part of the genealogy of data science and shape the ways in which data about human subjects are brought into being. Much more detailed genealogies will be required in the coming years as education data science becomes increasingly authoritative and disruptive in educational knowledge production.

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3

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

A Practical and Ethical Guide for Teachers

Erica Southgate

Introduction

In February 2020, I was contacted by a journalist seeking comment on the trial of a facial recognition product designed to replace traditional roll call in schools. The product had received a significant amount of commercialization funding from the Australian Government Department of Industry, Science, Energy, and Resources. The published article focused on the lack of Australian regulation related to this type of technology and raised questions about the "convenience of automating roll call procedures outweigh(ing) the sensitivity of collecting biometric information" (Basford, 2020, para. 7). The article hit several nerves regarding the best use for, and ethico-governance implications of, automation powered by artificial intelligence (AI) in schools (in this case, biometric technology that collects information from the student's body). As the article pointed out, the issue is not only how we can use AI "for good," but for what it is "good for" in educational settings.

To have informed conversations about the use of AI in education, teachers and policymakers must negotiate a dense multi/interdisciplinary web of knowledge comprising: technical information about systems and the mathematical and statistical methodologies that are used by machines to analyze data; ethical frameworks that do not necessarily provide definitive answers; and a fast-evolving, intricate legal and regulatory landscape. In addition, they must weigh up the potential benefits and risks of AI-powered systems developed (typically independent of educators) by small and large companies in the national and transnational educational technology (EdTech) sector. In response to this complex situation, the aim of this chapter is to introduce educators and policymakers to some foundational knowledge about AI so there can be critical and productive engagement with the technology. This chapter is translational research: it is an attempt to bridge the

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divide, in an accessible way, between the realms of the technical, the pedagogical, and ethico-governance issues associated with AI. I begin the chapter by explaining AI and its subfield of machine learning (ML) before proceeding to scope out current and potential uses of AI in educational settings. I then highlight some key ethico-governance challenges for educators and school leaders, policymakers, and industry stakeholders.

What Is AI?

Every day, in a myriad of ways, we interact with AI. Computing applications, such as Internet search engines, smart phone assistants and chatbots, social media facial recognition tagging technology and fun filters, ride-sharing apps that determine journey pricing, and recommended product advertising, are all powered by AI. AI can be embodied in robots (but not all robots have AI) or (often invisibly) infused into computing applications and systems. The Organization for Economic Cooperation and Development (OECD; 2019) define AI as "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy" (para. 12). AI are computer systems that can undertake tasks or activities that require features of human intelligence, such as planning, problem solving, pattern recognition, prediction, learning from experience, and logical action. AI researchers focus on developing machines that can think and behave in a rational manner according to mathematical assumptions and rules encapsulated in algorithms (these are instructions that tell the computer or machine how to accomplish a task or operation), with an increasing emphasis on building capacity for automated decision-making.

The field of AI is decades old, with the term first coined in the 1950s. Over time, there has been definitional tension within computer science about what constitutes AI. Maini and Sabri (2017) note that standards for what AI is remain open to interpretation and continue to change. They suggest as well that AI refers to how computers "figure out" and can perform tasks usually done by humans. When this occurs, there is a tendency for humans to reject that this is indicative of machine intelligence.

> This is known as the AI effect… Perhaps there is a certain je ne sais quoi inherent to what people will reliably accept as "artificial intelligence": So, does a calculator count as AI? Maybe by some interpretation. What about a self-driving car? Today, yes. In the future, perhaps not.
>
> *(Maini & Sabri, 2017, p. 10)*

Krafft et al. (2020) suggest there are differences between the way technologists and non-technologists use the term AI. They argue that AI researchers support definitions that accentuate technical functionality, while policymakers prefer more anthropomorphic explanations that relate to aspects of human thinking and behavior. Krafft et al. (2020) contend that the problem with this definitional mismatch is that functionality-related definitions are more inclusive of current AI technologies, whereas definitions that focus on human-like capabilities are often more applicable to potential applications. This becomes an issue if the latter deflects attention away from existing ethico-governance issues. While public education about what AI is, where it is present, and what it can be used for, requires an evolving rapprochement between technical and humanist modes of communication, it is important to understand why the technology has become ubiquitous in everyday applications.

Since the early 2000s, several developments have enabled the growth in AI technology. Advances in computer processing power have facilitated algorithm complexity and the ability to distribute and speed up processing across banks of computers. This is linked to increased data storage – especially cloud computing – with its ability to house and manage large amounts of data (often called "big data") and provide a platform to run ML algorithms. The availability of big data harvested from the Internet has facilitated ML at scale, with the growth of open source technical communities fostering AI innovation. Specifically, the field has benefited from improvements in computer vision, graphics processing, and speech recognition technology (Mitchell & Brynjolfsson, 2017).

Rapid advances in AI and its (often invisible) use in everyday computing have given the technology an aura of mystery. As Maini and Sabri (2017) point out:

> artificial intelligence will shape our future more powerfully than any other innovation this century. Anyone who does not understand it will soon find themselves feeling left behind, waking up in a world full of technology that feels more and more like magic.
>
> *(p. 3)*

Developing a foundational understanding of AI is vital if we are to reject romanticized and inaccurate ideas about machine intelligence. There is evidence that both children and adults anthropomorphize and overestimate the intelligence of AI in its embodied robot and non-embodied (diffuse) forms (see Southgate et al., 2019). There are typologies that can assist in dispelling myths about AI. Table 3.1 provides an overview of types of AI that currently exist and that may eventuate (although there is considerable debate about hypothetical types of AI).

Table 3.1 illustrates that we are currently in an era of narrow (sometimes known as weak) AI. Narrow AI can undertake the specific or focused tasks it was designed for. Reactive AI responds to input data but cannot "learn" from past experiences to inform decisions. Limited memory AI can accumulate "experiences" to programmed representations of the world, or "learn" as it goes, and has enough "memory" to take appropriate actions. While narrow AI does not exhibit

TABLE 3.1 Types of artificial intelligence from Southgate et al. (2019), adapted from Hintze (2016)

Superintelligence	*AI that exceeds human intelligence in every field.* *Example: None, as this type of AI does not currently exist*	
General AI	**Self-awareness** *Example*: None, as this type of AI does not currently exist	AI at this level would extend the "theory of mind" to predict the internal states of others. Having achieved human-like consciousness, it might choose to exhibit non-human abilities.
	Theory of mind *Example*: None, as this type of AI does not currently exist	This type of AI would have an updatable representation of the world that includes an understanding that other entities in the world also have their own internal states.
Narrow AI	**Limited memory AI** *Example*: Virtual assistants, self-driving cars	This type of AI receives current input and adds pieces of this input to its programmed representation of the world. This can change the way the AI makes current or new decisions.
	Reactive AI *Example*: AI chess player	Designed for a specific task, this AI receives input and acts on this input. They cannot be applied to different tasks, and past experiences do not affect current decisions.

the full range of characteristics and behaviors we associate with human intelligence, it can be equivalent to or outperform humans in specific areas. An example of this was when AI consistently defeated a human champion of the Chinese strategy game Go, which had been long considered too strategically complex for a machine to master. The next section provides an overview of ML, which is an important subfield of AI. Understanding the basics of ML is vital because many ethico-governance concerns stem from the way in which it works.

What Is Machine Learning (ML)?

A subfield of AI, ML is the science of getting machines to learn and behave like humans in an autonomous way by giving them data sets from the real world so that their learning can improve over time (Faggella, 2020). The goal of ML is "to enable computers to learn on their own. A machine's learning algorithm enables it to identify patterns in observed data, build models that explain the world, and predict things without having explicit pre-programmed rules and models" (Maini & Sabri, 2017, p. 9). ML is a technically and mathematically complex field. ML algorithms are used to classify, generalize, and predict with the accuracy of the algorithms improving when trained on greater quantities of data (Burrell, 2016).

There are a number of different approaches to ML. For example, supervised learning involves labeling or classifying initial input data to train an algorithmic model to identify patterns. It is supervised because the learning is guided by human pre-classification of input data that trains the model to make decisions on classification or predictions related to a specific task when new data are given to it. Supervised learning is used in applications that suggest the classification of something, for example, a student might take or locate a photo of an animal and the AI application recognizes the animal and provides information about it.

An unsupervised learning (UL) algorithm infers patterns in data that have not been labeled (hence being unsupervised) and creates its own structure (sets of features) that can be used for pattern detection or classification. This type of ML is used to explore and detect patterns when the outcome is not known or predetermined. For example, a company may use a UL approach to detect patterns in customer segmentation that were not previously known or understood. It is conceivable that with large enough data sets, unsupervised learning algorithms could detect patterns in learning behaviors or outcomes that were not previously known.

Reinforcement learning (RL) involves the algorithm interacting in an environment to find the best outcome through trial and error without training. The AI trains itself based on right or wrong actions to predict best outcomes when new data are collected. The best actions are reinforced until the model learns to solve the problem or get the best outcome. RL has been used to develop game-playing AI and to train chatbots.

Deep learning (DL) is associated with artificial neural networks (ANNs) that are inspired by the way neurons connect in human brains. In DL there are numerous layers of algorithms that interact to model data and make inferences. DL uses multiple ANNs at lower levels of abstraction to effectively solve chunks of a problem and provide these partial solutions to ANNs at higher levels to derive a larger solution (LeCun et al., 2015). DL is good for dealing with complex data, such as natural language processing, which involves complicated vocabularies or visual processing that has intricate pixel information (Maini & Sabri, 2018). DL could be used in a smart classroom that had sensors that input audio-visual data over time. DL would have different ANNs working on recognizing aspects of the biometric information from teachers and students (e.g., torsos, limbs, eyes, noses, mouths, fingers, palms, and voices). Other ANNs would use the results from these ANNs to classify the types of verbal and non-verbal exchanges, and yet other ANNs could process these results to detect patterns in non-verbal student interaction and between the teacher and students. This could then be fed into a dashboard to give teachers and learners insights into classroom interactions. While this is an imaginary example (and one that has ethical implications to be discussed later in this chapter), it is illustrative of how DL could process large amounts of complex data from the classroom.

It is important to grasp the basics of ML for several reasons. Some of the reasons include the need for humans to be able to identify when they may be interacting with an AI-powered system so it does not seem like "magic," but rather the result of complex mathematical models that automate responses often designed to "nudge" or influence people towards particular actions. As ML usually needs big data, sometimes invisibly harvested in real time as people interact with machines, questions need to be asked about privacy and consent.

Insights derived from ML are based on the data that algorithms learn from, and these can have biases or provide superfluous insights, even when harvested in real time. Who hasn't received a product recommendation on their social media feed that was totally inappropriate? Sometimes, the humans who choose data for ML do not check for or recognize the biases in the data because they are from a dominant social group; this ML generated bias can impact people's lives. For example, research has shown that facial recognition technology can produce a higher rate of incorrect matching (false positives) for darker skinned people than for lighter skinned people. This can cause problems with biometric passport systems and law enforcement authorities who are increasingly depending on the accuracy of the technology to identify suspects (Drozdowski et al., 2020). These are only a few instances of AI bias.

ML can also be opaque or a "black box" in the sense that the algorithms that make decisions are proprietary (the property of companies who will not open these for inspection) or so complex in their operation, like ANNs, that even the scientists who develop the systems are unable to completely understand the processes through which the machine makes its decisions (Martin, 2019).When ML affects life opportunities – i.e., when it is used to determine if someone gets a job interview, a debtors notice, a loan, arrested, or has access to a particular curriculum pathway in an computer tutoring system – serious ethical and governance issues arise. These issues will be discussed later in this chapter.

How Is AI Used in Education?

It is useful to think about how AI is used in education from several angles. At the level of schooling systems there is the integration of AI-powered products that are used to streamline or automate administrative procedures. There is also an interest in e-learning platforms and learning management systems that generate data that can use ML to provide organizational and classroom insights, for example, to describe and predict trends in academic success and provide early warning signals for students who may not be achieving expected academic outcomes (Kavitha & Lohani, 2019; Matetic, 2019; Nam & Samson, 2019). Higher education has led the way in using AI to understand student engagement in online learning and student attrition. Administrators of school systems are no doubt looking to the utility of AI with (sometimes contentious) moves to automate standardized testing (ABC News, 2018).

Understanding the technology's relationship to education means recognizing the growing ubiquity of AI-powered products not generally marketed under the

EdTech banner. Leaving aside the most obvious application (search engines), a range of other products used in schools are infused with AI. These products include: Adobe Photoshop, video products that use ML to facilitate the easy selection and altering of objects, collaboration applications such as Microsoft Teams that have chatbot functionality, and teleconferencing platforms that use AI to suppress unwanted noise during calls.

Beyond these products designed for more general markets, there is a specialist field called AI in education (AIEd) which has been around since the 1970s (see Isotani et al., 2019). AIEd's goal is to enable more personalized, flexible, and engaging learning, and to automate mundane teaching tasks such as assessment (Gulson et al., 2018; Luckin et al., 2016). There are large multinational corporations (such as Pearson) and smaller EdTech companies driving AIEd development and research at universities – some in partnership with industry – to investigate the efficacy of AI -powered applications for learning. AI is also used in a business intelligence sense for the production of learning analytics (the type teachers might see on a class dashboard) and in mining the data collected by educational organizations to provide insights into how people interact with systems.

Although wide-spread integration of AIEd is currently limited, there are several applications that have been continually under development. Intelligent tutoring systems (ITSs) simulate human tutoring by providing timely feedback, personalized instruction, and curriculum pathways for students without human intervention or with only targeted teacher oversight (Luckin et al., 2016). Some research suggests that ITSs have positive effects on learning, similar to that produced from real teacher-student interaction (du Boulay, 2016; van Lehn, 2011), with equivocal evidence of learning efficacy for college students (Steenbergen-Hu & Cooper, 2014). Further, mathematics ITSs for K–12 education can be beneficial for students with existing self-regulatory skills (Steenbergen-Hu & Cooper, 2013).

AIEd has sought to develop pedagogical agents (PAs), which are digital or virtual characters integrated into learning technologies. PAs display as human and animal avatars (or other types of virtual characters) and have instructional, motivational, and communication purposes (Johnson & Lester, 2016; Kim & Baylor, 2016). Interaction with PAs can be written or spoken, or in virtual worlds, through non-verbal communication. They can deliver information, demonstrate and model learning, coach, guide, and scaffold the student, and facilitate assessment. Students can even teach PAs. At present, PAs are mainly used for information delivery or for giving directions (such as chatbots). Evidence regarding the effectiveness of PAs is mixed, with one meta-analysis finding that they are probably more effective in K–12 than in tertiary education (Schroeder et al., 2013).

The Internet of Things (IOT) is a term used to describe the increasing capacity for common objects to connect to the Internet and interact with other devices (Timms, 2016). IOT has prompted interest in what "smart" classrooms of the future might look like. While mainly theoretical at present, smart classrooms could include interconnected devices and sensors that interact to automate functions such as security systems, climate control, and energy consumption. In addition, personal and professional computing devices, learning platforms, and administrative systems can connect to harvest and analyze data for learning insights (Li et al., 2015). This vision of schooling usually includes the collection of biometric data, such as the facial recognition technology example mentioned at the beginning of this chapter.

Biometrics is the automated collection of information related to the body that is analyzed using ML. Biometric data can be biological, including facial and voice recognition, fingerprints, iris patterns, heart rate, body temperature, or perspiration. It can also be behavioral, such as vocal patterns, eye tracking/gaze attention, gait tracking, or typing recognition. There is also the experimental use of the brain-computer interface that uses electroencephalography (EEG) devices to measure brain activity. Biometrics uses these unique physical characteristics for verification or identification purposes (Royakkers et al., 2018). Biometric data are not just information about a person – i.e., the type of information you share when setting up online accounts – but information directly of the person.

Affective computing is a controversial yet burgeoning area that uses a range of data types, including biometrics. Machine vision and natural language processing technology is used with ML to "identify" emotions so that applications can respond to a user in real time. There has been critique of this on several grounds, including: the inability of ML mathematical models to grasp the cultural and contextual specificity of emotional facial expressions (Barrett et al., 2019); the racially biased labeling of data sets used in supervised learning to train AI (Rhue, 2018); the lack of representation of children's data that leads to poor prediction outcomes (Bryant & Howard, 2019); and the ethically dubious use of technology to manipulate or "nudge" people's behavior without their knowledge or consent. Moreover, there are persuasive arguments that the use of biometric technology in EdTech is currently without evidence of efficacy for learning, and that it contravenes children's human rights (McStay, 2019).

Since most AIEd applications are pioneered in higher education, it is worth considering the findings of a recent systematic review. Zawacki-Richter et al. (2019) reviewed four areas of AIEd: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. They found a general lack of critical reflection of the challenges and risks of AIEd, a weak connection to theoretical pedagogical perspectives, and a need for more extensive research on the ethical implications of AIEd. It is to this last topic that we now turn.

What Are the Ethical Concerns with AI and Some of the Governance Implications?

The last decade has seen much international activity on developing an ethics of AI that can underpin its design implementation and governance (Cath et al., 2018). Dignum (2018) captures major ethico-governance concerns by asking:

> What does it mean for an AI system to make a decision? What are the moral, societal and legal consequences of their actions and decisions? Can an AI system be held accountable for its actions?… How can these systems be controlled once their learning capabilities bring them into states that are possibly only remotely linked to their initial, designed, setup? Should such autonomous innovation in commercial systems even be allowed, and how should use and development be regulated?
>
> *(p. 1)*

Education has been designated as a sensitive domain where automated mistakes can significantly damage humans (Campolo et al., 2017). I have previously explored the ethics of AI in education and its human rights significance in depth (see Southgate et al., 2019). The following is an abridged version of that work, with a focus on five key pillars that should underpin the design, use, and governance of AI in educational settings.

1. Awareness

There is a need for students, teachers, administrators, and policymakers to develop foundational knowledge of: what AI is, what it can and cannot do, where it is present (especially if it is invisibly infused in systems), how it operates (including algorithmic "nudging"), how it is collecting data (and for what purpose and what privacy and consent issues this entails), and its impacts on humans and the broader environment. School curriculum needs to raise awareness of these issues. Teacher professional learning based on independent expert advice on evidence of ethical use cases, legislation, regulation, and guidelines is required. Awareness is one foil against deceptive and malicious use of the technology.

2. Explainability

The very basis of education is the ability of educators to explain content knowledge and pedagogical and pastoral actions and their consequences. A vital pedagogical project lies ahead of the teaching profession. It involves the sustained development of formal public and school-based explanations about what AI is and its implications for education and broader society, including the world of work. As educators, we must be able to explain why an AI-powered system made its decision and how it affected student learning positively or negatively. For example, if ITSs are to be widely deployed, teachers must be able to explain why a student was directed along a particular curriculum pathway by the machine, what implications this had for student learning as opposed to other options, and the broader impacts on diverse groups of learners. It is vital that school communities ask ethical and pedagogical questions about AI products before they are used in schools, so industry can answer these questions in an accessible and honest manner. Schools (and even school systems) can lack access to independent technical advice required to ask relevant questions and enable comprehension of answers about AI systems. There is a profound difference in knowledge about AI between the schooling sector and the computing industry. Addressing this is vital for good governance.

3. Fairness

AI has the potential to radically disrupt the world of work and to exacerbate social inequality. This raises questions about the role of schooling in addressing inequality in an AI world, especially when digital inclusion is a major issue in many schooling systems. The benefits of AI for learning need to be evenly distributed. The digital rights of the child in this age of "datafication" and "dataveillance" need serious attention at curriculum and policy levels (Lupton & Williamson, 2017). To date, much of the bias, discrimination, and harm produced by algorithmic and automated systems have not been discernible until a significant time after their implementation, when adverse patterns have emerged. Significantly, it may not be possible to detect when harm is occurring, because it cannot be assumed AI will discriminate in similar ways as humans (Wachter et al., 2020). Schools need to understand and respond to this with new and tried ethico-governance measures.

4. Transparency

This area has received significant attention in computer science and philosophical literature. Winfield and Jirotka (2018) state that "an important underlying principle is that it should always be possible to find out why an autonomous system made a particular decision (most especially if that decision has caused harm)" (p. 8). The opaque nature of some AI means that it can be invisibly infused into computing systems in ways that influence our interactions, decisions, moods, and sense of self without us knowing (Cowie, 2015). The proprietary nature of AI products creates a situation in which industry is reluctant to open up the algorithmic workings of the product for public or independent scrutiny (Burrell, 2016). This creates a situation in which customers must rely on industry assurances rather than independent assessment. The opaque nature of some types of ML means that developers can use "black box" components in their software, the functioning of which they often do not fully understand. Deep learning, which is driving advancements in AI, has created a situation where developers will likely build AI systems that cannot always be guaranteed to operate exactly as intended in every circumstance. In addition, they may produce results that are unable to be fully inspected, validated, or justified by ordinary means, which leads to increased risk of undetected or unforeseen errors, biases, and harms (Institute of Electrical and Electronics Engineers [IEEE], 2018).

5. Accountability

Governance of and accountability for AI in education entails a multilevel approach that includes community consultation, development of mechanisms for ongoing contestability of the use of such systems, and policy development and risk assessment related to national and international laws, regulation, and standards. To be clear, the speed of AI innovation has largely outpaced governance structures and traditional policy levers with a significant technical and information differential existing between a small coterie of wealthy and influential multinational players (who mainly develop the technology and bodies that devise governance mechanism), and schools/school systems that procure products. This has called into question the fundamental ability of governments to regulate the technology in traditional ways (Guihot et al., 2017). There is the real possibility of regulatory capture in this space, which occurs when those in governance positions, whether in schools or bureaucracies, become dependent on potentially conflicting commercial interests for advice. The dependence on industry to provide most teacher professional learning in the EdTech space attests to how rapidly the influence of industry has grown. There is often talk about "trade-offs" with AI – of convenience, cost saving, and/or efficiency – however, how can trade-offs be considered with probity by teachers, school leaders, and policymakers without access to independent experts with commensurate depth of knowledge that exists in industry?

The IEEE (2018) elucidates on the difficulty of accountability in an AI world. They highlight how the complexity of autonomous and intelligent technology presents inherent difficulties for system users to understand the potential and limitations of such systems, even as they interact with them (p. 27). This opacity and the decentralized character of development and function tend to "complicate efforts to determine and allocate responsibility when something goes wrong with an AI system. Thus, lack of transparency both increases the risk and magnitude of harm (users not understanding the systems they are using) and also increases the difficulty of ensuring accountability" (p. 27).

Conclusion

AI-powered systems pose different levels and types of risks; some minor, others more significant, and some hazards and harms may not be identified until long after implementation. It is incumbent on educators to grapple with this uncertainty and equip themselves with knowledge so that they can decide when AI-powered systems might be beneficial, where they might be worthy of being trialed, and where they should never be used. This means substantially democratizing conversations about AI so that the teaching profession and whole school communities can be involved in its design, implementation, and governance.

There is exciting work going on in the area of AI literacy (Long & Magerko, 2020); however, this should always be under the broader domain of digital literacy and be cross-curricular in its approach for both students and educators. All students, their teachers, and preservice teachers should be learning about AI so that the technology is not viewed as magic. Schools and schooling systems need access to independent expert advice not only to deepen technical understanding but to guide them through evidence of efficacy for different types of learning and the ethico-governance implications of the technology. Consideration of AI-powered systems includes, but goes well beyond, usual considerations of consent and privacy. We require whole-of-school-community dialogue about the role of automation in education, what AI is and what it is good for, and when it may be too risky or dehumanizing to use. While this dialogue must include industry and government, it should be led by teachers and students. They should ultimately be the architects of AI in education.

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4

THE RELATIONSHIP BETWEEN HUMANS AND MACHINES IN PUBLIC POLICY

Brian Lee-Archer

Introduction

The digital economy is giving rise to a challenging paradox. Societies are leveraging digital data to help address the most wicked problems facing the planet, such as climate change, poverty reduction, and public health outcomes. In parallel to this public value creation, there is a growing gap in trust between citizens and their governments, and the use of digital data is a significant contributing factor. In an environment of falling trust in public institutions (Organization for Economic Cooperation and Development [OECD], 2018), support for public policy initiatives leveraging digital technology to deliver better educational outcomes for children is dependent on the human element in decision-making. As digital data moves through the data lifecycle of research, policy, program delivery, and evaluation, the way humans work with machines is vital to building public trust. This chapter examines the emerging relationship between humans and machines (often referred to as human+machines) in a decade dominated by artificial intelligence (AI) and the use of big data (Daugherty & Wilson, 2018). It is proposed that it will be innovation from within the human dimension, guided by a dynamic base of digital data, which provides the balance between managing risk (e.g., privacy, security, and ethics) and rewards (such as better educational outcomes for stronger societies). Stronger societies use existing assets, including their data, more effectively and promote citizen-led initiatives to enable them to take control of their affairs in a democratic and inclusive way (Russell, 2009).

Trust in public institutions and government is constantly challenged. Rises and falls in public trust come as no surprise, given that political leaders, governing parties, and public administrators come and go. Rather than getting caught in fluctuating public trust, policymakers can progress digital adoption programs by

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paying close attention to building public confidence in each digital initiative. A structured, process driven approach to AI and big data provides incremental building blocks for growing public confidence. Making the public aware of the way in which humans work with machines in an augmented fashion, will also contribute to building confidence in digital adoption.

Digital: It Is Not New, and It Is All around Us

Digital technology has become synonymous with breakthroughs in addressing societies' most wicked problems, such as poverty alleviation and rising inequality, the effects of climate change, chronic and life-threatening health conditions, and providing stability within global financial markets. Fundamental to addressing these problems is the on-going investment by society in human capital through education. As every aspect of human activity is increasingly influenced by digital adoption, education systems are called upon to supply skilled human capital. In keeping up with the demand for the digital skills of the future, the sector is challenged to digitally adapt at a similar rate of change.

Digital technology today is largely characterized by the rise of AI. AI is a collection of technologies that combine data, algorithms, and computing power (European Commission, 2020), and it is moving rapidly beyond the realms of science fiction into mainstream, everyday life. Phenomenal advances in computing power over the past two decades to put information in the palm of our hands (through smartphones), and the vast amounts of digital data generated every day, serve as catalysts for AI's potential to change the way we live, work, learn, and play.

While this rapid change occurs around us, we should reflect on the fact that, in 2019, the world celebrated the 50th anniversary of the Apollo 11 moon landing. While it was an incredible feat of human engineering, courage, persistence, and ingenuity, the role of digital technology in making the mission successful is less well known (IBM, 2011). At times, it may seem that digital technology is new and unique, particularly because the information technology industry is adept at making new products, software, or hardware appear far superior to whatever came prior. However, technology has been evolving for decades.

Digital technology has contributed to transformations across every industry sector, leading to rising living standards around the world. From the Apollo 11 moon landing through to the launch of the first smartphone – the Apple iPhone (Apple, 2007) – in 2007, it has been an upward trajectory of widespread value creation through digital technology. If there were any risks or downsides to the technology as it evolved, they were largely hidden or set aside by policymakers, and overshadowed by public enthusiasm for new technology.

The recent rise of AI – in particular, the way in which it exploits a person's digital footprint – is shifting public opinion. Consequently, the positive image of digital technology is now under threat as the risks become more evident and potential misuse of personal data by governments and commercial entities becomes a significant public policy issue. As a result, the discussions about risks in the ways personal data are used are likely contributors to falling levels of trust in government. One such example of data privacy concerns was evident in the COVID-19 pandemic, when several countries sought to contact trace the virus through an application (app) on smartphones (Meixner, 2020). As a public health and economic recovery initiative, it attracted significant public concern around data privacy. Falling levels of trust in government were likely contributors to people's concerns in how their personal data might be misused. These concerns act as an inhibitor to the take-up rate of the app in a potentially disproportionate manner to the potential societal benefits.

AI and big data provide opportunities for health, social, economic, and environmental domains to be addressed in ways never previously imagined. As society meets these challenges with insight gained from the linkage and sharing of digital data, the data related risks must be considered in parallel. Further, the ethics of responsible use of AI and the moral hazards of automated decision-making must also be addressed. It is no longer appropriate to stand back and marvel at the information technology industry. Without extensive public debate on how these technologies affect each member of society, people could end up living in world they do not want and/or were not expecting.

The COVID-19 pandemic has provided society with a sneak peek into the future as digital technology became the bedrock of human communication for business, education, and simply keeping in touch with family, friends, and colleagues. Not all experiences using such technology are currently productive or value adding, and there are downsides to this forced dependence on digital technology. While most people would agree that no technology is not an option, too much, especially without human intervention, is not good either. There is now an opportunity, after this glimpse into the future, to aim public policy towards a happy medium where people and technology work together in a complementary manner.

BOX 4.1 SELF-DRIVING OR AUTONOMOUS VEHICLES – THE HUMAN DIMENSION

In recent years, there has been extensive research and development into self-driving or autonomous vehicles. While significant progress has been made, moral and ethical dilemmas associated with AI and automated decision-making stand-out.

Consider the following proposition: The AI within an autonomous vehicle on a public roadway detects a potential collision with a pedestrian pushing a pram. There are two options available to avoid a fatal collision: (1) swerve into oncoming traffic, or (2) drive onto a footpath where an elderly couple are standing. Both options will potentially kill or seriously injure one or more people. The machine must decide what to do. Which option has more or less risk of causing death? Is one life more valuable than another? Should the machine prioritize a child's life over an elderly person's? Does the machine give priority to the people in the car it is controlling?

It may be possible to layout a rational decision-making process for AI to follow. The machine learning algorithm could learn and modify itself based on learnings from the experience. Would this be considered a responsible use of artificial intelligence? More importantly, is this the right question to ask? Is it a responsible use of artificial intelligence to allow an autonomous vehicle to travel on standard public roadways, shared with pedestrians and vehicles that do not have complementary technology? The most likely answer is no. Without significant changes in how roadways are constructed with pedestrians and cars kept apart, this hypothetical scenario for the responsible use of AI should be kept hypothetical.

It is the human element that makes the decision on where and how autonomous vehicles can be safely deployed. Mass transportation is an example where this is occurring. The Sydney Metro line from Tallawong to Chatswood, New South Wales, is a fully automated and driverless rapid transit system that opened to the public on 26 May 2019 (Noyes, 2019). It is human decision-making that deployed this automated metro system on a standalone rail system.

The term "digital technology" can be thought of as automation where machines perform the tasks humans are not good at (such as repetitive tasks) and/or are performed repeatedly. At the other end of the human+machines scale are tasks such as counseling and personal care that are best performed by a human. There are many activities in the middle of these two extremes where machines can augment human capability (Daugherty & Wilson, 2018). This middle ground is the domain of AI.

AI is rapidly emerging as the transformative technology of the information age. There are many risks associated with AI, and these are often expressed in terms of fears, hopes, predictions, and sometimes dire warnings (for example, "the machines are taking over"). AI, however, is a 60+ year-old technology. Since the term "artificial intelligence" was coined in 1956 (Tate, 2014), the fantasies of science fiction and a world controlled by robots have often found their way into the public discourse. AI has come to the fore in recent years as phenomenal advances in computing power, combined with the availability of data, have given rise to machine learning.

Machine learning is an application of AI where systems can automatically learn and improve from experience without being explicitly programmed (Hao, 2018). Machine learning focuses on the development of computer programs, in particular algorithms, that access and use data to learn for themselves, thereby improving algorithms without direct human intervention. Machine learning offers new ways to solve problems by developing and/or modifying existing algorithms and then training the machine with data captured and observed from the real world.

Society has reached a phase of rapid expansion in capability in addressing big problems through the use of AI and machine learning. The potential benefits within public administration are expanding at an incredible rate; however, so too are the risks, including the misuse of personal data, ethics, cyber security, algorithmic bias, and the moral hazards of decision-making with AI (Lee-Archer et al., 2016). This new class of risk is troubling for public administrators and the public alike. It is the "without human intervention" aspect of machine learning and AI that gives rise to some of the most troubling predictions of the unintended consequences of AI.

In recent years, the terms "responsible AI" and "responsible use of AI" have risen to prominence (Dignum, 2019). The ever-increasing volume of personal data coming into the hands of government is a source of great power, and with that comes great responsibility in ensuring the data are managed correctly and are used to create public value. From addressing national security issues to delivering better health and educational outcomes, public value derived through leveraging personal data at an individual or group level is contingent upon the level of confidence people have in the institutions charged with managing the risks (see the information on "Self-driving or autonomous vehicles – the human dimension" for an example of responsible AI and ethical considerations).

While there will always be demands for fail-safe guarantees regarding data security, these are, in the main, unrealistic. In the same way that the airline industry cannot guarantee an accident will never occur, the industry has a track record that gives the traveling public confidence in the safety record of individual airline operators. Establishing high degrees of public confidence for the airline industry to function effectively is dependent upon a structured approach to managing risks and demonstrating how the residual risks are outweighed by the potential benefits.

In terms of public policy, the Australian National Audit Office (ANAO), when examining governance mechanisms in the Australian Public Service to manage risk, stated the importance of establishing positive risk cultures in agencies where risk appetites and tolerances are clearly defined and communicated to staff. This sets up a paradoxical situation, as while the public generally expects some managed risk-taking by administrators as they improve services through innovation, there is a low tolerance for failure or error. The connection with innovation was also identified, when Grant Hehir (2018) – Auditor-General for Australia – stated, "positive risk culture is also an enabler of innovation. If staff are afraid to fail, they are unlikely to take calculated risks and be innovative" (para. 4). Encouraging staff to think outside the box but not be afraid of an acceptable level of risk when it comes to innovation, with the support of sound risk management processes, helps create enduring innovation for better policy and service delivery.

Rather than a negative hurdle that cannot be overcome, the presence of risk (when managed well) is essential to progress through to the stage of building confidence. Responsible use of AI in addressing the risks does not mean abandoning human effort or intervention. Instead, the way to manage the risks is to use machines to add, enhance, and complement the ability of people. While AI attempts to improve human effectiveness, an effective AI system cannot exist without human effort. It is this human and machine dimension of decision-making – where the potential benefits of AI are realized, and where the risks are known and managed – that is most powerful.

Despite concerns surrounding the use of AI, there are examples where humans have high levels of confidence in machines operating autonomously. One such example is the marking of multiple-choice exam papers using scanning technology and a set of rules to judge the accuracy of each answer. Conversely, there are areas where some people believe humans should be in complete control, such as evaluating a creative writing piece, because of the number of elements involved in discretionary decision-making; for example, an examiner's assessment of the language elements of a creative writing piece against a rubric.

These are things a machine could learn if trained by a human. With a piece of creative writing, AI could read the text and provide an assessment of the language conventions or elements used. A responsible use of AI would leave the final decision on the creativity of the piece within the domain of the human exercising judgement, but they would be guided by the automated assessment. In the multiple-choice assessment, a human could also guide machine learning algorithms to recognize the various ways students may annotate or color a form.

The important principle at play in these examples is that AI augments, rather than replaces, human decision-making. Daugherty and Wilson (2018) explained in their book "Human + Machine": "humans and machines aren't adversaries, fighting for each other's jobs. Instead, they are symbiotic partners, each pushing the other to higher levels of performance" (p. 106). Human oversight and guidance on where machines are used and how they are trained provide a basis for improving human decision-making within public policy development and administration.

Problem Solving through AI

AI is a powerful tool to augment human decision-making in analyzing and understanding the complex interactions between social determinants, which are addressed through the various arms of public policy. Through AI and machine learning, patterns (or correlations) can be identified providing the clues and potential pathways to addressing causality within intersecting public policy domains. Public administrative systems, such as education, are comprised of countless decisions across many actors, including policymakers, bureaucracies, school administrations, teachers, parents, guardians, and students. From policy to program design, regulation and education services and delivery, actors are innovating with digital technology to create value. As organizations use digital technology to solve complex business problems, they have to plan for the inevitable social and economic impacts of this value creation (Fjord, 2020).

Creating public value is the intended outcome from investing in digital technology by the administrative arms of government (OECD, 2014). Creating value comes via "digitization" (doing the same or similar things via digital means) and "digitalization" (using digital means to do things differently; Chair in Digital Economy, 2017). As in previous industrial revolutions, the digital economy involves the destruction of existing systems and structures, while driving a profound transformation in the world of work and the labor market as a whole (Palier, 2019).

A digitalization mindset is where public policymakers place the creation of public value ahead of technology adoption and deployment. For example, AI can be deployed in the public interest to reduce the costs of education services by augmenting human decision-making in allocating highly skilled and expensive resources (European Commission, 2020). A digitization approach, on the other hand, seeks to use technology to automate for efficiency, without solving a real business issue. This approach has the potential to achieve minimal benefits at a potentially high cost and is sometimes referred to as "lipstick on a pig" (Waller & Weerakkody, 2016, p. 19). This represents a digitization drive for efficiency without necessarily enabling an innovation led transformation, as policy instruments remain largely unchanged. Within the education sector, an example of this approach is making existing course work available online. Thinking creatively about how technology is used to transform education delivery leading to better outcomes (such as addressing distance learning challenges rather than making learning available online) is where true innovation occurs.

Addressing complex problems, such as educational disadvantage across socioeconomic cohorts, requires the capabilities of new technology to draw insights from the already large and growing quantities of data, in order to influence decision-making. Rather than replacing humans, the aim of digital technology and AI is to provide people with "superpowers" when making decisions, by providing insight into what does and does not work (Daugherty & Wilson, 2018). To succeed, business leaders need to commit to designing for human intelligence and optimizing the relationship between people and machines.

The traditional approach in implementing public policy through administrative systems is a one-size-fits-all approach. It can appear more straightforward in defending the perceived fairness of a standard service offering. However, this can lead to over servicing and under servicing.

Digital technology can enable better outcomes that are aligned with policy intent through mass personalization. The calibration of the service response can be tailored (including in real time) according to the context of the circumstances and the capacity of the actor in delivering the services. In education, this does not mean creating individual learning solutions for every person; AI assisted decision-making can determine where tailoring standard offerings can be most effective and efficient. To solve problems by augmenting human decision-making capability, AI and machine learning systems need to ingest vast amounts of digital data. Much of the data relate to people and their circumstances. Digital data, by its very nature, can be easily and rapidly misused (at scale, affecting whole populations or cohorts) with potential for profoundly negative impacts. Solving complex problems with digital data can be a risky business.

Building Confidence to Address the Risks

As people's expectations rise for digital service quality and experience through the responsible use of their personal data, there is a growing gap in trust in many countries between citizens and their governments. In fact, within OECD countries, only 43% of people trust their government (OECD, 2018). There are many factors contributing to this rising distrust, not least of which is an increasing power imbalance in favor of government, as public administrators enhance the capability of using digital data to inform administrative decision-making. When people are surveyed on their trust in government, their answers might reflect a one-off experience or be an amalgam of many experiences. Their views may reflect their most recent experience with the local public school, a collection of experiences with the health system over an extended period, their opinions on the current state of the political process, or any combination thereof.

Given the varied nature of the experiences that impact one's trust in governments, it can be difficult to ascertain the levels of trust in the broader government, or with a specific arm of government (such as an education system). Trust is often considered within a dimension of time, as it matures within an enduring relationship. People are likely to experience periods of satisfaction and displeasure with their government or an arm of the bureaucracy. Throughout this period, there may be a sense of overall trust, or they may inherently never trust the institution. Some people, perhaps a sizable cohort, will hold largely ambivalent attitudes to the institutions of government, including the school system. These people can be largely influenced by the circumstances of the moment.

When considering adoption and acceptance of digital services, such as AI assisted decision-making, a better place to start is to focus on building confidence. Confidence can be more easily expressed in the moment, and as contextual and value-based, for example, "how confident do I feel about this transaction or activity being successful and will it do me any harm?" A low level of confidence may be sufficient for a digital transaction or data sharing if the perceived value outweighs the risk.

Every experience a person has with a public entity can be considered a moment of truth in terms of confidence in the competency of the entity. Jan

Carlzon, CEO of Scandinavian Airlines, turned the airline industry service experience around in the early 1980s by focusing on every interaction with a customer as a moment of truth. Public entities can adopt a similar approach to building people's confidence in how their data are used at each moment of (digital) truth (Carlzon, 1987). A positive moment of truth in the digital realm might be the ease and convenience of registering for a new learning experience. It might be a personalized website experience or a simple transfer to a human operator for advice. Conversely, a poorly designed digital experience that raises concerns that personal data has been compromised and/or is being used for a purpose other than what consent has been provided would be a negative moment of truth.

The digital realm is providing new means for public administrators to create moments of truth by meeting people where they are at in terms of their need, capability, and readiness to engage in the digital environment. Rather than aiming for high expectations of an enduring relationship of trust, public agencies can be better served by focusing on the fundamentals of establishing moments of truth around each digital interaction to build confidence. This means designing digital services focused on enhancing the consumer experience. Each positive experience builds people's confidence in the competency of the public institution. As levels of confidence grow, support can be generated for expanding the social license for public institutions to collect, manage, and use people's personal data.

With every advance in using personal digital data, new risks emerge, such as individual privacy, cybersecurity, algorithmic bias, ethics, and moral hazards from automated decision-making. Notwithstanding the risk, it remains possible for a service or exchange to occur based on the relative confidence at the point of interaction, even when there may be broader questions or doubts influencing the trusted relationship. For example, a person may have an overall low level of trust in government, but may still perform digital transactions and data exchanges with public entities. Convenience, ease of use, and value can be sufficient enough to generate confidence, while having little to no effect on a person's assessment of trust.

A further illustration of trust versus confidence is where people readily give up their personal information on commercial digital platforms, such as Facebook, Google, Uber, and Amazon, despite any evidence of a trust-based relationship. This occurs because people have confidence in receiving more value in return from a transaction or information exchange, despite the known risks. It is not uncommon, however, for the same people to be reluctant to share information with public entities, citing a lack of trust in the institutions of government. Therefore, the lesson for public entities is to not aim for the elusive goal of a trusted relationship with digital services. Instead, public agencies should focus on addressing the risks associated with each service interaction, with the intent to establish confidence in the service offering.

Action and Reaction

The potential benefits of digital technology within public administration are expanding at an incredible rate, as are the risks. This class of risk is troubling for public administrators and citizens alike, and getting the balance of benefits and risks right is critical to success. The ever-increasing volume of citizen-related data coming into the hands of government is a source of great power, and with that comes great responsibility in ensuring it is managed correctly and used to create public value.

In seeking better public policy outcomes, policymakers' ability to take advantage of people's personal digital data is contingent upon the level of confidence people have in their interactions with the institutions charged with managing the risks. Policymakers and administrators must follow a structured approach to managing the risks involved with digital initiatives and demonstrate transparency in the way risks are managed. One way to consider these emerging risks is in the context of Sir Isaac Newton's Third Law of Motion, which states that for every action, there is an equal and opposite reaction (Westfall, 2020). Digital technology is enabling advances across every field of human endeavor. While these advances create forward motion, there is also the Third Law of Motion in play. With every forward change (progress) enabled by digital technology, there are opposing forces (risks). By adopting a structured approach to managing these risks, progress can be accelerated rather than held back.

The technology industry has, for much of the 20th century, been able to sidestep many of the negative aspects of technology led social and economic disruption. The risks have been accepted as inevitable consequences of digital led progress. However, as the pace of digital enabled change has accelerated in the first two decades of the 21st century, and as AI and machine learning have risen to prominence, public concerns are increasing over the risks associated with the use of personal data. Collectively these reactive forces are coalescing into significant inhibitors to collecting and managing personal digital data.

In the context of Newton's Third Law of Motion, the presence of reactive forces propel things forward. If society is to realize the potential of AI and machine learning in addressing public policy challenges, the risks need to be considered as the essential reactive force for enabling progress. To maintain forward momentum with the commitment to fair and equitable public policy, we need to lift our efforts in researching these reactive forces for the purpose of making them part of the solution, rather than immovable obstacles.

Finding a balance between the contradictory forces of progress and the risks from personal digital data can also be considered through the lens of Chinese philosophy. The principle of Yin and Yang treats things as inseparable and contradictory opposites (Cartwright, 2018). These opposites attract and complement each other in reaching a point of harmony. Applying this principle to digital transformation, the contradictory opposites are technological change powered by

AI and machine learning, and managing the rising consequential risks in relation to ethics and privacy. Thus, there is much to be gained from data driven insight for public policymaking, providing there is a corresponding acknowledgement and commitment to researching the counter forces.

Innovation, Regulation, and Oversight

People generally expect digital services from public entities to be of a similar standard, level of convenience, and ease of use to commercial applications such as travel sites, online banking, and social media. However, while there are good examples of commercial digital services where people's personal data are used in an ethical and responsible manner, there are many where this is not the case. As a result of some high-profile failures and data breaches in recent years, the technology industry has been called to account for how services are used and how they protect personal data. Given the amount of data within the digital education sector, there are even more reasons to challenge the technology industry and other public entities at risk of over-reaching in the use of people's personal data.

Around the world, there are examples of significant pushback against the misuse of data by technology companies, commercial entities, and governments. A major step in this direction is the European General Data Protection Regulation (GDPR) that came into effect in May 2018 (Proton Technologies AG, 2020). The GDPR is the first of its kind, and it is intended to align privacy and data protection laws across Europe. It was developed to provide European citizens with a better understanding of how their personal information was being used. A key principle of this regulatory framework is the way in which personal information is collected and used with the informed consent of users.

The introduction of regulation covering digital related activity is, at times, resisted by the technology industry, as there is a concern that over regulation may inhibit innovation. The technology industry's capacity for delivering continual innovation has been a significant contributor to global economic and social development since the middle of the 20th century. Innovation occurs at the intersection of business insight and technology invention (Ruetsche, 2008). It is business insight that tempers and redirects the excitement and enthusiasm for the next big thing in technology (such as AI and machine learning) from being used for the wrong purpose or in an irresponsible manner.

A structured and methodical approach to innovation is a key ingredient to success. Innovation is complemented by the discipline of public policy administration, rather than being incompatible with it. Having governance structures and processes to monitor performance and discontinuing non-performing programs are key components of an organizational innovation framework. Rather than thinking of innovation as simply digitizing everything and letting the technology industry control the innovation agenda through inventing new products and new technology, making effective and responsible use of digital data provides business insight on where and what to transform.

Positive storytelling can be an effective way to highlight public value creation arising from innovation initiatives. In the digital age, the power of positive storytelling remains just as relevant as it has through the ages. Organizations should be transparent and focus on generating positive stories centered on what works, highlighting where individual and public value are created from leveraging personal digital data (Accenture, 2019). To be credible, the stories need to be transparent on the identification of the risks and failures that may have occurred.

Conclusion: Better Public Policy through Digital

Public policy administrators seeking to accelerate the adoption of digital technology for value creation and reaching better outcomes for individuals and society are generally wary of new technology such as AI and machine learning. Education administrators have been even more cautious. This is understandable given the potentially compounding risks for children from the misuse of their personal data.

Sustained and enduring transformation comes from a digitalization agenda where innovation is used to change how things are done. Digitalization needs to be prosecuted ahead of digitization initiatives, where attention is simply focused on automating the current state. This means, however, opening up personal data and using it in a transparent, ethical, and responsible manner. By taking deep dives to find where value is created for stakeholders and remaining proactive in calling out and mitigating the risks, organizations can lead a digital transformation agenda built on hope and optimism from AI and machine learning, rather than one clouded in fear and uncertainty.

Focusing on people's experience though digital moments of truth can lead to the establishment of confidence. Confidence cannot be taken for granted. It is time limited and related to the purpose of a digital interaction. It needs to be reconfirmed as each new digital service or offering is made and consent is sought to use personal digital data. As confidence builds and people increasingly engage in digital initiatives, previously provided consent for data sharing should be re-confirmed with individuals on a regular basis.

The machines represented by the technologies of AI and machine learning, along with big data are already here. The role they play in public life is for public policy-makers, administrators, and human workers to decide in consultation with and through co-design with the people they serve. Following are four steps to guide leaders through this digital journey where machines augment human decision-making.

1. Create the Environment for Innovation

Tearing down barriers that inhibit innovation among teams is a key role of leaders. Build internal capability with appropriate external support (e.g., coaches) for addressing data sharing, linkage, and protection issues. Establish a sound framework and methodology for innovation. Where appropriate, actively encourage teams to innovate around the complex issues starting with policy intent, through to program design and service delivery. Resist the temptation to focus solely on efficiency gains or to adopt technology simply because it is available.

2. Nurture an Ethical Use Culture

Senior leadership has a responsibility to embed the ethical use of digital data within the culture of the organization. This aspect alone is crucial to creating and maintaining people's confidence in innovative digital initiatives. Much more than setting in place an ethics framework to guide leadership decision-making for projects, leaders must make cultural adjustments across the organization to ensure ethical considerations involving the use of personal data that are at the forefront of decision-making.

3. Make Risk Your Friend

The innovation mantras of "fail fast" and "don't penalize risk takers" from the commercial sector do not have the same relevance in public administration. It is the role of leaders to set boundaries for risk appetite and risk tolerance, consistent with public accountability and transparency principles. There are instances in which innovation is required to address an issue or solve a problem, and failure may not be an option. Some risks, if they materialize, can be catastrophic for individuals and the organization. However, a fear of risks materializing should not be an excuse for inaction or a lack of progress. See risks as a positive counter-balancing force against the potential for over-reach and misuse of personal digital data. Explore how these counterforces can inspire innovation rather than inhibit it.

4. Success in the Digital Realm Relies on Structure

Digital innovation is not usually an overnight success. Innovation is dependent on structure to be successful. While digital transformation is couched in terms such as "agile development" and "minimum viable products," successful outcomes are a function of well-defined scalable and flexible processes. Business and technology specialists collaborating through a co-design approach will achieve digitalization outcomes ahead of digitization. Organizations that consistently use business case analysis to assess each innovation initiative and conduct a return on investment analysis to evaluate implementation are generally more successful.

Public policy has long advanced its many causes by realizing the benefits of digital technology adoption. This has largely been achieved with strong public support. While there were risks such as labor market disruptions from automation, these were generally acceptable in terms of the overall gains in efficiency and effectiveness. Digital technology has now reached a point of advancement through AI, machine learning, and big data, where the risks are rising. These risks have the potential to significantly impact social stability as governments and corporate entities gain access to people's personal digital data. The value proposition for addressing societies' most complex social, economic, and environmental problems is strong. However, the downsides can be equally compelling. The way forward is highly dependent on how humans use the power of machines for the good of society. This demands a machine augmentation approach to human public policy decision-making.

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5

AMAZON GO FOR EDUCATION?

Artificial Intelligence, Disruption, and Intensification

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Introduction

Amazon Go grocery stores are "a new kind of store with no checkout required" (Tillman, 2020, para. 4). The Go concept is the latest extension of the automated warehousing capabilities of Amazon. There are no shop assistants, they are replaced by an application (app) on customers' phones. This app is powered by artificial intelligence (AI) that includes computer vision, deep learning algorithms, and sensor fusion technology (a system not dissimilar in general terms to that for self-driving cars; Tillman, 2020). The system registers products as they are picked up and as products leave the store. The app matches products automatically with customers. The system is constantly gathering data, not only about stock and process, but also about customer choices and behaviors in relation to products moment to moment. This kind of data is the so-called "oil" for future commercial AI development (Lee, 2018).

Amazon Go's use of AI does at least three things. First, it intensifies existing conditions of shopping by extending the existing automated checkout system where the customer scans the product. Second, this intensification produces new possibilities for data collection. Third, Amazon Go disrupts practices of face-to-face shopping at the same time as it disrupts the organization of labor with new kinds of efficiencies. As there is a complete removal of a physical checkout and related staff, customers learn to comport themselves – mentally, physically, and affectively – towards the system, with little or no access to human staff.

In this chapter, we try to think about the intensifying and disruptive capacities of AI in education. We try to imagine the implications of a kind of Amazon Go for education, in which educational experiences of various kinds might be drawn on as required, without any intermediating assistants, and perhaps without the

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need for the bricks and mortar of schools or even teachers themselves. Over the past 100 years, education institutions have largely assimilated technological developments, and have been relatively stable and very slow to change (Jónasson, 2016; Koschmann & Kolodner, 1997). In this chapter we ask: Will AI follow a similar path in its introduction? What will be the roles of schools, universities, and the forms of organization that are attached to them as AI is introduced? It is not a given that education institutions will remain the same. Will we still need or have schools, universities, or the forms of organization attached to them in anything like the form we have them now? It is not a given that they will remain at all.

The influential "historian of the future," Yuval Noah Harari, suggests the important questions for education today concern whether we can predict what to teach in an AI world. He suggests that we cannot know what the world will look like in 20 or 30 years' time. He is referring to not only,

> …the basics of geopolitics but what the job market would look like, what kind of skills people will need, what family structures will look like, what gender relations will look like. *This means that for the first time in history we have no idea what to teach in schools.*
>
> *(quoted in de-Feytas-Tamura, 2018, n.p., our emphasis)*

This final point serves as an important caveat for this chapter. While we have good evidence relating to past and current trends in education and technology, the nature of applications of AI coming into education requires us to consider a very diverse set of possible future scenarios. This requires us to acknowledge inherent limitations on our capacities for prediction and planning, and to perhaps think in terms of preparedness in relation to the unexpected.

This multiplicity of possible future scenarios is inherent in the term *artificial intelligence*, first coined by John McCarthy in 1955 to describe a heterogenous set of techniques and tasks, rather than a single "thing." Definitions of AI follow suit. Boden (2016) provides a simple but fluid definition of AI as describing the field that seeks "to make computers do the sorts of things that minds can do" (p. 1). This involves efforts to produce "systems that think like humans, systems that act like humans, systems that think rationally, [and] systems that act rationally" (Russell & Norvig, 2016, pp. 2–3). Nonetheless, there is still no common understanding of what AI *is* or what it will *become*. Greg Corrado from Google Brain underscores that the focus in AI research on new challenges is: "not about what a machine 'knows' or 'understands' but what it 'does', and – more importantly – *what it doesn't do yet*" (Lewis-Kraus, 2016, n.p.). Ironically, when successful, the development of new, specific AI capacities often results in the exclusion of these technologies from what is considered to be the domain of AI. Popular discussion about AI often conflates the term with "artificial general intelligence" (AGI) or "strong AI." While strong AI continues to be the focus of AI research, it is unlikely that it will significantly impact education in the next decade (Walsh, 2017). The focus of this chapter is on "weak AI" or intelligent agents that enable the automation of specific and narrow tasks using techniques primarily underpinned by machine learning.[1]

The chapter proceeds as follows. We first outline our conceptual apparatus and methodological concerns, based on speculation and the challenge for educational research of examining the conditions that are yet to appear. The second part of the chapter provides our review of literature and our speculations about the intensification and disruptive possibilities of AI in education. We do not think that intensification and disruption in education are mutually exclusive, rather AI in education involves a series of "conjunctive syntheses" (Deleuze & Guattari, 1983), which are not either/or but "and…and…and." Nonetheless, we separate these for heuristic purposes. We examine how the current organization of education may shape the ways any new AI technologies are adopted, including the influence of corporate interests and technological advances that will also shape this adoption. This view presumes that AI will intensify, complement, and supplement pre-existing practices and processes in education. We then look at possible substantive disruptions to education, focusing on issues of provision and knowledge. We conclude the chapter by identifying issues we think require further examination.

Conceptual and Methodological Note: Speculation as beyond Gray Literature

> "Prediction is very difficult, especially about the future."
>
> – *Niels Bohr*[2]

This chapter is based on secondary evidence. We reference academic work where it exists and have included few references to gray literature produced by organizations such as consultancy companies, or the rapidly growing body of popular books in this area.

Additionally, we locate this chapter within the conceptual resources from critical technology studies in education, new media studies, and science and technology studies. Almost any new technology in the past has involved a great deal of speculation that has proved to be highly inaccurate, or at least trapped in limited modes of thinking (Murphie & Potts, 2003, p. 8). It is worth also considering change from now will be simultaneously multiple – three of the largest changes are technical-media (AI and more), climate change, and broad social and political change. This will provide a "catastrophic multiplicity" (Murphie, 2018), in the sense of a dramatic turning away from how we think the future will unfold. It is difficult – likely distasteful, but necessary – to think through the demands of these changes together. In many ways, ours is truly a time without precedent.

Such demands and changes lead to a pressing question: How can education research – with its alignment to evidence-based research practices – deal with the consequences of technologies or ideas that do not yet exist? In this chapter, we want to put forward the use of speculative approaches as ways of thinking through the implications of the future. As an advocate of speculative methods within digital education research, Ross (2017) argues that "speculative approaches are aimed at envisioning or crafting futures or conditions which may not yet currently exist, to provoke new ways of thinking and bring particular ideas or issues into focus" (p. 215). Ross argues further that digital education research lacks an imaginative resource to take a strong position at the edges of educational change, where it is most needed (Ross, 2017).

While this imaginary resource is perhaps lacking within education research, it is still present within the larger education sector among a range of stakeholders and policy actors that now include technology companies. Amazon is just one example of that. The company's emerging technologies and company-funded research reports about their future implications are speculative devices and propositions themselves. However, in contrast to these primarily profit-driven speculations, it is important for education research to "offer counter-visions which address, for example, issues of equality, diversity and social justice" (Ross, 2017, p. 218).

Speculative research approaches are well-equipped to do this work, as they are complexity over certainty (MacLure, 2006), as a "speculative method is itself a proposition: neither the result of theories nor of practice, the rational nor the empirical" that "does not lead to vague ideas but starts from them to arrive at particular points of view" (Parisi, 2014, p. 240). Therefore, speculative approaches may be able to provide an imaginative resource for understanding the impact of AI on education. We attempt this in what follows.

Intensification

In this section, we are interested in the existing conditions of education that enable AI to either be already part of education or easily introduced. We focus on two kinds of conditions: one concerns education governance, the other computation and education.

Datafication and Data Infrastructures

The present conditions of education governance allow AI to be seamlessly introduced, with key aspects including education being *governed through datafication* and *administered via infrastructures*. Datafication, as the process of translating things and events into quantities, is accompanied by the building of data infrastructures in education, which both enable forms of datafication and are themselves an outcome of the focus on digital data. Without wishing to rehash a now widely covered discussion, data infrastructures as sociotechnical forms, in which people, networks, algorithms, and computational capacities are all central to data infrastructures in education (Anagnostopoulos et al., 2013; Hartong, 2018; Sellar, 2015).

Datafication and infrastructure can be seen as a continuation of the political rationality of measurement in governance including: i) education as a form of biopolitics and state management connected to the policy sciences in education; and, ii) "evidence-based" policymaking of the late 1990s that came into social policy areas as part of new forms of data-based policy provision. The introduction of more hardware and software – that is computing power – intensifies a computational political rationality in decision-making, one that is, therefore, far from antithetical to the policy areas of education. As such, computational decision-making based on techniques such as machine learning is easily introduced (Gulson & Webb, 2017; Williamson, 2016) as "the era of so-called 'big data' ushers in important new changes in educational policy, pedagogical practice, and institutional strategy" (Knox et al., 2020, p. 31).

Students in elementary, secondary, and especially post-secondary education are increasingly likely to encounter automated basic communications. Student management systems have already been established in multiple education sectors to collect and provide readable data, often in the form of data dashboards. This will likely continue, but will be combined with new forms of predictive analytics and data visualizations (Alexandru et al., 2015). AI will allow for the increased processing of data, in which decision-making done on the basis of extensive data from data warehouses will provide novel types of analytical insights. In higher education, learning management systems are already open to these developments, combining program and course administration with content provision, and can be further integrated with other systems, including student retention predictions, university administration and student records, ongoing program auditing, disability services, and special consideration processes (Del Bonifro et al., 2020; Hoffait & Schyns, 2017). AI is likely to expand the category of educational data to include things such as simple metrics like attendance; student movement around a campus, such as visiting the library (or not); in-class engagement (such as attention, interaction, and motivation; Subramainan et al., 2016); and metrics on the affective aspects of learning, gathered in conjunction with adaptive learning (Avramides & du Boulay, 2009).

The introduction of AI into education governance is part of what has been termed algorithmic governance, or predictive governance, as "a form of social ordering that relies on coordination between actors, is based on rules and incorporates particularly complex computer-based epistemic procedures" (Katzenbach & Ulbricht, 2019, p. 2; see also Webb et al., 2020). In algorithmic governance all aspects of schooling – the affective, the interactionist, the pedagogical, curricula, and assessable – become translatable, if not translated, into numbers (as datafication), and subject to algorithmic logics. These logics are not outside of the existing modes of education, but AI introduces new forms of black boxing into decision-making that other kinds of data infrastructures have not yet indicated or enabled.

Pre-automation and the Structuring of Professional Obsolescence

In predictions of professions under threat from automation, teachers have been identified as being at the lowest risk of all (Nedelkoska & Quintini, 2018), yet paradoxically as a profession, teachers been resigned to being made redundant (Selwyn, 2019). Either way, teaching roles are unlikely to stay the same. As Luckin (2018) notes:

> We live in times of financial stricture; there is therefore a risk that politicians, managers and decision-makers will be tempted by the inevitable enticements of a growing band of technology companies to believe that education and training can manage with fewer teachers and trainers, and that artificially intelligent tutors can be employed instead of human educators.
>
> *(p. 138)*

While Luckin points out that replacing teachers with AI tutors would be erroneous due to the required "human touch" of teaching, we can see that education provision, especially K–12, is increasingly focused on the "learning sciences," which identify and replicate aspects of teaching and learning using AI capabilities. As AI based on pedagogical models is combined with "on-screen teaching" to underpin adaptive learning, the role of the teacher will change (du Boulay & Luckin, 2016). Some aspects of teaching will be automated that would previously seem *the purview of human teachers*, such as giving feedback on student collaborations (Floryan et al., 2010).

While much of the discussion of teaching and AI has focused on the practice orientation of teacher replacement, we are also interested in the congruence of AI with some aspects of teaching (see also Selwyn, 2019). AI is very good at doing tasks that are part of highly structured hierarchies, and about identifying "a specific range of programmed events (e.g., skills) and collections of programmed events (e.g., expertise) via which we now work and live" (Murphie, in press). The design of education, and we use that word "design" specifically, has long focused on standards and outcomes. While on the one hand this can be seen as encouraging faith in the profession, the converse is that it can mean that teaching, in a sense already "pre-automated" (Murphie, in press), is ripe for fuller automations such as professional development that puts forwards toolkits.[3] This will in fact make it easier for full automation to occur, that is, a going beyond our behavioral automation to our full replacement. As Pasquale (2019) notes:

> The value of dialogue…in educational settings, should also be evident. There is wisdom in investing in human-focused… education teams, rather than dispatching these duties to smartphones and apps. Students… should resist pervasive appification because it is a short step to behaviorism.
>
> *(p. 92)*

But this type of functionalism is already part of the way schools are organized: ordering behaviors, and responses to the world, into basic elements and then reassembling into restricted and highly ordered diagrams and taxonomies allows things to more easily be "learnt" by machines, specific skill/expertise by skill/expertise.

That is, much of the current system of organization of education is already based on the (pre)automation of learning and teaching. One significant part of this is that the roles of human teachers and students, and the experiences of learning and teaching, are highly constrained from above (through audit cultures, learning outcomes, etc.). This is based largely on quite old thinking about organizations (Bloom et al., 1956). This could be a problem. For one thing, it means we are currently educating students and professionalizing teachers into a mode of engagement with the world which, by inducting them into pre-automated behaviors, actually positions them as workers to be the more replaceable by full automation. If education is organized according to these principles, down to such questions as "what skills do we need to meet the future of work?," we are essentially meeting automation by speeding it up. We risk making students and teachers more replaceable by educating them, via forms of organization and modes of thinking and behaving that induce the lifeless lives that are most easily replaced. For AI would perform these lifeless functions more efficiently, at much lower, or no cost, with a flatter structure. AI would also deliver such functions much more flexibly, more integrated into networked infrastructures, and with a potential for much faster adaptation to world changes. If we already assemble ourselves to operate algorithmically, why would an algorithm *not* be able to replace us?

Disruption

This section outlines three areas where we think there are interesting, if somewhat confronting, possibilities of disruption with the introduction of AI. We try to move past the common narrative of challenges to employment and skills to focus on the transformation of provision and knowledge.

Human-machine Learning

If the aim of AI research has often been assumed to model minds (Boden, 2016), this also has implications for our conception of human learning and our understanding of human brain function. Our conceptions of machine intelligence, human minds, and learning (human and non-human) are increasingly interconnected, with changes in one domain having potential impacts on thinking about the others. It is important to note that AI itself also needs to learn. Computer-based intelligent agents, particularly those based on artificial neural networks, are "machine learners" (Mackenzie, 2017) that are trained on patterns in big data sets and reinforce these patterns in their actions. While this is quite a straightforward equivalence of learning, based on an anthropomorphic attribution of learning, we could also entertain the possibility that in an AI world, our conception of learning and education could change, as could our perception of the world and ourselves through our engagement with AI embedded in new media.

Additionally, some unusual effects arise if AI is, rightly or wrongly, often strongly tied to concepts of human learning, even to the way the functioning of the human brain is conceived (so that when the way that neurons work is reconceived, this is often hailed as leading to a possible breakthrough in machine learning). In short, AI and education overlap because learning itself, and core assumptions related to learning, are central to both (Luckin, 2018). This poses a problem for trying to plan education, as when one aspect of the following equivalence changes, the others are often conceived differently.

> What is a machine <—> AI <—> learning <——> what is mind? <——> what is human?

That is, "learning" might change through notions that are carried over from other fields. AI itself, somewhat ironically, could propel education away from the 1950s model of cognitivism still common in educational assumptions about learning. That is, learning narrowly defined via data storage and retrieval for both human and machine. More recent versions of AI include new models of mind somewhat different to the old model provided by a 1950s computer, in favor of the importation of models of learning drawn from more open network computing and neural networks. Events of learning are seen to "emerge" stochastically across these networks, as opposed to the more structured module-based "cognitivist model" in "good old-fashioned AI" that still informs much of cognitivist educational thinking. The question arises if thinking is a matter of the logical processing of symbols based on learnt procedures and stored information (e.g., cognitivism), or is it a matter of many iterations of high-level pattern matching and recognition in response to a given situation (e.g., facial recognition; Mackenzie, 2017)?

At the same time, we might ask whether AI and human thinking have to be conceived in the same way, or whether this is not in itself a deeper outmoded assumption, one found in AI development itself often enough, but one also found in many educational assumptions, including those underpinning educational organizations. AI is assumed to replicate human-like skills, which is sometimes involved. However, why does AI have to be human-like, and why indeed does AI therefore have to be conceived as replacing humans? Music artists such as Holly Herndon and German duo Grandbrothers have for years worked across the differences between humans and machines.[4]

Education Technology Platforms as Education Providers

AI and related technologies enable new platforms and technical innovations that can disrupt entire industries and fields (Eriksson et al., 2019). For example, mp3 and file compression more generally disrupted not only the music, film, and book industries, but entire habits of engagement with music, film, television, and reading. The Internet and social media disrupted the entire journalism industry.

As noted, AI is easily introduced through data infrastructures in education, those already existing or emerging sociotechnical apparatus that allow for the integration and intervention of data into the life of schools and systems. Platforms extend data infrastructures, and as these are primarily proprietary, also add a new type of AI supported corporatization to education (van Dijck et al., 2018). Platforms create new connections in a "global-scale arrangement of planetary-scale computing" (Bratton, 2016, p. 44), and are an amalgam of technical aspects, computation, and new forms of sociality in which a platform is a "standards-based technical-economic system" (p. 141–142). As Srnicek (2017) notes, "platforms are digital infrastructures that enable two or more groups to interact. They therefore position themselves as intermediaries that bring together different users" (p. 43).

The growth of platforms is concurrent with the extension of AI applications into education. That is, there is a dual growth of corporate platforms and AI within education, as education providers are supported by AI, but also provide forms of entry to AI applications (Williamson, 2019). AI itself is a kind of non-platform, in that it can move across different platforms or experiences. One side to this is that when AI and data connect, there is a massive increase in the ease of distribution across the networks involved. This includes a potential distribution of learned functions, that is, learned by AI agents, and of educational events and content. It can occur across multi-scalar events of networking, from micro-instances of a learning behavior to global circulations. The result is that all systems in a network can almost instantaneously learn what another system has learned, a process that Walsh (2017) calls "co-learning" (p. 182).[5] Platforms (such as Moodle) often deployed in universities cannot hope to match many corporate deployments or the potential of AI. In part because they have nothing like the kind of technical capability or support needed, but also because they are plugged into forms of organization that run counter to ease of use and good user experience).

What is enabled through platforms, which perhaps gives corporate platforms an advantage, is the incorporation of automation through application programming interfaces (APIs). Mackenzie (2019) posits that APIs become more important as parts of platforms include AI, and move from "a mode of programmability focused on linking systems to a mode of programmability – AI or machine learning – centered on prediction" (p. 1990). APIs allow for the access of data, processing, new third-party developers and so forth. It means that within one platform there is a new dispersed spatiality to how education is delivered, providing a complex web of potential connections among disparate educational developers and providers. Understanding this allows us to understand more fully what platforms are enabling within education, when "platforms act: they perform specific operations (and others not); convey particular messages (and others not); draw some things in (and others out); make choices in what can appear (and what not); and how it is organized (or not)" (Decuypere & Landri, 2020, p. 4). Some of these platforms are specifically educational, such as Google Classroom and higher education platforms like U-Multirank (Decuypere & Landri, 2020). These platforms are both explicitly pedagogical (e.g., Google Classroom) or introduced as governance platforms, such as business intelligence systems (Sellar & Gulson, 2019).

Literacies and Skills in a "Third Media Revolution"

Our final section on disruption explores the ways that any response to new technologies requires epistemological transformations. Within education, these are broken down to questions of literacies and skills, which are key questions informing the organization of education itself. For example, in writing as a university president on the need for higher education to respond to the challenges of AI, Aoun (2017) calls for "new literacies" that comprise data literacy, technological literacy, and human literacy, arguing that people need digital not just analogue tools:

> they need data literacy to read, analyze, and use these ever-rising tides of information. Technological literacy gives them a grounding in coding and engineering principles, so they know how their machines tick. Lastly, human literacy teaches them humanities, communication, and design, allowing them to function in the human milieu.
>
> *(p. xix)*

This kind of multi-modal approach is common and is built into calls for 21st century skills in K–12 education, such as creativity, critical thinking, communication, collaboration, information literacy, and self-direction (Chung, 2017). These types of skills can be contrasted with, for example, a focus on coding that has been somewhat misdirected, as it is likely that some forms of AI will not need to be coded. As Luckin (2018) posits, building future AI systems "will be about clever design and comparatively less will be about writing computer code. To some extent at least our future AI systems will be able to code parts of themselves" (p. 134).

Yet, much of our current organization, social life, and indeed economy, are based on the literacy and skills needs within what Murphie (2018) calls a first and a second media revolution. The first media revolution involved the development of modes of expression more open to abstraction, especially writing. This changed the world in dramatic ways, from religions of the book to Western philosophy's take up of writing as a record of forms of reflection, to commerce, and capital's new ability to keep accounts. The second media revolution, from the printing press through to the present environment of social media and texting and, from some perspectives, computing itself, involved the copying and wide distribution of representations (words, picture, films, but also texts on mobiles, posts on social media pages, and code). This also changed the world dramatically and famously, in a scientific and technical revolution enabled by the distribution of knowledge, the rise of democracy, publics, and the nation-state, enabled in part by newspapers and national literatures, and much more (Eisenstein, 1979).

Much of the organization of education, the current form of which was very much developed to enhance literacies in writing (for example, rows of desks, and courses and programs with relatively fixed structures, that consist of representations to be "processed"). This reflects a long history of a certain kind of economy and social life, based on the circulation and engagement of representations; this is also how we usually think, too narrowly perhaps, of media and communications. Even more narrowly, much educational organization is conceived in the very particular second media revolution terms of the 1950s. In this, the "information" models (such as cognitive psychology) that inform much of the understanding and organization of education are based on the idea that knowledge acquisition involves the reception, storage, and possible retrieval when needed, of information (whether as "knowledge" or as "skills"), via symbolic processing and as symbolic representations.

Yet AI is part of a transition into a "third media revolution" (Murphie, 2018) along with: interactive technologies; virtual, augmented, and mixed realities in their transformation of perception; hyper-networking, global networks of sensors, and the Internet of Things (IoT); genetics and optogenetics, drones, robotics, and bots; and algorithms in financial trading. The third media revolution uses or intensifies elements of the first and second media revolutions. Yet it does so in a manner that changes the game significantly. Writing and representation lose their "primary" status in events.

In the third media revolution, media and communications are no longer content to just represent the world. Rather, third media revolution technologies aim to actively fold media and the world into each other. Media and the world transform each other via third media revolution technologies, often quite dramatically. These technologies read the world in order to act within it; think a drone attack or IoT technology that adjusts temperature and lighting.

AI for example is not only a matter of writing and representation but a media technology that can, for example in self-driving vehicles, respond to the world in real time. Indeed, the whole point of AI is to act in the world and to enable other technologies to act in the world (such as robotics). In the third media revolution, media find new forms and many new niches in the world, or order to modulate and be modulated by the world. It is this transformation of the world that is in part driven by AI. It still requires older literacies, but also requires new literacies. In fact, beyond "literacy" per se, it requires new understandings of activity, what it is, and what it is to be active in a world in which world and technologies so intensely modulate each other. Only one aspect of this might be an entirely new way to conceive of "active learning" as an educational potential within these modulating folds of world and media.

Avoiding Technological Somnambulism: Enlarging Our Considerations of AI in Education

Like other areas of social and political life, decisions about the uses of AI in education need to be enlarged beyond considerations of what is technically possible at this point in time. Winner proposes that the problem is not so much technological determinism, but rather "what might be called technological somnambulism – how we so willingly sleepwalk through the process of reconstituting the conditions of human existence" (Winner, 1983, p. 254)[6]. To attempt to avoid this technological somnambulism around AI in education, in this conclusion we try to identify issues that we think need to be further considered "to provoke new ways of thinking and bring particular ideas or issues into focus" (Ross, 2017, p. 215).

First, much of what we have covered as intensification and disruption assumes a continuation of the "place" of schooling, where schools are likely to remain important as "locally accountable organizations, committed to building viable and sustainable futures for everyone in their communities" (Facer, 2011, p. x). However, AI could, in tandem with hypernetworks and augmented reality, fragment, reassemble, and distribute education very differently, in a manner much more situationally sensitive. Due to the capacity to deliver not only content, but different pedagogical modes and assessments, it is likely that there will be a focus on mobile learning connected to new forms of collaboration (Woolf et al., 2013, p. 72–73). Additionally, the places of schooling may become networked beyond our current experiences. One would always have access to the world, and to specific, situationally required, learning experiences and knowledge. This could include education connected to new forms of virtual reality or augmented reality glasses (Southgate, 2020). Other networks may build on existing technology, such as Apple's AirPods (Brandt, 2016), which could be always worn in the ears and always connected not only to the Internet as we know it, but also to satellite systems, hypernetworks, the IoT in an updated version of William Gibson's cyberpunk world of *Neuromancer* (Gibson, 1984).

Second, education might be offered by a range of different providers. Where will schools and universities position themselves in the midst of this and why would students enroll in them?

Challenges will include making decisions about equity of provision, and regulations that will be necessary for delivery and for credentialing, in whatever forms these take, if indeed the latter survives in anything like its present form. Many of these issues will be able to draw on existing regulations concerning home-schooling and online forms of schooling, such as online charter schools (Barbour & Reeves, 2009). What might be different with AI is that we will need to consider what to do about regulating technology companies (Pasquale, 2020) not only in education, but also companies such as Google that are often located both inside and outside education.

Third, as an alternative to this, AI could disrupt the whole current culture of the proprietary platform. New technologies, including blockchain or post-blockchain technologies, could decentralize organizations away from large scale platforms – a vision that is part of the speculative fiction of the post-Internet world, such as the novel *Infinite Detail* (Maughan, 2019). While the focus of much work on AI in education is on the role of corporate entities, perhaps education will become a kind of trade among equal members of the community. It could lose its hierarchical forms of organization. In partnership with blockchain and other technologies, AI could assemble and communicate ongoing accreditation, in an accreditation that is much more nuanced, detailed, and responsive to the situations of workers and employers. While education could become like Amazon Go and become captured by platform capitalism, it could also be thoroughly democratized in platform cooperativism (Scholz & Schneider, 2016). Alternative forms of provision and alternative providers, from corporations to platforms allowing a kind of education marketplace to community or cooperative organizations, could drive down costs to near zero marginal cost. If so, what will this do to the revenue models of schools and universities, or government budgets providing education? Why would students pay for a certain kind of experience at schools or universities when they could get something that is better, cheaper, and more flexible, elsewhere?

None of this is a given (Walsh, 2017). However, all this makes it more dangerous to imagine the wrong world, based on poor or outmoded models, including within the organization of education. The most likely eventual educational world involving AI would be a complex world in which some things AI does are intrusions on current human activity, others might be totally alien to the human – *machine but not human interpretable* – and yet others somewhat alien but complementary to the human. This is before we get to the interaction of AI and education with other domains such as climate change (Doctorow, 2020).[7] Therefore, we think a particular ethos is needed here – to be open to the co-adaptation of humans and machines, both involved in learning, and both learning to work and to learn together. As Luckin (2017) contends, "we need to develop a culture of problem specification that encourages people to unpack educational problems, so that solutions that benefit from the symbiosis of AI and human intelligence can be developed" (p. 124).

All this makes speculation about the future more difficult, but all the more necessary, if we are to understand speculation not as prediction, but as exploration of a multiplicity of potentials events, given the current multiplicity of tendencies at work. AI and related technologies could not only intensify and disrupt the current provision of education, but entire habits of engaging with education itself.

Notes

1 Aspects of the above sections are reworked from the following report: Gulson et al. (2018). *Education, work and Australian society: A review of research literature and policy recommendations*. University of New South Wales/Gonski Institute for Education. Thanks to Sam Sellar and Simon Taylor for their contributions that are used in this chapter.
2 Variously attributed to Niels Bohr, an old Danish proverb, and so on. Only proving that it is just as difficult to ascertain the past as it is to govern the future.
3 Examples of toolkits include focusing on toolkits as ways of organizations (schooling) being "agile" and "adaptive" (see Evidence for Learning, n.d.).
4 Creative applications are well advanced in this area such as Holly Herndon (see Holly-herndon.com, n.d.) and the German duo Grandbrothers (see Peake, 2017).
5 Co-learning is when "an agent in a collective group learns EITHER directly for themselves OR indirectly from another agent" (Walsh, 2017, p. 182).
6 Thanks to Simon Taylor for alerting us to Winner's work.
7 Speculative futures writer Cory Doctorow (2020), who is also an "AI skeptic" as well as "an automation-employment-crisis skeptic" (para. 3), recently suggested that full employment was likely for at least 200–300 years due to the labor-intensive tasks that will occur due to remediating climate change.

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6

PEARSON'S DIGITAL TRANSFORMATION AND THE DISRUPTION OF PUBLIC EDUCATION

Anna Hogan and Sam Sellar

Introduction

Pearson characterizes itself as the "world's learning company" (Pearson Central Europe, 2020, para. 2), and it has a presence in more than 70 markets globally. The company has undergone significant restructuring over recent years, moving from an Anglo-American media holding company to a globally integrated education services company. In 2018, revenue from digital and digitally-enabled products and services accounted for 62% of sales, illustrating the extent of Pearson's digital transformation to date. In this chapter, we critically analyze Pearson's current key strategic priorities: (1) growing market share through digital transformation and (2) investing in structural growth markets (e.g., online provision and computer-based testing; Pearson, 2020a). Pearson is following the corporate vision of many technology companies that emphasize digital disruption to existing markets. Pearson's strategy is not informed by a coherent set of educational or social principles, but rather by the aim to protect and grow shareholder value. Pearson's corporate success depends, in part, on disrupting the public provision of education.

Pearson aims to lead the next generation of teaching and learning through the development of digital learning platforms, including the use of artificial intelligence (AI) in education (AIEd; Luckin et al., 2016). The company is also piloting AI technologies that it hopes will provide automated, real-time feedback to students in the form of a virtual tutor, much like Apple's Siri or Amazon's Alexa. This technology will be integrated into a single platform – Pearson Realize – that will deliver its digital services in an individually personalized way (Olson, 2018). Pearson envisions direct and lifelong relationships with customers to whom it will provide virtual schooling, professional certifications, assessments, and other digital

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services. The potential impacts of these developments on public education include: changes to funding and resource distribution; reductions in the need for, and benefits of, teachers; and the private accumulation of large volumes of student data, which creates a range of new risks.

In this chapter, we critically analyze Pearson's strategic priorities and broader corporate strategy. We begin by reviewing the digital transformation of the Global Education Industry (GEI) and discuss why Pearson and many other edu-businesses are focusing on "digital first approaches" to learning. We then conduct a scoping review of key reports commissioned by Pearson to show that it is steering contexts of policy influence in ways that align with its corporate strategy of digital transformation. We discuss Pearson's vision of the wide-scale adoption of personalized learning, which entails disruptive changes to teaching, curriculum, and assessment, and the organization and function of schools and universities. We conclude by raising two main causes for concern in relation to Pearson's vision and its implications for the integrity and sustainability of public education globally: firstly, the privatization of data and data infrastructures, through what Harvey (2004) describes as "accumulation by dispossession"; and secondly, and the transformation of the teaching profession and the broader social purposes of education.

The Digital Transformation of the GEI

There has been an explosion of edu-businesses seeking to capitalize on burgeoning education markets over the past two decades. A growing body of research has described the rise of the GEI and its key characteristics, including:

- public-private partnerships (Steiner-Khamsi & Draxler, 2018);
- the contracting of assessment services (Hogan, 2016);
- the private management of public schools (charter schools, academies, and free schools; Fabricant & Fine, 2015);
- the outsourcing of schooling to the private sector (low-fee private schools in Sub-Saharan Africa, South America, India, and parts of Asia; Srivastava, 2016); and
- the multitude of products and services on sale from the private sector to support the day-to-day practice of schools (for example, curriculum, learning resources, digital technologies, teacher professional learning, administrative tools; Molnar, 2018).

Major capital investment is now being concentrated on the digital transformation of education by major technology companies and venture capital investment firms (Williamson, 2017a). There is now unprecedented optimism for the potential of education technology to transform schooling, and in 2017 more than US$9.5 billion in investments were made to education technology (EdTech) companies (Morrison et al., 2019).

According to Metaari's (2018) commercial analysis reports, there are seven types of learning technology products: AI-based learning; mixed reality learning (i.e., the integration of augmented reality and virtual reality); game-based learning; mobile learning; cognitive learning (i.e., behavior modification products); location-based learning (i.e., learning triggered at geotagged physical locations); and educational robots (i.e., robots to teach programming and related skills). All of these products have a growth rate of more than 14% per year, with educational robots having the highest growth rate (30.5%) and mobile learning the lowest (14.4%). Interestingly, mobile learning revenues are the highest of all product types with global revenues set to double to $26 billion by 2023 (Metaari, 2018). Metaari suggests there are six market segments that buy EdTech products: consumers, Pre-K–12, higher education, corporations/businesses, federal governments, and state/local governments. The factors driving the demand for these products are different in each buyer segment; for example, in the pre-K–12 market, AI-based learning is experiencing a rapid uptake due to the promise of AI being able to achieve true personalized learning for the first time (Metaari, 2018).

The integration of AI into digital learning is currently the "holy grail" of EdTech, and one that is having a profound impact on the GEI. For example, the Watson Education Team at IBM has announced various partnerships with Pearson, Apple, Houghton Mifflin Harcourt, Scholastic, Elmodo, and others to bring AIEd to mainstream schooling. IBM (2019) argues that Watson is a cognitive technology that can "think like a human" by understanding, analyzing, and interpreting data; using machine learning to grow subject matter expertise in apps and systems; provide personalized recommendations based on understanding a user's personality, tone, and emotions; and interact using chat bots that engage in dialogue. Collaborations that combine education content with Watson's AI capabilities can generate various personalized learning products that can be sold to learning institutions. For example, Watson is used as a personalized, virtual, one-on-one tutor within some Pearson courseware products (Pearson, 2016).

Pearson is a particularly interesting case to explore the digital transformation of education. The company has an extensive portfolio of digital products and services, including courseware, assessment, and learning platforms that encompass many EdTech product types. Pearson previously specialized in education textbooks, but the company has shifted towards a digital learning model and providing more direct-to-client services. Initially, its profitability suffered under this model with former Chief Executive Officer John Fallon describing the transition from analogue to digital as being a painful period for Pearson. However, the potential for future profitability has driven Pearson to re-focus its business priorities over recent years by simplifying its portfolio to invest in its digital transformation. In 2016, Pearson invested £700m+ to drive the digital transformation of its portfolio of products and services, with the same financial outlay being made again in 2017 and 2018. The 2018 annual report announced a return to profit, despite a decline in sales, and an ongoing commitment to the recovery of the business through digital transformation (Pearson, 2018). However, Pearson has continued to struggle and has issued a series of profit warnings in recent years, including in response to COVID-19 disruptions (Pearson, 2020b).

Studies of the development of Pearson's education business have criticized its prioritizing of shareholder value over the interests of students, teachers, schools, and communities (Ball, 2012; Ball et al., 2017; Hogan et al., 2015; 2016; Hursh, 2015; Riep, 2017a; 2017b; Srivastava, 2016; Williamson, 2016). Of course, companies must prioritize shareholder interests, and Pearson has also actively pursued its corporate social responsibility, but its ambitions and growing influence in education risk creating an imbalance between the private value and public benefits of education. In this chapter, we explore a range of new and emerging concerns associated with the digital shift to education. For example, Williamson (2017b) raises concerns about patents and intellectual property in this new environment. He argues that corporations are using data infrastructures to mine and analyze big data in order to become powerful actors in educational research, knowledge production, and theory development. He states:

> these are by no means neutral, value-free or atheoretical approaches. They are the product of academic and commercial actors animated by a specific imaginary of a desirable future of educational research and development, working within a field of power defined by its economic, social and cultural capital, whose practices reflect a particular data scientific style of thinking that views learning in scientific terms as quantifiable, measurable, actionable and therefore optimizable.
>
> *(Williamson, 2017b, p. 119)*

Corporations can increasingly shape the pedagogic practices of teachers and the learning processes of students, and we argue that Pearson has also been working to steer contexts of policy influence in ways that align with its digital transformation strategy.

Methods

The chapter presents a scoping review of Pearson's commissioned reports in education. Specifically, we identify the reports published by Pearson through its "Open Ideas" forum between 2012 and 2018. Mays et al.'s (2001) definition of a scoping review is a process that aims to "map *rapidly* the key concepts underpinning a research area and the main sources and types of evidence available" (p. 194, emphasis in the original, in Arksey & O'Malley, 2005, p. 21). A scoping review can be conceived as a method in its own right, and can be undertaken to examine the extent, range, and nature of research activity, rather than to describe research findings in detail like a systematic review. Our purpose in undertaking a scoping study of Pearson's commissioned research is to ask what research narrative Pearson is creating around the digital transformation of education?

Arksey and O'Malley (2005) argue there is no definitive procedure to follow for a scoping review, but it is important to identify the research question, clearly define the inclusion/exclusion criteria of relevant studies, chart the data, and collate the findings. Only research papers published by Pearson through its "Open Ideas" forum were included in this scoping review. Using this criterion, we identified 16 research papers published between 2014 and 2018. Of these, six papers were excluded because they did not focus explicitly on digital transformation: one paper focused on behavioral sciences, one on teacher expertise, one on the "effect size" of popular education reform policies, two on effective pedagogies, and one on the development of business efficacy in education. The remaining 10 papers (over 60% of Pearson's commissioned research reports) directly focused on digital learning in K–12 schooling and higher education.

Charting the data involves identifying key items of information from the research reports being reviewed using a descriptive-analytical method (Arksey & O'Malley, 2005). Our coding scheme included the following information about each paper: year published, author, title, research focus, nature of analysis, and key outcomes/recommendations. The intention of this scoping review is not to present a view regarding the "weight" of evidence that Pearson provides in relation to digital learning in education. Our aim is not to assess the quality of evidence in research reports, and consequently we cannot comment on the robustness or generalizability of findings. Rather, we aim to identify the dominant areas of research into digital learning published by Pearson and the key recommendations.

Charting the Promotion of Digital Learning in Pearson's "Open Ideas" Forum

Pearson states that its goal is "to help people make progress in their lives through learning." They further note that "Open Ideas is one of the ways in which we do this. We work with some of the best minds in education – from teachers and technologists, to researchers and big thinkers – to bring their independent ideas and insights to a wider audience" (Luckin et al., 2016, p. 3).

The section below outlines the key information from the 10 reports included in this scoping review. It is clear, that since 2014, Pearson has focused on commissioning research that highlights the potential of technology to transform education. This began with the call to recognize the ubiquitous nature of technology and learning today, ensuring that all schools have the hardware, infrastructure, and staff capacities required for students to work with and benefit from digital tools and resources. The three reports published in 2014 all argue that technological advances are giving rise to a "next generation" of learning in schools. Each report details the "explosion" in student data that can be captured and analyzed through online learning, which can lead to more personalized and optimized learning for students, but involves a paradigm shift in assessment. Hill and Barber

(2014) and DiCerbo and Behrens (2014) argue that assessment should become integrated within personalized learning systems, providing continuous and immediate feedback to students on their everyday activities.

The focus on personalized learning is expanded in two reports published in 2016. These reports focus on adaptive learning (EdSurge, 2016) and AIEd (Luckin et al., 2016). EdSurge defines adaptive learning as tools that might have adaptive content, adaptive assessments, or adaptive sequences (for example, tools that continually collect and analyze student data to automatically change what a student sees next, from the order of skills to the type of content). They argue that the most popular adaptive tools currently in the K–12 market are those that focus on adaptive content for mathematics education. The EdSurge (2016) report suggests that the most successful adaptive tools will be "like an ever-present teaching assistant, supporting students with instruction while capturing information that is hard for teachers to regularly collect" (p. 30). Similarly, Luckin et al. (2016) argue that AIEd can be used to create

> the possibility of learning that is more personalized, flexible, inclusive, and engaging. It can provide teachers and learners with the tools that allow us to respond not only to what is being learnt, but also to how it is being learnt, and how the student feels.
>
> *(p. 11)*

The Pearson report published in 2017 moved from a discussion of the need for digital learning in schools to examine how schools and educators can ensure the efficacy of EdTech products they purchase. However, Means et al. (2017) explain that this is not as simple as asking "what works?," but requires understanding that it is difficult to "disentangle the impact of a learning technology from the effectiveness of the overall instructional system in which it's embedded" (p. 6). Indeed, their report recommends that successful implementation of software would include "instructor" professional development about the new practices expected of educators. The efficacy of a learning technology product cannot be separated from the interactions between students, instructors, and learning activities in particular contexts, and this means that organizations need to support teachers to use data about what is working and continually change their practice to support these ends (Means et al., 2017).

Finally, the reports published in 2018 expand the focus of digital learning from K–12 schooling to focus on higher education. The theme that emerges from these reports is that universities need to offer more flexible learning pathways for students and further embrace the potential of technology to provide enhanced personalized learning opportunities for students. The underpinning rationale is that new, more dynamic modes of delivery will improve student access and completion by instantiating a consumer model of higher education that enables individual students to want to engage with their learning in ways that best suit them.

A theme across all of the reports is that teachers need to be better supported in classrooms and that this is possible through the rise of personalized learning, adaptive tools, and AIEd. The teacher is re-imagined as a classroom facilitator, rather than an imparter of knowledge (Hill & Barber, 2014). Algorithms, not teachers, will set curriculum, assess learning, and report on outcomes. In fact, a common recommendation across the reports is that teachers need additional professional training to ensure that technology is implemented in ways that best support student outcomes (see Fullan & Langworthy, 2014; Hill & Barber, 2014; Means et al., 2017).

The 10 Reports from Pearson's "Open Ideas" Forum

1. (2014) Michael Fullan & Maria Langworthy: *A rich seam: How new pedagogies find deep learning*

Focus: New pedagogies, enabled and accelerated by pervasive digital tools and resources, measure and support deep learning at all levels of the education system.

Nature of Analysis: Report informed by interviews with "practitioners of new pedagogies and deep learning" including students, teachers, school leaders, and education experts that provide background to "deep learning" and evidence of this type of learning in practice.

Key Findings or Arguments: Technology is ubiquitous in schools today. This requires every student to have a device, digital resources that align with curriculum, technology training for staff, high-speed Internet access, integrated assessment and monitoring programs, reporting mechanisms to allow frequent learning from work, communication with parents, infrastructure that includes security and privacy protections, support and maintenance of equipment, and a digital citizenship policy.

2. (2014) John Behrens & Kristen DiCerbo: *Impacts of the digital ocean on education*

Focus: Big data can inform decisions about learning through systems that continually assess and provide feedback on student progress.

Nature of Analysis: Opinion piece informed by literature arguing for new conceptualizations of learning to embrace a digital-first, data-first world.

Key Findings or Arguments: Call for a paradigm shift in assessment that uses technological advances to collect data, identify patterns, provide immediate feedback, generate learner profiles, and recommend leaning activities, e.g., personalized learning.

3. (2014) Michael Barber & Peter Hill: *Preparing for a renaissance in assessment*

Focus: Digital technologies and personalized learning systems are transforming student assessment.

Nature of Analysis: Opinion piece informed by literature arguing for assessment reform through personalized learning systems.

Key Findings or Arguments: Assessment should be integrated into "next generation learning systems" that enable teachers to deliver personalized learning.

They call for a shift in pedagogy to much of learning time spent online with teachers focused less on providing knowledge and more on assisting students to apply knowledge.

4. (2016) Graeme Atherton, Constantino Dumangane, & Geoff Whitty: *Charting equity in higher education: Drawing the global access map*

Focus: Draw attention to issues of equitable access to HE, create a global access map, and argue for improved data collection from those who participate in HE.

Nature of Analysis: Report informed by secondary data analysis, a survey of HE experts in 50 countries and case studies in 6 countries.

Key Findings or Arguments: Recommend a "Global equity data charter" to improve data collection on HE access and participation. This data should be collected and made open access. Governments, international organizations, and HE providers all have a role to play in understanding what actions need to be taken to make HE participation more equitable.

5. (2016) EdSurge: *Decoding adaptive*

Focus: Defines adaptive learning and discusses the potential benefits and challenges of using adaptive tools in the classroom.

Nature of Analysis: Taxonomy informed by literature review, interviews with educators, product designers and academics, and reflection of adaptive tools.

Key Findings or Arguments: Adaptive learning needs a clear educational vision, will include teachers and technology in partnership (where adaptive tools can be an ever present teaching assistant), and provide educator friendly data that can be collected and collaborated across all adaptive tools and against a common set of data standards.

6. (2016) Rose Luckin, Wayne Holmes, Mark Griffiths, & Laurie Forcier: *Intelligence unleashed: An argument for AI in education*

Focus: Outline AI in education (AIEd) and what it can offer learning now and into the future.

Nature of Analysis: Opinion piece informed by literature detailing the importance of AIEd in education.

Key Findings or Arguments: AIEd will play a critical role in education system reform, needs to function in blended learning spaces (digital and "traditional" classroom activities), and involves teachers and learners in the co-design of appropriate AIEd. Calls for focusing AIEd funding, developing infrastructures, and creating demand for AIEd technologies.

7. (2017) Barbara Means, Robert Murphy, & Linda Shear: *Building efficacy in learning technologies, Volume 1*

Focus: Understanding the efficacy of learning technologies to enhance learning.

Nature of Analysis: Literature review that makes recommendations about identifying, planning, implementing, and evaluating learning technologies.

Key Findings or Arguments: Learning technologies are just one part of an instructional system, not as learning intervention in itself. This report makes recommendations about how the effectiveness of learning technologies can be evaluated and explores the importance of technology implementation by teachers for a successful impact on learner outcomes.

8. (2018) Joe Deegan & Nathan Martin: *Demand-driven education: Merging work and learning to develop the human skills that matter*

Focus: Demand driven education needs to take account of the global economy and be technology-infused, gig-oriented, and industry-driven.

Nature of Analysis: Report informed by interviews with 20 education and workforce experts in the US and UK.

Key Findings or Arguments: Education systems need to develop specific skills for complex thinking; utilize dynamic digital pedagogies while preparing educators to embrace new forms of teaching and learning; respond to needs of the labor market; create flexible and adaptive pathways for learning; and support changes that make the education landscape function better so that it enables traditional and alternative providers to participate.

9. (2018) Jeffrey J. Selingo: *The future learners: An innovative approach to understanding the higher education market and building a student-centered university*

Focus: Consumer model of HE requires "segmentation" to build new academic offerings and personalize campus services.

Nature of Analysis: Report informed by a survey of 2,600 participants aged 14–40.

Key Findings or Arguments: Institutions need to design more flexible pathways and offer alternative credential, certificates, and a broader range of delivery methods (students prefer independent learning, and technology greatly enhances their learning experiences). Need to move away from a "one-size-fits-all" system and better understand the diversity of students' needs.

10. (2018) Jeffrey J. Selingo: *The networked university: Building alliances for innovation in higher education*

Focus: How alliances between universities can develop strategic solutions – using technology – to solve HE's toughest problems related to access, retention, competition, and making good on the promise of digital education tools.

Nature of Analysis: Report informed by interviews – no mention of how many interviews were conducted or who with.

Key Findings or Arguments: The networked university will allow students to access courses at their institution and others across the consortium, and courses will be blended with a mixture of online and face-to-face content. Communication occurs on a shared network, underpinned by a digital library and personalized, on-demand virtual tutors. Essentially, universities work together to build a digital infrastructure that supports student opportunity to learn more flexibly in a largely online environment.

Digital Transformation and the Disruption of Teaching, Curriculum, and Assessment

As shown in the list of reports above, Pearson has commissioned policymakers and academics to produce "Open Ideas" reports that legitimize its corporate vision for digital transformation premised upon disruptive changes to the teaching profession, the delivery of curriculum, and assessment. In other words, Pearson is seeking to disrupt the three message systems of schooling (Bernstein, 1977) and, more broadly, the organization and function of education as a public good. While many have called for reform of schooling to modernize this 19th-century institution, particularly in regards to the provision of homogeneous curriculum, age-based learning, and traditional models of teacher-led instruction, Pearson is betting strongly that such reforms, coupled with its focus on digital approaches, including the development of AIEd, will pay off. In this section, we consider how Pearson is actively working to disrupt existing educational practices in order to make markets for its products and service and, in turn, the role of the "Open Ideas" reports in this strategy. We focus specifically on Hill and Barber's (2014) "Preparing for a renaissance in assessment" report, which is illustrative of the key messages that we have identified across the 10 reports in our review.

Disrupting Teaching

Pearson publicly promotes its support for teachers in its marketing, and through a range of programs and awards. However, its corporate vision, and the implications it may have for teachers, presents a more ambivalent picture. For example, Hill and Barber (2014) have argued that teaching needs to be transformed

> from a largely under-qualified and trained, heavily unionized, bureaucratically controlled "semi-profession" into a true profession with a distinctive knowledge base, a framework for teaching, well defined common terms for describing and analyzing teaching at a level of specificity and strict control, by the profession itself, on entry into the profession.
>
> *(p. 20)*

Hill and Barber state that teaching is currently an "imprecise and idiosyncratic process that is too dependent on the personal intuition and competence of individual teachers" (p. 38), implying that teachers cannot be trusted. They suggest that this challenge can be addressed by "overthrowing" and "repudiating" the "classroom teacher as the imparter of knowledge" and replacing them with "increasing reliance on sophisticated tutor/online instruction" (p. 23). This is just one example of Pearson commissioning an analysis that paves the way for the personalized learning approaches that the company is developing. While Pearson does not call for replacing teachers, it has aligned the company with the view that teaching will be transformed by AIEd and this will require new kinds of professional expertise (Luckin et al., 2016). For example, Hill and Barber (2014) envision teachers as professionals who complement personalized learning software by providing guidance, coaching, motivation, and management of students.

However, Pearson also endorses the deprofessionalization of teaching that has become popular in low-fee private schools in Sub-Saharan Africa, India, and parts of South-East Asia. Pearson is reducing the need for trained teachers, and consequently, the cost of teacher salaries for schools and school systems. Paying appropriate teacher salaries is a major obstacle for the profitability of low-fee private schools in the Global South. Pearson looks set to continue its support, explicitly or implicitly, for low-fee schools provided by companies like Bridge International Academies, in which staff are required to read prefabricated lessons word-for-word from a tablet device. Staff in these schools must not deviate from the script and must implement learning activities in a step-by-step fashion (Renshaw, 2017; Riep, 2017b). The routinization of teachers work increases its susceptibility to automation, rather than promoting complementarity and new kinds of professionalism, clearly departing from the aims expressed in the EdTech focused aspects of Pearson's marketing and corporate strategy. While arguing that the company is supporting the provision of education in contexts where it would not be available otherwise, Pearson is forced to produce highly contradictory messages about the different kinds of teacher professionalism it seeks to promote.

Disrupting Curriculum and Instruction

Replacing teachers as the central agents of learning will supposedly enable "truly personalized instruction" to be delivered (Hill & Barber, 2014, p. 21), which the researchers define as:

> instruction that is adjusted on a daily basis to the readiness of each student and that adapts to each student's specific learning needs, interests and aspirations. The fundamental premises of personalized learning have been a part of the writings of educators for decades but have, in recent years, become a realizable dream, thanks to the advent of new digital technologies.
>
> *(p. 56)*

Pearson's vision for "next-generation learning" is based on the digital management of curriculum, learning resources, assessment, data, and analysis. Pearson Realize – a single sign-on platform for accessing resources, assessment, student data, and management tools – will make decisions about what students need to learn through the continual monitoring and assessment of data generated by their engagement with learning and assessment tasks. Learning resources will be provided based on searches for materials "that most closely match students' learning needs, accessing both purpose-built, commercially available materials and the rapidly expanding collections of public-domain and creative-commons resources" (Hill & Barber, 2014, p. 54).

These next generation learning systems, Pearson argues, will "create an explosion in data" from the continuous tracking of individual students (Hill & Barber, 2014, p. 55). Information generated through these learning systems, through the application of data mining and data analytics, will be used to "revolutionize" educational research and generate evidenced-based strategies for teaching and learning (Hill & Barber, 2014). Such partnerships potentially increase the market share for both companies, as well as the number of users integrated into both platforms, which in turn increases the amount of data that can be generated and joined up.

There are a number of issues to consider in relation to Pearson's collection and use of digital data, including questions about privacy, consent, ownership, transparency, bias, as well as openness. Pearson collects a range of data from customers, including names, phone numbers, addresses, birth dates, jobs, course information, personal interests, credit card and billing information, shopping selections, and data about activity on their websites. Pearson also collects a range of educational data, including assignments, student coursework, responses to interactive exercises, scores, grades and instructor comments, and details of the books the customer has read or activities the customer has completed. These data are de-identified and aggregated to audit and analyze how Pearson's services are used, to conduct educational research, and to support strategic development of its products and services. Pearson may also share data with institutions that purchase its services, with other companies in its group, and with companies that purchase its business assets. As a joint report by the British Academy and The Royal Society (2017) notes, "the ability to protect personally identifiable information is an essential component of trustworthy organisations. However, this can be difficult, if not impossible to achieve, even with the help of advanced privacy preservation techniques" (p. 31). The risk of data breaches has become part of the lifecycle of large education technology companies.

Consent to collect and use the various kinds of data outlined above is not always explicitly sought. Pearson's privacy notice specifies that consent will be sought to share or use data in ways not covered by the notice, or to send marketing material to customers under 16 years of age. While users actively give consent to sharing their data when they enter it into online forms, for example, Pearson also collects other data about user interactions with its websites and platforms, and users may be less aware of this information collection or the consent that is given through use of the service. Moreover, the extent and nature of data collection by Pearson makes it difficult for users of its services to understand exactly what data are collected and for what purposes.

This relationship can complicate questions about data ownership and responsibility, as well as accountability for good management of data. Moreover, much of the data that Pearson generates from the use of its services, and thus has ownership of, does not appear to be openly available. If these data remain locked up in private corporate silos, then their potential benefit for all learners and society more broadly will not be realized. Pearson's development of digital education services is effectively privatizing aspects of the emergent global data infrastructure of education, the social benefits of which would be greatly enhanced if it were open and shared.

Disrupting Schools

The changes described above suggest that students will increasingly sit at computers for personalized instruction, reducing the need for brick-and-mortar institutions. In fact, Hill and Barber (2014) argue that schools reflect the demands of an outdated agrarian society, where the short hours of the school day and long periods of school holidays are not aligned with the needs of parents and guardians. Pearson’s Connections Academy, for example, already offers tuition-free virtual schools for K–12 students. The website for Connections Academy states that “in this virtual classroom, students can spend the school year reaching their highest potential through a uniquely individualized learning program” (Connections Academy, 2019, para. 2). While it is free for students to attend these public charter schools, in some Connections Academies there are costs for field trips – which offer important social opportunities for students and teachers to meet face-to-face – as well as school supplies, including computers and their maintenance. These schools are rapidly expanding in the United States, serving more than 70,000 students across 27 states in 2017/18.

Pearson also offers a fully accredited education from the United States to any student in the world via its International Connections Academy. Pearson’s 2017 annual report noted that the company is currently the second largest provider of virtual schools in the US, and there is a need to capitalize further on the fact that virtual schools are permitted in 34 states, covering 80% of the K–12 population, including the “big three”: California, Texas, and Florida. Currently, virtual schools make up only 6% of Pearson’s total sales (£274m), but it estimates that the current market is worth US$1.5 billion and states that it is growing rapidly.

Pearson’s new business strategy aims to accelerate the shift towards reduced need for teachers and schools in order to grow the market for data-driven personalized learning that is provided direct to consumers across their life course. Pearson’s vision for education is one in which the cost and contribution of teachers to public education is reduced, while the company plays a more central role in education provision globally through its new platforms and the data upon which they run. We argue that Pearson’s vision encourages the broad privatization of schooling. Its approach to individualizing learning potentially locks customers into proprietary online services (as opposed to owning and having use of textbooks in perpetuity) and follows similar models used by other large digital services providers, which are based on subscriptions and retaining control over content. Pearson is likely to provide off-the-shelf generic services that plug in to third-party systems, encouraging the growth of a private digital education ecosystem.

Conclusion

During the 19th and 20th century, governments and private companies built the infrastructure of modernity, such as roads and rails, pipes and wires. Building data infrastructure has been arguably the major project of the 21st century (Mayer-Schönberger & Cukier, 2013), and opening this infrastructure to a range of stakeholders creates opportunities for important advances in knowledge and the provision of public and private services. There is clearly a place in the GEI for private providers of education services, and private companies are generally better placed to provide a range of technical services that will underpin the next generation of teaching and learning. Moreover, providing profitable services in the interests of its shareholders is a reasonable objective for any edu-business.

However, Pearson's vision for the company that it wants to become raises two major causes for concern in relation to the integrity and sustainability of public schooling:

1. the privatization of data and data infrastructures, which enclose innovation and new knowledge about how we learn, turns public goods into private assets; and
2. the transformation and potential reduction of the teaching profession diminishes the broader purposes and outcomes of public schooling in favor of personalized learning that focuses on individual knowledge and skills.

Both of these issues arise from a particular approach to profiting from education, which Harvey (2004) described as accumulation by dispossession. Pearson is following the example of other technology companies by seeking to disrupt public schooling in order to privatize educational data infrastructures and profit from the data that it accumulates through the provision of its services. These data will be the "lifeblood" of new education platforms and will be crucial for gaining new insights into how we learn. Pearson's corporate strategy exemplifies "the corporatization and privatization of hitherto public assets (like universities)" and is part of "a new wave of 'enclosing the commons'" (p. 75).

Pearson's vision for education laudably promotes the benefits of technological developments and their combination with new kinds of teacher professionalism and new insights produced by the learning sciences. However, Pearson's efforts to contribute to the disruption of teaching and public schooling, including in the Global South, and its development of platforms that produce new volumes and varieties of education data, while raising new ethical concerns about openness, privacy, bias, and transparency, will create significant risks for public education.

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7

COSTS OF BIG DATA

Challenges and Possibilities of Cost-benefit Analysis of ILSAs

Laura C. Engel and David Rutkowski

Introduction

As part of larger global trends in the rise of big data and the datafication in education systems, the proliferation and prominence of international large-scale assessments (ILSAs) appear to rest on a basic idea that more (cross-national) evidence will lead to optimal solutions of (national) educational problems. While this rather basic idea that empirical knowledge and the ability to benchmark internationally yields better outcomes is not new, the rather narrow application of achievement outcomes to optimizing the quality and effectiveness of education system performance has become a defining characteristic of the so-called global turn in education. Since the 1990s, more systems around the world, including low- and middle-income countries, are participating in international, regional, and national learning assessments (Kamens & Benavot, 2011). Results from these assessments and especially from flagship ILSAs, such as the Programme for International Student Assessment (PISA) and the Trends in International Mathematics and Science Study (TIMSS) have emerged as important indicators of achievement and educational success in systems around the world. These ILSAs readily inform policy decisions undertaken, fueling new data infrastructures and platforms for policy purposes, ultimately leading to "new governmental constellations" (Hartong, 2016, p. 524). In interesting ways, therefore, ILSAs are both driving factors *and* resultant effects of larger trends in the datafication of educational governance.

ILSAs are generally a highly aggregated snapshot of students' ability levels in a given age or grade. Given the formidable scope of international assessment programs, such as the Progress in International Reading Literacy Study (PIRLS), PISA, and TIMSS, creative assessment designs are employed to allow for broad coverage in several content domains and so that assessed groups are measured

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with appropriate precision. To that end, ILSA programs commonly use a sophisticated assessment design whereby each individual student is administered just a small number of the total possible items; yet, all items are administered throughout each of the reporting groups. Importantly, this type of assessment design is viable given the desired level of inferences: population and subpopulation as opposed to inferences at the individual level. To contextualize achievement, depending on the assessment, information from the students, parents, teachers, principals, and national coordinators is collected. These data serve as a rich source of information regarding the context and correlates of learning. Background questionnaires seek information on, for example, affective and behavioral measures of students, teacher beliefs and practices, the home learning environment, and principal perspectives on school safety and resources.

Since the mid-1990s, ILSAs have continued to develop into what many in the policy community view as an essential tool that provides them with insights into how a system is doing with respect to others (Grek, 2009; Lockheed & Wagemaker, 2013). This is especially true in the United States (US), where policymakers have frequently sought out results from ILSAs to gain new insights and signal a sense of where it stands vis-à-vis other systems, often regarded as competitors.

While much has been written about ILSAs, in particular the uses, motivations, misuses, and limitations of these assessments, there has been only minimal accounting of the costs of participation (Engel & Rutkowski, 2018; Wagner et al., 2011; Wolff, 2007). Specifically, existing research has focused on some of the tangible costs of ILSAs in different settings (Wolff, 2007), including the role of bilateral and multilateral donor organizations that provide funding assistance to systems to participate in ILSAs, and develop direct policy advice to systems based on ILSA findings (Kijima, 2010). More recent research focused on direct and indirect costs of the PISA in the US revealed several interesting internal components about how PISA is organized and governed (Engel & Rutkowski, 2018). In particular, findings from this research suggested that costs include the overhead that systems pay to the Organization for Economic Co-operation and Development (OECD), and the costs of national implementation of ILSAs, which include drawing a sample, recruiting schools, administering the assessment, scoring open-ended items, and in the US, incentivizing participation of schools, teachers, and students.

A logical question emerging from this existing research is whether the costs associated with ILSA participation are worth the touted benefits. This seemingly obvious question, however, is fraught with complexities that make answering it a difficult, if not an impossible, endeavor. Building on previous research, in this chapter, it is our aim to take up and explore some of these challenges and opportunities associated with research on the monetary costs of participating in ILSAs. To do so, we focus on US participation in ILSAs, providing a brief overview of the history of US participation in ILSAs and what we know from the data related to US costs of both the PISA and TIMSS assessments. We concentrate on the example of the US as these costs are publicly available, but also because the country has been a driving force behind the initiation, development, and circulation of ILSAs globally. We then develop a discussion around core issues facing a cost-benefit analysis (CBA) of ILSAs, arguing that it is highly likely to be a futile endeavor due to the challenges in quantifying benefits and costs in the ways that CBAs require, and because CBAs tend to oversimplify situations, creating a narrow, economistic, and nationalistic view of what a system gains from participating in an ILSA. While we argue that CBA related to ILSAs may be problematic, we nonetheless frame costs of ILSA as a meaningful focus of future research. Specifically, by examining costs of ILSAs, we argue that critical questions are revealed related to how the architecture of ILSAs are constructed and become mobilized in different settings.

US Participation in ILSAs: What Does It Cost?

The US has participated in ILSA programs since they were initially developed, starting from the early International Association for the Evaluation of Educational Achievement (IEA) studies in the late 1950s. The primary purposes of ILSAs within the US context are concisely described by the National Center for Educational Statistics (NCES) in the US Department of Education call for proposals for the International Early Learning Study Pilot: ILSAs "provide comparable indicators on student performance and schooling practices across countries in order to benchmark US student performance" (NCES, 2017, p. 11). Plisko (2013), the former Associate Commissioner at the National Center for Educational Statistics, described the US engagement in ILSAs as derived from "both a legal mandate and a history of international collaboration among governments and among researchers" (p. 326). She notes several factors in vetting proposals for participation in ILSAs, including other budgetary priorities, other surveys, technical issues in administering the survey, and issues related to comparability and generalizability. To a certain extent, participation in ILSAs is also driven by the other systems that are participating. Plisko (2013) identifies that US participation attracts the participation of other nations. Additionally,

> … the US looks for signals from the major European countries and from other English speaking countries as to their willingness to engage in the assessments. Something of a critical mass is necessary to ensure sufficient resources to help defray the international costs and enable meaningful comparisons of results.
>
> *(p. 327)*

Although the US has participated in a full range of ILSAs, there are a few instances where they declined to participate. For example, the US has not participated in the last several rounds of the International Civic and Citizenship Study. Compared with IEA studies, the OECD studies work differently, as OECD member states are obligated to participate in PISA.

In both TIMSS and PISA, a number of US states have also participated as independent "adjudicated systems" where they also receive state-level results (Engel & Frizzell, 2015). There has been little consistency in state participation in studies over time. In PISA, these have included Connecticut, Florida, Massachusetts, and North Carolina in previous cycles. Other states have participated in previous cycles of TIMSS, including the nine (Alabama, California, Colorado, Connecticut, Florida, Indiana, Massachusetts, Minnesota, and North Carolina) who participated in TIMSS 2011 as part of the NAEP-TIMSS Linking Study.

For this chapter, we will focus on the two largest ILSAs that the US participates in: TIMSS, which assesses mathematics and science knowledge and skills acquired by fourth and eighth graders, and PISA, which measures mathematic, scientific, and reading literacy of school-enrolled students who are 15 years of age. Table 7.1 provides a general overview of the studies, who and what are tested, how often, the sponsoring organizations, and how many systems participated in the last cycle.

Important for this chapter is that TIMSS is administered in two cohorts (grades 4 and 8) and PISA is administered in one cohort (age 15). Also, PISA assesses three subjects with one of those subjects considered the major domain and the other two are the minor domains. The major domain alternates each cycle and includes more questions on the assessment. Some of the questions on the background questionnaire focus on that topic. One disadvantage of such a design is that it is not advisable to evaluate trend results from major domain to minor domain, meaning that countries can only validly assess their trend in any one subject over a nine-year period (Rutkowski & Rutkowski, 2016). TIMSS, on the other hand, equally assesses science and mathematics, allowing for trend analysis on both domains every four years. Also, TIMSS includes background questionnaires that focus on both subjects. Interested readers who wish to know more about the studies are encouraged to visit the studies' websites, which provide a great amount of detail on the studies and what is collected. For this chapter, readers should be aware that the

TABLE 7.1 General overview of ILSAs

	PISA	*TIMSS*
How often are tests conducted?	Every 3 years*	Every 4 years
Who is tested?	15-year-old students	4th and 8th grade students
What is tested?	Ability to apply skills and competencies to "real-world" contexts	Mathematics and science curriculum
Who sponsors the test?	OECD	IEA
How many systems participated in the last cycle?	79 (2018)	64 (2019)

Note. *Due to the COVID-19 global pandemic, PISA has been delayed one year until 2022.

studies are significantly different, and that while we focus on costs of both TIMSS and PISA, a direct comparison between these two assessments is not advisable. In the following section, we detail our research concerning the costs of ILSA participation for the US at the federal level.

ILSA Costs in the US

Information on costs of ILSA in the US was collected from publicly available documents (including open data on US participation costs) from the US Department of Education's National Center for Education Statistics (NCES) reports to the US Office of Management and Budget. NCES, by mandate of the US Congress, is the major federal agency responsible for the collection and analysis of education data in the US and internationally; "NCES fulfills a Congressional mandate to collect, collate, analyze, and report complete statistics on the condition of American education; conduct and publish reports; and review and report on education activities internationally" (NCES, n.d., para. 1; see also Plisko, 2013). Every time the US conducts a study, a package of materials is posted to the Federal Register for public comment, including the plan for the study, what the study includes, the design and rationale, and how much it costs the government. These proposals are "vetted through the annual budget process, as planning for participation must begin some years in advance of administering the assessment" (Plisko, 2013, p. 327).

In this chapter, we focus on PISA 2012, PISA 2015, and TIMSS 2015. We also collected national and sub-national policy statements about PISA participation, recruitment letters, and international technical reports and websites. As a secondary source used to triangulate information collected via public online sources, we also drew on data from interviews carried out with four government officials at the state and federal level in the US: two officials in the US Department of Education and two officials from state-level Departments of Education from PISA 2012 state-level participants (Connecticut and Florida: Engel & Rutkowski, 2018).

In looking at this information, the cyclical nature of PISA and TIMSS international assessments means that their true cost per a single administration of the assessment is not easily defined. Money spent in one year may be applied to a previous assessment *and* to a future assessment; therefore, figures provided by the NCES span multiple years (see Table 7.2).

Each assessment cycle also includes in-kind burdens. These costs include administrators' time, teachers' time, and students' time for preparing, administering, and taking each test. While these in-kind burdens are small compared to the total cost of the assessments, they are included in the total cost of the assessment cycle. In the supplemental documents provided by NCES for the PISA 2015 Main Study, PISA 2015 Field Test, TIMSS 2015 Main Study, and TIMSS 2015 Field Test, a cost for administrators, teachers, and students is calculated based on the number of hours each individual would be expected to participate. To account for time spent preparing for, administering, and taking PISA tests, NCES allocated $50.00 for each administrative

TABLE 7.2 Reported overall costs for PISA 2015 and TIMSS 2015

Study	*Cycle cost*	*Number of years*	*Annual cost*
PISA 2015 Main Study	$ 4,278,915	4	$ 1,069,728
PISA 2015 Field Test	$ 2,483,434	2	$ 1,241,717
TIMSS 2015 4th and 8th Grade Main Study	$ 10,658,124	5	$ 2,131,624
TIMSS 2015 4th and 8th Grade Field Test	$ 2,578,570	1	$ 2,578,579

All figures are from supplemental documents submitted by the NCES and publicly provided on the Federal Registrar.

hour, $35.00 for each school coordinator hour and each teacher hour, and $7.25 for students. The cycle cost in Table 7.2 reflects the in-kind burdens for administrators, school coordinators, teachers, and students (only for the school questionnaire). The majority of student time – spent on test directions and taking the assessment – is not factored into in-kind burdens for students. An independent calculation of student time for directions and assessment-taking time slightly increased the in-kind costs associated with PISA and TIMSS (see Table 7.3).

Possibilities and Challenges of Exploring Costs and Benefits of ILSAs

As we uncover new information about the cost of ILSAs like TIMSS and PISA, the logical turn is whether they are, in fact, worth the investment. We consider the cost both in terms of how actual taxpayer dollars are spent, but also the

TABLE 7.3 Calculated overall costs for PISA 2015 and TIMSS 2015

Study	*Reported cycle cost*	*Additional cost for calculated student hours*	*Number of years*	*Annual cost*
PISA 2015 Main Study	$ 4,278,915	$ 190,798.25	4	$ 1,117,428
PISA 2015 Field Test	$ 2,483,434	$ 45,638.75	2	$ 1,264,536
TIMSS 2015 4th and 8th Grade Main Study	$ 10,658,124	$ 262,783.50	5	$ 2,184,182
TIMSS 2015 4th and 8th Grade Field Test	$ 2,578,570	$ 47,545.50	1	$ 2,626,125

Note. These costs are not included because those hours are not subject to the Paperwork Reduction Act of 1995.

burden of these assessments on students, schools, and state systems. On the one hand, the costs detailed in the previous section are relatively small in relation to the expansive US federal educational budget of approximately US$60 billion per year (US Department of Education, 2019). On the other hand, we acknowledge that in a system of widening inequalities, the resources allotted to ILSA participation is in fact a significant amount, and that a judgement of the merit and worth of ILSAs is prudent.

In the US system, as with many other OECD countries, one popular method of judging the merit and worth of systems such as ILSA is by employing a cost-benefit analysis (CBA) approach. CBA is the practice of quantifying the total monetary costs and the total monetary benefits of a policy, program, or project. Largely based in both empiricism and economic thought, the underlying goal is to find a way to maximize social welfare through quantification and comparison. Normally, costs and benefits are determined and then converted into monetary units (e.g., dollars, euros, yen). By quantifying both units onto the same scale, analysts are empowered with mathematical properties where, for example, they can subtract the costs from the benefits to determine the overall worth of the program. Further, the conversion to monetary units also allows for cross program comparison. So analysts could study the costs and benefits of national participation in an ILSA, funding a universal school lunch program, and providing computers to all students. In each scenario, results can be compared side by side and the most efficient project can be funded; or so the theory goes.

Calculating all costs and benefits is not for the light hearted, and there are many factors that go into such a process. In fact, the field has developed to include a range of models and processes each resulting in their own monetary cost and benefit. Each approach to CBA incorporates a different way of addressing critical questions that emerge such as: Can all costs and benefits be determined? Should both direct and indirect costs be counted? Are benefits a direct or indirect result of the program? Should indirect benefits be discounted and if so, by how much? Interested readers are referred to Boardman et al. (2017) and Gramlich (1990) for comprehensive treatments of methods and techniques for developing a CBA.

Shapiro and Schroeder (2008) explain that CBA represents an empirically based rational decision method in the policy sciences. These authors further claim that CBA is rooted in the positivist notion of science, which was adopted by many in the policy analysis community to help legitimize the field. In particular, within positivism scientific knowledge only results from observation and empirical verification. Further, for rational and unbiased policymaking to exist, it is necessary for policymakers to have unbiased and rational policy tools to make decisions (a hallmark of positivism). CBA is thus designed to meet the rigor of the scientific process in a social setting. As such, for CBA to properly work, *all* benefits must be defined and quantified. If, for example, a benefit is not entirely quantifiable, it cannot enter the model and does not exist in the eyes of the analyst.

Levin and McEwan (2001) recognize the limits of analyzing all costs and benefits in monetary terms:

> Only under certain circumstances would one wish to use cost-benefit analysis. Those situations would obtain when the preponderance of benefits could be readily converted into pecuniary values or when those that cannot be converted tend to be unimportant or can be shown to be similar among the alternatives that are being considered.
>
> *(p. 15)*

An additional limitation of CBA is that defining benefits is easily biased by an analyst's policy preferences or life experiences. In fact, the idea of placing a socially constructed value to a benefit is neither objective nor unbiased, and open to many different interpretations. Of course, in the US, with a population of over 325 million people, simply defining the groups that benefit (let alone are harmed) by the assessments could be overwhelming. For instance, would one include all policymakers at the federal and state level? In the US, where local school boards have a large influence over educational decision-making, should they also be included in the calculation? Moreover, the results from ILSAs are used outside of the policy community and are a frequent topic in educational research. As such, would it be appropriate to include the benefits to the research community? Without adequately being able to address these complexities, CBAs risk oversimplification, where simple calculations of benefits end up creating narrow, economistic, and nationalistic views of what a system gains from participating in an ILSA.

Although we have raised concerns over CBA, we fully believe that there are important advantages and opportunities to focus on the costs of ILSA participation. In fact, we favor a larger and more extensive evaluation of ILSAs, which closely examines whether these assessments meet, or as may be the case possibly undermine, the needs of the educational community. By explicitly engaging in an evaluation of ILSAs at the system level, it is possible to pave a way forward in the hope of helping national governments determine whether ILSAs are meeting system-level goals and whether individual systems are well-served by continued participation. One issue with evaluating ILSAs, however, is that the goals of participation are often poorly stated and difficult to evaluate. For example, the NCES provides two purposes for participating in ILSAs: "To learn about the performance of US students and adults in comparison to their peers in other countries; [and] To learn about the educational and work experiences of students and adults in other countries" (NCES, 2019). Such broad goals make it nearly impossible to truly judge if the assessments are meeting the needs of the system.

As such, we would encourage the US to clearly describe the purpose for participating in each study, allowing for clear analysis of the stated goals. To that end, we would also invite a more robust dialogue and debate from the education community about decisions *not* to participate, such as in the case of the International Civic and Citizenship Study. Second, we also recommend that the US government consider the needs of the research community that often spends extensive amounts of time and energy engaging with the secondary data emerging from ILSA to inform both research and policy. More active participation from stakeholders (policy and research) in developing what should be collected and why may be key to improving ILSAs and evaluating their larger worth to society.

Additionally, while we see CBA as limited with respect to ILSAs, we would argue that through a focus on the actual costs of ILSAs, it is possible to generate new knowledge about the ways in which ILSAs contribute to mobilizing new governance structures and generate varied uses and impacts across education policy spaces. This seems particularly valuable as a greater number of economies, including those that do not have national assessments and for whom ILSAs may become cost-effective assessment tools at the country level, are participating. We would invite additional cross-national investigations that generate new knowledge about costs of ILSAs, which are fruitful in better deciphering how the architecture of ILSAs are both constructed and mobilized in different settings. Key to understanding trends in datafication of education systems, examining costs of ILSAs allow us to critically investigate elements such as: (1) what policy actors identify as key driving factors of participation; (2) how systems mobilize resources to participate; and (3) what organizational governance structures surround ILSA participation. In each of these dimensions, costs help illuminate factors that bolster critical understandings of ILSA.

We would also like to propose that transparency of ILSA costs helps illuminate the linkages and social relationships *between* various actors, from international organizations like the OECD to government officials, edu-businesses, policy entrepreneurs, and other non-governmental actors (Ball, 2012; Lingard & Sellar, 2013). This is especially timely given that the scholarship on the rise and expansion of ILSA has begun to map the formation of networks and interrelationships across multiple educational stakeholders and places where education policy is influenced and made (Sellar & Lingard, 2014). Moreover, understanding costs may illuminate *how* policy flows across multiple sites and builds new knowledge about "the production, multidirectional flows and usages of data in forms of comparison and governance in education within new spaces produced by globalization" (Gulson et al., 2017, p. 229). By examining the costs of TIMSS and PISA within the US context, a couple of interesting features are revealed in how major ILSA are governed and utilized in the US context. For example, these data reveal the utilization of contractors and sub-contractors, such as Westat, Pearson, and Windwalker Corporation. Examining costs reveals also that US schools, school coordinators, selected teachers, and students are each offered financial incentives for their participation.

In light of the above considerations, we have three recommendations. First, countries need to be more transparent concerning the costs of participating in

ILSAs. The research presented in this chapter was time consuming to collect and only uncovered after multiple interviews with government officials and deep dives into complex budgets. Such complexities will be exponential in participating systems with funding structures that include international/regional organizations and/or private donors (Kijima, 2010; Rutkowski & Engel, 2010).

Second, while it may be the case that ILSAs pose minimal monetary costs for most participants, they do require resources, and it may be the case that those resources could be better allocated. As such, taxpayers, students, teachers, and administrators participating in assessments have a right to know the exact reasons that governments are expending resources to participate in ILSAs and what is to be gained from participation. Ambiguous goals and purposes for participation result in less accountability allowing governments to pick and choose when and how they use the assessment results. We are not suggesting that we monetize the benefits, but rather propose the need for clear and measurable goals. One example of such a process can be found in a framework proposed by Oliveri et al. (2018). This framework is designed to help countries consider why they are participating in ILSAs and if the given ILSA can meet the participants' needs. The process ensures that countries enter ILSAs with a clear purpose that can later be evaluated to ensure that the ILSA has met the needs of the country. Greater transparency also becomes important so that systems understand the penalties of *not* participating or only partially participating in ILSAs (Liu & Steiner-Khamsi, 2019).

Lastly, existing research has made evident that there is misuse of ILSAs, and this misuse needs to be monitored and mitigated (Zhao, 2020). While we have some understandings of what and how policy actors use ILSA data, the field continues to need a critical group of policy scholars aimed at generating new knowledge about the dynamics of ILSAs as they relate to larger trends of datafication and the rise of big data, and to ensure that governments are using the data correctly (Singer et al., 2018). Again, we are not suggesting that such information can or should be quantified; however, the misuse of ILSA data is an important thing to consider when judging the merit of ILSAs.

Conclusion

Our aim in this chapter was to focus on the US participation in two of the major ILSAs (TIMSS and PISA), detailing what we have learned to date about the costs. In discussing costs of system participation in ILSAs, we recognize the temptation to embark on a CBA. Undoubtedly, CBA has remained popular, largely because it serves the interests of a number of powerful constituencies, including the US government and the OECD, which are both proponents of the method. Our argument for this chapter is that when understanding ILSAs, calculating costs and understanding benefits may be noble endeavors, but the ability to truly calculate *all* costs and *all* benefits, as demanded by CBA, is futile and fraught with complexity and personal bias. We do, however, maintain that costs of ILSAs are a particularly fruitful set of evidence from which to better understand ILSA from more of a critical governance perspective. In particular, we noted how costs could provide vital insight into how ILSAs are built and sustained in different contexts, including by whom, for what purposes, with what organizational and financial supports, and with what consequences.

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8

DATA INFRASTRUCTURES AND THE (AMBIVALENT) EFFECTS OF RISING DATA INTEROPERABILITY

Insights from Germany

Sigrid Hartong, Annina Förschler, and Vito Dabisch

Introduction

With digital data playing an increasingly substantial role in educational practices and system monitoring, so too do the efficient and effective organization of these data. This organization refers to the networks of objects (the data itself, hardware, and software, but also policy "fragments," such as educational standards or funding formulas) and subjects (e.g., technicians, administrators, school actors, and intermediary agents) assembled around data and their socio-technical decontextualization, and recontextualization processes (data infrastructures; Hartong, 2018, p. 135). The implementation of such data infrastructures usually includes the advancement of data interoperability, which has been defined as the "ability of different information systems, devices or applications to connect, in a coordinated manner, within and across organizational boundaries to access, exchange and cooperatively use data amongst stakeholders" (Healthcare Information and Management Systems Society, Inc., 2020, para. 1). Data interoperability provides, as reform promoters argue, tremendous benefits, including fast data exchange (i.e., for teachers who need information about mobile students, for districts or schools who need to fulfill ongoing reporting requirements), an easy way to adopt personalized digital learning technologies to foster data-intensive research, and much more (US Department of Education, 2020). Pangrazio (2019) asserts that efficiencies can be achieved, saving time and money, if school data systems are made interoperable so that they can "speak to" each other without a "human intermediary." She continues that this has the advantage of enabling

> greater fluency of data across the various domains of a student's schooling experience – from enrolment and behavioral information to learning and

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> reporting. Interoperability has the potential to streamline the sharing of information in ways that impact upon all aspects of student success and wellbeing.
>
> *(para. 7)*

Driven by such potential, numerous initiatives and massive investments have emerged worldwide to increase data interoperability, including the implementation and/or expansion of so-called interoperability frameworks and/or standards. Examples include the globally active Schools Interoperability Framework (SIF) by Microsoft (now Access4Learning; see Sellar, 2017, SIF Association, n.d., Wyatt-Smith et al., 2019), the US-provider "Ed-Fi Alliance" (see Ed-Fi Alliance, LLC, 2020), but also a range of smaller or sector-specific initiatives and standard-promoting actors, such as the German Alliance for Education (see Bündnis für Bildung [bBfB], 2019). At the same time, data interoperability is also dependent on underlying technical infrastructure that allows data to be collected, processed, and used, which, as reform promoters bemoan, has remained widely deficient in many countries.

In fact, such a functional yet often technically framed understanding of data infrastructures still shapes many debates on the opportunities (i.e., infrastructures are built and interoperability increased) and challenges (i.e., both are hindered) of digitalization (Förschler, 2018; Hartong & Förschler, 2019). Simultaneously, however, there is an emerging body of scholarly work that uses data infrastructures as a fruitful conceptual and methodological tool to trace the ongoing datafication and digitalization of education from a critical perspective (Sellar, 2015, 2017). Equally, the focus is placed on the organizational process of datafication (including data interoperability), yet this process is understood as carrying substantial power nested in the selective "relation-making" and the "in-formation" of objects and subjects into "flowable" data (Hartong, 2020). In other words, attention is paid to the ongoing socio-technical (de)recontextualization practices ("infrastructuring") needed to make data relational with other data. This is to legitimize these data as neutral, valid, and "holistic" representations of education, and to make these data relevant for educational actors.

This relational understanding of data infrastructures also explains why they could be substantially disruptive for education, through the creation of a different form of policy or practical context "that 'deforms' the existing jurisdictional systems and relationships" (Gulson & Sellar, 2018, p. 10). This can occur between educational actors, institutions, or systems, as well as between public and private or between state and non-state entities. Put differently, there appears to be a pressing need to understand the who and how of data "in-formation" and relation-making, which includes multiple "data mediators" (Hartong, 2016) or "boundary brokers" (Williamson, 2016) acting within or around data infrastructures. This understanding also needs to consider the often-hidden logic of infrastructural rule-setting and valuation (Mau, 2019), which may deeply affect how education is governed based on infrastructural (de)contextualization.

Data interoperability standards are a good example for tracing such moments of rule-setting and valuation as well as (de)contextualization. This is because they build on the definition of meta-data and data models, which not only regulate which data can enter the infrastructure and be transferred from one place to another, but also how they can be algorithmically processed and, consequently, what type of information can ultimately be produced from the data infrastructure (Kubicek et al., 2019). It is standardized rule-setting (including defining data formats, data business rules or terminological frameworks of data collection) which makes data interoperability a moment of significant "disruption," as it appears increasingly important with every investment in reducing data duplication and data alternatives for measuring "apparently" the same phenomenon.

Additionally, while the initial development of data interoperability frameworks might involve substantial debate and multiple stakeholders, such frameworks have become "ready to use" products, often promoted by powerful alliances or aligned with already dominant commercial software products (such as Microsoft), and willingly accepted by educational actors who lack time and technical and financial resources. As Pangrazio (2019) observes,

> given the commercial tensions and competing interests in many areas of data and software use, the push for establishing interoperability in particular markets and sectors often falls to industry-wide groups and community interests who act as catalysts for awareness-raising, campaigning and eventual brokering of agreed standards.
>
> *(para. 5)*

While data infrastructures and data interoperability offer multiple fruitful entry points to increase critical awareness for their disruptive potential, this goes well beyond the rise of "big data," but rather occurs for any kind of data collected through such infrastructures. Simultaneously, it seems important to not underestimate the high level of context sensitivity associated with data infrastructures. For example, as more recent comparative data infrastructure analyses show, influences of national, sub-national, and local factors – such as specific accountability regimes, politico-administrative traditions, or data protection legislation – can deeply affect the actual emergence, operation, and partly also deliberate restriction of data infrastructures (Hartong & Förschler, 2019; Lingard, 2019; Takayama & Lingard, 2019). A similar contextuality occurs when distinguishing between different types of data infrastructures, such as infrastructures for policy development, for accountability, or for school practice (Hartong et al., in press). There might also be great differences between different "stages" of development or sectors within individual data infrastructures, such as modelling, administration, piloting, data collection, or reporting (Hartong & Piattoeva, 2019; Kauko et al., 2018). Finally, distinctions must be made regarding different types of data interoperability, which not only include its level (for example, the interoperability of data formats or of workflows), but also whether data collection is actually centralized or if subsystems are made interoperable without data centralization. An example of this is the German Core Data Set (Kerndatensatz [KDS]), which is discussed in detail later in this chapter (see Kubicek et al., 2019).

Following such a context-sensitive approach to better understand the disruptive potential of data infrastructures and interoperability, the goal of this chapter is to provide empirical insights into the German case which, when compared with other countries, can be regarded as a datafication and digitalization latecomer. Still, over the past decade, major transformations have been initiated, which have not only included significant expansion, standardization, and centralization of both administrative and performance data in school systems (Hartong & Förschler, 2019; Lange et al., 2014), but also – and particularly since 2012 – a growing investment in digital teaching and learning tools. While we demonstrate how context-specific conditions of possibility (Savage, 2019) strongly mediated and partly restricted data infrastructuring in Germany, we also show that emerging data infrastructures have started to change these very same conditions and will most likely become more powerful in the future. We explicate this (see "Understanding the 'disruptive' potential of data infrastructures" section below) using the transformations of standardized testing, state school monitoring, as well as school platforms/learning management systems as examples. The chapter closes with a summarizing discussion and questions that are yet to be addressed.

The German "Context" of Datafying and Digitalizing Education

Different from countries that have already created extensive educational data infrastructures and systems of e-governance such as Australia, the United States, or the United Kingdom (Hogan et al., 2016; Koyama, 2011, Ruppert, 2012; Williamson, 2016), in Germany, datafication and digitalization policies emerged much more cautiously. There are different context-specific reasons that can be identified for Germany's reluctance (see Hartong, 2019; Hartong et al., 2020). One is the German federal constitution, as states hold almost all responsibility for educational governance and use bodies, such as the Standing Conference of the Education Ministers of the German States (KMK), to defend this authority against the Federal Ministry of Education (BMBF). This also includes the centralization of data. Simultaneously, German federalism is characterized by a distinction between inner and outer school responsibilities, with the states being responsible for everything related to the content of schooling (including hiring and paying teachers, curriculum development, monitoring) and local communities being responsible for school buildings, administrative staff, and technical infrastructure (Hartong et al., 2020). To date, this distinction is reflected in the lack of links between school administration systems, statistical data, monitoring systems, and performance data.

After a shocking performance in the Programme for International Student Assessment (PISA) in 2001, German policymakers announced a "turn" towards data-based, output-oriented governance (including the implementation of national education standards and standardized testing), followed by broad initiatives to expand, better coordinate, and centralize both administrative and pedagogical data, including performance data (Lange et al., 2014). Part of these initiatives was the KMK Core Data Set resolution in 2003, in which – for the first time in German history – the states agreed to record a defined amount of nationally standardized, individualized data (including school, student, and teacher data, yet excluding test performance data). In subsequent years this initiative strongly pushed the infrastructuring of educational data across policy spaces within the German federation. At the same time, and as mentioned earlier, the KDS did not nationally centralize the data collection, but rather all disaggregated data remained within the individual state data systems. Still, however, there was a significant increase of interoperability because state data was now (supposed to be) collected in the same way. A centrally assigned student identification number – which was discussed in the beginning stage of the KDS implementation – was abandoned due to heavy protest from many states, teachers, and students. Instead, numerous states introduced their own student identification systems.

During that reform period, the influence of context also became clearly visible regarding a strong traditional skepticism against the marketization and for-profit actors in the governance of education. Hence, within emerging data infrastructures it was often research and public institutions (sometimes even established for that purpose) that became responsible for (and potentially then contracted out elements of) the development of testing, reporting, and data management tools. To date, it has remained significantly more difficult for the EdTech industry to build up or directly enter the datafication and digitalization market in Germany, compared with other countries around the world (Hartong & Förschler, 2019).

Finally, the German context can be characterized as a system of rather high teacher professionalism and autonomy, long governed through a combination of extensive professional training and the state provision of "input" resources. As a consequence, skepticism against any kind of high-stakes data, standardized or external testing, and ranking of schools has remained high, which also means teacher (but also student) data related to any performance measurement are highly protected.

While all these factors deeply affected the implementation and operation of data infrastructures and restricted data interoperability, policy developments also show how these *de facto* factors became increasingly confronted with the centralizing and standardizing, often self-reinforcing, dynamics of data infrastructuring (Hartong & Förschler, 2019), as well as with a growing number of reform promoters, particularly with the rise of the "digital agenda" after 2012 (Förschler, 2018). Since 2012, there has been a remarkable explosion of new intermediary policy networks, which brought together actors from various sectors and levels of policy, either directly (e.g., Bitkom, Digital Education Pact) or more indirectly (e.g., Alliance for Education/BfB, Forum Education Digitalization/fbd), interwoven with EdTech interests. All of them characterized Germany as dramatically lagging globally, regarding either digital education in general, or data infrastructures and interoperability in particular, as well as hanging on to an outdated federal policy architecture. Simultaneously, actors such as Dataport (see Dataport, n.d.) or the IT planning council[1] (see IT-Planungsrat, 2020), increased their investments in cross-state collaboration, data system transfer, or harmonization, as well as in coordinating the work of statistical offices at state and national levels (Hartong, 2019). This to a growing extent fostered cross-state (not supra-state) data infrastructuring, while bypassing the "old" political conflict. In various states, this also included multiple data security law adaptations, which explicitly allowed individual data to leave the schools, but not the states, if anonymized.

In 2016, both the BMBF as well as the KMK responded to these shifting policies by politically cementing a digital agenda, which heavily supported data infrastructuring, centralization and standardization. Pushed by the BMBF and KMK initiatives, 2017 and 2018 saw extensive digitalization, including the implementation of numerous digital education platforms that increasingly use single sign-on (SSO) identification tools. Such products not only envision the digital classroom, but also facilitate the linking of data generated via learning tools with other monitoring data, such as school information systems, test data, and school statistics (Hartong, 2018).

While it remains to be seen how these developments will further change the German education context, the policy transformations thus far point to the ambivalent role data infrastructuring has played, ranging from contextual restriction/mediation to infrastructure-driven change (disruptive potential) of educational (policy) context. The following section is devoted to a better understanding of this ambivalence, using three different examples.

Understanding the "Disruptive" Potential of Data Infrastructures: Three Examples from Germany

The three examples illustrated in this section point to data infrastructures that emerged for distinct purposes (for example, data to inform policymaking, monitoring of schools, and/or improvement of classroom practice). These reflect the influence of the contextual conditions of possibility mentioned earlier in this chapter, but simultaneously the substantial de-/re-contextualizing dynamics set free by the processes of infrastructuring.[2]

The Transforming Infrastructures of Standardized Assessments

After the turn to the 21st century, two "nationally" standardized assessments were introduced in Germany: (1) the sample-based Bildungstrend to compare aggregated performance data of the states and their subsequent fulfillment of the national standards set in relation to the reforms, and (2) the census-based Vergleichsarbeiten (VERA) to improve classroom practices, based on the measurement of individual students' performance, which was again oriented towards the fulfilment of national standards.

Both assessments originated from different contexts. The Bildungstrend had its roots in an oversampled PISA study to compare the states' performances in the assessment, but after 2006 it was transformed and re-designed to monitor the states' educational standards achievements and was then institutionally transferred to the newly established Institute for Educational Quality Improvement (Institut zur Qualitätsentwicklung im Bildungswesen [IQB]), under the supervision of the KMK. Still, the Bildungstrend was supposed to generate meta-knowledge about states' average performance and thus inform national policy and overall system monitoring.

In contrast, VERA originated from a test initiative by seven German states in 2004, coordinated by a university in southern Germany but used individually and very differently in each of the states to support teachers in improving classroom practices. VERA was not used for accountability or for policy development. Triggered by the emerging national reform agenda and the monitoring strategy of the KMK, however, both assessments became integrated officially into one coherent testing infrastructure, obligatory for all states and aligned with the national education standards, with the IQB taking over coordination (Hartong, 2018). This is an example of the way in which changing infrastructure alters the policy and governing context of schooling, with the IQB now not only producing extensive datapools between local, state, national, and also international contexts, but also aligning these different test contexts and contents into one coherent, standardized (and in that sense interoperable) meta-frame.

Still, however, the testing infrastructure remained significantly restricted, which is clearly visible when looking at the different parts of the infrastructuring process of test data. While the IQB is completely responsible for developing, administering, and reporting the Bildungstrend, VERA has taken the lead in developing, piloting, and scaling the tests (which also is an important practice of valuation), as well as providing standards-aligned learning tasks for teachers to support test preparation and test-related skill achievement. The states have remained responsible for administering VERA and for mediating the test data between schools and administration individually, including optional adaptations and modularization of the test due to schools' individual needs (see IQB, n.d.-a). Additionally, no individual test data are reported back to the IQB, but only aggregated data samples for test piloting and further development. The states are required to refrain from grading the test or publishing and publicly ranking the test data of individual schools (KMK, 2018). As a result of these restrictions, VERA not only still varies considerably between the states, but there is also a deliberate waiver of interoperability regarding the links between test data and grading, public platforms and also supra-state collection of individual test data (see Hartong & Piattoeva, 2019). Nevertheless, there are still significant consequences of the ongoing VERA transformations, which refer to the gradual centralization/expansion of testing into/within the IQB (lately also including the development of nationally standardized school graduation tasks, see IQB, n.d.-b). These transformations have made state test data gradually more, though not fully, interoperable. It remains to be seen how this will change further with VERA now gradually transforming into an online assessment (for example, Institut für Schulqualität der Länder Berlin und Brandenburg e.V. [ISQ-BB], for the states Berlin and Brandenburg, see ISQ-BB, n.d.) and some states already grading and reporting the test results via digital online portals (e.g., Zentrum für Empirische Pädagogische Forschung [zepf], see zepf, 2020). At the same time, there is also growing data interoperability *within the individual states*, namely between VERA data collected in the schools/for classroom development and the data systems used in the state agencies for monitoring school performance and development, explicitly made possible with the KMK's VERA resolution of 2018.

The Transforming Infrastructures of State School Monitoring

With the rise of the national education reforms, German state-level education agencies (Bildungsbehörden auf Bundeslandebene) have been urged to produce growing amounts of nationally standardized data (including the KDS and the aforementioned tests) and to use that data for more effective and efficient school leadership and monitoring. Consequently, over the past decade, investments in data infrastructures and interoperability have significantly increased, which includes data transfer between individual schools and state agencies, but also includes data transfer within different state agencies' institutions, departments, or sectors.[3]

Again, the German states approached data system transformations differently. States opted early on for either a centralized solution, in which data from all schools within the state were collected within the same data systems, or they held on to a decentralized solution, in which school data systems vary but a growing amount of standardized data reports are required to be submitted to centralized state databases (Hartong et al., 2020, p. 7). Unsurprisingly, the number of states choosing a centralized (though potentially voluntary) solution has grown, and this trend seems likely to continue in the future. This is also due to the fact that in many cases, states have either joined forces and bought (or received free-of-charge) systems from other states, or they have partnered with external providers that produce solutions for multiple states. Some of the many examples of this are Hamburg, which adopted and further developed Brandenburg's school management software WeBBSchule, and Bavaria and Baden-Wuerttemberg, which each developed its system in collaboration with the private provider ISB AG (which hosts the system edoo.sys; ISB AG, 2020).

At the same time, as mentioned above, in many states, there has remained a significant infrastructural gap between the organization of performance data – often exercised by newly founded quality and/or school monitoring institutes (Rürup, 2018) – and the more traditional organization of school statistics and resource planning. Often this occurs in concert with the statistical institutes of the states, which serve more sectors than education. For example, in Hamburg, most education data within the state school agency are centrally stored within a data warehouse, and data generated by the quality institute are still organized within a separated database. For the quality institute's work with statistical data, it receives selected data cubes from the state agency. Thus, the fragmentary nature of many school monitoring infrastructures (see Breiter & Lange, 2019) goes well beyond the gap between statistical and performance data.

Despite this fragmentation, there has been a clear shift towards data-based school supervision and consultancy practices, such as setting target agreements with principals for school development. Data used for this purpose range from financial and resource information, to aggregated test or graduation exam data and class cancellations. Different from the IQB that aligns tests nationally (see previous section), data are usually reported separately, often based on distinct data formats, time frames, or meta-data, even though some states (such as Hamburg, Brandenburg, and Bremen) try to integrate them into "at a glance" school data profiles. As mentioned previously, the German system is also characterized by a rather high skepticism towards high stakes testing data, which is especially true in relation to the usage of such data for holding individual teachers accountable. For instance, individual class or student VERA data should not be included in school supervision[4], but also unfulfilled target agreements or performance measurements in most cases do not lead to any formalized "hard" consequences for the schools (such as in the United States; for Berlin, see Baur, 2016). Importantly, this does not mean that the context of school supervision and consultancy has not become, or is increasingly becoming, affected by the ongoing infrastructuring dynamics, but rather that it seems important to closely trace how and where it is occurring.[5] Hereby, a key role is apparently played by a growing number of anonymization initiatives (in Germany, it is referred to as "pseudonymization"), which in many states have made it possible to process individual (particularly longitudinal) student and teacher data beyond the school level. Additionally, as recent debates on the implementation of a national education register indicate, transformations may lead Germany to nationally centralized individual databases (Fickermann & Weishaupt, 2019).

The Transforming Infrastructure of School Platforms and Learning Management Systems

The third example that illuminates the ongoing dynamics, as well as the disruptive potential of data infrastructuring in Germany, is the rise of school platforms and learning management systems (LMS).[6] Driven by the goal to support digital learning and teaching, while simultaneously making school data management more efficient, such platforms or LMSs often combine features such as file storage, communication interfaces, calendars, curriculum development tools, learning analytics and grading management, classroom organization, school administration, and human resource management. This means that a context-sensitive approach needs to consider the included features of a particular platform or system, how it is used by different users, and how it relates to other kinds of data infrastructures.

While school platforms or LMSs are still less common in Germany than in many other countries, their implementation significantly increased with the rise of the digital agenda after 2012, particularly with the national digitalization initiatives of 2016. As a result, a growing number of schools have implemented some kind of LMS, either individually or as part of a city- or state-led initiative. Again, there are substantial differences between the states, meaning that they each offer different market conditions for vendors. Some states developed one "ready-to-use" LMS (either through in-house initiatives or through the buy-in of vendor products), and they actively encourage schools to use that standardized technology. At the same time, even though particular vendors operate within different state markets (such as the platform itslearning), there is, at least so far, no cross-state LMS or platform operation. This disparity recently caused the federal government to initiate a national school platform solution (named School Cloud) by the SAP-associated (SAP, n.d.) research institute Hasso-Plattner-Institut (HPI; see HPI, 2020). While this initiative is still in its infancy, it recently gained tremendous momentum with COVID-19 school closures.

Simultaneously, and in response to this competing national platform initiative, mid-sized LMS providers increased their efforts and gained substantial market influence in Germany, such as itslearning. Originating from a Norwegian initiative in 1998, itslearning has become one of the leading LMS providers in Europe and beyond, until it was recently sold to the global investment organization Sanoma (Sanoma, 2019)). Itslearning is a web-based platform for learning materials, grading, curriculum design, communication, and school administration, while simultaneously offering multiple interfaces to applications, including encyclopedias, online-tutoring, and subject-specific learning tools. At the same time, itslearning actively promotes data interoperability among different stakeholders, including automated data exchange across school, parent, and state agency databases, but also features classroom data for monitoring and reporting purposes (itslearning, 2020).

In Germany, itslearning gained particular attention as part of a public-private partnership in the state of Bremen, where the state education agency not only made the platform available to all its schools, but also integrated itslearning into standard preparatory training for principals at the Bremen Institute for Teacher Training. The platform receives individual student and teacher data from the central state school monitoring system to more easily create classes, courses or to assign tasks to students.[7] At the same time, the vendor and the Bremen school consultancy agency (Institute for Schools [LIS]) worked together to refine and adapt the platform to the German/Bremen context. Importantly, this included prohibiting (technically deactivating) the processing of teachers' and students' log data and also the usage of itslearning data for any kind of supra-school monitoring.

Additionally, despite its state-wide application, schools in Bremen still widely differ in how they use itslearning. While some schools and individual teachers use the platform primarily as a file storage and communication tool, others transferred significant amounts of pedagogical tasks to the platform. Interestingly, as with the dynamics described previously in this chapter, the more schools work with itslearning, the more it seems to stimulate more extensive usage, digital centralization (of administrative and pedagogical/performance data), and the elimination of alternate products.

Conclusion and Outlook

As the three examples show, Germany offers an interesting case to trace both the importance of (restricting) conditions of possibility when seeking to understand data infrastructures and interoperability, and the actual power, or the disruptive potential, of data infrastructures for education policy, governance, and practice over time. As argued at the beginning of this chapter, this potential derives mostly from ongoing standardization (as visible in the alignment of state school monitoring infrastructure among states) and centralization (as visible in the VERA testing infrastructures or in the case of itslearning). Both include significant shifts of discourse, actor constellations, but also substantial decontextualization and recontextualization regarding which data are collected, how, by whom, and for what purpose. While the German context might, in many ways, still thwart the infrastructuring of data a lot more than is the case in other countries, in Germany such discourse and actor shifts as well as de- and recontextualization processes are already clearly visible. As an example, while the implementation of a national student identification number was heavily pushed back 15 years ago, more recent debates on a national student register go almost unnoticed by the opponents of data centralization. One important reason lies in the aforementioned shift towards "pseudonymization" as a working solution to protect individual student data, while still making these data usable for policymaking or research (see Fickermann & Weishaupt, 2019).[8] Here, Germany mirrors global discourses on data infrastructure and interoperability, which today have often either shifted towards questions of (deficient) functionality or towards requesting "good" data security laws (often named "safe data"), the fulfillment of ethical considerations or the alignment of data (collection/processing) to standards (see Wyatt-Smith et al., 2019).

While we do not argue that legal and ethical issues are not extremely important, particularly given that data misuse or abuse is still prevalent, our point is that a critical perspective on data infrastructures and interoperability should not focus on these issues alone. Put differently, important questions could be neglected as soon as the focus is put solely on the definition of standards, ethical checklists, or data ownership – all of which are not only limiting, but actually also further push (because they legitimize a particular way of) data infrastructuring. For example, what is the actual difference between individual data being collected anonymously or non-anonymously within a nationally centralized database, when in both cases these data cause "real" consequences for policy and governance? Why could it be problematic to have all data collection (done either by public or private actors) following the same standard instead of provoking disagreement, tension – or even critical reflection – on rules of data in-formation and, thus, on the ongoing politics of data and data infrastructures?

Consequently, if we take these kinds of questions seriously, a major implication for action lies in strengthening the awareness and critical understanding of data infrastructuring as the emergence of "educational settings" (Decuypere, 2019), which to a growing extent "in-form" what is made visible and acted upon as schooling. In other words, only if we better understand why such infrastructures are educational, or disciplinary, on whom and how (and here is a pressing need for further research), the modes and effects of their disruption can be grasped, problematized, and ultimately regulated. This does not mean that infrastructures form fixed modes of governance. As the case of Germany shows, data infrastructures reveal an ongoing dynamic, while always being dependent on their actual enactment, for example, by people using the data. At the same time, as the illuminated examples made clear, even for the latecomer Germany, it is this ongoing, self-reinforcing dynamic that warrants sustained global attention.

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Notes

1 Even though it is not specific to the field of education, a major federal reform in 2009 was the newly inserted Article 91c of the Basic Law, which heavily promotes infrastructure of administrative data. It promotes, "the legal prerequisites for seamless electronic communication among federal, state, and local government agencies" (IT Planning Council, 2020, para. 2). To implement this article, the federal and state governments adopted the State IT Treaty, which also included the establishment of the IT Planning Council as the body responsible for information technology cooperation in Germany.

2 The findings illuminated in this chapter derive from research data generated and analyzed by the authors from a range of previous and ongoing research projects. All projects are built on the analysis of policy documents, laws and ministerial circulars, website information, interviews with policy actors, and school officials, as well as (in the case of itslearning) participatory observations. For more detailed methodological explanations, see Datafied (2020), Hartong and Förschler (2019), and Hartong and Piattoeva (2019).

3 This for example includes interfaces between the local resident registries and school information system to monitor student numbers and school attendance, as in Hamburg or Bremen.
4 Yet allowing it at all to be used for supervision (and thus accountability) purposes can already be interpreted as an effect of data infrastructuring.
5 In four German states, this is currently analyzed in the Datafied project (see Datafied, 2020). One example of tracing these dynamics is the transformation of social indices for schools (Hartong & Breiter, in press).
6 For the purpose of this chapter, we use the terms LMS and learning platform interchangeably to refer to a particular type of data infrastructure. We simultaneously acknowledge the challenge of clear definitions, which also applies to School Management Information Systems (SMIS), Learning Content Management Systems (LCMS), and School Clouds (Breiter & Lange, 2019; Hughes & Attwell, 2009).
7 A similar development can be observed in Hamburg, where itslearning has become linked to the centralized state school portal eduPort.
8 The infrastructure of research data has been an often-underestimated driving force in the overall emergence of data infrastructure in schools. For example, and similar to the OECD, the IQB acquired an enormous database of student performance data and background information. This database is further integrated with other datasets (e.g., PISA) within an IQB in-house research database, which makes it available for re-analysis and secondary analysis.

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9

DATAFICATION AND SURVEILLANCE CAPITALISM

The Texas Teacher Evaluation and Support System (T-TESS)

Jessica Holloway and Steven Lewis

Introduction

The election of Donald Trump as president of the United States (US) in November 2016 will likely be remembered as one of the greatest upsets in modern political history. What was thought to be a sure win for candidate Hillary Clinton quickly turned into a shocking defeat, leaving political experts rattled and searching for new analytical tools to help explain their miscalculations. More recently, details have emerged about the (previously) little-known data analytics company Cambridge Analytica and its role – and that of data more generally – in securing the Trump Presidency, reflecting the increasing power that big data and technical analytics exert over the daily lives of citizens. What the public learned was that their seemingly private participation on various websites (such as Facebook) was being tracked and collected, often without their knowledge or express consent. These data were then "mined,"[1] sold, and analyzed for profiling potential demographic and political factions within the US electorate, meaning people were targeted for political grooming via specific advertising and content.

Although polling techniques and political targeting are constant and consistent features of modern politics, what made Cambridge Analytica so unique was its purposeful disregard for the human candidate. While traditional campaign techniques might start with a candidate's policy position and then use polling data to craft a targeted message for a particular constituency, Cambridge Analytica started with the data and instead worked backwards. The company first used data mined from social media sites to identify the "mood" of constituents, before testing various emotive messages to craft a policy position. Relying on years of harvested data and message testing, Cambridge Analytica helped manufacture the perfect primed candidate for any given electorate. The candidate needed not be

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ideologically sound, socially pure, or experientially prepared, but merely "programmable"; that is, capable of being encoded with tried and tested scripts, be they "Make America Great Again," "Build the Wall," or "Lock Her Up."

Under these circumstances, the government outsider, Donald Trump, cannot alone be credited for orchestrating the defeat of Hillary Clinton and the political establishment writ large. Rather, he was in many ways the vessel for a broader resurgence of reactionary nativism, parochialism, and protectionism, albeit tempered with the predictive power of contemporary big data and technical analytics. Indeed, then-Chief Executive Officer of Cambridge Analytica, Alexander Nix, was recorded observing that "they're politicians, they're not technical. They don't understand how it [data analytics] works" (McKee, 2018, para. 12). In this brave new world of datafication, it is the (exceedingly private) world of software engineers, data miners, and program developers who steer campaigns, forge candidates, and shape public opinion.

While the public grapples with the unprecedented and unforeseen influence of "big data" and analytic techniques in recent campaign and election processes, other public domains are similarly being subjected to the datafication of practices, services, and people. Education, for example, has been particularly reconceptualized by digital data, as well as the technicians and statisticians that produce, analyze, and disseminate such data (Williamson, 2016a, 2016b). In this chapter, we look to the schooling system in Texas (US) to illustrate how schools and teachers are becoming sites for data collection that can potentially feed the growing market of what Zuboff (2019a) called "surveillance capitalism." We analyze the public-private partnerships (PPPs) between Texas public schools and three organizations: SAS Institute Inc., Responsive Learning, and the National Institute for Excellence in Teaching (NIET). In collaboration with the Texas Education Agency (TEA), these groups have built the Texas Teacher Evaluation Support System (T-TESS), which is used state-wide to manage a broad array of schooling processes. T-TESS is an ensemble of digital services, applications, and analytic reporting that relies on various modes of statistical calculation, prediction, and computational processing to monitor and evaluate teachers. Our purpose in this chapter is two-fold: first, we identify the roles, techniques, and features of the partners' contributions to the T-TESS, and second, we use contemporary thinking around "datafication" (Bradbury, 2019; Williamson, 2015) and "surveillance capitalism" (Zuboff, 2019a) to examine how these actors contribute to, as well as stand to benefit from, their partnerships with schools in Texas.

Specifically, we will look at how the T-TESS platform and evaluation system has enabled external organizations to establish prominent positions in the Texas education system. The varied expertise, capabilities, and strategic efforts of these organizations have secured them roles as key providers of evaluation, professional development, and data-related support. This has led to, for example, revenue incentives and streams for non-public institutions, and the ability for private actors to gain access to data that can be used for private, business-oriented purposes. In concert with the intensifying datafication of education, and the abundance of personal data through interactions with software platforms such as the T-TESS, we suggest that schooling, and the teaching profession itself, are becoming increasingly positioned as fertile ground for the unleashing of surveillance capitalism.

The Datafication of Teachers and Teaching: Providing Fertile Ground for Surveillance Capitalism

In recent years, there has been a significant increase in data collection and use in education globally, reflecting the relevance of numbers (Ozga, 2016), data (Selwyn, 2015), data visualizations (Williamson, 2016b), and software platforms (Decuypere & Landri, 2020; Lewis, 2020) for purposes of measuring, comparing, and governing school performance. Powerful trends in educational policy to establish high stakes teacher accountability systems have led testing, evaluation, and dis/incentivization to become key drivers that shape teacher practice and define teacher "quality" (Bradbury & Roberts-Holmes, 2017; Holloway et al., 2017; Lingard, 2010), informing such significant considerations as performance pay, promotion, and retention. There is now a growing consensus within education literature that this form of high stakes accountability undermines teacher expertise, authority, and professionalism; constrains the capacity of teachers to act on their own professional knowledge, experience, and discretion; and risks endangering reputations, career progression, and jobs (Hardy, 2018; Holloway, 2014; Thompson & Cook, 2014).

Indeed, the notion of teachers being deemed "risky" subjects (Hardy, 2015; Holloway, 2019) has itself become dominant within high stakes accountability regimes and political rhetoric, with teachers discursively positioned as potential impediments to future student performance and national economic prosperity, and in need of policy interventions that might mitigate such risks. Following such logic, compliance-based teacher accountability has become increasingly prevalent, and at the same time, particularly challenging to teacher professionalism, as modes of standardization, datafication, and evaluation narrow the possibilities for teachers to rely solely on their professional knowledge, training, and experience (Hardy, 2018; Lewis & Holloway, 2019). Rather, teachers face increased pressure to employ numerical data (i.e., from standardized literacy and numeracy tests), evaluative tools (e.g., observation rubrics), and prescriptive definitions of "what works" (Lewis, 2017a, 2020) to guide their pedagogical decisions and classroom practices (Bradbury & Roberts-Holmes, 2017).

This emphasis on using (largely numerical) data to inform teacher practice and school policy is concurrent with moves towards what have been described as digital, or algorithmic, modes of governance (Williamson, 2015, 2016a, 2016b), reflecting the "apparent power, agential capacity and control that algorithms command of our lives" (Neyland, 2015, p. 199). Such developments have accompanied the unprecedented growth and use of digital forms of data in education governance, expressed as increasing volume, velocity, and variety (the "three Vs"). This has resulted in school practices increasingly collapsing into data management practices, typified by what Selwyn et al. (2015) have tellingly described as teachers and principals having to curate "200,000 lines on an Excel spreadsheet" or "the biggest spreadsheet in the world" (p. 771), rather than focus their attention and energy on more educative considerations (such as pedagogy and curriculum). Central to understanding the logic that underpins algorithmic modes of governance, the power attributed to algorithms emerges through "non-numerical objects" (e.g., teachers and students) being rendered in numerical terms (such as, value-added scores and teacher observation scores), with algorithms recursively defining numerical outputs as the basis for subsequent inputs (Neyland, 2015). Translating complex social domains and practices like schooling into numerical data to be iteratively fed into a centrally coordinating algorithm also, arguably, provides fertile opportunities for digital software platforms and their providers to occupy a significant role in policymaking and practice.

As such, we find ourselves in a moment when the unprecedented need for, and generation of, performance data in education is drastically reshaping schooling. Alongside demands for increased accountability and transparency in public schooling, these data have produced new urgencies around finding "evidence-informed" (Lingard, 2013) solutions to putative problems of policy and practice. This desire for "fast policy" solutions (Lewis & Hogan, 2019; Peck & Theodore, 2015) and the increasing centrality of digital software platforms in school governance have produced a new market for policy populated by new service providers, with efforts to identify "what works" occurring in tandem with the increased presence of non-government organizations in education. As such, powerful transnational private policy networks, which encompass intergovernmental organizations, for-profit businesses, not-for-profit agencies, and the philanthropic sector, now contribute to a global education industry that is reportedly worth more than US$4 trillion annually (Verger et al., 2016).

As others have argued elsewhere, the involvement of private actors in public matters (like education) is problematic for a number of reasons, including the possible fundamental conflicts between private and public interests (see Lewis, 2017b; Verger et al., 2016). However, recent developments have seen the focus of these concerns shift from the presence of private actors in public spaces, such as schooling (for example, for-profit edu-businesses providing services), to what is potentially now the wholesale collection and selling of private (as in personal) data by private organizations. In her book, *The age of surveillance capitalism: The fight for a human future at the new frontier of power*, Zuboff (2019a) develops this critique to suggest that private companies not only make money for the services they provide to public entities, but that it is the data these companies can collect via such arrangements that hold the real value. Here, the "primary" service provided by the company serves as a vehicle through which the company can collect user data, rather than the product or service being the primary end goal for the company. Zuboff (2019a) argues we are currently experiencing a massive shift towards surveillance capitalism, with the underlying focus being the raw data that companies (such as Google and Facebook) collect and then use for other business purposes. This is colloquially referred to in the technology industry as "data exhaust."

Importantly, such an approach dictates that all data are valuable, regardless of their original purpose (either actual or perceived by the user) or the means by which the data were collected. When big data analytics are applied to these massive data sets, inferences can then be drawn about all types of matters (e.g., political preferences, hobbies, religious affiliation), and this information can be used to inform targeted advertising. Zuboff (2019b) suggests that the evolution of capitalism involves the commodification of non-market products and practices. She further suggests that this is,

> how we turned making a living into "labor" and nature into "real estate." Surveillance capitalism now claims private human experience as free raw material for translation into behavioral predictions that are bought and sold in a new kind of private marketplace. And it takes place almost completely without our knowledge.
>
> *(para 4)*

While a given public consists of people from different geographic locations, demographics, political persuasions, and so forth, surveillance capitalists flatten these differences to see people simply as "users"; that is, generators of data via "private human experience" that can then be commodified and on-sold. This transforms the complexity of our (otherwise private) thoughts, desires, intentions, dreams, fears, histories, etc., into a digital dataset, the analysis of which enables these subjective human dispositions to be profitably identified and steered.

It is also worth noting that surveillance capitalism is entirely dependent on a dual process that Zuboff (2019a) has termed "rendition," whereby human experience is translated, so to speak, into a datafied version that is amenable to collection and analysis. The polysemic quality of the term "to render" is especially helpful here. On one hand, it describes how something is intentionally converted from one form to another; on the other, it means to deliver or surrender something, often in an obliging way, as in the invocation to "render unto Caesar" in the Gospel of Saint Matthew (see Zuboff, 2019a, p. 234).[2] Taken together, we can see how surveillance capitalism requires rendering private human thoughts and actions into data (as datafication), as well as our active (and often consenting) giving of these data via engagement with technologies and software platforms that can perform these collections and translations.

While we are admittedly yet to see the broad adoption of surveillance capitalism in education specifically, recent trends in datafying teachers and teaching –

often for purposes of accountability – arguably position schooling as fertile ground for development by surveillance capitalists. This is especially so in the US, where the use of certain accountability tools and mechanisms, often by external providers, has historically been legislatively mandated or, at least, incentivized by federal grant initiatives (such as the Obama Presidency's "Race to the Top" program). Given the already close relationship between schools in the US and private technology firms that frequently provide these data-related services, there is the risk that processes of datafication might, if unchecked, provide the ideal conditions for surveillance capitalism to emerge. In order to explore these possible concerns, we now turn our attention to the T-TESS, which is a specific example of a technology-based school accountability platform in the state of Texas.

Teacher Accountability and the T-TESS

Texas has a long and contentious history with test-based accountability. In fact, the No Child Left Behind (NCLB) Act has been largely credited to the Texas education system (and the Houston Independent School District, in particular), which was described by then-President George W. Bush as the "Texas Miracle" (Leung, 2004). Regarding teacher accountability, Texan teachers have faced high stakes consequences for decades, including (to varying degrees) termination for failing to "add" enough "value" to their students' test scores on large-scale standardized assessments (Amrein-Beardsley & Collins, 2012). The state's current teacher evaluation system is the Texas Teacher Evaluation Support System (T-TESS). This comprehensive, state-level framework is comprised of three main components: goal-setting and professional development, evaluation, and student growth measurement.

In terms of goal setting and professional development, and evaluation, the T-TESS provides rubrics and resources for schools and teachers, including video training modules, handbooks, and conference templates. The third component, student growth measurement, requires districts to develop an appropriate system for determining student achievement growth, and this can be in the form of portfolios, student learning objects (SLOs), or value-added measurements (VAM). VAM, the most controversial approach – but arguably the most statistically sophisticated (Berliner, 2018) – has been used widely across Texas (and the US more broadly) for decades. It is designed to measure student growth from one year to the next, on state-wide standardized achievement tests, and link that growth to their teacher. In effect, student performance gains become a proxy for teacher effectiveness. The teacher's VAM score is then used to inform evaluation and various personnel decisions, such as retention, professional development, and promotion. In the T-TESS, the overall student growth score is combined with observation scores to calculate the teacher's cumulative evaluation score (which is perceived to be a measure of their effectiveness).

While high stakes teacher evaluation is by no means new in Texas, the T-TESS is unique in three main ways: its use has been mandated for the entire state;

it was designed almost entirely by private agencies (which will be detailed in the analysis section of this chapter); and most of the T-TESS operates digitally via an online platform, with the T-TESS applications used for teacher observation and evaluation. In addition to features associated with teacher accountability, "T-TESS Cube" provides online professional development and training modules for teachers and appraisers to learn about the T-TESS and increase their respective T-TESS scores. Participation in these courses can also be tracked by school and system leaders. Altogether, the T-TESS generates and collates as many data points as possible to build a development and proficiency profile for each teacher, with each domain of a teacher's professional practice (including their engagement with the T-TESS platform) able to be datafied and tracked.

Our analysis of the T-TESS began with Selwyn's (2015) prompt to engage with

> empirical work that strives to understand and account for the manner in which data are accumulated; to make visible the flow and circulation of data and begin to understand the ways in which data are then integrated back into everyday education practices.
>
> *(p. 76)*

The current chapter picks up where Holloway and Lewis' original analysis left off (see Holloway & Lewis, in press), by explicating the actors and agencies involved in the T-TESS, and exploring how the T-TESS might serve as a vehicle through which companies can prospectively engage in surveillance capitalism within public schooling systems. To this end, we collected and analyzed all publicly available resources associated with the T-TESS. This included, but was not limited to, service contracts, company websites, terms of service agreements, implementation guides, training materials, and reports associated with external partners (e.g., reports produced by SAS Institute Inc.). Guiding our analysis were three specific questions: (1) What agencies and actors are involved in the creation of the T-TESS?; (2) What types of data are collected via the T-TESS?; and (3) How might these data serve the processes and logics associated with surveillance capitalism?

The T-TESS Ensemble

The T-TESS comprises an ensemble of actors and agencies who work in partnership with the TEA (the official state-level department for education in Texas), with these digital and analytic groups providing the technical expertise and services for calculating, analyzing, and evaluating teacher practice and performance. For this chapter, we have focused on three of the main private organizations that have contributed to the T-TESS, even though others have been peripherally involved over time: (1) SAS Analytics Inc., (2) Responsive Learning, and (3) the National Institute for Excellence in Teaching (NIET). Next, we provide a brief description of these groups, including their primary services and involvement in the Texas education system.

Rendering Teacher Performance as Data: SAS Analytics Inc.

SAS Analytics Inc. is an analytic software company that owns the Education Value-Added Assessment System (EVAAS), which is a sophisticated value-added model (VAM). VAMs are statistical algorithms that operate by predicting how students should score on standardized achievement tests, comparing their actual achievement score to the predicted score, and attributing this difference (positive or negative) to the student's teacher. This number represents the degree of "value" the teacher has added to (or subtracted from) student growth.

The school year following the analysis, teachers receive a value-added report and a diagnostic report, which display statistics related to their growth measure, standard error, and effectiveness levels, as well as their students' overall progress. These reports are expected to be used to inform teacher practice, even though the reports are received well after the students (and often teachers) in question have progressed to another grade level. All of these predictions are calculated from large data sets that allow data analysts to group students according to "like" testing histories. Using these historical trends, they then employ a predictive algorithm to determine how much growth a student should make in a single school year. This approach to measuring student performance putatively provides a more nuanced and unbiased view of a teacher's influence on student achievement, even though research has shown consistently that VAMs are still biased and unreliable (see Johnson, 2015).

As of 2016, it was intended for SAS Analytics Inc. to partner with the entire state of Texas to provide VAM services. However, after the No Child Left Behind Act was reauthorized, and subsequently changed to the federal Every Student Succeeds Act (ESSA), states could return control of determining the student growth component of teacher evaluation back to local education authorities. Although Texas still required districts to maintain some form of a student growth model in their teacher evaluation systems, districts were permitted under ESSA to choose their own VAM. At the time of writing, SAS Analytics Inc. still partners with several districts in Texas to provide VAM services via SAS EVAAS. They have also partnered with schools and/or districts across the US, making them one of the most prominent for-profit providers of VAM methodology in the country (Amrein-Beardsley, 2008).

Rendering Teacher Behavior as Data: Responsive Learning

Responsive Learning is a for-profit, online learning platform that works with schools and other education agencies to develop online courses, such as professional development courses for teachers. According to their website, the company "brings together thought-leading authors, trainers, and practitioners to create engaging online professional learning for teachers that builds a bridge to instructional practice in the classroom" (Responsive Learning, 2019, para. 1). TEA partnered with Responsive Learning to develop T-TESS Cube, an online professional development site where teachers can take various courses to help improve their performance as measured by the T-TESS. The online library consists of hundreds of videos, with many tagged specifically for the T-TESS preparation and development. A small number of these videos are specifically designed for the T-TESS itself (such as "Unpacking the T-TESS Rubric"), while the vast majority of the videos cover related topics that have subsequently been identified by Responsive Learning as being relevant to specific elements of the T-TESS framework. Principals or superintendents can request a free license that provides their teachers with access to a series of 15-minute mini courses that each align with the T-TESS rubric dimensions. All other videos and/or courses require payment for each participant, be they teachers, principals, or superintendents.

Rendering Teacher Experience as Data: NIET

The TEA has worked with the NIET for many years. The NIET is a non-profit organization that develops education programs closely aligned with various federal grant schemes. For instance, their TAP System for Teacher and Student Advancement (hereon referred to as the TAP System) has been particularly prominent within various federal grant schemes. The TAP System is a comprehensive evaluation system that incorporates ongoing observations, targeted professional development, VAM scores, and performance-based pay. TEA initially became involved with the NIET after winning a grant, after which TEA adopted the TAP System as their performance-based teacher evaluation system. At the conclusion of the grant, TEA kept major components of the TAP System rubrics and procedures, and these provided the basis upon which the T-TESS was subsequently designed. More than 200 schools in the US have since implemented the NIET's TAP System, making it one of the most popular teacher evaluation system providers in the country.

Together, SAS Analytics Inc., Responsive Learning, and the NIET have produced the T-TESS framework, which defines what it means to be a public school teacher in Texas. Although each of these actors is located outside of the education profession, their analytic and digital experts have developed a technical program that defines quality for teachers and teaching in the state. Within the broader processes of datafication, these three organizations have been authorized by the state of Texas to develop and administer the T-TESS, which also entails the wholesale collection of private data when teachers engage with the platform. It is also worth noting that the obligatory nature of the T-TESS, insofar as core aspects of teachers' work (e.g., goal-setting, evaluation, professional development) must be completed on the platform, means that T-TESS ensures a steady stream of user data for SAS Analytics Inc., Responsive Learning, and the NIET alike.

Discussion and Conclusion: The Possibilities for Surveillance Capitalism via the T-TESS

Surveillance capitalism is, foremost, imbued with an economistic logic, which allows one to imagine the value of data not only for their present intended use (such as optimizing search terms on Google) but for what they might reveal in the future about the private interests, desires and actions of the human actors generating these data (e.g., voting intentions). It marks a significant departure from the modernist project in which one generates empirical data to respond to a particular known problem or question. Instead, data are cast as exchangeable and tradable commodities, to be bought and valued by different actors to provide solutions to as-yet unknown questions. Despite the behavioral predictions that might be derived from mining big data sets, or the actors or organizations who might seek to gain influence (or be influenced) by these predictions, it is the overwhelming collection and analysis of data that clearly animates this entire process.

Turning to teacher accountability generally, and the case of T-TESS specifically, we can see an entirely new and unprecedented means of datafying teachers throughout their career trajectory, a cradle-to-grave approach that encompasses initial teacher education, teacher evaluation, and ongoing professional development, with the resulting data collected, stored, and analyzed on a single software platform. In the context of teacher accountability, which is a central consideration in the US, the increased scope and scale of data collection via the T-TESS need not imply that all such data renderings of teachers are now considered "high stakes." While the T-TESS clearly includes data used for purposes of teacher evaluation and promotion (or sanction), such as the value-added scores provided by SAS EVAAS, it can also collect and analyze data that is altogether more mundane, at least at first glance. For instance, the platform has the capability to determine the time teachers spend on the learning resources provided via the T-TESS Cube, which resources they access, and how they interact with these resources (including time on screen, attempts made, and mouse clicks); that is, the secondary metadata that Zuboff (2019a) describes as "data exhaust."

While these data are unlikely to inform critical decision-making around a teacher's nominal effectiveness, and thus impact their tenure or retention, these data are still valuable in the sense that they provide a digital record of a given teacher's interactions with the T-TESS platform. Through the lens of surveillance capitalism, it is these data that are potentially most valuable, at least in a monetary sense, as they can render teachers – their actions, their thoughts, their aspirations and fears – as data to inform subsequent targeted marketing of products and services (e.g., teacher professional development, university courses, professional memberships, and mindfulness retreats). In some cases, it might not even be entirely clear what the data could be used for in the future. But, given that surveillance capitalism positions data as a valued resource in itself, this may well distort the incentive for private providers to (for instance) develop VAMs that are more or less useful for teachers, or even to improve VAMs to be more precise measures of teacher quality.

Although the TEA may have primarily aimed for the T-TESS to provide feedback on teacher effectiveness as a notional benefit to public schooling, the data traces left by teacher activity on the platform still have the ability to be commodified and exploited for private profit by those who administer the platform. Moreover, this provides the developers of the T-TESS – all private for-profit and not-for-profit entities – with the ability to gather an unprecedented amount of data on the teachers involved, the danger being that the data are then used to better know and steer teacher behavior through strategic promotion and incentivization. We also note that financial motivations risk displacing, or at least pose a significant challenge to, more educative public objectives around enhancing student learning.

To reiterate, our intentions here are not to impugn the motivations or intentions of the various for-profit (SAS Analytics Inc., Responsive Learning) and not-for-profit (NIET) actors associated with developing and administering the T-TESS ensemble. Nor do we seek to make specific claims to their actual present (or prospective) uses of the data, especially given that much of this information is obscured by commercial-in-confidence agreements and other contractual arrangements. Rather, we have sought to draw attention to the new and varied means by which all facets of teaching can now be rendered as data via the T-TESS platform, the prospective implications for how these data can be commodified and sold, and the potential ways this exposes teachers (as both individuals and private citizens) to targeted means of advertising and influence. As noted earlier in this chapter, while many of the tools and techniques of the T-TESS are similar to more traditional forms of teacher observation and evaluation, the comprehensive collection and storage of data on a single digital platform, developed by multiple private organizations, creates its own unique set of concerns.

Revisiting our earlier provocation about the influence of data analytics in the governing of social domains, and how this provided a previously unimaginable pathway for the election of President Trump, we would emphasize the danger associated with the ubiquitous nature of data analytics – and especially the commodification of data – in our everyday lives. Using the T-TESS and its contributing partner organizations as a case in point, we have sought to demonstrate how datafication in schools provides fertile ground for surveillance capitalism to infiltrate and take hold, with these new private logics and practices often contradicting more publicly oriented motivations. As Zuboff (2019c) asserts, surveillance capitalism is on "a collision course with democracy" (para. 4). We must therefore acknowledge the privileged positions of the actors and agencies who have been authorized to participate in the Texas schooling system, as well as the financial and political opportunities that these privileged positions afford. As schooling becomes increasingly datafied, and thus becomes a more attractive target for surveillance capitalism to (mis)appropriate, we must be ever vigilant against the possibility that data, rather than student learning, become the most valuable product of education.

Notes

1 The commodification of data is implicitly suggested by the popular and academic adoption of the verb "to mine" (that is, data mining), which we would argue equates data to any other such interchangeable or fungible commodity (such as oil, coal, or gold) that can be extracted, refined, and then sold for profit, with no concern given to the actual producer of the commodity.

2 A more recent (and unfortunate) interpretation of the term "rendition" occurred in the context of the so-called War on Terror, in which the US Government-sponsored abduction and extrajudicial transfer of "illegal combatant" prisoners, often for purposes of detention and torture, was euphemistically described as "extraordinary rendition." While of an altogether different nature, the rendition associated with surveillance capitalism is perhaps more dangerous because of the extent to which it has become normalized and accepted in contemporary society; that is, because of its sheer "ordinariness."

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10

GOVERNING BY DASHBOARD

Reconfiguring Education Governance in the Global South

Radhika Gorur and Ben Arnold

Introduction

There is something distinctly different being imagined by global aid agencies about how education is, or should be, governed in low-income nations. In the race to achieve the globally agreed goals under the United Nations Educational, Scientific and Cultural Organization (UNESCO)'s Agenda 2030, a discourse of crisis is being evoked. This crisis is not so much a learning crisis, as a data crisis (Gorur, 2019). The data crisis is epitomized in the words of two of the most influential global actors in education today: Silvia Montoya, Director of the UNESCO Institute for Statistics (UIS; which is the custodian of education data under the Sustainable Development Goals [SDGs]), and Luis Crouch, Senior Economist at RTI International. Montoya and Crouch (2018) assert that without the appropriate data on a range of indicators, the most well-meaning and determined Ministers of Education in the Global South could not succeed in improving education. They identify that in many countries:

> … education ministers simply don't have the data to avoid or even mitigate a global learning crisis, which is engulfing more than half of all children of primary and lower secondary school age, according to estimates by the UNESCO Institute for Statistics.
>
> *(p. 2)*

Conjured up here is not just an abundance of data, but a particular arrangement of data in the form of a dashboard. The beleaguered education minister sits behind a dashboard of "navigation instruments" – lights flashing and machines beeping – urgently trying to correct a system headed for disaster. The visualized

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data are ready to go – transformed into actionable levers that can be pulled and pushed to instantly elicit desired responses.

Dashboards signal not just urgency, but agency. Like pilots in a cockpit, ministers and policymakers are depicted as being able to control the destiny of the enterprise through deft management. This image of "governing by dashboard" (Bartlett & Tkacz, 2017) is not just an intensified version of the datafication and governing by numbers of the past three decades (Gorur, 2015; Lingard & Rawolle, 2011; Miller & Rose, 2008); it represents a new phase, bringing together understandings of how governments ought to run with new technologies to enable decision-making. This mode of governance is not about periodic surveys, five-year plans, commissions, and reviews premised on a systematic, managerial, bureaucratic approach. Instead, governance is a pitched battle, fought in real time.

This sense of urgency and agency, and the imaginaries of new modes of tech-enabled, data-rich governance, are now reflected in evolving global approaches to aid effectiveness. The failed African aid projects of the 20th century taught aid agencies that technical and financial assistance would be ineffective unless the political and policy environment and the bureaucratic machinery were also transformed (Kaufmann, 2009). Consequently, aid agencies sought to also reform these enabling conditions, namely the socio-political and administrative apparatus of recipient nations. This kind of "systems thinking" emerged as a paradigm shift in the field of development (OECD, 2019). Now, aid recipient nations are "partners" who "own" the development project. They are expected to reflect global priorities in policy formulation and to reform in-country systems to enable more effective deployment of aid (OECD, 2020).

Even as recipient nations are delegated greater responsibility for aid effectiveness and urged to "own" the program, they are also closely monitored to ensure ongoing compliance. Recent decades have witnessed the rise of global data infrastructures that serve as sophisticated monitoring mechanisms (Jensen & Winthereik, 2013). Beyond the significant functions of transparency and accountability, these infrastructures provide common epistemic frameworks for aid and development. This enables the task of harmonization and alignment of goals. Data infrastructures fold in particular epistemologies of education governance and nudge particular types of action. The systems thinking adopted by aid agencies has enabled data infrastructures to also serve as governance infrastructures. Dashboards are now increasingly popular features of global governance infrastructures, representing a style of governance that is vigorous, responsive, and results oriented.

In this chapter, we explore the phenomenon of global governing by dashboard, with an empirical focus on the Global Education Policy Dashboard (GEPD) being developed by the World Bank in conjunction with DFID (the United Kingdom's Department for International Development) and The Bill and Melinda Gates Foundation. The GEPD is set to be piloted in 13 countries across Africa, Asia, the Middle East, Latin America, and Eastern Europe (Root, 2019).

Currently five countries have been identified for the first phase of trials, with work at an advanced stage in Peru. The GEPD aims to facilitate the monitoring of the indicators that "drive" learning, from teacher preparedness and school management to "politics, [and] other actors that are affecting everything that is happening in the service delivery level" (World Bank, 2019d, p. 62).

While the dashboard itself is not yet publicly available for viewing, a substantial amount of information is available in World Bank materials about the dashboard, as well as the indicators that underpin it. In our analysis, we have drawn on press releases, presentations and policy briefs about the GEPD; the World Development Report 2018 (the theoretical framework used for the dashboard); the Human Capital Index website (the parent project for the dashboard); and a range of other materials, including "Teach" reports and instructions, the Bureaucracy Lab website, the World Management Survey website, and the Systems Approach for Better Results (SABER) website.

Williamson (2016) notes that dashboards are "the hybrid product of political aspirations to manage and orchestrate the flow of… data [and] the capacity of software to provide an apparently neutral, non-political interface" (p. 131). We build on this understanding to demonstrate that, beyond influencing governance through orchestrating data flows, dashboards are a sociotechnical imaginary that imagine and promote particular forms of governance. We seek to describe and highlight the politics of global data dashboards because their politics, though extremely consequential, are not always obvious or even visible. We have refrained, for the most part, from critiquing particular instruments because we wanted to maintain focus on demonstrating how the governance prescriptions embedded in such dashboards, which seek to improve aid effectiveness, might inadvertently be undermining some key principles of aid effectiveness.

Dashboards in Governance

Stephen Few (2007) states that "a dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance" (p. 1). Originally designed for monitoring activity with a view to informing action, dashboards are also a means of dealing with information overload, since they present purposefully curated data on a single screen (Yigitbasioglu & Velcu, 2010). Most widely deployed in business intelligence, dashboards are now used in a variety of contexts including health management, education, and smart city governance (Sarikaya et al., 2019).

Muscular, tech-savvy, data-driven "governance by dashboard" is part of the contemporary sociotechnical imaginary of governance. Jasanoff and Kim (2015) describe sociotechnical imaginaries as "collectively held, institutionally stabilized, and publicly performed visions of desirable futures, animated by shared understanding of forms of social life and social order attainable through, and supportive of, advances in science and technology" (p. 4). The notion of sociotechnical imaginaries draws together the technical and the social as mutually productive. For Jasanoff and Kim (2015), sociotechnical imaginaries are not only about norms and discourses, but also about science and technology; consequently, the social and technical must be analyzed together. Understanding the relationship between the social and the technical requires also taking account of the "often invisible role of knowledges, expertise, technical practices and material objects in shaping, sustaining, subverting or transforming relations of authority" (Jasanoff, 2004, p. 4).

The sociotechnical imaginary of "governance by dashboard" anticipates certain relations, effects and forms of authority. "They encourage more intensified forms of monitoring and analysis. Through their increased presence, they change the empirical basis from which decisions are made and also the criteria for what counts as a good decision" (Bartlett & Tkecz, 2017, p. 8). The Number 10 Dashboard, designed for the Prime Minister of the United Kingdom, illustrates dashboard governance in action. "With a few taps or swipes of his fingers, [the Prime Minister] can see very quickly what important new information has come to light, how certain government services are performing and a selection of relevant and important news reports" (Cabinet Office, 2012, para. 4).

Bartlett and Tkacz (2017) argue that "government, too, was becoming part of the big data revolution" (p. 7). The Number 10 Dashboard used "the latest technology to pull data from a huge variety of sources" (Cabinet Office, 2012, para. 8), and the Prime Minister "liked the statistical side, where we could give him quotable facts about what was going on. He found it useful to have a hard evidence base" (para. 6). The Number 10 dashboard gave the Prime Minister "instant access to GDP, bank lending, jobs and property prices plus polling data and Twitter feeds" (Gibbs, 2014, para. 6).

Dashboards also usher in new opportunities for digital democracy and citizen participation. Many are open to the public, expressing government's commitment to open communication and transparency. The visualization techniques used in the dashboard make data accessible to a wide range of users, and interactive interfaces allow citizens to provide suggestions and set visualization preferences. Perhaps the most visible and interesting use of dashboards has been made in governing "smart cities." In the United Kingdom, for example, a stream of real-time data (including London Underground rail line status, the availability of bikes for hire, weather and air pollution levels, live local news, and stock market updates) combine on large displays – or iPad walls – to enable citizens to interact with the dashboard in passing. These dashboards also allowed the Mayor of London to "look over the capital digitally as well as physically" (Bartlett & Tkacz, 2017, p.12). As Kitchin et al. (2015) report, "open data and dashboard initiatives are changing… the relationship between government and the public" (p. 7).

In international development, dashboards have emerged as a popular tool to monitor outcomes in a range of fields, including health, education, the environment, peace, justice, and security. The SDG Dashboard tracks the progress of nations towards all 17 SDGs. The World Bank, The United Nations Children's Fund (UNICEF), and DFID supported the development of several national and sub-national data dashboards with funding and expertise to ensure policymakers, bureaucrats, and other stakeholders have relevant, up-to-date information to enable good decision-making. The World Bank (2019a) believes dashboards serve as a form of accountability, providing donor agencies and local citizens easy-to-interpret data on the progress made towards development objectives. While development agencies have long been producing and publishing education data, these dashboards broaden and deepen the scope of data to encompass many different aspects and levels of systems (often in granular detail), while representing this complexity in a simplified and user-friendly format. Consequently, dashboards change "the empirical basis from which decisions are made and also the criteria for what counts as a good decision" (Bartlett & Tkacz, 2017, p. 8).

Despite the growing popularity of governance by dashboard, a number of problems have also been identified. Sarikaya et al. (2019) argue that dashboards "bring together challenges of at-a-glance reading, coordinated views, tracking data and both private and shared awareness" (p. 1). There are epistemological and organizational consequences to governing by dashboards, as data scientists and visualizers introduce new vocabulary, and new ways of understanding, manipulating, and communicating with the data (Bartlett & Tkacz, 2017). Most importantly, "by introducing a new emphasis on metrics, indicators and measures, [dashboards] can create a greater focus on operational issues rather than longer-term strategic ones" (Bartlett & Tkacz, 2017, p. 5).

The Sociotechnical Imaginary of the GEPD

Launched in 2019, the GEPD seeks to provide low- and middle-income governments with the tools necessary to "better monitor the quality of their education systems" and enable "policymakers to take real-time decisions to ensure that all children are learning" (World Bank, 2019e, para. 1). The project has four overarching aims:

1. "develop tools to collect data at all levels of the system on a regular basis;
2. embed innovative measurement approaches in a coherent, system-wide framework;
3. present a user-friendly dashboard interface; and
4. make resources available for implementation in all developing countries" (World Bank, 2019a, p. 2).

To support policymakers in monitoring the education system via the dashboard, the GEPD project draws on particular, inter-related imaginaries of the education system, the classroom and the "user." These imaginaries are inscribed into and operationalized by the indicators, tools and instruments used in the dashboard. In this section, we examine these imaginaries.

The Imagined "System"

Dashboards inscribe within them a range of understandings about the factors that are relevant to education policy decisions and the relationships between these factors. The GEPD is underpinned by the World Bank's change theory, which holds that:

> the learning crisis has multiple causes: poor service delivery in schools and communities, unhealthy politics and low bureaucratic capacity, and policies that are not aligned toward learning for all. To tackle the crisis and improve student learning for all, countries need to know where they stand on these three key dimensions – service delivery, policies, and politics.
>
> *(World Bank, 2019b, para. 3)*

This new, broad approach radically links "the learning crisis" and school failures with service delivery policies, expanding the scope of reform objects. In this formulation, the key drivers of improved student outcomes are not better resourced classrooms, better educated teachers, child-friendly classrooms, or school nutrition programs, which have been the staples of previous reform. Instead, this new imaginary seeks to enhance student learning outcomes by focusing reform efforts on the whole system of education (Filmer et al., 2018).

This "systems" approach looks beyond the typical unit of analysis (schools) and takes into account the various elements (politicians, bureaucrats, managers, policies, institutions, accountability systems, bureaucratic structures, financing, corruption, etc.) that constitute the larger structure of the "education system" (see Figure 10.1). The learning problem is translated into one of misalignment between different elements of a complex system (Filmer et al., 2018). In this formulation, a range of different technical and political barriers, including the complexity of the system, the large number of actors, competing interests, and the difficulty of moving out of low-quality equilibrium, all frustrate the development of the education system. On the other hand, if systems can overcome these issues and align different actors toward learning, remarkable learning outcomes can be achieved (Filmer et al., 2018).

Emphasizing the importance of the interdependencies between diverse and multi-level factors on learning, the World Bank argues that "no single instrument pulls together data on all these areas" (World Bank, 2019a, p. 1; see Figure 10.2). The GEPD aims to remedy this lacuna by creating an instrument to "give governments a way to set priorities and track progress as they work to close those gaps" (World Bank, 2019b, p. 2).

The GEPD focuses on four aspects of student learning: (1) learner preparation (a complex indicator that includes such things as access to pre-school education, poverty, and health); (2) teaching; (3) school management; and (4) infrastructure. The school-level aspects are combined with other system measures, as "the policies and politics that determine the quality of service delivery," ultimately

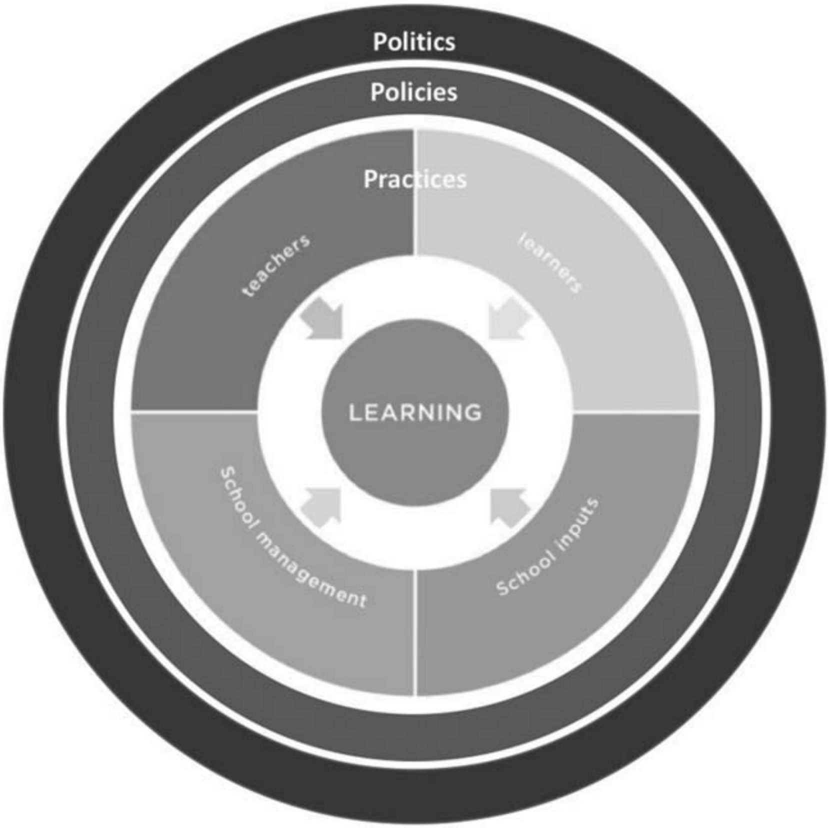

FIGURE 10.1 The GEPD's conceptualization of the education system (World Bank, 2019a, p. 1)

contribute to the development of "a set of indicators that is comprehensive but also focused so stakeholders can pay attention to what is really most important" (World Bank, 2019b, p. 2).

To realize this multi-level framework, GEPD draws on an eclectic combination of global indicators and scales, including SABER, the Service Delivery Indicators (SDI), the Measuring Early Learning and Quality Outcomes (MELQO), the World Management Survey, and the Bureaucracy Lab surveys (World Bank, 2019b). In addition, classroom observations and interviews with various actors add finer detail. In this way, the dashboard aims to comprehensively cover the education system "from the level of the learner to the level of the system" (World Bank, 2019a, p. 2).

While some of the data are gathered specifically for the purpose, many of the instruments employed in this dashboard have been developed at different times and for different purposes. For example, the World Management Survey was

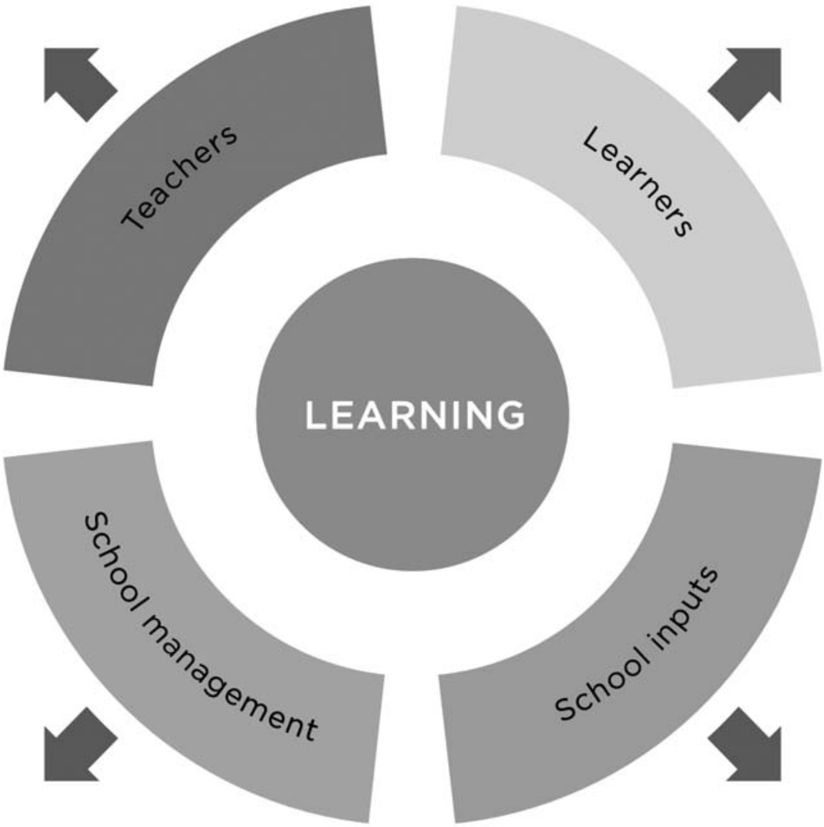

FIGURE 10.2 The World Development Report: "technical and political factors" that "divert schools, teachers, and families from a focus on learning" (Filmer et al., 2018, p. 13)

initially developed to measure management practices in manufacturing and then adapted for use in education. As such, these dashboards are "epistemological and methodological pastiche(s)" (Mattern, 2015, para. 31) that represent one of the many ways that the education system could be defined and understood. This pastiche is a result of the World Bank's preference for research and instruments from the field of economics (most of those involved in the GEPD project are developmental or labor economists), the dashboard imperative of presenting all the key data on a single screen, and the trust in standardized scales and measures, some of which have already been in operation for several years. Thus, the GEPD operationalizes a different imaginary of governance, one that addresses learning from factors at the individual and school level, all the way to the bureaucracy, policy, and the political ethos. The ability of dashboards to present diverse information from a variety of sources on one screen creates new relationships between data. Underpinning the numbers on the screen are epistemologies and world views that come to be inscribed into the data. Once established, these representations potentially become the "defacto… epistemology" (Kitchin et al., 2015, p. 7) through which policymakers measure their systems, act upon them, and review performance.

The Imagined Classroom

Despite the widening of the reform focus to include the political, policy, and bureaucratic functioning to address the learning crisis, the classroom – and more specifically, the teacher – remain key sites of reform. To measure the quality of the classroom, the GEPD uses an instrument called "Teach," which is designed to capture what occurs inside classrooms (World Bank, 2019c). "Teach" makes a distinction between the structures of teaching – such as teachers' qualifications and professional development, salaries, and years of experience – and "process quality," which refers to student-teacher interactions. While the former variables have been part of input data in many surveys, it is the latter, "Teach" documents state, that are of more consequence. They cite a range of studies that showcase the difference made by particular teaching practices in middle- and low-income nations, and link specific teaching practices with an improvement in learning outcomes, citing effects of between 0.07 and 0.18 standard deviations (Molina et al., 2018, p. 3). Although it is recognized that improved student outcomes are dependent on a complex set of factors, in this formulation, differences made by teaching practices can be identified in granular detail.

The "quantity and quality of instruction" is broken down into "(i) the time teachers spend on learning and the extent to which students are on task, and (ii) the quality of teaching practices that help develop students' socioemotional and cognitive skills" (Molina et al., 2019, p. 2). The "Teach: Observer Manual" (Molina et al., 2019) explains how this is done: "Time on Task component, 3 *snapshots* of 1–10 seconds are used to record both the teacher's actions and the number of students who are on task throughout the observation." This is complemented by the Quality of Teaching Practices component: "organized into 3 primary areas…Classroom Culture, Instruction, and Socioemotional Skills. These areas have 9 corresponding elements that point to 28 behaviors." These behaviors are the classified: "low, medium, or high, based on the evidence collected during the observation." These are then represented on a "5-point scale that quantifies teaching practices as captured in a series of two, 15-minute lesson observations" (p. 2). To ensure that the observations are performed in a standardized manner, an observation tool was developed. Figure 10.3 is the aspect of the observation tool for recording the practices related to socioemotional skills.

The World Bank's imaginary elaborates observable behaviors that are expected to occur in similar ways in classrooms across the middle- and low-income world. Elements such as providing students with choice, encouraging goal setting, and

c.	SOCIOEMOTIONAL SKILLS						
7.	AUTONOMY	1	2	3	4	5	
7.1	The teacher provides students with choices	L		M		H	
7.2	The teacher provides students with opportunities to take on roles in the classroom	L		M		H	
7.3	The students volunteer to participate in the classroom	L		M		H	
8.	PERSEVERANCE	1	2	3	4	5	
8.1	The teacher acknowledges students' efforts	L		M		H	
8.2	The teacher has a positive attitude towards student' chalenges	L		M		H	
8.3	The teacher encourages goal setting	L		M		H	
9.	SOCIAL & COLLABORATIVE SKILLS	1	2	3	4	5	
9.1	The teacher promotes students' collaboration through peer interaction	L		M		H	
9.2	The teacher promotes students' interpersonal skills	L		M		H	
9.3	Students collaborate with one another through peer interaction	L		M		H	

FIGURE 10.3 Teach observation tool (Molina et al., 2019, p. 14)

promoting peer interaction are seen as universally desirable behaviors that are as relevant in Pakistan as Rwanda.

Despite the brevity of observations, "Teach" is seen to have multiple uses beyond measuring teacher practices, including "as a system diagnostic and monitoring tool" that can help "governments identify bottlenecks in service delivery, monitor the effectiveness of their policies, and focus efforts to improve teacher practices" (Molina et al., 2018, p. 3). As a professional development tool, "Teach" is able to "identify individual teachers' strengths and weaknesses and coach teachers to improve their practice" (p. 3). Thus, it not only measures what occurs in classrooms, it is also an epistemic tool that is used to coach teachers to teach in ways that are valued by the instrument. When this occurs, learning is one-way, as observers learn nothing about other teaching methods that may be novel and culturally appropriate, nor do they learn whether the recommended strategies are problematic in specific contexts. Despite the acknowledgement of the importance of context in development work, such instruments are remarkably acontextual.

"Teach" is one of several instruments used in the GEPD. Like "Teach," each of these instruments brings its own set of assumptions and prescriptions, epistemologies and ontologies, and they each encourage particular understandings and actions, irrespective of the contexts in which they are employed.

The Imagined User

One of the ambitions of the GEPD is to provide national policymakers with information about their education systems. Within the GEPD, the policymaker appears to be remarkably like the minister of education evoked by Montoya and Crouch (cited earlier). The World Bank (2019a) observes that education policymakers in low- and middle-income nations are committed to enhancing student learning "often find themselves flying blind" (p. 1).

> They see the budget that goes into education and (sometimes) the learning that students come out with, but they lack information on the crucial factors

> in between—the practices, policies, and politics—that drive those learning outcomes. The new Global Education Policy Dashboard initiative will fill that gap.
>
> *(p. 1)*

Here, the unspoken assumption is that policymakers in low- and middle-income nations are not aware of the complexity of their education systems, nor are they able to deal with complex data. This is evident in a number of statements, such as the assertion that policymakers do not have the necessary evidence, and that they need to be assisted by external experts (Haus, 2019). Dashboards are designed on the basis of the perceived needs of inexperienced users, since they can succinctly and simply convey key information, through clever visualization techniques, while delegating complexity to the dashboard itself, black boxed and layered beneath the surface.

Moreover, these policymakers are thought to operate in environments characterized by "poor service delivery… unhealthy politics and low bureaucratic capacity, and policies that are not aligned towards learning for all" (World Bank, 2019a, para. 3). In contrast to high performing systems where "bureaucrats and teachers can devote much of their energy to improving outcomes for students" (Filmer et al., 2018, p. 15), policy actors in aid recipient countries are thought to have conflicting motives and interests. Filmer et al. argue that, "many systems are stuck in low learning traps, characterized by low accountability and high inequality" (p. 15). They continue that these low learning traps "bind together key stakeholders through informal contracts that prioritize other goals such as civil service employment, corporate profits, or reelection, perpetuating the low-accountability equilibrium" (p. 15). Such actors, Filmer et al. suggest, "juggle multiple objectives" and also rely on "each other in an environment of uncertainty, low social trust, and risk aversion" so that it is often in their interest "to maintain the status quo – even if society, and many of these actors, would be better off if they could shift to a higher-quality equilibrium" (p. 15). In this formulation, the policy actors and administrators who use the dashboards to drive change are themselves also targets of change. By making their own performance appear on the GEPD dashboard, these actors open themselves up to public scrutiny as well as the scrutiny of international aid agencies.

These depictions highlight the tension between the "partnership" and "ownership" of aid effectiveness, and the desire to intervene and develop policymakers who are seen to be crucial to a project's success. While, on the one hand, the GEPD aims to assist high-level national policymakers to take control of their systems, hold actors at each level to account and address misalignment, it is premised on an assumption that the policymaker is incompetent, unreliable, and self-interested. The GEPD, then, becomes an example of "choice architectures" that encourage policymakers to make particular decisions that are perceived to be more appropriate (Jones et al., 2013).

Conclusion and Discussion: Contradictions and Conundrums

The sociotechnical imaginary of education and policymaking mobilized by the GEPD is complex and based on a systems logic, which promotes a "realist epistemology" in which "the world can be imagined as visualized facts" (Kitchin et al., 2015, p. 7). This epistemology ignores the performativity and the ontological politics of such representations (Pickering, 2017). Like all frameworks, the GEPD is based on specific, normative conceptions about education systems and how they ought to be governed. The GEPD's ideal education system is fully aligned, each part working in harmony with the others. Although the tools and instruments used in the dashboard appear neutral and apolitical, decisions about which instruments to use, which items to select, and how to bring them together, are political decisions that have consequences for how the system is imagined and governed.

The GEPD grapples with a series of contradictions and conundrums. The expanded focus on a range of system-level factors is premised on the idea that context matters, and that a range of contextual factors influence the effective deployment of aid. However, the GEPD deploys standardized instruments and benchmarks, which rely on standardized understandings of ideal classrooms, systems, and policy processes. The use of standardized instruments is important for the World Bank and other international partners because they offer a way to monitor a nations' progress in a comparative way, and they allow progress (or lack thereof) to be rewarded (or sanctioned). Using existing standardized tools also keeps costs down while expanding the scope of analysis, since these tools circulate in several other global indicator systems. When standardized tools are used to measure the phenomenon of context, it is inevitably configured by the standard, and important specificities are sacrificed. In a dashboard, these simplifications accumulate and multiply.

The GEPD's contradictory assumptions about the policymaker represent a key conundrum of trust. While aid agencies must assume that the systems and officials to whom they are providing aid are trustworthy and knowledgeable, the GEPD project is premised on an assumption of their lack of knowledge and expertise, and their suspect ethics. Critiquing the GEPD's assumption that policymakers in low-income countries are "flying blind," Martin Haus (2019) insists that:

> the underlying disrespect for governments and bureaucrats of the targeted countries is astonishing… Policymakers in low- and middle-income countries are not stupid. They often know at least as much, usually more than, World Bank consultants about their education system and its inner workings. *(para. 8)*

The tacit view of the low-income nation policymaker as unsophisticated and requiring outside expertise is materialized in dashboards that present data in digested and simplistic formats. A key feature of dashboards is that they use visualization techniques to present complex ideas in widely accessible ways. While this enables actors with varied levels of data literacy to access the dashboard, it also comes at a cost. The translation from the phenomenon to the "visualized fact" involves a series of complex, often opaque maneuvers, which has the potential to change the meaning of the data in subtle but consequential ways. When complexity is outsourced to different groups of experts such as statisticians and/or data visualizers, and then mediated through dashboard design, the policymaker is presented with a limited range of possibilities for action. Data that are already simplified through the use of standardized tools are further translated and simplified through various representational requirements of the software, the size of the screen, the technological architecture, the adaptations required for Internet speeds, and the assumed data literacy of the user. As a result, the meaning of the data could become significantly distorted. The policymaker previously characterized as "flying blind" might be worse off now, armed with data that look precise and complex, but whose richness and complexity are not guaranteed.

Dashboards can, therefore, deeply impact the way problems are understood, because they are presented to the policymaker in curated, at-a-glance visual forms that make both the problem and the solution appear to be self-evident. The GEPD promises to present policymakers with distinctly practical knowledge, including the policy options that need to be addressed and the appropriate levers for action. In this imaginary, the ultimate authority to determine policy action is centralized, while the agenda-setting power is dispersed into networks constituted by the World Bank, its partners, and global technical experts and analysts. In this way, dashboards like the GEPD plug policymakers into global knowledge communities that claim to have the expertise to analyze, diagnose and improve every nation's education system. However, this approach provides only a narrow framework for policymakers to analyze policy choices, it minimizes the role and expertise of sub-national policymakers, and ignores the way that policies are constructed, namely through complex political deliberation and compromise.

Metaphors matter. Conceptualizing policymakers as air traffic controllers or pilots evokes an image of governance as the work of powerful and passionate individuals, belying the apparent commitment to the notion of systems and complexity. Dashboard governance evokes a policymaking process that can be sped up, a sense that policy measures involve instant responses using real-time data and real-time action to achieve immediate results. However, quick fix solutions in education do not exist and the results of any decisions or changes in practice may take years to manifest. Prioritizing instant results could lead to a focus on the more superficial elements, and to seeking short-term gains at the expense of deep and sustained reforms that may take time to bear fruit. Moreover, such solutions can only work if democratic political processes are bypassed. While the GEPD attempts to account for the complexity of education systems by gathering data about various levels of the education system, it presents a simplified caricature of the processes through which policies in education are identified, developed, and approved.

The global aid industry has become impatient and anxious that it may not reach the SDG4 goals by 2030. This sense of impatience spills over into the creation of dashboards that can speed up capacity building by delegating these capacities to the instruments and technologies of the dashboard. While the expanded notion of education governance as encompassing a complex set of factors is to be welcomed, GEPD's instruments smuggle particular epistemologies and ontologies that may or may not be ideal for low-income nations. Unless utmost care is taken, the "politics by stealth" (Gorur & Addey, in press) of international governance dashboards has the potential to be yet another manifestation of neo-colonial policy prescription from the Global North.

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11

NEXT GENERATION ONLINE ASSESSMENTS, TECHNICAL DEMOCRACY, AND RESPONDING TO DIGITAL DISRUPTION

Greg Thompson

Introduction

Education systems, institutions, and individuals who work in them are witnessing a shift in the ways that intractable problems are framed, policy solutions offered, and how those policy solutions "hit the ground," or are enacted in specific school and systemic contexts. As market logics promoting choice, competition, and accountability through transparency agendas have become dominant in the governance of education, there has been an increased emphasis on policy designed to reform education in specific ways. The suite of policies that aims to reform schooling has, more recently, become largely fixated on assessment as a means to both deliver improvements through altering behaviors and structures. Traditionally, these policies have focused on standardized testing data and test-based accountabilities as the key lever or "catalyst" for change (Lingard & Sellar, 2013). Recently, however, the centrality of the traditional standardized test has been challenged by the emergence of new generation, online assessments that utilize advances in digital infrastructures, algorithms, and adaptive technologies that aim to produce 21st century learners amid anxiety regarding skills required for the "jobs for the future." Digital technologies are now a central vector of education reform, working across multiple discursive traditions as they promise greater individualization or personalization through their capacity to be responsive to individual student needs, while also improving the efficiency and effectiveness of instruction through such slogans as "just in time learning," personalized learning, and adaptive assessment.

In Australia, this can be seen in the ways that the National Assessment Programme – Literacy and Numeracy (NAPLAN) census standardized test shifted to become an online adaptive test (Masters, 2017; Thompson, 2017). Despite the

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political enthusiasm for the online testing and positive reports on student motivation and subjective test experience in the online mode (Martin & Lazendic, 2018a), significant concerns were raised regarding the mode equivalence of the tests; the NAPLAN technical report showed that there were significant differences in the results depending upon whether students did the test online or in the traditional pencil and paper version (ACARA, 2019). These problems with NAPLAN Online appear to have energized debates around ending census standardized testing, and have resulted in political leaders calling for new, more "intelligent" forms of assessment.

One result of this has been the emergence of the Online Formative Assessment Initiative (OFAI) that is being developed in Australia by governments, statutory authorities, and private vendors as an "innovative assessment solution" integrating "resources, data collection and analytical tools in one 'ecosystem' that is easily accessible, interactive and scalable to meet future needs" (OFAI, n.d., para 3). Part of the justification for the OFAI is concerns regarding the consequences of NAPLAN itself, and the emergence of calls for new forms of adaptable, standardizable assessments that will signal the end of the traditional, standardized test.

This chapter will proceed, first, by outlining the educational and policy contexts in Australia in 2020. Second, an account of the implementation (and enactment) of NAPLAN will follow, before a discussion of the emerging discourses around digital technology as a policy solution for the "wicked problems" of schooling in Australia. Subsequently, a detailed analysis of the OFAI follows, with an emphasis on how it represents the problem of assessment and what solutions it proposes. Finally, two concepts will be developed, that of displacement and technical democracy, to argue that one critical consideration with new generation assessments like the OFAI concerns how susceptible it will be to the problem of the displacement of the teacher from the assessment process. The "black boxing" problem regarding new forms of adaptive, digital technology refers to the "knowledge problem" that occurs within systems "whose workings are mysterious; we can observe its inputs and outputs, but we cannot tell how one becomes the other" (Pasquale, 2015, p. 3). One solution is to adopt a more technical, democratic focus that locates the data users/decision-makers as essential stakeholders within these systems. This is what is meant by technical democracy in assessment systems (Callon et al., 2009; Thompson et al., 2019).

Education Reform in Australia

A common feature of many reform agendas is the leveraging of data to drive behavior. Datafication, which has changed in scale and intensity as faster and more extensive digital tools emerge, uses the data that schools produce as "catalyst data" to elicit specific responses in schools and systems (Lingard & Sellar, 2013). The most obvious example of this is the use of test-based accountabilities in systems and schools. This catalyst data often have perverse effects, as schools and systems respond to the datafication of value by strategizing how to get the maximum returns from data, which often stand as a proxy for school and teaching quality. These perverse consequences can include teaching to the test, narrowing curriculum focus and choice, displacement of broader educational goals, and increased stress and anxiety experienced by students, teachers, and principals (Thompson, 2013).

In Australia, the election of the Rudd Labor Government in 2007 crystallized a "national system of schooling" (Lingard, 2010, p. 131; see also Savage & O'Connor, 2019) that used data, test-based accountability and financial incentives (Klenowski & Wyatt-Smith, 2012) to effectively set up a national bureaucracy governing education. The values of these reforms were organized around human capital theory. With such theory, "the market is taken as the grand metaphor for all human activity, sees education's value as stemming primarily from its capacity to generate capital that can be traded for jobs and wealth in the marketplace of the global economy" (Clarke, 2012, p. 181). Clarke goes on to argue that the politics of policy at work in Australia naturalizes "social logics of competition, atomization, and instrumentalization" and inevitably "glosses over the tensions between its aspirations for inclusiveness and its preference for audit and accountability mechanisms" (p. 187).

While the Australian Constitution guarantees that the States manage schooling in their jurisdictions as a residual power, at least since the 1970s, there has been a creeping nationalization as the Commonwealth has assumed more and more control over schooling. For example, post the 2007 election the new Federal government set up three powerful organizations that texture this nationalization. First was the Australian Curriculum, Assessment and Reporting Authority (ACARA), a statutory authority responsible for the Australian Curriculum, national assessment including NAPLAN, and reporting on schooling in Australia. Second was the Australian Institute for Teaching and School Leadership (AITSL), a company wholly-owned by the Commonwealth of Australia responsible solely to the Minister for Education and responsible for initial teacher education accreditation, the cultural competency of teachers, the development of resources to support high quality professional learning, assessing and evaluating links between the Australian Professional Standards for Teachers and teacher effectiveness, and strengthening the preparation and ongoing support of school leaders and principals. Finally, in 2010, Education Services Australia (ESA) was formed, a national not-for-profit company owned by the state, territory, and Australian Government education ministers to provide technology-based services for education. These services extend to researching; testing and developing effective and innovative technologies and communication systems; promoting e-learning and supporting national infrastructure to ensure access to quality-assured systems and content; and interoperability of individuals, entities, and systems.

These three organizations exemplify a defining feature of this national education system. It shows the centrality of data infrastructures to enable a variety of practices. These include linking systems together through common data collection and reporting standards, the use of common data to report on and compare systems and sub-systems, and the use of comparative data to track and "steer at a distance" actors within the various jurisdictions that constitute the Australian national schooling system (Heffernan, 2018). There are three noteworthy elements of this infrastructure. First, a central aim is governance by comparison which necessarily requires the capture, storing, and analysis of data in order to make jurisdictions commensurable. The second, the structure of these governance entities is corporate rather than statutory. Finally, the emphasis on e-learning, digital solutions, and commercial innovation is best exemplified by ESA's management of the National Schools Interoperability Program (NSIP). NSIP was established in 2010 to support the interoperability of information systems used by government and non-government schools and school systems across Australia. NSIP uses interoperability standards to enable data sharing between schools and school systems (Lingard et al., 2017).

This data infrastructure has created new markets and partnerships in Australian schooling for education technology companies and consultants (Sellar, 2017). The invisible work of data, or information ontologies, has to be a critical focus of research amid the growing implementation and joining up of data management systems across various scales, from individual schools to national school systems. Ontology has a dual sense in this context, first as a "philosophical concept describing the metaphysical questioning of being," but also as it has been "developed in the field of information science where it has a distinct definition as a conceptual schema or simplified model of a world" (Sellar & Thompson, 2017, p. 494). Ontologies "enable the formalization of data… that can be communicated within and between systems," while also laying claim to how actors or agents come to understand the nature and purpose of the systems that they operate within (p. 495).

These data ontologies inform the production of standards to make the collection of multiple forms of data sharable and communicable across multiple systems and contexts. Interoperability standards produce new possibilities for digital technologies to be developed that can be used across jurisdictions, reducing the time and costs of product development and enabling generic solutions that eliminate specificities of context. Of interest is the ways that the NSIP enables policy to be constructed through partnerships between politicians/bureaucrats and commercial educational technology vendors. Vendors are able to use interoperable data to test their products, while systems are (hopefully) provided with digital products and services responsive to their needs (Lingard et al., 2017).

The "data turn" in education policy represents a new mode of governance as comparison became a central element of it (Ball, 2006). This mode of governance is affected not just through testing regimes, but through the ways that these regimes combine with, and intensify the effects of other policy instruments. Consider, for example, the ways that the publication of results in league tables turns standardized assessments into high-stakes assessments. The ways that assessment has become central to policy is worthy of note for two reasons. First, assessment is seen to be a device to drive behavior within systems, and as such is seen as a means to direct action. Second, if we were to typify the ways that policy conceptualizes assessment, it would be fair to say that most of the emphasis is on reliability (understood as the consistent and stable production of scores), rather than validity (understood as the inferences made from the data assembled). As will be detailed below, while there were many recognized problems with NAPLAN, these were not about standardization, but about inferencing and decision-making based on those inferences. It is noteworthy that the NSIP slogan on their website is, "The right information in the right place at the right time" (https://www.nsip.edu.au).

Problems with NAPLAN Census Testing

NAPLAN has been a feature of Australian schooling since 2008, with the MySchool website that published and compared school results first online in 2010. The tests were aimed to "create a learning environment that encourages innovation and excellence from school leaders, teachers and students" (Rudd & Gillard, 2008, p. 31). The MySchool website was intended to provide students, parents, and teachers with evidence needed to make "informed choices" about learning programs, schools, and school enrollments (p. 31).

The National Assessment Program's aims are "to help drive improvements in student outcomes and provide increased accountability for the community" (ACARA, 2011, n.p.). The first aim of driving improvement is based on the logic that testing data can drive school improvement because it provides "detailed information about how [students] are performing, and they can identify strengths and weaknesses which may warrant further attention" (n.p.). Furthermore, for systems and bureaucracies,

> the NAP provides Ministers of Education with information about the success of their policies and resourcing in priority curriculum areas. The NAP also provides ministers with the capacity to monitor the success of policies aimed at improving the achievement of different student groups, such as Indigenous students.
>
> *(ACARA, 2011, n.p.)*

The second claimed benefit is that the testing benefits the public because of its "accountability function" as "Australians can expect education resources to be allocated in ways that ensure that all students achieve worthwhile learning during their time at school" (ACARA, 2011, n.p.). Together, the intertwined logics of comparable data and teacher/school accountability are expected to "inform future policy development, resource allocation, curriculum planning and, where necessary, intervention programs" (n.p.).

Since its inception, there has been widespread criticism of NAPLAN as high stakes tests can have a negative impact on pedagogy, curriculum, and the stress levels of students and teachers (Cumming et al., 2016; Roberts et al., 2019). Researchers have argued that "teaching to the test" has become a part of teachers' practice within the classroom and the focus of the curriculum has narrowed to the specific outcomes that are expected to be tested (see Lingard et al., 2016). There is concern that these factors may lead to a less diverse and creative classroom environment, and ultimately, a narrowing of the goals and purposes of education. Of particular concern is the increased pressure that teachers report to ensure students achieve certain metric outcomes as measured by the NAPLAN tests (Rogers et al., 2018; Thompson, 2013). The pressure felt by teachers exists in part because of the use of students' NAPLAN results as surrogate evaluations of teaching performance (Hardy & Lewis, 2017).

Although some have argued that the change to accountability structures has been beneficial, and perhaps even necessary for the teaching profession, others have suggested that test-based accountability only serves to "narrow" the curriculum and bring the commencement of formal schoolwork to earlier years of schooling (Gable & Lingard, 2015; Roberts et al., 2019). This can result in students having to "grow up fast" as they are forced to cope with more rigid and formal learning. Significantly, other key aspects of a broad education may be neglected as teachers are required to give more attention to NAPLAN style questions (Lingard et al., 2016). Other authors have argued that this type of accountability can contribute to the perception of a "crisis" of teacher quality in Australia (Mockler, 2014, 2016). NAPLAN has had an impact on the way equity and similar social justice constructs are defined and acted upon as simply the strength of the correlation between students' socio-economic backgrounds and test scores (Lingard et al., 2014).

One of the most telling criticisms of NAPLAN has concerned its usefulness as a diagnostic tool. Teachers found that they received the results too late, sometimes six months after the students sat the tests. In the meantime, students had learned, developed, and made progress, such that it was only helpful in a very small number of cases (Lingard et al., 2016). This criticism partly led to ACARA moving towards online testing, which better enabled automated marking. NAPLAN Online was trialed in 2018, and in 2019, ACARA reported that 50% of schools sat NAPLAN Online. Interestingly, ACARA extols that "feedback about the online test has been positive, with students saying they find the format engaging" (ACARA, 2018, n.p.).

While students have found the online version more engaging (Martin & Lanzendic, 2018a) and reported higher levels of motivation in the online assessment (Martin & Lazendic, 2018b), there have been ongoing criticisms of the online test. These include a reported mode effect, which means that there can be different results depending upon whether students sit the online or paper version (Thomas, 2019), and problems with computer hardware and/or connectivity problems, the shutting out of many students, and the machine marking of written responses (Perelman, 2018). These concerns led many Education Ministers to express concern about NAPLAN online. For example, in Victoria, Education Minister Merlino removed Victoria from the online assessment, saying "despite states and territories raising repeated concerns about the test, the national bodies responsible for the administration of NAPLAN online have let us down for the past two years" (Carey, 2019, para 17). These and other criticisms have led some to argue that we are witnessing the end of census testing in some countries. In Australia, there is a move to augment testing by a new generation of online formative assessments that are fundamentally standardized, yet able, as claimed by supporters, to be responsive to context, learners, and classrooms. This complementary assessment is best represented by the work in progress on the OFAI.

The Online Formative Assessment Initiative

The core aspect of the OFAI is the use of learning progressions. These progressions were developed by ACARA and the New South Wales Department of Education based on the observable elements derived from the Australian Curriculum to "efficiently and effectively identify where students are in their learning" and to assist teachers to "make informed decisions about what to do next" based on that information (ACARA, ESA, & AITSL, 2020, n.p.). The learning progressions are expected to capture the skills, understandings and capabilities expected in the curriculum that develop as a result of engagement with a learning task. These skills, understandings, and capabilities are typically acquired as an aspect of mastery of a particular part of the curriculum. The OFAI Information Sheet produced by ACARA, ESA, and AITSL says that the learning progressions "are robust and evidence-based and have been validated using empirical data where available" (n.p).

The aim of the OFAI is to produce a technical "ecosystem" where all of the information, resources, tools, and assessments that a teacher needs are available via one online portal. This technical ecosystem,

> will assist teachers to identify where students are, what they need, and what resources will be most useful to support learning progress. Teachers will have seamless online access to the data and the resources they need to adapt their teaching practice to meet the needs of their students. These digital tools can complement the ways teachers are already working. Students will also have access to information about their own learning progress.
>
> *(ESA, 2020, n.p.)*

OFAI is organized around a series of formative assessment tasks. The information sheet outlines that the technical ecosystem consists of three components that work together. The first of these is a series of online tools such as "tests, quizzes and other digital content" that use the learning progressions as "the common content base for the initiative." The second, named as the integrated system, utilizes a "common measurement scale" so that all information collected via the online tools "can be compared and connected with the insights derived from other assessments that are integrated with the system" (ESA, 2020, n.p.). In other words, the common measurement scale creates a commensurable system that enables comparisons across the national system of schooling. The third component is the creation of a digital portal that collates all evidence from student learning and enables easy monitoring and plotting of student learning against the learning progressions. A key part of the OFAI is the development of professional learning activities and resources "for teachers and school leaders to support and assist effective implementation" (n.p.).

The most interesting part of the assessment concerns decision-making. The ecosystem aims to create a "suggestion engine" that lists resources matched to individual student needs that teachers can give to students. Essentially the ecosystem hopes to use machine learning, matched against the learning progressions, to deliver a personalized teaching intervention (targeted teaching) based on plotting students' learning against both the learning progressions and against other students.

While the technical documentation that accompanies the website uses Kane's (2006) theorization of validity as an individual argument based on each inference made from an assessment (O'Leary, 2020), it is telling that the website itself makes the simplistic claim that its assessments are "reliable and valid," seemingly to suggest that validity is a property of tests, rather than their inferences (ESA, 2020, n.p.). This remains an ongoing problem with many centralized approaches to assessment – how is it that validity is being understood, enacted, and given back to the profession to take ownership of? As I will argue at the end of the chapter, seeing validity as a both a technical and a democratic problem or possibility, suggests a way that many of the unintended consequences that have plagued standardized testing could be avoided or alleviated.

The OFAI is a next generation assessment that aims to target teaching and learning through making the interventions more personalized, and therefore engaging. This is an example of the emerging vector of education reform named as the logistics of engagement that uses adaptive assessments and algorithmic feedback to keep students engaged and moving through the required syllabus.

The Logistics of Engagement

Many education systems remain paradoxically torn between the problems of "basic" skills such as literacy and numeracy and 21st century skills such as creativity and computational proficiencies. It is not unusual to find policy papers extolling back to basics approaches sitting next to visionary talking about the jobs that do not as yet exist. At the same time, classrooms, schools, and school systems are opening themselves up to external forces in ways perhaps unseen in their relatively short history. Data, evidence, informed decision-making, target setting, value-added measures, and school rankings are just some of the ways that technology is reshaping school practice and producing new subjectivities. In 2014, the Education Technology Industry Network (ETIN) of the Software & Information Industry Association (SIIA) commissioned a report that looked at the education technology market in P–12 schools in the United States (Richards & Struminger, 2014). The report estimated that in 2013, the industry was worth US$8.38 billion. The largest category was in assessment, which was estimated to have earned US$2.5 billion in the period (Richards & Struminger, 2014). Within this, the report found that Personalized Learning Environments (PLE) that "included incorporating the use of blended learning environments, expanded use of digital learning platforms, and using adaptive instructional software" were one of the growth areas for profit in the sector in the coming years (Richards & Struminger, 2014, p. 39). This emerging market included the growth of cloud-based services, app development for mobile devices, "big data" analytics, and social networks customized for educators.

Learning personalization (LP) is one of the key goals of the next generation of digital assessments in education. The US National Education Technology Plan (US Department of Education, 2010, p. x) defined personalized learning as those "learning experiences…that mirror students' daily lives and the reality of their futures." Furthermore, technology is often assumed to enable a static, linear progression of learning that "is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners [and]… the learning objectives and content as well as the method and pace may all vary" (US Department of Education, 2010, p. 12). What seems missing in these accounts is recognition of the speed and scale of the computations possible, and the how these may be thought of as "opening up new ways of thinking and acting, new problematizations, new authorities, new technologies and new conceptions of the subject" (Rose, 2004, p. 273). Thinking that LP is simply a process that adds to the existing repertoires of educational institutions seems somewhat naïve; radical transformations to core processes, relationships, and normative ideals are more likely.

LP is characterized by the

> real-time rendering of learning resources and social suggestions based on the profile of a learner through the ability to track each learner's physical and online interactions, analyze skills and competencies, and then compare learner knowledge with the mapping of knowledge in a discipline.
>
> *(Siemens, 2013, p. 1392)*

LP focuses on constructing the learner through datafied patterns that profile and can adapt to offer the learner's next move or activity. LP is that process in which educational resources and learning environments are continually modified, such that each learner feels motivated to attain the highest level of knowledge possible for that learner in a specific field of knowledge. In the OFAI, this is the ultimate aim of the technical ecosystem, the promise of improved, if not complete, learner motivation, as the learning content, environment, and tasks are continually updating and responsive to the learner through building profiles due to the datafied patterns emerging.

Computerized technologies that enable the collection and analysis of large data sets in short periods of time result in a surface where the continual modification of activities and objectives is designed to maximize engagement. This constant deformation, to induce the greatest and most effective effort on the part of that learner, a "logistics of engagement," is crucial to the individuating path that unfolds, while also enfolding a learner. If learning personalization is to involve continual modification of learning environments, then various means of making that environment personal (and effective) for the learner must be available in the system. The learning personalization system must contain a variety of possibilities with respect to: presenting a learning environment, modifying the features any learning agents that may be at work in that environment, altering the grammar of the written or spoken material involved, changing styles of presentation (verbal to visual), and so on. These modifications need not be done to overcome a lack of motivation, as it is also done to effect continuing motivation. This can involve intrinsic rewards and extrinsic rewards. Making a learning environment increasingly sophisticated provides intrinsic rewards, whereas badges and leveling-up are examples of extrinsic rewards.

Understanding LP, firstly, requires "mapping" the content or knowledge field of what is being learnt against which the learning behaviors and preferences can be profiled. OFAI does this through the learning progressions, derived by ACARA and the New South Wales Department of Education from the Australian Curriculum. This datafication of the field of knowledge requires re-rendering its attributes to be captured through digital representations – the process that ACARA refers to as identifying the "observable elements" of progression through the Australian Curriculum. This can involve tagging by experts, but can also involve automated tagging processes, which either employ tags created by experts or mine the Internet to map the knowledge domain. This is referred to as knowledge tracing, which "involves representing the knowledge required to master a domain, and, from traces of online user behavior, diagnosing user knowledge states as a profile over those elements" (Pirolli & Kairam, 2013, p. 140). The progressions "were developed using evidence-based research in consultation with literacy and numeracy experts and practicing teachers" (ACARA, ESA, & AITSL, 2020, n.p.).

Finally, and of particular significance, knowledge tracing and learning behavior operate through and on learner motivation. Motivation, or learner disposition, is datafied and incorporated in such a way as to enable the continual modification of a learning environment so that it unfolds, reportedly to most effectively engage that learner. Personalization is not simply a matter of overcoming declining levels of motivation, but also of inducing even higher levels of motivation from those who are already motivated. An effective learning personalization process is designed to induce the highest levels of motivation possible for all learners. It must have the capacity to adapt in whatever ways are necessary to maintain the highest possible level of motivation as often as possible.

What remains interesting about the OFAI, and presents a potential new frontier in the relationships between teaching, learning, and assessment and the necessary underpinning evaluative expertise, concerns the way that it aims to promote, or nudge, teacher decision hyphenate making in light of teaching methods referred to as high-impact teaching practices. The centrality of cognitive and learning sciences in designing the algorithms[1] that work to profile students and then select appropriate resources for teachers remains somewhat of a "black box." What is not clear is how decisions are made, how matching occurs, and how profiling of individual learners, teachers, and classroom contexts is operationalized and subsequently modeled. While the OFAI might best be considered the most recent example of the use of technical and technological prostheses that aims to improve efficiency and effectiveness (and to an extent, save time for teaching by automating processes such as assessment, ongoing planning and modification for student learning) the effects of this remain to be seen. Ball (1994, 2006) usefully reminds us that research should always be alert to the first and second order effects of policy shifts:

> First order effects are changes in practice or structure (which are evident in particular sites and across the system as a whole). And second order effects are the impact of these changes on patterns of social access and opportunity and social justice.
>
> *(Ball, 2006, p. 51)*

With than in mind, I suggest three areas of possibility, and perhaps caution, regarding the effects of the OFAI. The first regards data and ownership, the second addresses the problem of the possible displacement of the teacher through seeing validity as a problem requiring a technical democracy approach, and finally reflecting on how it is that teaching and learning will change as a result. In a sense, I am mindful here of Guattari's (2013) caution in regards to technology: the important question is not that of destructive change caused by exponential increases in technical-machinic power, but rather why, given dramatic technological development, we still see "a reinforcement of previous systems of alienation, an oppressive mass-mediatization, infantilizing consensual politics" (p. 4). The ongoing dilemma relates to expertise; decision-making and the capacity of data-users to make decisions, sharpened through the formative assessment ecosystem. Equally, how is it that students come to own their data, and be assisted to make decisions about the purposes to which it is used and by whom. Technical democracy goes beyond labeling the problem of black boxing (hiding the workings of algorithms that shape technological decision-making) to suggest a number of solutions to digital disruption.

New Possibilities: Owning Data and Responding to the Displacement of the Teacher

The idea of first and second order effects sets up an ongoing provocation for thinking about the relationships between assessment, datafication, commercialization, and the challenges that these present for the expertise of the teacher. This is the assessment problem of *displacement* and unintended consequences (Thompson et al., 2019). Displacement is the spatio-temporal arrangement of expertise and the "distance of travel" from the site of technical expertise to the site of pedagogical decision-making. One way to understand why there are unintended, and sometimes perverse, consequences when policy is put to work in specific contexts, is that the work is often done to decision-makers (such as teachers and principals), rather than with them. The political expedience of the slogan that more and better data will fix education fails to recognize this problem of displacement. In many fields there is an opposite effect where too much data (the data deluge) actually makes decision-making more difficult. Making better decisions with data is critical; paradoxically as displacement increases, we see the rise of unintended and perverse consequences.

If we return to traditional standardized testing, it has become very clear that the evaluative expertise needed to understand, and critically use, the data produced remains problematic at the classroom level. When researching the effects of NAPLAN on school communities, I asked many teachers what they knew about testing itself (Thompson, 2013), particularly given their frequent concerns about NAPLAN, and how the publishing of school data for comparison, created environments where they felt their pedagogical choices were coerced with a diminished professional expertise. Always lurking within these testing and reporting systems is the problem of accountability for results and how this influences behavior, often in unintended ways. This is what I would term the "commonsense" argument about datafication, namely that it strips teachers of their expert role (or professional judgement).

However, I think there are problems with this argument. First, it oversimplifies a complex history of teacher expertise. Second, historically, teaching has had a relationship with data in one form or another (at least since schools became influenced by Taylorist notions of efficiency in the early days of the 20th century; Callahan, 1964). While we have always had data, we have never had so much, so available, and so malleable to calculation. Also, while expertise has always been conferred/deferred, the distance from the classroom (in both an experiential/somatic sense and an epistemological sense), where expertise is wielded, has grown alarmingly.

This leads us to the opportunity of the OFAI. On one hand, expertise recognized in the OFAI remains held by a small group of test-designers, psychometricians, and bureaucrats whose work then authorizes certain modalities of teaching. The list of "consultants," as outlined in the OFAI documentation, represents the usual suspects involved in the "metricization" of schooling (Mau, 2019). There is something of a perfect storm here, the national system of schooling, and the standardization (the data ontology) of data enabled by NSIP is producing new opportunities for commercial access to schooling. As these tests become even more complex (for example, NAPLAN morphed to a computer adaptive test), the technical expertise required to understand, and critically evaluate these tests, will be so advanced that it is even less likely that teachers will be able to muster the insight into assessment required of a profession. This leads to significant problems of expertise with no simple solutions. Of course, much corporatization operates through providing solutions to real and imagined crises. For example, in Australia, testing has acted as a Trojan horse for new, commercial expertise in testing situated in EdTech companies and other edu-businesses.

On the other hand, what stands out in the OFAI is the careful and methodical way that schools, principals, and teachers have been consulted during the design of the assessments. The website outlines that a core design principle is "stakeholder consultation and engagement into all stages of the project" and the website lists schools that have come on board as partners (ESA, 2020, n.p.). Generally, stakeholder engagement in these matters is usually kept to the "front end" of the design, perhaps because the overarching emphasis is on assessment reliability rather than validating inferences. The opportunity for the OFAI is to consider how to include teacher expertise in decision-making, and indeed the ongoing validation of decision-making, through all stages of the assessment ecology[2].

As we have argued previously with regards to international large-scale assessments (ILSAs), the idea of ongoing and thorough validation studies conducted by teachers who understand best not the inferences that *should* be made, but the inferences that *are* being made, do more than simply identify the problem of the assessment black box (hidden judgement and decision-making), it opens up a new form of accountability to data. Thompson et al. (2017) note, "ILSAs can involve teachers and their various collective voices (such as professional associations, subject associations and teacher unions) playing a role in testing and improving the validity of inferences in their contexts" (p. 62). They suggest further that the validity of the tests would be enhanced, if domain experts (teachers) and technical experts came together to learn from each other. It is not being suggested that teacher voices should be "privileged over technical experts," but that the coming together of both would enhance test validity (p. 62). The danger, of course, is that this critical work is handed over to commercial entities, often outsourced by regulatory authorities such as ACARA and ESA, whose interest will always be modified by commercial realities such as profit, market share, and leveraging further financial opportunities.

If displacement might be meaningfully countered by a technical democracy approach to validation, another glaring issue concerns the ownership of data that is produced by (largely) students, and used by teachers for education purposes. The types of arrangements favored by ESA, and that are evident in both the NSIP and the OFAI, concern a particularly blurred public-private relationship. Vendors are central to both the design and technical governance of these systems. These corporate and business entities access public school data, including that produced by students as part of their day-to-day activities, and use this to improve their products, which they sell back to those systems. Data dashboards, visualization tools, automated decision-making systems that flag aberrant data patterns, and so on, require that vendors be given access to student data to test their products, usually without the awareness, let alone permission, of the students involved. Ongoing ethical dilemmas include how public systems guarantee data privacy, the ethics of seeking consent from these students and their parents for data to be used in these ways, and who ultimately benefits from these technological systems that rely on data produced for "free."

The solution seems to be that students, teachers, or principals could come to own their data and decide who and how it is used. How would the system change if the onus was on the vendors to convince the data producers that it was in their best interest to provide their data because it would benefit them in tangible ways? This also speaks to a key aspect of technical democracy (Callon et al., 2009; Thompson et al., 2019), a recognition that there are significant political and ethical issues at work, and the OFAI represents the potential for far more complex, technical assessments, which represent the new frontier of commercial investment in education. As assessment systems become more and more advanced, indeed as they learn strategies for optimization themselves, how can the teacher, parent, or even the student make sense of how they work, how decisions are made, and how meaning is formed on the basis of adaptive algorithms? A result of datafication is that teachers are finding that their professional life is accelerating, partly due to the power of the displaced authorities. An approach grounded in the philosophy of technical democracy appears to be a hopeful response.

It is important at this point to stress that we should be cautious of framing the emergence of new assessment regimes such as the OFAI in terms of good/bad binaries. As Foucault said, the point of critical work "is not that everything is bad, but that everything is dangerous, which is not exactly the same as bad. If everything is dangerous, then we always have something to do" (Foucault, 1983, p. 231). The French philosopher Bernard Stiegler has argued that the problem with the speed of technological change, and its proliferation and seemingly omnipresence in the human world, is that culture is reprogrammed by new technological systems in any given epoch. Stiegler's argument is that culture is no longer keeping up with, and therefore, renewing, technics, causing an alienating disorientation when technology becomes an end in itself. "Contemporary disorientation is… linked to speed, to the industrialization of memory resulting from the struggle for speed, and to the specifics of the technologies deployed in that struggle" (Stiegler, 2009, p. 7). How the OFAI lives up to its stated aim of producing a new culture based on "a suite of professional development options for teachers and school leaders to support and assist effective implementation" (ESA, 2020, n.p.) depends on how it is able to step outside the prevailing policy culture of assessment *as* and *for* efficiency. This move is essential to install an ethical system that considers rights, obligations, and ongoing commitments to learners, teachers, parents/carers, and the wider community.

Conclusion

The concern with arguing for the end of a policy or individual test is always about what will replace it with regards to the problems that it claims to solve. I have argued that the ways that next generation assessments combat ongoing problems of displacement and of data ownership will be critical. Without addressing these problems, there is a danger that next generation assessments will become instruments that simply recreate the problems of summative, standardized testing that they are partly meant to solve. For example, using the results to create league tables, narrow curriculum, or create perverse incentives because individuals are being held to account for test results will likely mean that the OFAI fails in creating new assessment cultures. Simply doing the same things, faster, or at more points in time, or relying on automation that effectively "black boxes" (masks or obscures) the bases of judgement and decision-making in assessment is unlikely to solve the problems of displacement. In thinking about the OFAI, we need to consider what has been learned from decades of standardized testing. We also need to interrogate how likely it is that the next generation of assessments is going to overcome the problems that defined previous attempts to use data to steer education at a distance. The OFAI is a very interesting and dangerous development within the Australian context. The extent to which the platform will overcome the problem of displacement is a concern. The first and second order effects that this assessment ecology is going to have on schools and schooling still remain to be seen.

Notes

1 Algorithms can be designed and self-productive in relation to machine learning.
2 It should be noted that there is no approved body of data or curriculum methodology related to the progressions.

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12

"LENSES ON COVID-19"

Provocations

Provocation #1: Digital Education in the Aftermath of COVID-19: Critical Hopes and Concerns

Neil Selwyn

Introduction

These are difficult times to be attempting to make sense of the "digital disruption" of education. I write this in June 2020, a moment when some people are beginning to entertain hopes that we have seen the worst of COVID-19. Of course, with hindsight it might well transpire that we are only a short way through the full pandemic. So far, things have been changing so rapidly that anything that is written runs the risk of appearing hopelessly off-the-pace by the time it is read. For the time being, then, it feels unwise to presume to have a clear critical grip on any aspect of society. As Dave Beer (2020) recently wrote:

> beyond the speed of change and a lack of focus, there is also a sense that the thing I'd normally be analyzing – society – will not be the same… It's hard to do sociology and social science when you aren't quite sure what the social is and how it is working.
>
> *(para. 8)*

Yet regardless of how this current crisis eventually unfolds, I am fairly sure that it makes little sense to carry on critiquing the digitalization of education in exactly the same ways that we were a few months ago. Without wishing to descend into hyperbole, it seems sensible to assume that things are not going to be the same

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again. Of course, all of the broad issues and concerns that were guiding our work prior to COVID-19 remain as important as ever. However, we need to rethink and reframe such matters through the lens of this pandemic and its aftermath.

Judging by the industry gambits and political powerplays that have taken place around EdTech during the opening few months of the pandemic, it seems clear that COVID-19 is going to have a lasting impact on the ways that education and digital technology come together for years (if not decades) to come. Current conversations around remote schooling and online university teaching convey important shifts in tone, pace, and intent that need to be factored into any critical discussions of digital education. Despite the prevailing rhetoric from those who stand to gain most from such changes, this is not a "new normal." Instead, we find ourselves thrust into a period of fast-moving reform of public education, and we need to react accordingly.

As has been observed across most areas of life, this pandemic is bringing many long-simmering political tensions and social struggles to a head. So, for the foreseeable future, any construction of the "digital disruption" of education needs to be focused firmly on ensuring that the pandemic is not used as an excuse to push through further corporate reforms of public education. Instead, those of us involved in the critical study of digital education need to work quickly to develop counter-narratives and alternate agendas to foster hope that this extraordinary event might perhaps act as a catalyst to reimagine better forms of public education for us all. Let me explicate these two points in a little more detail.

Point 1: COVID-19 as cover for the Corporate Reform of Education

The first few months of the pandemic saw a range of long-established technological trends, plans, and agendas being accelerated under the guise of being "emergency short-term fixes," but nevertheless looking set to be more permanent in nature. Beyond education, this logic is evident in the haste with which population surveillance, tracking, and tracing apps were deployed hurriedly without due oversight and regulation. In educational terms, this logic is apparent in the haste with which universities have been coerced by governments to pivot to industry-relevant short courses, ditch unprofitable humanities and arts provision, merge institutions, or even close altogether.

In terms of digital education, then, there needs to be sustained scrutiny of the emergency actions and logics that are being put into place. In particular, we need to pay close attention to how the global pivot to "emergency" forms of remote teaching during the first half of 2020 is subsequently being used as justification to radically rethink the future shape and character of education provision. As Frederick Hess (2020) observed in the initial weeks of the lockdown, "a few education analysts have started to sound positively giddy about this exciting opportunity to spitball ideas and try out nifty new programs" (para. 3). Thereafter, EdTech gurus such as Sal Kahn proved remarkably quick to talk of the "silver lining" of COVID-19 being a mass uptake of what is beginning to be termed "direct-to-student" technologies (cited in

Pound, 2020). Governor of the US state of New York Andrew Cuomo channeled this sentiment when arguing for a permanent switch-over to sophisticated "remote learning" across the education system. He observed:

> the old model of everybody goes and sits in a classroom and the teacher is in front of that classroom, and teaches that class, and you do that all across the city, all across the state, all these buildings, all these physical classrooms
>
> *(Kelley, 2020, para. 6),*

then he asked, "Why, with all the technology you have?' Regarding the potential of this technology, he added, "It's hard to change the status quo. But you get moments in history where people say, 'OK, I'm ready. I'm ready for change. I get it.' I think this is one of those moments" (para. 6).

Such statements betray serious intent to significantly alter the conditions and character of public schooling through the widescale digitalization of education provision. Commentators in the United States are rightly horrified by the idea of Eric Schmidt and the Gates Foundation being given a lead in the reform of New York schools, yet it is understandable that state authorities and city leaders around the world are keen to follow similar courses of action. Switching to data-driven "personalized" forms of blended education provision offers a likely cost-saving measure in the face of an impending global financial meltdown. Yet the digital education infrastructures that we choose to erect in response to the current crisis will come to (re)define public education for decades. As Woodrow Hartzog (2020) argued with regards to the rapid rush to COVID-19 surveillance and tracking, once any technological infrastructure is established, there is an inevitable inertia to roll it back at a later date. "Norms get set and practices and tools become entrenched… industry and government [rarely] have the resolve and humility to double-back and try a different approach" (para. 12).

The exact nature of the "digital solutions" that will be pushed onto public schooling over the ensuing months and years of the pandemic and its aftermath remain to be seen. However, these are unlikely to involve bespoke new forms of technology that have been designed carefully and sympathetically to address the social frailties and economic fault lines that the COVID-19 crisis has exposed and exacerbated. Instead, any "new solutions" are likely to rely heavily on the repackaging of EdTech products that have long been in the ether, such as personalized learning systems, learning analytics, online adaptive assessments, online exam proctoring, etc. As such, COVID-19 is already being used as an opportunity to reanimate ideas and logics of digital education reform that had been long pursued prior to the pandemic by the likes of Gates, Schmidt, and those who follow in their wake.

So, it follows, that policymakers and education leaders appear to be setting off down dangerous paths toward realizing many of the key concerns that have been raised within the critical studies of education and technology over the past few years, not least the restrictions of proprietary platforms, classroom automation, surveillance-led teaching, and data-mining of lucrative student information. Concerns here range from straightforward profiteering through to less obvious misappropriations of digital technology in ways that sideline (or overlook completely) structural inequalities. As Moeller and Tarlau (2020) reasoned:

> while reimagining and redistributing educational resources and opportunities is imperative, research shows that philanthropic experts often work to find technical solutions to systemic inequities without addressing their underlying causes. If we are to truly transform our nation's inequitable educational system, turning to philanthropists with a track record of failing to improve public education is not the answer.
>
> *(para. 8)*

If taken to their logical conclusion, these shifts will fundamentally alter the conditions and characteristics of public education, hastening the implicit agenda of corporate education reform that has underpinned much of the EdTech "innovation" over the past 15 years or so. Indeed, the corporate and philanthropic actors that are now being called upon to lead the reconfiguration of post-pandemic schooling have long-standing ambitions for the digitally driven "unbundling" and "transformation" of mass public education systems. Critical education scholars, therefore, need to be hypervigilant of the ways in which COVID-19 will be misused to force radical education reforms by those who stand to profit directly from them.

Point 2: Establishing Alternate Agendas and Counter-narratives

Of course, scholarly vigilance and critical awareness are not enough. Pushing back against the COVID-19-mandated digital dismantling of established schooling also requires resistant actions. Perhaps the most helpful role that academic researchers can play in supporting such actions is working to establish powerful counter-narratives and alternate sets of discussion points. There are a few lines of reasoning along which such conversation might be pursued.

For instance, a strong case can be made that COVID-19 has already done much to discredit the idea of the technological fix, starkly exposing the limitations of Silicon Valley illusions of digital "innovation." As I write, the much-hyped rollout of COVID-19 tracing apps are failing spectacularly in comparison to manual tracing techniques. Elsewhere, we have abruptly seen the limitations of artificial intelligence (AI) systems that find themselves lacking the appropriate training data to adapt to these extraordinary times. In short, the initial months of the pandemic have starkly illustrated that there is no quick app-based solution to this crisis. Instead, our hopes are pinned on the necessarily slow and methodical route of scientists working to develop vaccines and treatments. In short, this pandemic has already proved to be an object lesson in the limitations of digital technology solutionism when it comes to public health. The parallels with public education need to be stressed repeatedly and forcibly.

Indeed, the COVID-19-driven pivot to temporary remote home schooling could be reframed as a moment when a wide range of the public are now well-attuned to the social limitations of educational technologies when used in situ. One can now talk with school leaders and policymakers about the "digital divide" and "homework gap" within communities, and there is general agreement (rather than the usual pre-pandemic response of denial or downplaying the inequalities in the assumption that "we are all online now"). Similarly, one can talk to parents and teachers about the sub-standard nature of platform-based learning, and find large numbers of people with recent first-hand experience.

In this sense, the immediate aftermath of the emergency turn to remote schooling provides us with a critically engaged public, who are receptive to difficult conversations about EdTech. This moment needs to be seized before the memories of the remote schooling of 2020 fade away. Conversely, it could also be argued that official educational response to the pandemic saw some precedents being set that we might like to argue are worth fighting to repeat. For example, it was heartening to see governments suddenly subsidizing the cost of laptops and Wi-Fi connectivity for disadvantaged families otherwise lacking access. It was also reaffirming to see countries like Australia suddenly suspend the nationwide standardized NAPLAN testing of children. Actions such as these set a precedent for alternate future policy approaches and agendas. Rather than kowtowing to the corporate reform lobby, a strong case might be made for the continuation of these other "new" logics, that is enshrining a commitment to continue to invest in the social safety net and establishing an education infrastructure built around values of care and collective support, rather than relentless assessment and measurement.

Conclusion

Regardless of how this pandemic unfolds, it is important that such discussions take place and establish new lines of argument and fresh sets of imperatives. Above all, it is important to diversify the voices that are called upon to set these agendas. As Bianca Wylie (2020) wrote in the aftermath of Toronto's "Sidewalk Labs" debacle, "technology procurement is thus one of the largest democratic vulnerabilities that exists today" (para. 8). Above all, then, it is important that we work to ensure that conversations about post-pandemic education are not framed solely around technology issues and/or led solely by technology interests. It is important to push the counter-narrative that the reimagining of public education is not a "tech issue." Instead, these conversations need to be pivoted firmly toward the heart of the matter – that is, focused on the fact that education is a social concern.

In short, critical education scholars have a clear role to play in ensuring that the conversations that take place around education and digital technology are radically different from what has been promoted to date. In this sense, we need to ensure these conversations are led by the interests of education and society, which is in stark contrast to the IT industry and philanthropic actors who are currently being called upon as "experts" to "develop a blueprint to reimagine education in the new normal" (Office of the Governor of New York State, 2020, para. 1). Critical education scholars have raised and explored many lines of reasoning and sensemaking over the past 30 years that can feed into this current moment of uncertainty. We should not make the mistake of watching from the sidelines.

Note

An earlier iteration of this provocation appeared in the self-published "zine": Selwyn, N., Macgilchrist, F., & Williamson, B. (2020). Digital education after COVID-19. *Techlash #01*. Digital Education Research, Monash University, Melbourne, Australia.

Provocation #2: Education without Borders, Rule without Limit

Nick Couldry

Introduction

If Ivan Illich, the author of "Deschooling Society" (Illich, 1973), were brought back to life today, he might for a moment think his vision had come true: parents tutoring their children at home, and universities dispensing with the classroom to teach students across locations and time-zones. The means for this are fast home Internet access and video-conferencing platforms; the pretext is the COVID-19 pandemic and the decision of governments almost everywhere to impose social distancing measures since March 2020. But Illich was always wary of the possibility that taking education out of schools might usher in other forms of power and constraint. Like Illich, we, too, should be wary of the risks posed by this hasty rearrangement of our educational institutions, not just because of the well-publicized privacy and security limitations of platforms such as Zoom, but more importantly because dismantling the physical classroom, even for a few months, creates lasting opportunities for governing students and teachers more intensively, and substituting the profound inequalities of everyday living spaces for the common resource of the classroom. In this provocation, I will focus on the first danger – changing the regimes of power and rule within digital education – because it threatens to disrupt the educational process itself in a profound way for all students, rich and poor, and disrupt the role of education in wider society.

The Impact of COVID-19

There are many reasons to think that the COVID-19 pandemic and the drastic measures it has prompted will transform everyday life in a lasting way: the economic disruption, new anxieties about travel and interaction, and the possible dismantling of the real estate investments that have, until now, enabled the spaces where much of daily life outside the home goes on. But there are also reasons to see the COVID-19 shock not as disrupting, but as simply reinforcing trends that were already under way. In the lockdown, most people used social media platforms to keep threads in their life going, and almost everyone has become more reliant on the Internet for information, and to order home deliveries of various sorts; however, the increase in both trends has been under way for two decades.

Education is no different. The lockdown has provided exceptional opportunities for businesses that have already invested for years in online universities, conferencing platforms, and other digital interfaces that "support" education. When the Governor of New York, Andrew Cuomo, invited Google's former Chief Executive Officer Eric Schmidt to lead a commission to "reimagine" New York's education and health sectors in early May 2020, the emphasis was more on continuity than drastic change. As Schmidt stated in a news conference with Cuomo, "my own view is that we need to use these moments to revisit things that are not getting enough attention and we have systems that need updating" (CNN Newsroom, 2020, 2:11). The systems of digital education were very much already being built, and Schmidt's wider goal of "us[ing] technology to make things better" (2:09) is a cliché, almost an article of faith, for large sectors of business and government that have worked in this area for the last two decades. While it is far from being new, the idea that societies should turn to technologists "to bring that kind of visionary aspect to government and society" (1:01) is what digital educational providers rely on to fuel their business growth. However, the depth of the educational transformation invoked through the pandemic has not yet been appreciated in public debate, and unless citizens everywhere are alerted to it, it will, with the benefit of COVID-19 headwinds, be installed before there is a chance to challenge it.

What has been changing in education over the past decade is not simply the degree of technology use, or even the degree of different surveillance. Under way more broadly, is a "reengineering" of the educational process (see Frischmann & Selinger, 2019). To highlight the level at which change is happening, let's borrow a phrase from Illich's final book "In the vineyard of the text" (1993) in which he recounts deep shifts in human relations to written text that took place in the 12th century. Illich describes his topic as a change in "the relationship between the axioms of conceptual space and social reality insofar as this interrelationship is mediated and shaped by techniques that employ letters" (Illich, 1993, p. 4). Substitute the word "computers" for "letters" and we capture the revolution in which global educational players like Pearson and IBM are involved; it is the axioms of how collectively we think about education that are being reworked.

As Jun Yu and I detail elsewhere (see Yu & Couldry, 2020), the growth of digital platforms for supplementing classrooms, tracking coursework, monitoring pupil progress, managing timetables, and governing school processes, is potentially reshaping the whole nature of education. I write this not as a specialist education researcher, but as a sociologist of media and data practices who is increasingly concerned with the rise of data colonialism as a disruptive force in society worldwide (see Couldry & Mejias, 2019). The claim that it is on digital platforms that many aspects of education are best managed – including basic interactions between students and teachers – is not just an innocent technological supplement to the classroom's integrity, but a bid to substitute the platform for the classroom as a source of pedagogic knowledge. The colonizing logic of platforms knows no boundaries. As legal theorist Julie Cohen states, in the commercial context, "platforms do not simply enter markets, they replace (and rematerialize) them" (Cohen, 2019, p. 42). Public sponsored domains like education will fare no better.

The result is to disrupt the public values that, even in the world's most marketized society, the United States, shape and form education (Van Dijck et al., 2018). But arguably, the result is even wider: to dismantle and reassemble the components of education as a process. Consider first the space of the classroom, until now it has been a space managed by the eye and voice of the teacher. Second, the resources of teaching have now become exclusively sourced online. Third, the time-space domain where evaluation takes place, has shifted from discrete evaluation periods within the broader teaching timetable to continuous processes of monitoring that are conducted entirely online and according to system constraints. Finally, the evaluative authority of the teacher has changed as they become a manager of data, or as Max Ventilla, the founder of the Alt School movement in the US, states, a "data-enabled detective" (Mead, 2016, para. 31). In a system of knowledge production, it is data systems that have the largest power. It is true that digital platforms claim to give teachers an unprecedented level of surveillant power over pupils. As Impero, a digital education provider in the United Kingdom, reports, their product (Impero Education Pro) enables

> teaching staff to monitor students' online activity from their screen in real-time. A thumbnail view of all student screens, in one central view, allows potential risk (or other instances of misconduct) to be dealt with as and when they occur.
> *(Impero Solutions Limited, n.d., para. 8)*

However, authority in this surveillance system lies with the system, not the teacher.

The current digital transformation is best summed up in Pearson's vision of the "digital ocean," a metaphor for a world of education that has been completely datafied, from whose vantage-point the world before continuous online tracking of students is a digital desert. Authors of the report state,

> We can see the digital ocean of data slowly rising from our post on the edge of a historical era we call the "digital desert." In the digital desert, data collection and

> storage was expensive, limited, and isolated… [with] no systematic large-scale way to monitor outcomes… The absence of mobile computing devices and information networks in the digital desert inhibited the movement and comparison of data across social situations and groups… [Conversely,] the data of the digital ocean is not simply more data as we knew it in the pre-digital era… It is ubiquitous (coming from all manner of activity) and persistent, and it reflects social connection.
>
> *(DiCerbo & Behrens, 2014, pp. i, 1–2, 6)*

As an example of naturalizing discourse, this is remarkable. To parse it lightly, the pre-digital teaching space where teachers could interact vigilantly and intensively in the classroom with pupils, but without the need to rely on continuous tracking of their actions (including their actions outside the classroom, for example on social media), becomes a desert, because it lacks continuous data generation. Conversely, the "full-screen" world of continuous tracking becomes a life-giving ocean, because it is full of data. In that old digital desert, where teachers have taught for centuries, it is implied, we would have eventually died for lack of data, whereas in the new corporatized world of continuous data extraction, it is implied, we will live.

Conclusion

But what exactly is it that will survive in education's digital ocean? A regime of continuous "anytime-anywhere" rule, for sure, in which the historic authority of teachers to embody knowledge and humane care has been displaced by an all-knowing automated system; no doubt too, a process for extracting financially valuable data about pupils whose storage and control remains fundamentally unclear. But an educational process that can still hope to guide young people along a path towards creative imagination, reflexive freedom, and civic responsibility without fear? That is the human resource whose existence we are today wagering in return for the convenience of locking in the current crisis's convenient technological solutions.

Provocation #3: The Electric "Shock" of the COVID-19 Crisis on Schooling

Anna Hogan and Ben Williamson

Introduction

The effects of COVID-19 are being felt worldwide at the time of writing this provocation. Across more than 200 countries, 1.6 billion children have been affected by school closures (UNESCO, 2020). In attempting to facilitate the continuity of education, many systems have adopted remote learning. The rapid shift to online instruction has been touted as "the biggest EdTech experiment in history," and as the OECD's head of education, Andreas Schleicher, has claimed, the "red tape" preventing innovation in education is now gone (Anderson, 2020). Many assume Klein's (2007) theory of the "shock doctrine" or "disaster capitalism" is at work, in which the private sector has provided free-market solutions to solve the seemingly insurmountable problems of the pandemic. Indeed, EdTech players have sprung up as "emergency respondents" offering free or heavily subsidized access to a vast array of educational products and services. The question is whether this emergency electronic "shock" to schooling will fade out or reconfigure education systems for the future.

The research informing this provocation (see Williamson & Hogan, 2020) has identified that many actors and organizations view the current emergency of school closures not just as a short-term opportunity for supporting educators, students, and parents, but as a long-term opening for pursuing business interests, generating revenue, gathering data, and influencing policy agendas. The global education industry (Verger et al., 2016) has continued and accelerated its expansion during the COVID-19 emergency, with potential long-term consequences for education systems, schools, educators, and students around the world. These developments remain in motion, and require more sustained study in order to understand their evolution over the longer term. In this provocation, we briefly highlight some key implications and questions arising from the project, and invite readers to read the full report for further details.

New Global Policy Networks

Commercial actors have played a significant role in maintaining education during school closures, but this cannot be interpreted simply as the commercialization of state education. Multiple organizations, actors, and governments have coalesced around shared aims that, in a compressed period, have become the core of a global policy agenda in which EdTech is a major component. The pandemic has created a catalyst for new forms of networked policy. These policy dynamics operate at global, national, and regional scales, involving a mixture of international multilateral organizations, global technology and education businesses, philanthropic grant funding and investor schemes, national and subnational government departments, public bodies and civil society organizations, as well as more "local" EdTech businesses and associations. The reformatory aspirations of organizations with global scope and influence (e.g., UNESCO, the OECD, World Bank, Pearson, Gates Foundation, Microsoft, Amazon, and Google) have translated into 1) short-term emergency responses to the pandemic, and 2) long-term reforms enabling education systems to recover from the pandemic in technologically transformed ways.

Pandemic Prototyping

New imaginaries of education futures circulated by commercial organizations and like-minded advocacy networks are proposing a radical "reimagining" and new prototyping of education systems. While some schools might continue to use digital management platforms to organize teaching and learning activities, more interesting are the proposals that some hastily adopted online schools, like Britain's Oak National Academy, are here to stay. They are pandemic prototypes for system-wide transformation. Oak National Academy, for example, has government backing plus the support of various education organizations, many with overtly reformatory aims, private sector links, and governmental connections. It has been proposed as a model for a future of schooling that would involve public and commercial partners working together. Oak National Academy is a clear example of the move towards privatization in public schooling, where governments work in partnership with private, commercial, and philanthropic actors to deliver core public services.

Private Infrastructures

A key way that private sector education businesses and global technology companies have intensified their commercial agendas in public education is through the provision of digital infrastructure for online teaching and learning and, importantly, school data storage, management, and analytics (e.g., Microsoft 365, Google G Suite, and Amazon Cloud). This has consolidated the market share of key private infrastructure providers, especially those that can not only host online learning, but also provide the back-end cloud services for long-term digital learning and school data processing. Even when schools re-open, many will have new agreements in place for technology companies to provide services and resources. These efforts are part of a larger project to reimagine the whole infrastructure underpinning school pedagogy, management, and curriculum provision, as market reformers and EdTech companies have capitalized on the crisis to push technical services ever further into post-pandemic public education (Cohen, 2020).

Pandemic Profit Making

The global education industry has advanced the idea of education as a sector for investment, profit making and management by private organizations. In particular, commercial EdTech businesses have profited from venture capital investment and rapidly escalating customer demand (Williamson, 2017). The commercial EdTech industry has made considerable inroads into "privatizing" schooling, with additional rapid growth of market opportunities during the pandemic. The emergency business plan adopted by the EdTech industry can be summarized as "support now, sell later," where businesses are expanding their services now in the hope they might lock schools and parents into long-term subscriptions once the pandemic ends (Wan, 2020). However, this plan is uncertain, as while usage of free EdTech products and services has grown dramatically, there has been a decrease in the use of paid offerings. The long-term "cost" of free access needs to be tracked into the future to understand whether schools were the short-term beneficiaries of EdTech social responsibility, or whether the EdTech industry was able to capitalize on the dramatic growth of paid subscriptions.

Conclusion

Beyond the few implications we have highlighted, a number of unresolved challenges and risks remain. The rush to embed EdTech in education is likely accentuating issues of data protection, privacy, consent, and exploitation, particularly given reports in the United States that existing data privacy laws were waived at district-level to ensure schools could use digital platforms (Lieberman, 2020). There are also concerns about ownership of the data being collected, and who is controlling the curriculum. These are not new concerns, but should be paramount in understanding the longer-term effects of the COVID-19 pandemic on global schooling. In the removal of red tape, it is important to wonder: What has slipped through the cracks? Indeed, this returns us to Klein's point about the workings of the shock doctrine. In the rush to find solutions to this crisis, and often uncritical acceptance of those offered by the private sector, what technology-based policies are being pushed through – as part of an electronic shock to education systems – that might deepen education inequalities and enrich the elite?

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Provocation #4: Teachers, the Anti-heroes? The Global Pandemic Crisis and the Construction of Teachers as the Problem "Other"

Sotiria Grek

Introduction

At the time of writing this text, a lethal global pandemic is still unfolding, claiming hundreds of thousands of lives. As we struggle to achieve some kind of understanding of the "new normal," we are confronted with the swift construction of novel discourse that is comparing hospital admissions and excess deaths globally and in real-time. Language became crucial for making sense of our rapidly changing circumstances: for example, public health messaging on how to take the necessary precautions against the disease transformed into a tool for unity, gave some sense of control over chaos, and offered hope. Many new terms, like "social distancing," "hotspots," "infection rates," the infamous "R number," among so many others, have become commonplace not only in the media but also in everyday talk. COVID-19 is not only a pandemic disease; it has also ignited an epidemic of new terms and concepts (Treichler, 1987), the majority of which are the linguistic signifiers of quantitative measures. As everyday life and politics become "scientized," this is still a world of uncertain public health data that, no matter how incomplete and unreliable, it is still the best we have and can depend on.

However, the new pandemic discourse is not only built on the numerical construction of this new reality. Coupled with a renewed trust in science, it is also constructed on the basis of a moral discourse that glorifies the work of "key workers" (sometimes called essential workers). These are not only doctors and nurses, but also hospital cleaners, supermarket workers, bin men and women, delivery drivers, social care staff, and plenty more. In many countries around the globe, key workers were described as "heroes," on the efforts of whom we all rely, in order to maintain the pillars of a functioning society[1]. We all stepped out of our front doors and onto our balconies to thank them, by clapping and promising that we would not forget their contribution to the "nation." Within a few weeks, "key workers" became the embodied and symbolic representation of the belief that professionalism and a solid sense of service were the cornerstones of a well-functioning society that could shield its citizens from harm.

The Changing Narrative

As the crisis has further engulfed the globe and showed its catastrophic potential, the war rhetoric reached a new intensity; this is a battle that we could only fight with the heroic efforts of those at the "frontline." Nonetheless, teachers were perhaps the only group of professionals, still working either from home or in "hub schools,"[2] that did not receive the same amount of praise or attention. At least in the United Kingdom (UK), the case of which primarily informs this piece, there was little media mention of the key role of teachers in supporting parents with home schooling and looking after the children of key workers. Indeed, in England, when the first steps towards exiting the lockdown were being planned, the focus quickly turned to the need to re-open schools and for teachers to "return to work," as if they were absent before. Re-opening schools, after all, is seen as the only possible route to restart the economy.

After a disastrous handling of the pandemic in the UK, with the country mourning many tens of thousands of deaths, the teacher unions questioned the government's claims that it would be safe for schools to reopen.[3] Their doubts were soon backed by the governmental Scientific Advisory Group for Emergencies (SAGE; Government of the United Kingdom, n.d.), who warned about the dangers for reopening schools both for staff and students, but also the population as a whole (Toua, 2020). It is important to note that unsafe working environments have been one of the key UK public debates and criticisms of the government from the start of the pandemic; daily newspaper headlines and reports discuss the lack of personal protective equipment for medical staff and care workers. However, when teacher unions expressed their justified fears of teachers getting sick, they were immediately faced with a backlash of critical commentary (see Whittaker, 2020), which shocked even those of us aware of the systemic distrust that the English education system has towards its teachers. Teachers became the anti-heroes, those who were "scaremongering" about the dangers of reopening schools, and those who were not patriotic enough to "do their duty," as other workers did (Chakrabarti, 2020). Even worse, the government rhetoric, with Gavin Williamson, the Secretary of State for Education at its helm, went further and attacked teachers by almost pitching them against the general public in a blame-game. A letter addressed to Williamson by a teacher of a secondary school is telling of the depth of feeling among teachers in England. The letter stated, "You are our voice, yet you did not speak for us. You spoke in divisive, hyperbolic rhetoric of how 'we owe it to the children' and that the unions had a 'duty' to get teachers back to school" (Collins, 2020, para. 9). The letter continued, "It is unhelpful and unwarranted attacks on teachers like this that demonstrate both a lack of leadership and a lack of understanding from people running our country. We are still working, much like parliamentarians are: at a distance" (para. 9).

None of the above would have been worrying if it were not for the specific national context within which they have happened; these sorts of "rows" between unions and the government are commonplace. Yet, there is an important undercurrent here that needs our attention. Teachers as professionals have been under continuous attack in England since the mid-1970s, when teachers were no longer trusted to operate with a degree of autonomy justified by their expertise. Conservative governments' reforms of the '80s and '90s exacerbated the distrust in teachers by pushing for school improvement through the creation of "quasi-markets" (Furlong, 2005). New Labour's "third way" further "de-professionalized" teachers (Ozga, 1995) with an emphasis on "raising standards" by increasing the datafication of education and its performance micromanagement. These developments, coupled with the rise of international comparative assessments and large international organizations' reports on the need to improve teachers' "effectiveness" (OECD, 2005), meant that teachers in the UK have, for decades, been represented in public discourse as the weak link and as untrusted professionals in need of reform.

Conclusion

The global pandemic has not only been a major crisis of public health; it has already had a very large impact on education, the implications of which will unfold for a long time to come. One of the most discussed consequences is the tight grip of the global education industry, which has seen the crisis as a major opportunity to push for new digital infrastructures of teaching and learning, through the development of learning management systems and online teaching applications. These new promises have, yet again, captured the attention of policymakers and politicians who always seem to long for new education reimagining, alongside, of course, their powerful non-state philanthropists and friends. New York Governor Andrew Cuomo "rocked the education world" (Strauss, 2020, para. 1) by questioning why school buildings exist. He said,

> The old model of everybody goes and sits in the classroom, and the teacher is in front of that classroom and teaches that class, and you do that all across the city, all across the state, all these buildings, all these physical classrooms – why, with all the technology you have?
>
> *(para. 3)*

Despite the dystopian dreams and market calculations of some education players, COVID-19 will almost certainly not negate the need for schools and teachers. However, it will lead to a major rethink of what we value and how we offer education, not only (or primarily) as the institution that looks after our children while we work, but crucially as the vital human right that education is. In a context of rapid change, when crises are seen as major market opportunities, we need to be alert to discourses that construct teachers as anti-heroes and as obstacles to learning. Schools need to open, and they will do, for they are the places where cheerful laughter and hope for the new post-pandemic world will be born. Teachers are our most precious professionals who will get us there.

Note

A shorter iteration of this provocation appeared in the Social Policy Association blog, June 4, 2020 (see Grek, 2020).

Provocation #5: The COVID-19 Pandemic Creates Opportunities to Repair the Infrastructure of Public Education

Sam Sellar

Two well-worn lines kept coming to mind as I tried to make sense of the COVID-19 pandemic during the lockdown imposed across the UK in March 2020. The first is attributed to Lenin, who apparently claimed, in relation to the Russian Revolution, that "there are decades when nothing happens; and there are weeks when decades happen." The second was "never let a good crisis go to waste," which is often attributed to Churchill but has a longer history. Both statements express the truth that real change is rare, and every crisis is an opportunity. The pandemic has certainly created new opportunities for commercial actors to benefit from the disruption of schooling and higher education. However, in this short provocation, I draw on Shoshanna Zuboff's (2019) analysis of surveillance capitalism to suggest that the crisis may also create opportunities to repair the infrastructure of public education, the very infrastructure that education technology companies seek to disrupt.

During the early months of the pandemic, Ben Williamson (2020) provided insightful analyses of how "emergency EdTech" moved quickly to create "pandemic markets" and embed their digital platforms, rehearsing the familiar promise that "education is broken, tech can fix it" (para. 12). Many people quickly came to rely upon new technologies to teach, learn, and meet after the pandemic caused the closure of schools and universities. The acceptance and embedding of these technologies over a few months may indeed have resulted in change that could otherwise have taken decades.

The increased use of online platforms creates more and more opportunities for the collection of data from us. Data is now the most coveted source of value for technology companies, and it is the lifeblood of surveillance capitalism, which involves locking customers into digital platforms. The use of these platforms enables a process that Zuboff (2019) describes as "rendition": "the concrete operational practices through which dispossession is accomplished, as human experience is claimed as raw material for datafication and all that follows, from manufacturing to sales" (p. 233). As we use digital interfaces every day, our experience is "rendered" into data, and we are forced to "surrender," often unknowingly, to the logic of surveillance capitalism. Rendition destroys our privacy by privatizing our information. The pandemic should give us even more cause for concern about data privacy in education, because the widespread move to online teaching and learning provides an incentive for companies to accelerate the roll out of products and business models that are premised upon rendering as much data as possible from users.

Zuboff (2019) suggests three strategies for resisting the advances of surveillance capitalism and protecting our privacy: taming, hiding, and indignation. We can seek to tame the power of technology companies through legal instruments such as the European Union's General Data Protection Regulation. However, it is not easy to tame large and powerful companies, and the capacity of regulations to effectively limit the exploitative practices of companies remains to be seen. We can also hide from the gaze of surveillance capital by disconnecting from digital platforms and masking our identities and activities. However, hiding implies acceptance of what we are hiding from and often involves the use of other platforms and software to protect us. The pandemic further undermines both strategies by creating a state of exception in which we are encouraged to set aside concerns about data privacy in order to sustain "business as usual," which requires agreeing to a proliferating array of end-user agreements that enable rendition. This leaves us with indignation. Zuboff (2019) argues that an important condition for the emergence of indignation is the recognition that advances in surveillance capitalism are not inevitable. Indignation can arise as dissatisfaction with the mediation of our lives through digital platforms, and the rendition of our experience into data, "teaches us how *we* do not want to live" (p. 524).

The pandemic is a particularly propitious moment for such a lesson. The rapid extension of digital infrastructures for learning is occurring at the same time that many students and families have felt the loss of physical spaces dedicated to education. Schools and universities are critical "public things" that provide a "world-stabilizing infrastructure" for action in concert (Honig, 2017, p. 96). These institutions serve as spaces in which we teach and learn collectively, as opposed to the personalization of learning that education technology companies promote. As Susan Leigh Star (1996) observed, we generally only notice infrastructure when it breaks down. The shutting of schools and universities created a "glitch" in this critical social infrastructure that drew attention to aspects of education that were previously taken for granted. The question is whether we can repair the infrastructure in ways that do not merely restore what was taken for granted, nor replace it with alternatives, but instead *strengthen* the publicness of education that becomes more noticeable when spaces of public education are closed (Berlant, 2015).

Every crisis is an opportunity, and almost always more than one. While the COVID-19 pandemic has created fertile conditions for further privatization in schooling, and for the expansion of business models and digital platforms premised on extracting data from us, it might also teach us how we do not want to live. Those concerned with public education have an opportunity now to highlight the problems of commercializing education amidst a structure of feeling that is more acutely attuned to the possibility of decades changing in weeks, and the transitory nature of what so recently felt solid. Changing the way we educate feels more possible now that schools and universities have been forced to do so. Moreover, students, educators, families, and communities around the world have been affected by the disruption to their education caused by the pandemic, and many of them must surely feel dissatisfied with the digital alternatives on offer. The crisis thus also creates fertile conditions for recognizing that a gradual dispossession of our educational experiences through the growth of digital platforms and personalization is not inevitable. This recognition could provide a basis for collective efforts to repair the infrastructure of public education in ways that strengthen its most important qualities.

Notes

1 It is interesting that in some national contexts, teachers were included in the key workers category. This has been the case in Australia, where the valuing of and respect for teachers has grown substantially during the pandemic and the necessity of schooling at home. This point demonstrates the significance of path dependency in the valuing or otherwise of teachers.
2 During the coronavirus outbreak, hub schools in England and Scotland were the schools that remained open to cater for the needs of the children of key workers.
3 Schools in England closed on Friday, 20th March 2020 and were instructed to open again on the 1st June 2020. Some local authorities in England, especially in the north, decided they would not reopen, due to a higher infection rate in these regions and hence the associated dangers for teachers and students alike.

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GLOSSARY

In producing this Glossary, we have drawn on the writing of the authors of the chapters in this collection, along with other publicly available definitions and descriptions. The latter include the OECD, various other agencies, and other authors (see references below).

Algorithms Mathematical processes designed to solve a problem. They can be implemented computationally and configured for the purposes of achieving particular tasks, developing decision-making rules, and producing predictive and potentially actionable insights. While algorithms are initially human created, once they are created, and in use, they are able to connect with other algorithms in a self-generating process as part of machine learning and analysis of big data.

Artificial intelligence (AI) No single definition. This is because every digital tool including AI is created for its own distinct purposes and has its own unique process (Leins, 2020). However, as defined by the OECD, AI is "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy" subject to their purposes (OECD, 2019).

Artificial Intelligence in Education (AIEd) A specialist field in AI to enable more personalization and flexibility, and to create more engaging learning opportunities with the aim to automate and eliminate the more routine tasks of teaching such as multiple-choice testing and scoring.

Big data Generally refers to large volumes and variety of data, unstructured or structured, and too big for common software and thus usually cloud stored, that are produced continuously and at high velocity.

Bioinformatics An interdisciplinary field in which software tools and methods are developed for working and understanding large and complex sets of biological data. Examples in the context of education, include eye tracking software, tracking of neural pathways, and software and hardware for tracking physical responses.

Biometrics The automated collection of biological data related to human characteristics, including facial recognition, body temperature, and perspiration. As a result, it is often used as a form of identification and control. Examples includes body scanners and automatic temperature checking at airports, and face identification scanners for use at borders.

Blockchain A decentralized database system that links existing or previous blocks of information.

Clickstream data The list of pages viewed in order by visitors to a website from a series of their mouse clicks. In an education assessment context, this refers to data collected from how test takers and users of other online programs address questions, the time they take, the mistakes they make, and how often they access them. Thus log-file and click stream data can record online actions and events in real time and produce psycho-emotional data about users and students. The data can be used for purposes of assessing personality traits, attitudes, cognition, and abilities.

Computer Adaptive Testing (CAT) Online tests that use branching to match test items with student ability based on responses to initial and subsequent questions. Algorithms determine a student's pathway through a test in determining the appropriate level of difficulty of the question sequence.

Data An elusive term – data can come from both analogue and digital sources. Data can be referred to as "numerical information in digital formats" (Sellar, 2017, p. 341). Data become information and evidence when systems, school leaders, and teachers infer meaning from them, use them and take action accordingly.

Data analytics The science of analysis of data using an algorithmic process to derive meaningful correlations and insights for decision-making and action.

Data dashboard A customizable information management tool designed for centralization and easy visualization of data for tracking key performance indicators. A data dashboard provides an interactive interface for tracking, measuring, and extracting applicable data in an accessible way.

Datafication Refers to the technical processes involved in the rendering of experience as data, which is then digitalized through software. This process raises philosophical and translation issues; for example, can and should all human experience be rendered as data (Zuboff, 2019)?

Data infrastructures Refer to digital storage systems that enable sharing, consumption, and use of data across networks of objects and of people. Used in plural form to acknowledge the variety of systems in the context of interoperability.

Data literacy Knowledge and skills to interpret, understand, and apply data so as to transfer into decision-making and inform action.

Data science When large amounts of data are curated, interpreted, and made meaningful for decision making purposes.

Digital disruption The ways in which the affordances of digital technologies have significantly affected key aspects of the functioning of society. These include modes of communication, news media, the economy, industry, workforce, health sectors, work of governments, practices of citizenship, research and development in universities, and schooling. There have also been significant digital impacts in how individuals experience their lives, make civic and community contributions, experience leisure, communicate locally and globally and construct their identities.

Digitization and digitalization Often seen as being synonymous but we distinguish between them. We define digitization as putting online of non-digitized materials (e.g., taking a pen and paper test online using a USB), while we see digitalization as referring to the impact, mediation, and changes that occur when matters such as data and experience are digitalized (e.g., computer adaptive testing). Digitalization of assessment requires and enables different designs for assessment including multimodal approaches. These open up different ways of engaging young people, taking account of student differences and enabling assessment to be potentially more authentic.

Edu-business Business corporation or privately-owned company (usually for-profit) with a market in educational based products (e.g., textbooks, educational software and technology, data management, and infrastructures).

Education technology (EdTech) Educational related businesses or corporations that design, market, and sell educational technology products to governmental agencies and educational institutions (usually software and apps for testing, teaching, and data management tools and analysis for systems).

Extended reality (XR) Real and virtual combined environments, and human-machine interactions generated by computer technology and wearables. An umbrella concept that brings AR, VR, and MR together.

Immersive assessments (IA) Assessment that allows the test taker or student to be immersed within varying degrees of a 3D-based scenario, with the use of AR, VR, MR, and XR.

International large-scale assessments (ILSAs) International large-scale assessments administered to school students and that test large samples to provide an international comparative perspective on student performance to inform national educational policy and practice. Examples include the OECD's Program for International Student Assessment (PISA), The International Association for the Evaluation of Educational Achievement (IEA)'s Trends in International Mathematics and Science Study (TIMSS), and Progress in International Reading Literacy Study (PIRLS).

Internet of Things (IoT) Network of physical objects embedded with technology such as microchips and linked via the Internet (often toys, virtual assistants).

Interoperability The capability, interactivity, and compatibility of software and computer systems used to integrate and link data.

Learning analytics Tracks students through their data traces in relation to all types of online work, including testing and curriculum work. Just as CATs enable more "personalized" testing, learning analytics potentially enable "personalized" learning through feedback to teachers and students. What is called emotional learning analytics seeks to provide analyses about students based on their non-cognitive and affective experiences collected online.

Machine learning (ML) ML and AI are prevalent in discussions of big data. ML drives AI. Here computers bring algorithms to big data analysis and surface patterns in the data. This is a "learning process" that sets computers up for dealing with increasing volumes of data. In this way the ML functions as the vehicle driving AI (see Chapter 1).

Mixed reality (MR) Sometimes called hybrid reality, MR is the merging of real and virtual worlds where physical and the digital co-exist and interact in real time.

Personalized learning Educational computer programs, software, and/or instructional approaches created to cater to the diverse learning needs, interests, and contexts of individual learners.

Predictive analytics Uses advanced analysis of historical data to produce real-time insights and predict future patterns of performance and behavior.

Psycho-informatics Applies to computer science techniques, including psychological tracking, measurement, and analysis "of behaviors, emotions, personality traits, attitudes, cognition and abilities. It makes use of behavioral data sources and analytical platforms employing techniques from data mining and machine learning to detect, characterize and classify behavioral patterns and trends" (Williamson, 2019, p. 66).

Socio-technical education data imaginary A normative imaginary concerned with appropriate and educative relationships between education data, digital technologies, and the work of policymakers and educators (see Chapter 1).

Virtual reality (VR) Immerses participants in completely virtual environments. Usually with viewing through a headset and the creation of sound and movement.

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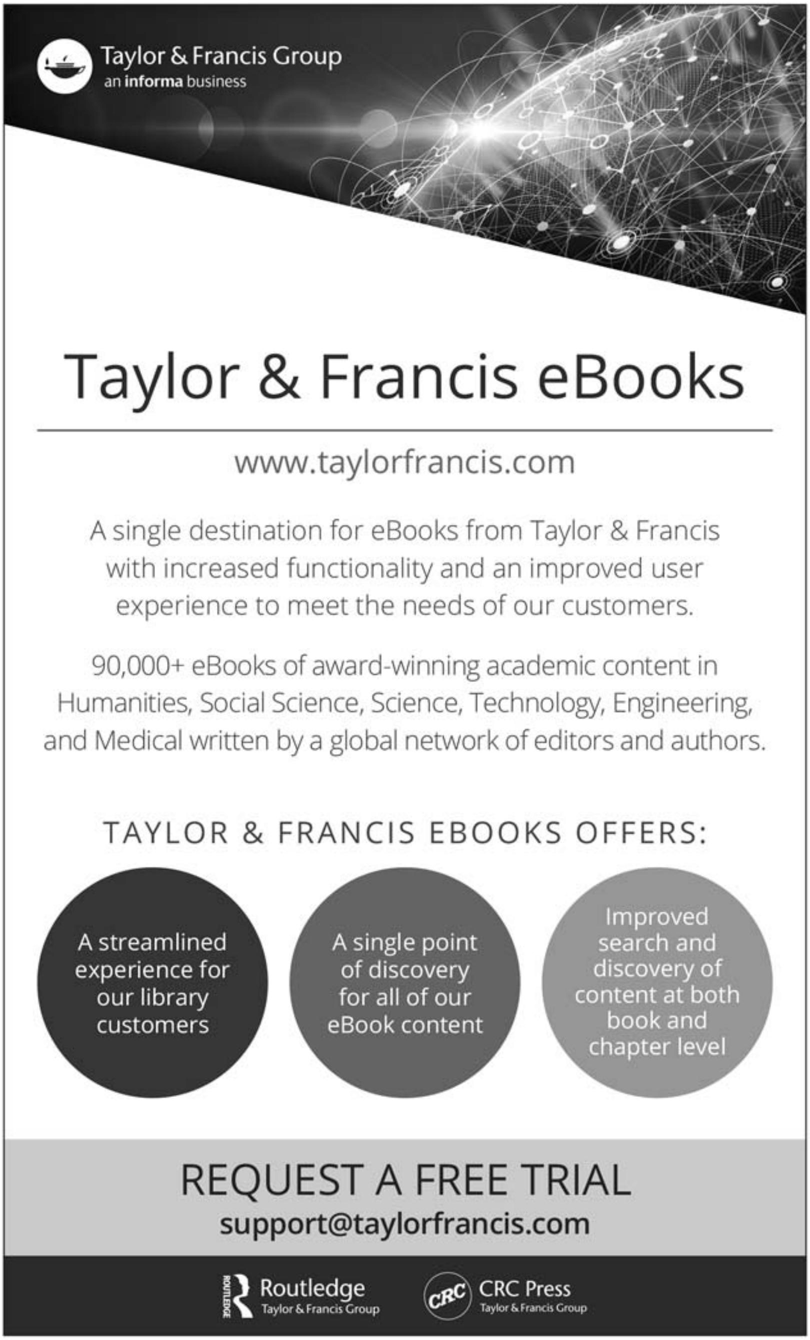
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