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DIGITAL LEARNING ASSESSMENTS AND BIG DATA:

Implications for teacher professionalism

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ABSTRACT

Big data and digital learning assessments are becoming a central part of schooling systems, affecting education policy as well as school and classroom practices. Such growing centrality must be understood as part of the broader digital disruption that has resulted in data playing a more substantial role in educational practices and system monitoring. This disruption can be traced to enhanced computational capacity, but also to the rise of neoliberal politics and the re-structuring of governance according to accountability principles. The potential of big data and digital learning-assessments is widely recognized. However, there is also growing awareness of the many challenges and risks entailed by such transformations. This paper aims identifies and discusses these challenges, and suggests possible strategies to tackle such issues. Particular attention is paid to the impact of digital disruption on teachers' identities and work, including a risk of deprofessionalisation. The paper

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argues that teacher professional judgment needs to be at the centre of quality school provision and be used in conjunction with the data produced through digital learning assessments. This move requires, in turn, a reprofessionalisation effort – that is, to provide teachers with the opportunity to develop the skills involved in analysing and turning data into pedagogical action. We argue that debates about whether ILSA participation is 'worth it' must take account of the diverse *purposes* of participants in these assessments.

INTRODUCTION

TBig data and digital learning assessments are becoming more important in policy and practice terms in schooling systems, schools and classrooms around the globe. They 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. In education, digital disruption can be considered desirable and part of innovation, especially regarding the new affordances that the technologies may create. However, the potentially negative implications for teacher professionalism are also significant. While there have been digital disruptions in the practices and organizational arrangements of medicine, law, banking and many other civic and public policy provisions, education has tended to lag somewhat to the present. At the aggregated level these disruptions are fundamentally affecting the ways in which societies now function and make new demands upon citizens. Historically, education has been understood as social, relational and context bound. The affordances of new technologies are challenging this deeply held view amongst the teaching profession, who, by and large, remain outside the logics and practices of the new data paradigm.

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Data are not inherently disruptive. It is the datafication of experience and the digitalisation of data that are the source of disruption (Zuboff, 2019, p. 234). In respect of schooling, we can regard datafication as referring 'to the transformation of different aspects of education (such as test scores, school inspection reports, or clickstream data from an online course) into digital data' (Williamson, 2017, p. 5). Datafication occurs through digitalisation and in schooling now includes data well beyond the usual academic test data – for instance, affective data relating to student motivations and ways of working. We need to acknowledge the deep philosophical and epistemological issues involved in rendering experience, including the multiple experiences of schooling, as digital data. Furthermore, there are also technical and psychometric issues involved in translating the broad purposes of schooling and curricula into test items and digitalising them as surrogate or proxy measures of the quality of achievement of the purposes of schooling, or the quality of performance of individuals and cohorts of interest (Gorur, 2011).

THE GROWING IMPORTANCE OF BIG DATA AND DIGITAL ASSESSMENT

Changing modes of governance

Some of the key factors of the growing importance of big data and digital assessments are the rise of neoliberal politics as well as the re-structuring of governance according to accountability principles – as data are crucial to these new modes of governance. In addition to enhancing computational and digital capacities, there are a number of political, policy and state restructuring factors that have contributed to the growing importance of big data and digital assessments (Williamson, 2017). A full consideration of these is beyond the remit of this paper, but a brief account will be provided as these factors affect the way data now work in school systems and schools.

> [...] a number of political, policy and state restructuring factors that have contributed to the growing importance of big data and digital assessments of data that now circulate within countries and globally.

Globalisation, following the end of the Cold War, has witnessed a seeming dominance of neoliberal politics, which involve private sector actors in matters of government and governance and the working of schooling systems, the assumption being that competition among schools will produce the best learning outcomes.

Accompanying this has been the restructuring of the bureaucratic state - through new public management but also through network governance (Rizvi and Lingard, 2010; Ball and Junemann, 2012). These together have witnessed the state steering through broad agenda-setting and accountability for the achievement of these agendas, outsourced to sites of policy implementation such as schools. This accountability has worked through performance indicators and multiple forms of data. The call for evidence-informed policy making also strengthens the significance of data in the governance of school systems, as do new related test-based modes of accountability, and school choice and differentiation policies that rely on data to enable choice. Data of multiple kinds have been central to the structuring of systems, as has been the creation of data infrastructures (Ozga, 2009; Lawn, 2013; Sellar, 2017). Today, this new mode of governance functions globally. In schooling, one consequence has been the emergence of a global education policy field and new modes of global accountabilities in schooling, linked to international large-scale learning assessments and other globally circulating data such as the OECD's Education at a Glance (Lingard, Martino, Reza-Rashti and Sellar, 2016).

The call for evidence-informed policy making also strengthens the significance of data in the governance of school systems, as do new related test-based modes of accountability, and school choice and differentiation policies that rely on data to enable choice.

Prevalence of private actors

Network governance has seen the enhanced involvement of private sector actors in all aspects of the policy cycle, from agenda-setting through policy development, enactment and evaluation. Private sector actors have been networked with governments and the state in new ways with heavy private sector involvement, particularly in relation to data infrastructures, big data and digital assessments. This new mode of governance in schooling systems always plays out in path dependent ways in different nations, but also precipitates significant questions about who should determine the purposes of schooling and curricula in democratic nations. These issues in relation to big data and digital assessments catalyse a tension between the common good motivations of the state and for-profit motives of the edu-businesses now heavily involved in the data work of schools and systems in teaching and assessment.

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A growing digital divide

While much of the globe has been connected, we also need to acknowledge the digital divide between and within countries, including between and within low-, middle- and high-income countries. For example, the UNESCO Institute for Statistics noted that, in 2016, only 46% of primary schools worldwide had access to the internet, with the figure at 16% for low-income countries (UNESCO, 2019). This has implications for the place and role of both big data and digital learning assessments in schooling systems in different nations.

CHALLENGING TEACHERS' WORK AND IDENTITIES

Professional judgement

Central to these issues is the role of teachers and their pedagogical and assessment expertise. This expertise is taken to include teacher professional judgements, as applied to curriculum, pedagogy and assessment for both formative (learning improvement) and summative (reporting) purposes. Assessment in the 21st Century includes teachers knowing their students through various assessment practices, digital and otherwise, as well as developing students' expertise in self-directed learning and self-assessment. These core aspects of teachers' work and identities are being challenged by the digital disruption manifested in the affordances of big data and digital learning assessments in schooling and the availability of large volumes and varieties of data. Such digital disruption, however, does not overcome the tensions between system and school site validity of all kinds of academic testing, given that the former works with standardization and the latter works with the idiosyncratic specificities of students in classrooms (Freebody and Wyatt-Smith, 2004). This is the question of who should control the field of judgement in schooling

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(Ball, 2003) and the related consideration of the impact of the shift of such control to test constructors, psychometricians, data and learning analytics and policy-makers on teacher professionalism and professional judgement (Nichols and Berliner, 2007; Popham, 2014).

De/Reprofessionalisation

TBased on substantial research, we know that it is the quality of teacher professional knowledge and practices (pedagogical and assessment) that are central to the enhancement of learning for all students (e.g., OECD, 2005, 2011; Hayes, Mills, Christie and Lingard, 2006; Hattie, 2008). In the global context of the digital disruption, the quality of teaching remains central in realising the potential of both learners and how new technologies can be applied to enhance learning in inclusive and differentiated ways. It is also central so as to avoid the threats and unintended consequences of digital disruption in schooling that might precipitate the deprofessionalisation of teachers in low-, middle- and high-income countries. This brings with it the danger in low-income countries of schooling being provided by unqualified teachers and machines, along with scripted curriculum, pedagogy and assessment (Riep, 2015, 2017; Junemann and Ball, 2015). Lupton and Williamson (2017), for example, note the opportunities for replacement of teacher professional judgement by insights from learning analytics and the narrowing of the education provided by dependence on the assumptions encoded in algorithms. For example, in Liberia, India and Pakistan, technology is profoundly reshaping the provision and experience of schooling predicated on the assumption that qualified teachers can be substituted with paraprofessionals and machines offering scripted curriculum and pedagogy. Further, in some middle- to high-income schooling contexts, it is becoming routine for teacher e-readers to connect to smart phones with the data going to and from teacher computers to storage in the cloud and setting next step teaching.

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Thus, in this context, the professionalisation of teachers all across the globe is imperative to achieve productive complementarities: between the work of human beings (teachers and students) and the multiple modes of human expertise and machine learning in using big data. Teacher expertise in using the affordances of technologies should be located at the core of efforts to maximise educative potentials. Not to do so runs the risk of exacerbating inequalities in the schooling experiences and outcomes for diverse groups of students in and across nations (Chmielewski, 2019).

EMERGENCE OF A CULTURE OF AUDIT AND DATA

The centrality of (big) data in the policy and accountability work of schooling systems and related moves to digital assessments of students are manifestations of the new mode of governance and indeed of broader social changes. Here, Power (1997) talks of the 'audit culture', while Thrift (2005) speaks of 'knowing capitalism' as capitalism becomes a knowledge project of itself. The widespread utilisation of 'data and indicator-based methods of evaluation and monitoring' (Mau, 2019, p.2) suggests, according to Mau (2019), that we live in a 'metric society' and are witnessing the datafication of the social world down to the level of individuals. Zuboff (2019) refers to the present as 'the age of surveillance capitalism', where the data we readily surrender on our digital devices and social media are used to surveil us and create niche or personalised markets to sell products to us[2]. In related fashion, in schooling systems there has been what has been called a 'doublethink of data' (Hardy and Lewis, 2017); schools and teachers 'have to capture data, but are also captured through data' (Williamson, 2017, p, 82). Individual identities are constituted and reconstituted as constellations of data points capable of change over time. The same data logics associated with social media also underpin the development of data-based personalised learning in schools and systems. Indeed, schooling systems, schools and the work of teachers, and the place of their professional judgement have been and will continue to be affected by the issues raised in this introduction: new modes of network governance, datafication, digital assessments, global, national and personalised, big data, edu-businesses, resulting perhaps in the datafied teacher and datafied students (Lewis and Holloway, 2019).

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2 For a discussion of broader social changes see also Srnicek (2017) who speaks about 'platform capitalism' and Williamson (2017) who refers to 'digital capitalism'

WHAT ARE DIGITAL LEARNING ASSESSMENTS AND HOW ARE THEY EVOLVING?

THE EVOLUTION OF DIGITAL ASSESSMENTS

From pen and paper to computer-based tests

At their simplest, digital learning assessments are the conversion of standard testing practices to an online form; that is, they can be seen as pen and paper tests simply taken on a computer. The computer replaces the pen and paper as the technology for completing the test. Of course, this modifies the capacity for analysing the results of the tests and the speed with which this can be done, particularly with multiple choice questions. So, for example, the OECD's Programme for International Student Assessment (PISA), was conducted online for the first time in 2015 by all OECD member countries. This entailed a translation of the pen and paper test to a computer format, which meant that students completed the test on a computer.

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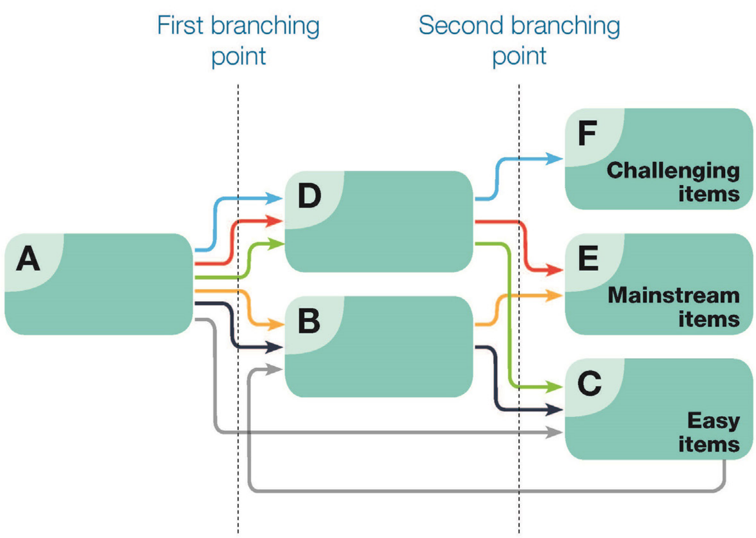
From digitization to digitalisation: the rise of Computer Adaptive Testing (CATs)

However, such assessments have been evolving away from this translation model to Computer Adaptive Testing (CAT). CAT is designed to adapt the test to the test taker's ability to answer questions, thus transforming the nature of the tests, the test taker's experience of the test, and potential modes of test data analyses, log-file data, and feedback. This evolution might be grasped through the distinction between digitization, as with PISA 2015, and digitalisation, as with the introduction of adaptive testing in PISA 2018.

CATs are constructed through a detailed item bank. An algorithm selects the items for test takers in response to their success or otherwise in answering initial or subsequent test questions. This entails 'branching'. This branching or adjustment of test items to test taker can occur after each item or after various stages of the test, called Multistage Adaptive Testing. **Figure 1** presents an example of how branching works in adaptive testing.

Figure 1: Test tailored design with branching



Source: Australian Curriculum, Assessment, and Reporting Authority (ACARA) (2014). Reproduced with permission[3].

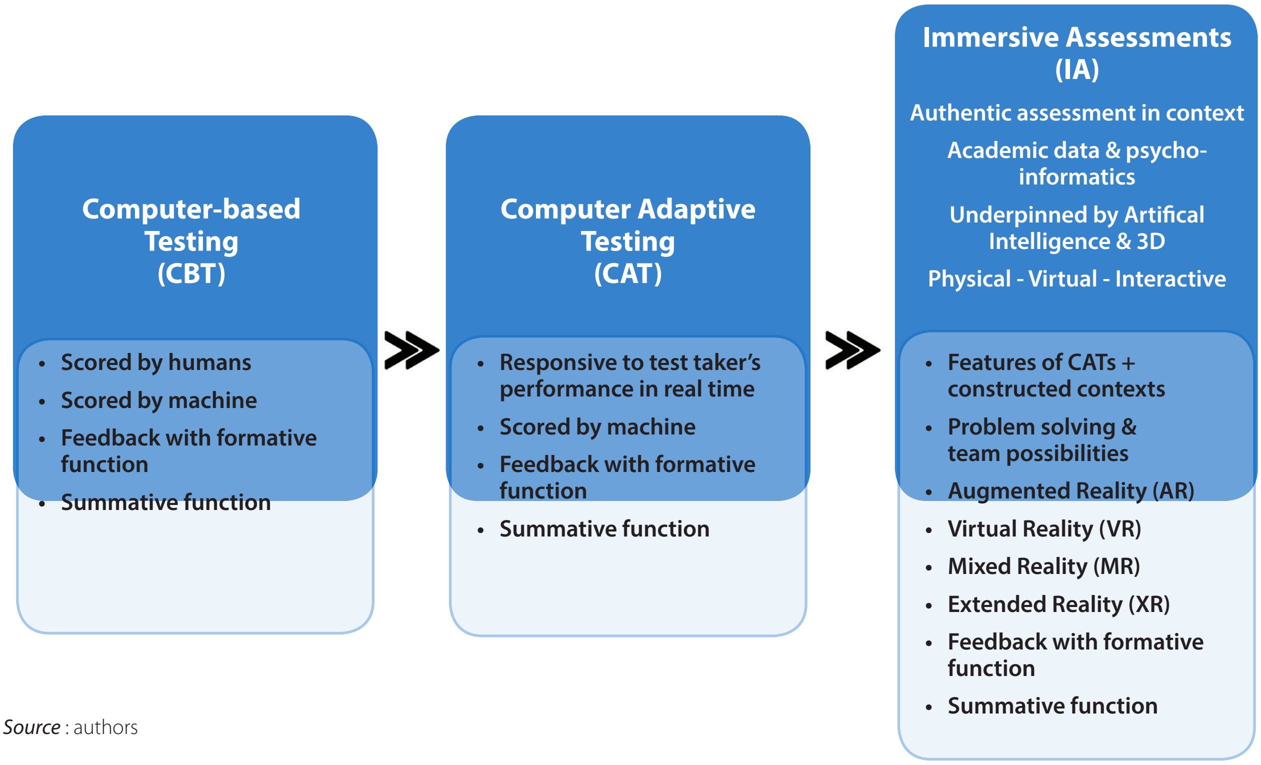
3 ACARA does not endorse any product that uses its material or make any representations as to the quality of such products.

From CATs to Immersive Assessments

Beyond CATs, new technologies of Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR) and Extended Reality (ER) are also being used to provide authentic, conceptually and perceptually enriched experiences in which assessment could occur, also referred to as Immersive Assessments (IA). Figure 2 displays the evolution of digitally-mediated ways to assess student progress authentically in context. There is no intention to suggest that this evolution is straightforward and linear, and that all countries are at the same point on this continuum. There is also no intention to suggest that all knowledge forms lend themselves to immersive assessments, nor that they should be so captured. These new technologies can become the means for bringing the world outside of schools virtually into classrooms. AR, VR, MR and XR rely upon artificial intelligence (AI) and 3D to maximise the experiential and cognitive potential of digital learning assessment and related data, including psycho-informatics. These are emergent assessment practices and, as yet, their use is not widespread. Immersive assessments carry forward the benefits of Computer-Based Testing (CBT), CAT, as they pertain to scoring efficiency and feedback possibilities with the added benefits of affording opportunities for more authentic assessment through a range of constructed reality, as illustrated in **Figure 2.**

Beyond CATs, new technologies [...] are also being used to provide authentic, conceptually and perceptually enriched experiences in which assessment could occur.

Figure 2: The evolution of digitally-mediated ways to assess student progress authentically in context



Source : authors

THE POTENTIALS OF COMPUTER ADAPTIVE TESTING (CATS)

Providing timely feedback

The appeal of CATs lies in its promise of personalised learning (sometimes called individualised learning), and of faster and more pedagogically useful feedback to teachers and students to inform their practices. Another important function of testing on computers is the matching of student capacity and test item to maintain student interest to ensure completion of the test. A last one is to provide more useful nuanced data to teachers across the full range of student ability. A common criticism of pen and paper tests

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has been that they provide little constructive evidence or feedback regarding very high and very low performing students – and CATs is about alleviating this issue.

Informing pedagogical reflections

Testing on computers, including CATs, can provide additional useful information for teachers of how a test taker has cognitively and affectively addressed any given question. Thus, CATs provide more than straightforward test result data and potentially can inform teacher pedagogical reflections. There is also the possibility of continuous assessment of this kind in both CATs and intelligent tutoring systems for personalised learning. This would enable the tracking and assessment of learning of each student each day and of the effectiveness of teacher pedagogical strategies, and could potentially lead to individualised and personalised learning and pedagogy and change the focus from the school and classroom to the individual student (Hill and Barber, 2014). This is where learning analytics comes into the picture.

Human designed and machine mediated algorithms determine which sets of questions test takers should take in CATs. While initially designed by data scientists, algorithms then work independently with other algorithms to produce a wide range of data on students, in addition to test scores. The data and insights so generated about individual learners and particular pedagogical practices are referred to as learning analytics and enable personalised and individualised learning and are discussed further later in this paper.

Setting the foundations for computer marking of prose tests

> [...] there are frailties in relation to both human marking and marking based on algorithms, and that high reliability can be achieved through training and calibration.

While CATs enable rapid computer marking of certain types of test questions, particularly multiple-choice questions, there have been attempts underway for some time to develop computer marking of prose text. These attempts reflect two factors, namely the issues of reported low reliability and high costs of human essay marking, both dating back decades (Page, 1966; Diederich, 1974).

There is a debate about the reliability and validity of such computer marking of prose. Some suggest this provides results indistinguishable from human assessments (Page, 1966; Attali and Bursten, 2006; Attali, Lewis and Steier, 2012), yet there is considerable debate about this claim. Perelman (2018), for example, argues that much more research is required in relation to justifying these claims. As mentioned below, we would argue that there are frailties in relation to both human marking and marking based on algorithms, and that high reliability can be achieved through training and calibration.

CATS DO NOT COME WITHOUT RISK

Hype sometimes accompanies the potentials of new technologies in relation to schooling and is apparent in hopes held out for CATs. Thompson (2017) on this point observes:

> One of the somewhat utopian promises of CAT measures is that they can operate as 'teaching machines' because they can respond far more quickly to student patterns than an individual teacher or a conventional test. In this, they clearly manifest a techno-managerialist philosophy of education. Equally, learning is constructed as developmental, measurable and constituted through an outside knowledge, skill performance that can become 'internalised' within the deficit student learners. (p. 4)

At the same time, edu-businesses, and some philanthropic organizations, have been big supporters of the development and potential of digital learning assessments and learning analytics (Hill and Barber, 2014; Sellar and Hogan, 2019). This raises questions about who ought to construct the purposes and functioning of schooling systems in democratic societies. There are also issues here to do with the individualising of schooling to the possible neglect of the broader socialisation purposes of schooling and potentially deprofessionalising impact on the work of teachers. In low- to middle-income countries, this could extend to the replacement of professionally qualified teachers by private company provided standardised CATs-based personalised learning approaches and a reductive curriculum (Sellar and Hogan, 2019). The unit of analysis of learning analytics, linked to big data, is the individual. Thus,

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their usage could possibly see a curriculum focused solely on individual learning to the neglect of the currently valued collective, social and civic purposes of schooling. With the evolution of testing on computers, we see the emergence of big data in schooling, continuous real-time collection of a variety of data and analyses linked to personalised learning, disconnected from the larger purposes of schooling. This provides an opening for considering the appropriate role of the public sector and legislation in regard to data ownership and use in schools and systems.

WHICH ASSESSMENT DATA CAN BE CLASSIFIED AS BIG DATA?

UNPACKING THE CONCEPT OF BIG DATA

A working definition

While big data remains an elusive concept, some attempts to demarcate it have been made. Williamson (2017) has proffered the following technical definition of big data drawing on the similar 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)

Key features

We see here the commonly referred to characteristics of big data as volume (necessitating cloud storage), variety, and velocity. De Mauro, Greco and Grimaldi (2016) define big data in a way, also derived from the literature, that stresses that it is an asset, implying its potential monetisation. They note: '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.

BIG DATA: UNRESOLVED CHALLENGES IN EDUCATION AND BEYOND

Infrastructure

These definitions raise a number of issues about big data. The first relates to the necessary computational and infrastructural capacity to collect and store such volumes of data. There are substantial costs involved here and, under conditions of network governance, the potential for the private sector to enter with profit-making motives. Data infrastructure 'can be understood as an active and changing platform for storing, sharing and consuming data across networked technologies' (Sellar, 2017, p.345) and indicates the necessity of interoperability of data across different platforms. There are also social relations that constitute data infrastructures. Technical, soft and hardware capacities are necessary to allow and facilitate system interoperability. As a result, a number of interoperability standards have been developed. In the US, the UK and Australia, the most influential of these standards has been Microsoft's Schools Interoperability Framework (SIF), developed in conjunction with 18 other software companies and the US Software and Information Industry Association (Sellar, 2017).

[...] big data can be both a way to provide solutions to problems, but also invade privacy – as captured by the notion of dataveillance.

Privacy and data ownership

A second issue relates to analytical capacity to design algorithms, which draw insights from multiple data sets. There are also questions to do with the functioning of algorithms, particularly when algorithms work in a machine-mediated way to link with other algorithms to produce multiple kinds of data to inform policy and classroom practices. The continuous collection of data as central to big data also raises questions about surveillance and control through data. As Boyd and Crawford (2012) have argued, big data can be both a way to provide solutions to problems, but also invade privacy – as captured by the notion of dataveillance, understood to refer to the collection and monitoring of personal data. There are important issues here concerning data privacy and ownership, particularly when data infrastructures are privatised, as an element of what Easterling (2014) refers to as 'extrastatecraft'.

For example, an Australian study found teachers were deeply concerned about student data being in private hands (Lingard, Sellar, Hogan and Thompson, 2017). In the USA, the collapse of the InBloom initiative in a group of Eastern states, which attempted to create data infrastructures and interoperability between multiple data sets, occurred because of organized parental opposition to the involvement of private companies, issues of data privacy, and the potential for student data to be sold to third parties by the edu-businesses involved in the project (Bulger, McCormick, and Pitcan, 2017; Lingard, 2019). In Japan, data privacy has also been a source of concern, where legislation ensures data collected by governments can only be used for the explicit purposes for which they were collected (Takayama and Lingard, 2019). This situation prohibits data practices endemic in big data analytics, namely the making interoperable of multiple data sets of various kinds to enable algorithmic analytics.

From causality to correlation

> With big data various extant data sets can be integrated and then algorithms used to produce 'patterns' and insights, reducing emphasis on causality and focusing instead on correlations, meaning we will know not why something occurred but what occurred.

Unlike standard science research practices where research questions are framed prior to data-analysis efforts aimed at understanding causality, with big data there are no a priori hypotheses established or research questions created to determine the data to be collected. Rather, various extant data sets can be integrated and then algorithms used to produce 'patterns' and insights. This means reducing emphasis on causality and focusing instead on correlations, meaning we will know not why something occurred but what occurred (Mayer-Schonberger and Cukier, 2013, p. 7). Human decision-making can be brought to bear to interpret such meaning and what it may mean for future action. The huge volume of data fed into computers enables the inferring of probabilities and thus big data is also about predictions (Mayer-Schonberger and Cukier, 2013, pp.11-12). It is the function of predictive analytics that makes big data attractive to policy makers. However, there is also potential for analytics to be misleading, as well as to cause potentially harmful actions on the basis of false correlations. In Australia, in the New South Wales Department of Education, the Centre for Education Statistics and Evaluation (CESE) is seeking to utilise big data and predictive analytics to inform policy making and practice. There has been some criticism of this kind of big data work in terms of its backward-looking lens and potential impacts on democracy and equity (O'Neil, 2017), assuming the future will be a seamless continuation of the past. At its most useful, predictive analytics is for informing human decision-making about actioning a better future.

Individualszation and curriculum ownership

To this point, we have defined big data in a general sense and raised some issues concerning it. How does it specifically apply and work in education? Cope and Kalantzis (2016) have rearticulated a definition of big data in education. They define it in this way:

> (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)

This definition raises issues of students working continuously on computer-based curricula, pedagogy and assessment. This is the individualisation aspect of big data as it meets the classroom. There is the potential here for schooling to be reduced to what can be produced online and we need to acknowledge that such data 'recreate the world' rather than simply represent it (Espeland and Sauder, 2007). With data-based individualisation, the broader social and citizenship goals of schooling will potentially be considerably down-played. Such computer-based curriculum, pedagogy and assessment will also potentially see these message systems privatised as edu-businesses establish these online programs. Questions are raised here about who ought to develop curricula in government schools in democratic societies[4] .

> There is also the potential to change the role of the teacher to being simply an adjunct to computer based scripted curriculum and pedagogy, and thus reduce the need to produce professionally educated teachers.

Replacing teachers and changing their role

As Sellar and Hogan (2019) argue, there is the potential for the replacement of teachers in schooling systems in low-income countries, where the largest educational expense is teacher salaries. There is some evidence of this occurring already in some in sub-Saharan Africa and other low- to middle-income countries, where low-fee for profit schools provide scripted curricula to students (Riep, 2015). There is also the potential to change the role of the teacher to being simply an adjunct to computer based scripted curriculum and pedagogy, and thus reduce the need to produce professionally educated teachers in low-income countries. The Global North is however not alien to these dynamics. Research in New York State with activist parent groups has shown their deep concern about such developments, about too much screen time, about the for-profit motives of the edu-businesses, of the reductive curricula effects, and of the potential deprofessionalisation of teachers (Lingard and Hursh, 2019). Sellar and Hogan (2019) also raise many questions regarding privacy, consent, ownership, transparency and openness in respect of data collected by edu-businesses in relation to their development of data-driven personalised learning programs.

ASSESSMENT AND BIG DATA

National and cross-national large-scale learning assessments

In terms of the definitions provided above, there are few assessments that might be defined as big data, yet some at least manifest some characteristics of it.

The case of Australia's National Assessment Program Literacy and Numeracy (NAPLAN) (see **Box 1**) illustrates how little big data there might actually be in extant school assessments, despite the fact that NAPLAN is a census-based test. This is a future aspiration rather than an actual extant reality (Thompson, 2017).

> NAPLAN is conducted every year and includes all Year 3, 5, 7 and 9 students in all schools across Australia. The data derived from this national testing are certainly huge in volume (census testing), but are not continuous (occurring once per year), yet they do have a longitudinal element, with results reported yearly from the first year of the test, 2008. The specific performance data on the test are linked to other data about schools and students, for example, the Index of Community Socio-economic Advantage (ICSEA) and to factors such as students with a Language Background other than English (LBOTE). This might be seen as pulling together a variety of digital data sets made possible through developments in data linking across large administrative data-sets. Work underway concerns linking education data to health and social services, and this is facilitated by these data sets being in a digitalised form. It is scheduled that NAPLAN will be fully online for all students in 2020. However, problems in the administration of the online test in 2019, when about half of all participants took the test online, have raised issues about the capacity to effectively implement the universal online administration of the test. Questions have also been raised about the comparability of data collected online with that collected from pen and paper tests. It is hoped that in the future NAPLAN will be a fully Computer Adaptive Test taken online and that it will be able to be taken at different times over the school year, with the potential for continuous real time testing and feedback. Given technical failure in the administration of the test in 2019, this aspiration for NAPLAN to eventually take on a big data format seems a long way from being achieved. The aspiration for the future of NAPLAN is that it will take on a CAT mode and provide big data for analytic use and predictions and policy and practice interventions.

Box 1: Australia's National Assessment Program Literacy and Numeracy (NAPLAN)

4 One of the most highly cited papers on digital assessments was written for an edu-business (Hill and Barber, 2014), which wants to market data-driven personalised learning.

Source : authors

The same can be said about international large-scale learning assessments in relation to big data. They use sample data rather than census data, and are one-off tests every three years, not continuous; feedback is usually provided twelve months after the tests are administered and is aggregated at system level. While they are taken online now by most participating nations, they are not as yet in a Computer Adaptive mode, yet aspiring to move in that direction. Large-scale learning assessments are therefore not generating what may be classified as big data.

Formative assessments

In high-income countries today, there is widespread use of formative assessments - apps and intelligent tutoring systems (e.g., Reading Eggs, Mathseeds, Mathletics and Quizlet) for online learning, and apps for behaviour management (e.g., Class Dojo[5]). There are also some of these in middle-income countries such as India (e.g., BYJU's – The Learning App). These are mainly privately developed. There is the potential with these formative assessment apps for the use of a big data disposition. However, often the insights from such analytics are utilised by the private companies to improve the app to increase its attractiveness for purchase by schools, teachers and by parents. For example, there is also a parental Class Dojo app that complements the data collected at school. This again raises issues of who owns the data and of informed consent to data usage- particularly as edu-businesses have been amongst the main advocates of a big data approach to reforming schooling systems and schools (Hill and Barber, 2014; Williamson, 2017; Sellar and Hogan, 2019).

> The question of ownership of data collected about teachers and students relates to bigger questions about data ethics, matters of consent, and issues of data privacy.

WHO OWNS BIG DATA IN EDUCATION?

We argue that the question of ownership of data collected about teachers and students relates to bigger questions about data ethics, matters of consent, and issues of data privacy. These issues are very apparent in respect of 'continuous tracking and monitoring of "streaming data" through real-time analytics rather than the collection of data through discrete temporal assessment events' (Williamson, 2017, p.90) and particularly when this tracking and monitoring are done by private edu-business or funded by philanthropic organizations such as t he Bill and Melinda Gates Foundation, and the Chan Zuckerberg Initiative. Whether consent is given to the collection of such data and who owns it are interesting and complex issues, particularly when this mode of assessment is conducted by private actors, but done within and sometimes contracted by government schooling systems or schools.

Data protection and privacy: positive developments

A report prepared for the European Commission explored issues to do with data privacy in relation to big data (Berendt, Littlejohn, Kern, Mitros, Shacklock and Blakemore, 2017) and recommended that data protection and data privacy be incorporated into the actual design of big data systems. How this is to be achieved is another question, of course. Polonetsky and Jerome (2014) shave considered a wide range of ethical and privacy issues regarding the exponentially expanding usage of data in US schools. They explore legislative frameworks, which appear inadequate to the task to this point, especially with the enhanced involvement of edtech companies and other edu-businesses in respect of data work. The report divides the data collected in US schools into four categories, namely, administrative, instructional (e.g., apps and online homework), assessment/measurement/testing and other optional data (e.g., fundraising). Polonetsky and Jerome highlight the intricacies of student and parent consent in respect of these various data sets.

Pending ethical and legal challenges

> [...] complex legal and ethical issues [...] in respect of data ownership [...] are becoming more significant to the public and legislators.

This US-based report very well encapsulates the complexities of consent and ownership of data in schooling systems and schools, especially given the enhanced role of private companies in this data work. There are complex legal and ethical issues here in respect of data ownership that demand fulsome consideration beyond the scope of this paper. These matters have not been resolved, but are becoming more significant to the public and legislators, indicated by privacy and usage concerns about the data that citizens readily render to social media (e.g. Facebook) (Zuboff, 2019). As Williamson (2017, p. 121) notes, 'considerable unresolved concerns remain about the adequacy of contemporary

5 See Manolev, Sullivan and Slee (2019), for an overview, analysis and concerns of Class Dojo and its potential for surveillance and performative classroom culture.

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'. We would suggest exactly the same about issues of data ownership in the current moment of digital disruption to schooling.

THE ADVANTAGES AND POTENTIALS OF ALGORITHMS

BEYOND HUMAN CAPABILITIES

> [...] algorithms both permit a scale of analysis and a complexity of decision-making beyond human capabilities.

Broadly speaking, discussions of learning analytics, machine learning and algorithms typically focus on situations where data are gathered, analysed and reported in relation to learners and their environments by the use of algorithms to enable greater personalisation (Knox, 2017; Reyes, 2015; Siemens, 2013; Thompson and Cook, 2017; Williamson, 2018). Taking a positive perspective, Larusson and White (2014) state, '[l]earning analytics ideally attempts to leverage data to provide insight into the activities taking place within the classroom. What metrics are derived can then be fed back into pedagogy or applied with consequences even well outside the classroom itself' (p. 15).

In addition to the well-recognized efficiencies of technologies and their affordances to generate models, novel patterns and new knowledge, and make predictions, it is also clear that algorithms both permit a scale of analysis and a complexity of decision-making beyond human capabilities.

In practice, though, the use of algorithms in education has been oriented by a narrow agenda. While simplistic decision-making algorithms and complex profiling algorithms have been used in various domains, including clinical decision support systems, predictive policing systems, banking, insurance and government internal revenue systems, or employment screening, the developments in education have had more limited range, driven by testing companies and edu-businesses. Not surprisingly, the focus has tended to be on issues about the efficiencies, reliability and effectiveness of systems and processes, including scoring processes, with investigation of the suite of issues around the nature and function of human judgement less prominent, as discussed below.

COMPLEX INTERACTION BETWEEN HUMAN AND ALGORITHMS

Mittelstadt, Allo, Taddeo, Wachter, and Floridi (2016) made two key claims of direct relevance to human judgement and decision-making that merit consideration in the context of education: drawing on Matthias (2004), they note that 'the human operator does not need to understand the rationale for decision-making rules produced by algorithms' (p. 179); also ,and drawing on Tutt (2016), they observe that 'algorithms increase in complexity' and interact with the outputs of other algorithms as a basis for decision-making, which then raises a number of ethical issues, which they warn can have 'severe consequences affecting individuals, groups and whole segments of a society' (Mittelstadt et al., 2016, p.2). Both of these considerations provide an opening for considering the nature of the interface between the human operator of the machines, the teacher, and the student, and the functions of human judgement and decision-making, including control over decision rules as they pertain to algorithms, new inputs, and new knowledge, including predictions.

> [...] algorithms are not free from bias and ethical challenges, with potentially severe consequences.

BIAS, SUBJECTIVITY AND THE ROLE OF HUMAN DECISION-MAKING

While human judgement has long been criticised as being subject to bias and subjectivity, thus exhibiting limited reliability, research suggests that algorithms are not free from bias and ethical challenges, with potentially severe consequences. There was an historical claim that algorithms lacked bias, which has now been challenged. Research on the automation of human decision-making is increasingly recognizing that algorithms can make biased decisions. Mittelstadt et al. (2016, p.7) assert this more strongly, stating, 'Algorithms inevitably make biased decisions'. The reason for this is that 'an algorithm's design and functionality reflect its designers and intended uses to the extent that a particular design is preferred as the best or most efficient option'.

Coding and software inevitably shape what is measured, as developers specify operational parameters and as these are configured and reconfigured by users. An observation made by writers dating back more than two decades ago (e.g., Friedman and Nissenbaum, 1996; Johnson, 2006, 2013; Nakamura, 2013) is that this shaping occurs as users and designers act on interests, values and assumptions, and in this way, they come to be not only embedded, but also privileged in the development process. Importantly, this aspect of shaping typically remains hidden in the development process, being deeply embedded in the algorithm, occurring without leaving traces of human decision-making. Building on this insight, Mittelstadt et al. (2016) asserted that, 'Identifying the influence of human subjectivity in algorithm design and configuration often requires investigation of long-term, multi-user development processes. Even with sufficient resources, problems and underlying values will often not be apparent until a problematic use case arises' (p.2). These authors' mapping of the ethics problems prompted by algorithmic decision-making is a useful framing, along with their caution that the ethics of algorithms should be considered as connected to issues of implementation and therefore, the roles played by computer programs, software and information systems, all once again involving human decision-making. This provides the opening for considering necessary caution concerning potential situations whereby 'determining whether a particular problematic decision is merely a one-off 'bug' or evidence of a systemic failure or bias may be impossible (or least highly difficult) with poorly interpretable and predictable learning algorithms' (Mittelstadt et al., 2016, p.2).

The ethics of algorithms should be considered as connected to issues of implementation and therefore, the roles played by computer programs, software and information systems, all once again involving human decision-making.

NARROWING CONCEPTIONS OF LEARNING AND WHAT IS TAUGHT

Digital learning assessments that use adaptive technology and big data tools (CATs, intelligent tutoring systems for formative assessment via apps and online programs, and in general, learning analytics) are often viewed as flexible and efficient for assessment and positive for learning (Timmis, Broadfoot, Sutherland, and Oldfield, 2016). Yet, such technological adaptation can narrow conceptions of learning and what is taught. In the instance of for-profit edu-businesses that develop and market these assessment programs, personalisation of learning via such adaptation through real time automated testing and analytics can control the content and curriculum delivery based on subscriptions to a various company's services and products (Sellar and Hogan, 2019). As a result, Sellar and Hogan (2019) comment, such predicated actions eliminate the element of being surprised by spontaneous moments of student success, as it can stream or box students into pathways as directed by the algorithms on these digital platforms.

Digital learning assessments that use adaptive technology and big data tools are often viewed as positive for learning.Yet, such technological adaptation can narrow conceptions of learning and what is taught.

The narrowing of teaching and learning resilience is another concern, as learning analytics does not allow a child to fail, thus overlooking the 'educational value of failure' and learning from mistakes (Willis, 2014 in Knox, 2017, p. 742). In addition to these concerns are the implications of displacing expert professional judgement of the teacher, and as a result, the further risk that children's opportunities might be narrowed by the assumptions encoded in the algorithms; consequently, further contributing to the potential loss of children's own decision-making processes. As Lupton and Williamson (2017) note, '(l)earning analytics and adaptive learning platforms make data-processing algorithms and predictive analytics technologies into key techniques for the personalisation of education, therefore erasing children's own embodied experiences and voices from decision-making processes about their learning' (p. 790). This is particularly the case given how data are collected to build profiles of learners in order to personalise learning and related assessment (Thompson and Cook, 2017).

These observations raise key questions about the prospect of standardisation of schooling and learning within and across countries as likely. Should the latter be considered desirable, then the issues of ethics, risks and unintended consequences call for serious sustained investigation, as do core concerns tied to how the digital learning assessment meets fitness-for-purposes within and across divergent cultural contexts. The pressing need is for a large scoped body of research to be planned on a variety of issues including data access/sharing/ ownership and privacy, which raise legal issues of the rights of the child/ student, parents and teachers and teacher aides. Optimally this research should be undertaken in partnerships involving government agencies at national and international levels, edtech businesses and education providers.

THE CHANGING ROLE OF TEACHERS

AN URGENT NEED FOR HIGHLY SKILLED TEACHERS

At this juncture, we highlight that teaching and learning are always and inevitably cultural and linguistic practices, inextricably connected to specific contexts. That is to say, learning occurs in and through the use of language, text and social interactions in context. At the same time, it is widely recognized that, across contexts, 'Expertise and attention play a critical role in the various phases of learning, which consists of a series of 'Instruction, Practice, and Assessment' cycles and further, that 'learning depends on the number of learning opportunities, in effect, the number of such cycles and the quality of assistance available in each cycle' (Dhar, Nilekani, Maruwada and Pappu, 2016, p.138).

> [...] teaching and learning are always and inevitably cultural and linguistic practices, inextricably connected to specific contexts.

Against such a context, teacher expertise is of paramount importance. However, shortages in trained professional teachers, particularly in some subject areas such as Mathematics and Science, are now reported in a growing number of countries. This is a worldwide problem – in low-, middle-, and high-income countries alike. Indeed, already existing and looming trained teacher shortages are a phenomenon reported in several high-income countries, including the United States, Australia and Norway. Against this backdrop, we discuss how the role of teachers is likely to continue to change in an era of strengthening focus on individual performance (teachers and students), analysed and predicted in real time through comparative big-data methods, and through approaches that combine learning analytics and psycho-informatics platforms.

CULTIVATING TEACHERS' DATA LITERACY

Rethinking and extending teacher expertise

Traditionally, teachers' work has centered on curriculum, pedagogy/instruction and assessment. We propose that this trilogy remains central, though the increased focus on data literacy will require a reprofessionalisation of teachers. While teachers will continue the roles of training, explaining, and sustaining learning, new workplace practices will be called for as teachers interact with learners participating in Computer Adaptive Testing and Immersive Assessments. Essentially, teachers will be among the workforce involved in what Daugherty and Wilson (2018) refer to as the Missing middle (p.138). We propose that teachers' roles in this new space will be what these authors refer to as hybrid (p.138), with human and machine interaction normalised in learning contexts, both in and beyond the institutional setting of the school.

> While teachers will continue the roles of training, explaining, and sustaining learning, new workplace practices will be called for as teachers interact with learners participating in Computer Adaptive Testing and Immersive Assessments.

We also propose a rethinking of teacher expertise that extends to i) using a range of data to evaluate the impact of teaching and modes of learning, and ii) developing in learners' abilities not only to learn and self-assess effectively, but also to transfer learning for innovation and problem-solving, individually and collaboratively. For the teacher, this calls for (i) developing an enquiring mindset into the nature of knowledge and learning - how knowledge is used and can be created - and a related positive disposition to socio-technological change and problem solving; ii) a repertoire of practices aligned with the evolution of computer enabled testing from computer-based testing to Computer Adaptive Testing to Immersive Assessment, and; iii) a knowledge and skill set necessary to infer meaning from assessment data and to use it to improve teaching and learning.

A new approach to diagnosis and intervention

The potential of predictive analytics is that teachers and education systems could move from the current model of intervention (action after a problem has been identified) to a model of prevention informed by diagnostic data about student readiness to proceed. This would effectively short-circuit the negative consequences that can result from unidentified gaps in student knowledge that lead to barriers to academic success. Working from this position, the move to Computer Adaptive Testing and data analytics makes it possible to mine far more information than just students' responses to test items. According to Hill and Barber, online assessment can produce 'a more rounded and complete picture of a student's achievements and capabilities' (2014, p.45). This move could reshape the role of the teacher in not only using output measures, but in engaging with efforts to predict through the capture of 'intimate cognitive and affective data' for the purposes of identifying learning and motivational problems. We argue that teachers have a significant role to play in defining personalised pathways through courses or prescribed remedial pedagogies, informed by their critical understanding of data including person specific performance information. As the optics of assessment through big data are refocused on more intimate details of the individual, the role of the teacher will change – moving to the middle, mentioned above - dependent on how the outcomes of personalised assessments are made available at local levels and in policy expectations and related regulation in practice.

[...] teachers have a significant role to play in defining personalised pathways through courses or prescribed remedial pedagogies, informed by their critical understanding of data including person specific performance information.

Connecting the classroom level to the macro-level

Beyond this is the potential turn of data analysis to discover the patterns and relationships within the vast number of transactions that occur routinely within classrooms. Researchers have long searched for means to capture classroom talk and interactions across teachers and students and between students. The potential of new quantitative and qualitative analyses of big data (Mills, 2019) from classrooms is what they could reveal, as Williamson (2018) describes through, 'real-time, up- close analysis based on the continuous collection of digital traces of student activities and automated, adaptive feedback based on predicted outcomes'. If the teacher has the mindset and skill set, 'intimate analytics that operate in real time' could be used to compare 'cognitive and affective data generated from individuals within classrooms with norms and averages calculated from massive volumes of fine-grained data from whole populations' (Williamson, 2018, p.60).

As a matter of fact, data collected at the school and local level holds potential, but require teachers to better understand data collection and data use for both informing and improving practice. At this point in human history, the role of the teacher is at a crossroads, bound up with how big data and local school and classroom data, generated by teachers, come to be valued in national education policy and local decision-making and action. These two types of data are intersecting in ways previously not available with implications for the teaching workforce and student populations, and subgroups. At a local or school level, capacity building in digital assessment and subsequent data use for improving pedagogical practices requires an understanding of the purpose and aims of data collection (Kippers, Poortman, Schildkamp and Visscher, 2018). As Cope and Kalantizis (2016) comment, 'to teach and learn in such environments requires new professional and pedagogical sensibilities. Everyone becomes to some extent a data analyst' (p. 8).

At this point in human history, the role of the teacher is at a crossroads, bound up with how big data and local school and classroom data, generated by teachers, come to be valued in national education policy and local decision-making and action.

Building teacher capacity in educational data use

Wayman and Jimerson (2014) describe 'data' as 'any information that helps educators know more about their students which can be codified in some way' (p. 26) or, as Lai and Schildkamp (2013) note, information that is collected and analysed to represent some aspects of schooling. Data types can include input data, such as school demographics, process data, related to the quality of pedagogy, outcome data, including student performance, attrition and retention rates, and satisfaction data, such as opinions from teachers, staff and students (Ikemoto and Marsh, 2007). Developing from this are the skills to understand and analyse data, or data literacy. As Mandinach and Gummer (2015) note:

> Data literacy for teaching is the ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data (assessment, school climate, behavioral, snapshot, longitudinal, moment-to-moment, and so on) to help determine instructional steps. It combines an understanding of data with standards, disciplinary knowledge and practices, curricular knowledge, pedagogical content knowledge, and an understanding of how children learn. (p. 2)

Cultivating teacher's data literacy is not an easy endeavour. This definition above is helpful, highlighting the connections across data, standards and teacher knowledge. Further to this, teachers' beliefs largely influence how they work with data. Thus, Datnow and Hubbard (2016) observed that teachers sometimes bring pre-existing beliefs that can influence how they view data and its use. A related observation is that, 'teachers may arrive at attributions of data through processes of sensemaking, in which they draw on their beliefs and experiences' (Bertrand and Marsh, 2015, p. 872. See also Lai and Schildkamp, 2015). In their study into data use and teacher collaboration, Van Gasse, Vanlommel, Vanhoof and Van Petegem (2017) identified how teacher beliefs, self-efficacy and attitude to data use were significant in how teachers collaborated in the use of data. Building capacity in effective educational data use includes the understanding of multiple sources of data, the purposes and aims of data, the skills involved in analyzing and turning data into instructional actions, the beliefs, sense-making and dispositions teachers bring to data use, and how to work collaboratively.

Accompanied teachers' guidance is indispensable

Over recent years, different projects have explored how children can learn via computers as self-organized learning. This is for instance the case of The 'Hole in the Wall' (HiWEL) project in India and Bhutan, derived from a study published in 2000-2005 from earlier work in this area (Mitra, Dangwal, Chatterjee, Jha, Bisht and Kapur, 2005). This study explored children's ICT use with a minimally invasive education (MIE) pedagogy in which the learning environment is used to generate social learning (or rather learning in groups) of children with minimal teacher intervention. As noted in response to the earlier published studies, 'according to Mitra and Rana (2001), "acquisition of basic computing skills by any set of learners can be achieved through incidental learning provided the learners are given access to a suitable computing facility, with entertaining and motivating content, and some minimal (human) guidance"' (p. 276).

> Despite the perception in some contexts that children use such technology with ease, it is navigating this technology critically and effectively, where children still need guidance and understanding.

We argue, though, that the optimal situation is reprofessionalised teachers working with the available data. Learners' exposure to technology is of course helpful, but it is important that educators have digital skills to develop and manage effective digital assessment practice with their students (see also Adams Becker, Freeman, Giesinger Hall, Cummins and Yuhnke, 2016; Groff, 2013; Johnson, 2019; Selwyn, 2013). Despite the perception in some contexts that children use such technology with ease, it is navigating this technology critically and effectively, where children still need guidance and understanding to get optimum value from these opportunities, and for their teachers, parents/caregivers and the wider system to understand how to best utilise such technology (Burroughs, 2017; Carrington and Robinson, 2009; Dezuanni, Dooley, Gattenhof, and Knight, 2015; Groff, 2013; Livingstone, 2016; Livingstone and Sefton-Green, 2016; Livingstone and Third, 2017; OECD, 2010; OECD, 2011; Wilken, Davies and Eynon, 2017).

CULTIVATING TEACHERS' DIGITAL LITERACY

New pedagogical practices for a changing environment

Students face important challenges when navigating the digital environment. For example, PISA results indicate that 15-year olds 'do not automatically know how to operate effectively in the digital environment, as has sometimes been claimed' (OECD, 2011, p. 120). Digital literacy is complementary to data literacy as a skill set that educators (and their students) will require, thus establishing further digital inclusion. Considerable work needs to be done here (Istance and Kools, 2013; OECD, 2010; OECD, 2011; Wilken, Davies and Eynon, 2017).

> [...] teachers are required to respond and address a variety of challenges and adopt new approaches in terms of content delivery, learning support and assessment, constructing new and updated learning environments.

However, the acquisition of such skills can build on different learning models. As noted in the 2016 Horizon Report from the New Media Consortium, teachers can benefit from learning models such as the TPACK (Technological and Pedagogical Content Knowledge) framework, from Koehler and Mishra (2009), derived from Schulman's (1986) Pedagogical Content Knowledge (PCK), as a means to successfully integrate technology into classrooms (Adams Bhaecker et al., 2016).

In addition, teachers are required to respond and address a variety of challenges and adopt new approaches in terms of content delivery, learning support and assessment, constructing new and updated learning environments. As noted in the New

Media Consortium (NMC) and the Consortium for School Networking (CoSN) Horizon Report: 2016 K-12 Edition, 'teachers are increasingly expected to be adept at a variety of technology-based and other approaches for content delivery, learner support, and assessment' (Adams Becker et al., 2016, p. 24). This is in addition to preparing and constructing learning environments for their students to learn 21st Century skills including digital literacy (see also Gibson, Ostashewski, Flintoff, Grant and Knight, 2015; Hartong, 2016; Koehler and Mishra, 2009; OECD, 2010; Scott, 2015a, 2015b, 2015c). As a result, teachers' own pedagogical practices are changing and evolving, and the acquisition of such skills can take place in a variety of programs. To keep up with such change, teachers have taken to engaging in professional development activities found online with social media, professional learning networks and other external providers (Adams Becker et al., 2016).

Ethical challenges entailed by the data explosion

Professional judgement and related knowledge in how to plan with curriculum to meet learner needs have been construed traditionally as part of a teacher's repertoire. The emerging frontier is how to bring into scope the cognitive and emotional correlates of learning, combining learning analytics and psycho-informatics platforms. In regard to the ethics of data mining and predictive analytics, we recognize the suite of complex issues of ethics, the rights of the child and parents/ carers, privacy, and the law all come into play in considering the role of the teacher in human and machine hybrid activities in learning (Johnson, 2013). For example, the potential exists for the role of the teacher, as a goal, to take up active remoulding of individual capacities toward preferred forms of behavioural, embodied and emotional conduct. While this is a goal that teachers and education systems have valued for decades, this has been indirectly or subtly addressed, rather than manifested as an explicit goal of instruction. The need for reprofessionalisation of the workforce in the 'know-how' of using such data outputs that touch on what could be categorised as 'moral' in kind is significant.

The emerging frontier is how to bring into scope the cognitive and emotional correlates of learning, combining learning analytics and psycho-informatics platforms.

Making sense of social and emotional learning data

There is growing attention to the need to collect or make sense of social-emotional learning data, bringing further challenges to the teaching profession entailed by these trends. It is undeniable that educational systems face or will face struggles of a range of kinds with digital data rights, and how to advise parents, students and teachers about the best ways in which to protect private and personal information (Lingard and Hursh, 2019; Livingstone, Stoilova, Nandagiri, 2018; Polonetsky and Jerome, 2014). In high-income countries, the implications of social-emotional learning data are beginning to be addressed, along with the intensifying debate about how government investment in non-cognitive skills could ethically generate a substantial return in the shape of productive human capital. A notable example is the OECD's current Skills for Social Progress project that includes a computer-based large-scale assessment founded on personality theory that makes a strong argument to governments that assessing socioemotional skills can produce indicators of socioeconomic outcomes. This project shows the broadening reach of datafication and education metrics, noting Sellar and Lingard's (2014) earlier reference that, 'OECD's education metrics now seek to quantify not only what people know or can do, but who people are and who they can become' (p.927). The turn appears to be to the enumeration of embodied, cognitive and affective processes and functions, with the role of teachers being to personalised learning content in ways that motivate the learner. However, we note that there is considerable hype concerning the possibilities of digital learning assessments and big data in education. Much of the literature about their potentials for teachers, schools and systems remains aspirational.

THE COSTS AND CHALLENGES OF REPROFESSIONALISATION EFFORTS

The cost and provision of hardware, software and data infrastructures necessary for a reprofessionalisation effort, along with human data analytical, algorithmic and mathematical capacities, should not be underestimated. This applies in all countries, but especially in low-income countries. Such capacities and related costs are best understood, however, in conjunction with the cost of providing fully trained and professional teachers to work with and augment such developments.

Teachers' professional judgement cannot be replaced by data analytics; such judgement remains central to effective decision-making and student learning. We would argue, though, that reprofessionalisation as outlined

Teachers' professional judgement cannot be replaced by data analytics; such judgement remains central to effective decision-making and student learning.

above, is not an optional extra if digital learning assessments are to have positive learning effects for all students. Here we raise the criterion of transparency, recognizing the opaqueness of big data systems and processes that are well recognized internationally to be profoundly reconstituting teachers' work. There are present and serious threats to realising these positive learning effects in relation to transparency, including accessibility and comprehensibility of outputs from algorithms and from the processes applied to the analysis of the data, and from large-scale testing and continuous collection of learning evidence from classroom settings. Such threats are exacerbated because of the substantial involvement of for-profit edu-businesses and historically, the fact that curriculum and education experts have limited training in psychometrics. School systems, curriculum experts, policy-makers, assessment researchers, teacher educators, teachers and parents/carers, tend to be non-tech savvy users of big data. In the absence of explicit systems and processes to develop such expertise, they are likely to remain closed out of major decision-making about big data and learning analytics, especially as they relate to rich accountabilities applied in context. A pressing question at this moment in educational history is, 'Whose interests are being served in the current and emerging practices of learning analytics?', especially as they become corporatised and monetised in the absence of an explicit role for government.

CONCLUSION

The digital disruption of schooling and the rapid development of digital learning assessments and big data have many implications for teacher professionalism. This is true both in the Global North as well as in the Global South. While there is considerable hype concerning the possibilities of digital learning assessments and big data in education, much of the literature about their potentials remains aspirational. While costly, the provision of fully trained and reprofessionalised teachers to work with and augment such developments is necessary. This is critical if we are to harness technologies for the public good and social cohesion to the benefit of all. Addressing these issues will be central to realising the 2030 Sustainable Development Goals (SDG), and specifically, SDG4 on education.

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