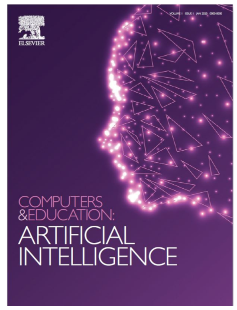
Journal Pre-proof



Educational data journeys: Where are we going, what are we taking and making for AI?

Sarah K. Howard, Teresa Swist, Dragan Gasevic, Kathryn Bartimote, Simon Knight, Kalervo Gulson, Tiffany Apps, Juliana Peloche, Nathanael Hutchinson, Neil Selwyn

PII: S2666-920X(22)00028-5

DOI: https://doi.org/10.1016/j.caeai.2022.100073

Reference: CAEAI 100073

To appear in: *Computers and Education: Artificial Intelligence*

Received Date: 31 July 2021

Revised Date: 10 January 2022

Accepted Date: 19 April 2022

Please cite this article as: Howard S.K., Swist T., Gasevic D., Bartimote K., Knight S., Gulson K., Apps T., Peloche J., Hutchinson N. & Selwyn N., Educational data journeys: Where are we going, what are we taking and making for AI?, *Computers and Education: Artificial Intelligence* (2022), doi: https://doi.org/10.1016/j.caeai.2022.100073.

Understanding educational data journeys: Where are we going, what are we taking and making?

A/Prof Sarah K. Howard, University of Wollongong, Australia
Dr Teresa Swist, University of Sydney, Australia
Prof Dragan Gasevic, Monash University, Australia
Dr Kathryn Bartimote, University of Sydney, Australia
Dr Simon Knight, University of Technology Sydney, Australia
Prof Kalervo Gulson, University of Sydney, Australia
Dr Tiffany Apps, University of Wollongong, Australia
Juliana Peloche, University of Wollongong, Australia
Nathanael Hutchinson, University of Wollongong, Australia
Prof Neil Selwyn, Monash University, Australia

Corresponding author:

A/Prof Sarah K. Howard
School of Education
University of Wollongong
Wollongong, NSW 2522 Australia

sahoward@uow.edu.au

Educational data journeys: Where are we going, what are we taking and making for AI?

Abstract

Educational systems generate huge quantities of digital data. Digital educational data is captured and used at all points -- from classrooms and schools, to the level of educational departments. As growing trends in 'data-driven instruction' suggest, all these data have great potential to support student, teacher and leadership practices, help guide work and learning decisions, and inform policy development. Moreover, an increasing focus is being placed on the development of artificial intelligence to automate and improve how data are used. Yet, stakeholder data practices remain invisible and little understood, which complicates how artificial intelligence can be embedded in this context. In this paper, we introduce an educational data journeys framework to frame dynamics of data power, data work, identities and literacies. This approach is employed to explore educational policy reveal data flows and frictions in school improvement and what this may imply for the development of artificial intelligence in education.

Keywords: educational data; data journeys; educational policy; infrastructure; data practices

1. Introduction

Internationally, contemporary school improvement and assessing teacher effectiveness are increasingly 'data-driven' (Jerrim & Sims, 2021). This is in part fuelled by rapid changes in and access to data-related technologies in schools, which includes AI-embedded tools. Beliefs about the potential of educational data and its capacity to aid in reforming education are often strongly positive and run parallel to increased expectations of positive outcomes for the sector, for schools, and for individual students as a direct result of data use (e.g. Luckin et al., 2016). However, in reality the actual use of data to evaluate and assess educational practice at scale, to support development of artificial intelligence in education (AIED) for these purposes, is complicated by limitations of data quality and infrastructure (e.g. Winne, 2017), lack of agreement/alignment regarding goals for schooling and notions of education success amongst various actors in the system (e.g. Ball et al, 2012), as well as potentially conflicting views and understanding of the purposes of data use e.g. performance, improvement, understanding (e.g. Perrotta & Selwyn, 2020). As a result, there are at times competing demands on schools by way of data-informed educational policy on the use of data in decision making and improvement. Further, the degree to which educational data is seen as relevant or connected to the work of students and teachers varies enormously across the system (Wiseman, 2010).

The aim of this article is to explore expectations of, and implications arising from, the complexity of educational data in school improvement agendas. This investigation hopes to contribute to an understanding of where we are going with educational data use, what we are taking with us and what is being made. To begin this work, we present a conceptual framework of educational data journeys and the key dynamics shaping data production and use as part of sociotechnical infrastructure: educational policy and data power, educational monitoring and data work, teacher and student identities, plus knowledge beliefs and data literacies. Sociotechnical infrastructure refers to how humans and machines work together, also known as sociotechnical systems (e.g. Passmore et al., 2019). To explore the role of data in this context we draw on Bates et al. (2016) notion of 'data journeys' (p. 1), through a case study of standardized test data used to enact educational policy, in a large school department. The case study illustrates data flows and frictions in school improvement. We consider transformations of the data as it is employed for various purposes in schools, by leadership and teachers. Critical points in this journey where participatory work occurs, or where it could occur, are explored. Critically, illustration of the data journey reveals a number of questions about how data is expected to be used, by whom, and to what effect/impact. Implications of these expectations are explored as data practices are scaled up and automated are examined.

2. Introducing an educational data journeys framework

We propose that Bates (2016) and colleagues' data journeys methodology offers a novel way to explore the dynamics of educational data production, processing, and distribution. The concept of data journeys is adapted for this study to unpack the complexity of educational data. Originating with a study of UK-based weather data, Bates, Lin & Goodale (2016) piloted the novel 'data journeys' methodology to surface how data was produced and used across different sites of practice (state, science, market, and civil society). Findings from their critical, qualitative methodology showed the complex 'life of data' in three keyways: the socio-material constitution of digital objects (data production), the friction arising from data movements across time and space (data processing), and the mutability of data across different sites of practice (data distribution). The data journeys methodology has since been applied to health data in Finland (Aula 2019), children's data across corporate, government and university contexts (Swist et al., 2019), and the sciences (Leonelli, 2020) – yet its application to the education sector is underexplored.

To adapt the data journeys framework to the current educational inquiry, we introduce the concept of 'educational data journeys' defined as:

i) *the socio-material dynamics of how education-related data is produced, processed, and distributed for a range of short and long-term research, policy, and practice interests; and,*

ii) these data journeys are informed by, interrelate with, and exert influence upon, educational decision-making across multiple sites of practice: the classroom, school organisation, region (state/territory), national sector, and global system.

In the following sections, we unpack each of the four key dynamics. This is followed by our approach to conduct a systemic exploration of educational data.

2. Background

Rapid changes in and access to data-related technologies in schools, which includes AI-embedded tools, has significantly contributed to an increase in 'data-driven' assessment of teacher effectiveness (Jerrim & Sims, 2021). Beliefs about the potential of educational data and its capacity to aid in reforming education are often strongly positive and run parallel to increased expectations of positive outcomes for the sector, for schools, and for individual students as a direct result of data use (e.g. Luckin et al., 2016). However, in reality the actual use of data to evaluate and assess educational practice at scale, to support development of AIED for these purposes, is complicated by limitations of data quality and infrastructure (e.g. Winne, 2017), lack of agreement/alignment regarding goals for schooling and notions of education success amongst various actors in the system (e.g. Ball et al, 2012), as well as potentially conflicting views and understanding of the purposes of data use e.g. performance, improvement, understanding (e.g. Perrotta & Selwyn, 2020). As a result, there are at times competing demands on schools by way of data-informed educational policy on the use of data in decision making and improvement. Further, the degree to which educational data is seen as relevant or connected to the work of students and teachers varies enormously across the system (Wiseman, 2010).

In Figure 1 we present a conceptual framework of educational data journeys, to consider these competing socio-technical dynamics. The objective of ‘socio-technical’ theory and design is “the joint optimization of the social and technical systems” and the perspective that “every socio-technical system is embedded in an environment that affects the way it behaves” (Mumford 2006, p. 321). A sociotechnical framing helps to think critically about the complexity of ‘data infrastructures’ (Kitchin, 2014), such as dashboards, shared drives and other method of accessing and storing data, are “embedded within a larger institutional landscape of researchers, institutions and corporations, constituting essential tools in the production of knowledge, governance and capital” (p. 20).

< insert Figure 1 here>

Our framework illustrates the key dynamics which co-constitute educational data journeys. These four dynamics represent critical practices that shape the journey of educational data in contemporary school improvement agendas.

2.1 Educational monitoring and data work

This dynamic considers the labour associated with educational monitoring (compliance, performance, diagnostic) and attendant work mechanisms and obligations, e.g. dashboards, data-entry. To begin to understand how educational data is used, we first consider it in terms of the range of monitoring systems and data work done at schools - mostly steered by compliance, performance, and diagnostic agendas (Richards 1988). There is a growing interest in using digital data in schools, which is often aligned with increased adoption of digital technologies such as learning management systems and adaptive learning systems (Baker et al., 2021). Research shows that the most common types of data used can generally be classified into three groups: assessment (e.g. standardized tests), attendance, and student growth (e.g. academic performance, wellbeing; Selwyn et al., 2021c). Data from the above three groups may be gathered at the classroom and school level, or at the system level. Data are used for different tasks such as monitoring of student retention (Baker et al., 2020), prediction of participation in careers (Almeda, 2020), and evaluation of impact of individualised interventions (Sales et al., 2018) through various recontextualizations of the data, such as use in predictive modelling and early warning systems (Carl et al., 2013). The combinations of data being generated, and actors engaging with the data, has increased the complexity of its use as evidence to understand and improve learning, teaching and schooling.

Whether captured locally or at the system level, this use of data requires extensive combination of stakeholder groups and infrastructure elements, which results in "an assemblage of people, technologies, protocols, processes, expectations and pressures relating to addressing the broad imperative for schools to now to be 'doing data'" (Selwyn, 2021b, p. 362). In particular, in schools data infrastructure is essential to enable use of the above types of data. Schools need to make significant investments into data infrastructure to enable data collection, storage, and use. Although technical dimensions are often highlighted (Kitto et al., 2020), data infrastructure has equally important social dimensions with implications for relevant stakeholders (Chatti et al., 2012; Siemens et al., 2013). Data infrastructure also has implications on 'invisible' workloads of teachers who are to perform additional technical and secretarial tasks, often insufficiently appreciated, to produce and assure completeness and quality of data. Collection of digital data also has implications for additional labour requirements of teachers and leadership in schools (Selwyn, 2021b). Teachers are required to regularly record data about their students regarding assessment and other types of activities that happen in the classroom.

At the system level, large-scale standardised test results are an example of educational measurement and assessment efforts becoming data - data that are then used for a multitude of purposes, many never originally envisaged and bearing unintended consequences (Lingard & Sellar, 2013). These data are often used in isolation, removed of context, and often heavily politicised. This reflects pressure put on standardised test results to do what various actors in the system need it or want it to. They become data 'done' to jurisdictions, schools, teachers, students, and their parents when used as single metrics. However, when these data are combined with other assessment information they can provide a more complete picture of student learning (c.f. Gewirz et al., 2021). When this work is done by teachers and the school, it places ownership of data and assessment expertise in the classroom and the school where it is most meaningful.

2.2 Educational policy and data power

This dynamic addresses system-level expectations and implications related to data production and use. Educational data serves as a basis for education policy, and gives those that control the reporting of it, data power. As Lawn (2013) notes, '[t]he rise of data to describe, represent or explain education systems, and their constituent parts, is a mid-nineteenth century invention, associated with the rise of schools and budgets' (p.7). More recently however, a major shift for policy, which can be crudely separated into both policy makers and users, is the use of digitized data for policy making. This digitalisation means that education data are now potentially more accessible, and yet schools and systems are dealing with what is known as a *data deluge*, where a proliferation of data is provided often separately from the question of why data has been generated, collected and analysed. This creates doubts around the applicability of data to policy. The question of what data counts as significant for policy questions continues to be part of contestation over what matters in schooling, and what counts as evidence (Hammersley, 2005; Wiseman, 2010).

One element of contestation pertains to the status of policy knowledge and expertise - or what we might see as the application of analysis from data. That is, data and hence policy making is seen as distant from where it was generated (classrooms, schools) and where it will be applied. Whether this is a new problem is debatable – there has always been an historical gap between bureaucracies and the site of practice, or what is known as the site of implementation or enactment (Ball et al, 2012). What might, conceivably, be different now is that policy can be not only implemented, but responded to, through the creation of school-based data generation and analysis (e.g., through data analytics as part of school information systems). There is a possibility for school leaders and teachers to become more active policy participants in ways that were not previously possible. Data use can mean expertise that seems distant from teachers, and 'data done to teachers' (e.g. use of data science in governmental departments). However, the same phenomenon can open up new spaces for teacher agency about decision making (e.g. via school based data use).

2.3 Teacher and student identities & data-informed practices

This dynamic highlights the use of data in schools to evaluate and assess teachers' work and student learning Teachers and students are continually engaged in cycles of data-driven assessment and feedback to monitor, compare and improve learning. Attendance, learning, engagement, current and future performance, behaviour and wellbeing are quantified and analysed through digital tools, dashboards, 'walls' using a range of data (e.g. Lucking et al., 2016). Collectively such practices normalise the generation and use of digital data as meaningful evidence in teaching and learning cycles. On one hand, data has been used in decision making and student support to identify at-risk students, create intelligent tutors, and evaluate interventions and initiatives (e.g. Williamson & Enyon, 2020). However, there have also been concerns raised around privacy, dramatically incorrect classifications and predictions of student performance and progression, loss of teacher autonomy, and inappropriate management actions taken by leadership on the basis of data interpretation misunderstandings (e.g. Gewirtz et al., 2021; Williamson, 2017).

It has long been held that good teaching practice involves making informed judgments, be it through the examination of critical incidents (Tripp, 2011), utilising a range of assessment and other learning information, reflective practice, peer review, or application of research. Now, discourse associated with ‘data’ and ‘evidence,’ as a way of objectively knowing students and improving learning, is commonplace (e.g. Spina, 2020). Evidence-informed practice moves beyond evidence-based practice and the application of research to teaching practice (Spencer et al., 2012) to the “integration of professional judgement, system level data, classroom data and research evidence” (Nelson & Campbell, 2017, p. 129). The incorporation of data as a key element in evidence-informed practice leads us to then consider terms such as data-based decision making (Nelson & Campbell, 2017) and more generally the role of evidence in decision-making.

The notion of evidence-based decision making has accompanied society’s data revolution (Kitchin. 2014). The notion of a data revolution is associated with an improvement agenda. In the education setting, this improvement agenda is highly influential. It speaks to several ideas relating to the purposes of schooling e.g. to promote egalitarianism and provide equity, intergenerational mobility (Hallinan, 2006), but also the notion of accountability that is associated with the data revolution (writ large). Students are represented through digital data and by educational platforms in various ways. These practices reposition teachers’ professional judgement and situated understanding of their students and as subordinate to objective data (Williamson, 2017). However, the use of this data to inform practice is complex and presents challenges for educators (Mandinach & Jimerson, 2016; van Leeuwen, van Wermeskerken, Erkens, & Rummerl, 2017). It also presents challenges for school leaders as to the use of student data, particularly achievement data, and its relative importance in relation to a raft of other teacher evaluation possibilities (Peterson, 2000).

2.4 Knowledge beliefs and data literacies

This dynamic considers teachers and leaders' beliefs about and capacity to work with data to fulfil expectations, evaluate teaching and innovation, and assess students. Two intertwined key factors affecting how data is used are knowledge beliefs and literacies. On a broad scale, "data are presumed to be the mechanism to improve educational outcomes" (Thompson, 2017, p. 828). Data are also presumed to reveal 'quality' teaching and student needs (ibid.). At the level of practice, certainly teacher numeracy and beliefs regarding the potential of assessment data for formative purposes are important elements in how data will be used. However, these beliefs can vary widely, from feeling the data is: largely irrelevant for practice; primarily for accountability; or as useful input in classroom teaching and learning (Barnes et al., 2017). However, these beliefs must be seen in the wider context of teacher practice, and in terms of how teachers must incorporate technologies and various assessment practices in their work (Wasson & Hansen, 2016). Specifically, teachers' beliefs are bound up with their data literacy, wider practices of learning design, technology use, and institutional organisation and infrastructure (Alhadad et al., 2018).

Working with data to inform practice, a dimension of data literacy, is now central to schooling and teaching (Gummer & Mandinach, 2015). Therefore, considerations of data infrastructure in schools need to pay attention to stakeholders' data literacy to enable stakeholder participation and avoid inadvertent effects of data misuse in schools (Mertala, 2021). This change is embodied internationally through teacher standards, electronic reporting requirements and increased use of digital assessment and feedback mechanisms. Thus, while Mandinach and Gummer (2016) identify 41 skills that make up data literacy – from accessing, generating and analysing, to interpreting and acting on data – these skills should not be conceived in isolation from the wider context of teacher practice and the actual data they work with in their moment-to-moment and longer-term interactions.

Moreover, Timperley and Earl (2009) highlight, having relevant data is not enough, using this data is a human activity that requires learning conversations that shape and are shaped by our actions and (data informed) judgements of their impacts. That is, in understanding data literacy, there is a need to consider not only teacher engagement with provided examples (such as those from standardised assessments), but also in developing 'research-rich' teacher practices, in collecting data to guide practice, understand student progression, and inform decision making (Mills et al., 2021). In this context, it is also crucial to understand the various stakeholders involved and their roles in learning systems, including teachers, the important role of leaders in promoting data informed decision making, government agencies, and professional development providers (Mandinach & Gummer, 2013). As we discuss here, the ways in which data is created, framed, re-framed, and moves between these stakeholders is a significant consideration in the data journey.

In this section, we have unpacked the four key dynamics of educational data journeys. Each of these four have an effect on expectation around data use, how data is created/captured and repurposed across educational contexts. However, they are also intertwined in data use and practice. These implications will affect the ultimate conclusions that can be drawn from data, but also the experience of leaders, teachers and students in their day-to-day education experiences and decision making. These effects, interaction and possible experiences will be explored through the data journeys analysis.

3. Methods and approach

The aim of the study is to explore expectations of, and implications arising from, the complexity of educational data in school improvement agendas. To explore how educational data may move through schools as sociotechnical infrastructures, as outlined earlier, we draw on the concept of the 'data journey' (Bates et al., 2016). The concept of a data journey provides a framework to explore the ways data are repurposed in data production, processing and distribution activities. Bates et al. (2016) acknowledge methodological influences such as actor network theory (ANT) and science and technology studies (STS) yet articulate their point of difference as being the *journey* of data over time in relation to various infrastructures and sites of practice. At each point, data activities are affected by socio-cultural values and sociomaterial conditions that influence 'the form and use of data and their movement across infrastructure' (Bates et al., 2016, p. 2). Therefore, analytically this approach can help inform how stakeholders are using data and associated practices. Specifically, we consider where educational data is going, how it is being taken along this journey and what is made at the end. This knowledge is needed to better understand potentially conflicts and purposes of data in school improvement, and ultimately if it is to be scaled and/or used in automation.

3.1 Data source

For this study, we draw on publicly available policy documents from one state in Australia. We have chosen to address policies around school improvement, specifically the notion of 'school excellence', which is defined as being at the "core of all work...focusing on continuous school improvement" and it "encompasses all areas of school planning, ongoing self-assessment, reporting and external validation" (New South Wales Department of Education [NSW DoE], 2021). The use of educational data is embedded in these policies to support a range of targets, which support school improvement.

The broad set of policies accessed for this analysis sit within the domain of 'School excellence and accountability' (NSW DoE, n/d). The School Excellence policy is its own section of this domain. The School Excellence policy was chosen here as the starting point because policy implementation is not just about a policy document, but also includes specific sites of enactment, along with a range of stakeholders and targets, such as system-identified targets, school leadership and student needs. A key tool in the School Excellence policy is the 4-year School Improvement Plan (SIP), which includes a mandatory reporting component and must be developed and/or reviewed by school leadership each year. Throughout the process of developing and implementing the SIP, a wide array of system and school educational data are recommended to school leadership for use as 'evidence' to support improvement initiatives. Standardised test scores form a key part of these processes, as a feature in school rankings for parental and ministerial attention, for school leaders in understanding and improving, and individual teachers and students in administering and taking tests and the range of formative pedagogic activities around this.

As a starting point for this analysis, we have chosen to map the journey of standardized test data based on suggestions, expectations and recommendations of data use at schools, in the School Excellence policy. In Australia, the most commonly known standardized testing data is from the 'NAPLAN' test. This is data from the National Assessment Program, Literacy and Numeracy (NAPLAN). A key objective of the national assessment program (NAP) is to monitor student progress over time. The specific literacy and numeracy tests (NAPLAN) are delivered annually for Year 3 (age 8-9), Year 5 (age 10-11), Year 7 (age 12-13) and Year 9 (age 14-15) students. Every three years the NAP also includes sample assessments such as science literacy, civics and citizenship, and information and communication technology literacy, and international assessments. Simply, the NAPLAN is designed to assess skills "that are essential for every child to progress through school and life" (NAP, 2016).

3.2 Analysis

The analysis of NAPLAN data was conducted in two stages. The first was a 'heuristic walkthrough' to identify how NAPLAN data was identified and explicated for use as part of the School Excellence policy. Walk-through methods have been widely used in studies of digital technologies, in particular gaming (Light et al., 2018), software development and usability (Mahatody et al., 2017). School Excellence policies and supporting documentation were all provided on the publicly available department website: https://www.education.nsw.gov.au/.

The heuristic walkthrough method is based on a list of task guides and related thought focusing questions (Sears, 1997). For this analysis, the questions were: i) Where was educational data identified for specific purposes (e.g. data linking), and ii) Where was stakeholder use of data expected (e.g. to evaluate a program)? This is a two-pass approach (Sears, 1997). The first pass is 'free-form' and with the intention of exploring tasks from a list, in any order. The second pass is guided by a 'task-oriented' introduction to a system and a list of heuristics. They then explore for usability issues. Adapting this method for the current analysis, in the first pass the researchers engaged in free-form use of the School Excellence website as though they were a school leader and planning to develop a four-year school improvement plan. The researchers documented their paths using Google Draw and creating a flow-chart. In the second pass, they went through again and elaborated on the flow-charts to identify points where NAPLAN data was recommended as evidence for a particular aim or process in a school improvement plan and its relation to one of the four dimensions of the framework: data power, data work, identities and literacies. Importantly, usability of the website was specifically not addressed, other than how educational data was expected to be used by school leaders and teachers. This process provided a way to reliably triangulate results from the first and second pass. The approach provides way to consider tasks from different positions: to confirm data-related tasks, their expected aim and how they related to other tasks identified in the policy (e.g. Flick, 2018).

In the second stage of analysis, these representations and recontextualizations were examined in more depth through the four dynamics of educational data journeys. First, the life of NAPLAN data was explored, which include the development and infrastructure which can then point to key moments in the data journey and related practices. The life of NAPLAN data was available online through the National Assessment Program website. Related state-level practices were identified in the first stage of analysis and included in the flow-charts. The flow charts then provided an initial mapping for the data journey (Bates et al., 2016). NAPLAN data use was then considered in relation to:

i) *how and when was the data produced, processed, and/or distributed and for what purpose; and,*
ii) how was the data related to or positioned in educational decision-making, at what level and by whom?

In the analysis, the journey of data through different possible sites and with different stakeholder practices. The conditions, contexts and socio-cultural values related to these movements and practices comprise the data journey.

4. A data journey

In the following section, we map the data journey of NAPLAN data in relation to school improvement policies. At a national level in Australia, the Alice Springs Declaration highlights the need to boost understanding and capacities to leverage educational data to inform planning, policy, teaching and learning. At the state level, digital educational data is captured at a wide range of points -- from classrooms and schools, to professional learning and educational policy. In the last decade, states have had an increased focus on 'data-driven instruction' and 'insights-driven education' suggest (Lingard & Sellar, 2013). One of the forms of data that has been widely used to assess school improvement, teacher quality and student needs, has been standardized testing data.

Analysis suggests that, in response to educational policy, NAPLAN data flows across multiple time periods and experiences a number of transformations in that process in relation to data production, data processing and data distribution:

1. Data production – The origin of NAPLAN data is from students' participation in a national standardized test, in school years 3, 5, 7 and 9.

2. Data processing – The first NAPLAN data transformation is three months after students complete the national standardized testing exercise. At this point, student data is received by the state education department it is transformed into system-level data.

3. Data distribution – System-level data can be access through a state-controlled online dashboard to be used to assess school improvement and change. This is a second data transformation, which is also detailed in expectations of schools' four-year improvement plans.

4. Data processing – The third transformation may happen any time after the NAPLAN data is made available through the dashboard. Here, educational policy expects that NAPLAN data will be used by school leaders and teachers as evidence of school improvement over time, as part of School Improvement Plan policy.

5. Data distribution – A fourth transformation, detailed in School Improvement Policy, is return of evidence of school improvement over time, through the use of NAPLAN data. This evidence is then returned to the system, specifically uploaded through another dashboard, to evidence change and improvement on system-level targets.

In the following section, this data journey is unpacked and examined in relation to:
i) *how and when was the data produced, processed, and/or distributed and for what purpose; and,*
ii) how was the data related to or positioned in educational decision-making, at what level and by whom?

5. Unpacking the journey
Educational policy suggests numerous points where data can be processed and distributed and recommended as ways to support decision making in the form of evidence. Expectations for use of educational data for these purposes interact with the four key dynamics in ways that offer opportunities and complications. Two key findings reveal themselves. The first is the level of autonomy in the system for school leaders to determine their own targets and uses of the data, to a degree. However, a complication sits in relation to the number of ways data is recontextualized and the resulting abstraction of data as it moves further from its designed purpose, particularly over time. These issues, in relation to the four dynamics of schools as sociotechnical infrastructures, are explored in the following discussion as where we are going with data use, what is being taken and what is being made.

5.1 Data production: Origins of the data
Resources state that NAPLAN specifically focuses on "student performance" in literacy and numeracy, which includes numeracy, along with reading, writing, spelling, grammar and punctuation for literacy (NAP, 2016). The test is taken in Years 3,5, 7 and 9. Results are reported along a common 10 band scale. The bands represent increasing complexity of skills from 0 to 10. The bands are graded, in that Year 3 covers bands 1-6 up to Year 9 which covers 5 to 10. Higher level bands represent achievement in more complex skills and knowledge. Using the bands, student performance can be monitored over time for an individual and nationally, which is a key dynamic in the educational data journey. Individual student and school NAPLAN results are reported in each year as mean, scale and score and in comparison to national standards. National reports are publicly provided online, but datasets are only available upon request. Score reports are provided to students' families and each principal, in each year (NAP, 2016). This data can be accessed by various stakeholders and from various locations, at any time.

In terms of educational policy as a key dynamic in data journeys, an identified state target has been that more students would be achieving in the two bands for both numeracy and literacy, across all four years. As an example, we propose that a data journey may begin with a nine-year-old child in Year 3, who may be performing at that level or may not. The student taking the test is the point of production. The child attends school, along with peers across Australia, and for the first time sits the four NAPLAN tests over three consecutive days in May, each lasting between 40-65 minutes. Tests are administered on paper and online via the schools networked computers, usually outside of their regular classroom. At the time of the test, the child may be tired or well-rested, confident or apprehensive, anxious or calm, agitated or bored (see Thompson, 2013). Their performance will be affected by their complex unique selves shaped by their subjective life experiences. The test captures data about the child's performance on test items at this moment, and again in Years 5, 7 and 9. In this way, the child becomes a monitored data subject, and their response to each question a data point, marking the start of the data journey.

5.2 Data processing: 'System-level' data

At the Department level, state NAPLAN data are received in August, approximately three months after the student sits the test. Once received, data is stored and then processed for various monitoring and policy purposes. The processed data is made available to stakeholders in a range of forms, such as through dashboards or in pre-processed reports. This first point of transformation and recontextualization of data begins soon after the data is received. The processed forms remain accessible for several years. These forms of system-level processed data are made available, and identified, in the School Excellence policies. This suggests possible complications and/or conflicts with the original intentions of NAPLAN data and its possible futures as evidence across the system (e.g. Lingard & Sellar, 2013).

Part of the School Excellence policy is to create a 4-year Strategic Improvement Plan (SIP). A key component of creating this plan is the identification of 'strategic directions', which form the basis of school planning for improvement. It is mandated that system-negotiated targets are included in the SIP. An identified system target of the state is to "increase the proportion of public school students in the top two NAPLAN bands for literacy and numeracy" (NSW DoE, 2021a). A school's strategic direction related to this target must be achievable in four years. Illustrating the dynamic of data power in the data journey, improvement must be measurable in a range of ways and using a range of data sources (e.g. Gewirz et al., 2021). Further, this is often expected to be 'against baseline data' as a form of on-going monitoring.

One of the recommended data sets is NAPLAN. This means NAPLAN data is now positioned as evidence at the school level, but at the same time addressing a target at the system level. The data is being asked to serve two purposes and suggests a complexity of stakeholders engaging with this data for a range of purposes (Selwyn, 2021b). Over the next four years evidence of school progress on this target is gathered, interpreted and input into a system-created online platform. There it is tracked for progress and external validation of improvement, which further demonstrates the power given to data in the educational system.

5.3 Data distribution: Becoming evidence

Digital data convey specific sets of values, logics, interests and agendas (Perrotta & Selwyn, 2020), which structure the key dynamic of data practices. In this analysis, two forms of NAPLAN data are identified as forms of evidence through policy and distributed through two platforms: a state Educational Data Hub and data reporting accessed through a data analysis dashboard. These are by no means the only places this data is distributed, but they are two commonly used access points and frequently identified as sources in the policy documentation. First, pre-processed NAPLAN data summaries are publicly available to any audience through the Education Data Hub. Specifically, there are four data sets available that address performance in the 'top two NAPLAN bands'. This provides an easily accessed and generic form of evidence and a specific data practice that schools can bring into their school improvement work.

A second location where school leadership are directed to access NAPLAN data is a 'school dashboard'. The dashboard is a "data and analysis platform, developed to provide better information about our schools, easily accessed in one central place" (NSW DoE, 2020b), which comprises various student and school performance measures. The data is made accessible through a range of 'modules' to use data to 'assess' and 'evaluate' student performance and experience. A specific data practice embedded in the dashboard, illustrating data power and usage expectations, is the Bands over Time report (NSW DoE, 2020a). In this report, NAPLAN data is used to assess the implementation of a school maths program, through performance over time and impact. The report can be extracted from the school dashboard. As a way to mitigate the key dynamic of data literacy, the website suggests to cross-reference results with individual assessment scores. This is a critical part of the data journey, but one that is suspectable to users' literacy and beliefs about data, which are further affected by different frames of time and location of the data from its origin. In that this is pre-processed NAPLAN data being extracted from the dashboard to assess program success, rather than student performance which was the original intent of the data (e.g. Gewirtz et al., 2021). This raises a number of questions about how data would be interpreted to determine program success and impact, given its decontextualization, leadership's data literacy and the resulting possible misunderstandings (e.g. Williamson, 2017). This echos concerns about how educational data is repurposed and for what purposes, particularly as an evaluation tool and determining effectiveness and quality (e.g. Webb et al., 2020).

5.4 Data processing: Assessing school improvement

The journey of NAPLAN data can be further transformed from a broad perspective of school-level student performance, to the classroom to address school improvement through improving teacher quality. For example, it could be assumed that leadership determines that teachers require professional learning for students to achieve in the top two bands on the NAPLAN exam. To progress on this target, a professional learning self-assessment tool is linked to the School Excellence policy. In this self-assessment tool, identification of specific data practices to determine professional learning are detailed. Specifically, assessment of 'student needs', "identified through analysis of progress and achievement data at system, school and classroom level" is highlighted (NSW DoE, 2021c, p.2).

Through this particular data practice, teachers would be expected to use powerful system data, such as NAPLAN data, to assess student needs. However, the same data could also be used to assess their own capacity to deliver quality teaching. This presents potentially conflicting data practices, particularly in a high-stakes environment where their professionalism is being assessed (e.g. Mandinach & Jimerson, 2016; Peterson, 2000). Moreover, this type of practice also invokes issues of data literacy and beliefs about data use, and this kind of assessment (Mills et al., 2021) and puts teachers at risk of negative impact on their well-being, without real gains (Jerrim & Sims, 2021). Considerable vision and leadership would be needed to build common values and beliefs around this data practice, which may or may not occur within the four-year SIP timeframe. Regardless, policy documents suggest that this collection of data practices, using NAPLAN data to monitor student needs and teacher quality over time, provides some form of insight into school improvement.

5.5 Data distribution: Returning to the system

Schools use NAPLAN data to monitor school improvement over time. Results from this data practice are then put into the online reporting system as evidence of school improvement. Importantly, the online reporting system does not accept all forms of evidence that a school may use to demonstrate school improvement. This has two implications and possible effects on what is provided as evidence. School leaders and teachers may avoid using evidence that is difficult to demonstrate. If it cannot be uploaded into the online reporting system, it may be considered less legitimate and to have less power. It is possible they use evidence they do not fully understand or value in their own practice, because it is compatible with the system. Either way, limitations of this data practice likely to affect how improvement is reported and also understood by evaluators (cf. Perrotta et al., 2021). It is not clear in the online documentation what is or is not accepted in the online reporting system, so it is not possible at this point to know more about possible effects.

For the transformation of NAPLAN data, over the four years of the SIP, and through analysis by school leadership and teachers, this is the final step on the journey: its transformation into school improvement data and distribution to inform the system-level target. This may be over one year and up to four years after the genesis of the NAPLAN data, or even longer if schools are drawing on insights from further back. At the system-level, the school data is aggregated with other schools to build power in data-based assumptions, to run comparisons in relation to their geographic groups, as 'like schools' and in relation to other social demographics. In some cases, funding is based on these results or even staffing (e.g. Lingard & Sellar, 2013; Gewirtz et al., 2021).

The steps of the NAPLAN data journey discussed above present where the data was produced, several points where data is processed and distributed, as part of a data journey. Analysis illustrates some of the ways policy mandates monitoring, creates data power and shapes data practices, but where these practices are subject to limitations based on beliefs and literacies. Implications of the four key dynamics within the data journey approach has provided a way to isolate and examine how data use and practices occur, how they may occur over time and how data could be asked to move between different locations. This provides some gains in making data practices more visible and potentially identifying where more participatory work could happen in this process, to improve the process and possible outcomes. In the following section, we unpack some of these implications in light of schools as socio-technical infrastructures.

6. Implications and future work

This discussion considers how we can better understand issues related to educational data journeys, to make visible the range of stakeholder data uses and practices, to consider implications of scaling up data for implementation of AIED. Therefore, as a starting point, the aim of this analysis was to explore expectations of, and implications arising from, the complexity of educational data in school improvement agendas. As part of this investigation, we asked: where we are going with educational data use, what we are taking with us and what is being made. The main finding from the data journeys analysis is the range of transformations that can potentially take place within even a short data journey. This has illustrated how far data can travel from its origin and some of the potential misinterpretations and effects that can occur on that journey. Our focus upon data work, power, identities, and data literacies intersect, highlights avenues of future research aligned with the following three questions.

Where are we going? In response to this question, we propose the need for future educational data journeys research to explore the challenges and opportunities of emerging AI technologies. This considers data practices in light of scaling up to automation and development of AIED. However, this does not mean that aim is universally accepted in an education system, at schools or the aim of policy. Each stakeholder group has their own assumptions about the goal of educational data use (Barnes, Fives, & Dacey, 2017). This becomes increasingly meaningful when these beliefs and intentions coincide with infrastructure. In terms of educational monitoring and data work, the possibility of misinterpretation is high given the possibility of low data literacy and/or conflicting beliefs about knowledge at all points in the journey (Williamson, 2017).

What are we taking? In response to this question, we propose the need for future educational data journeys research to co-create data infrastructures with diverse stakeholders. There is a risk when stakeholders are not involved in the development of data practices and expectations placed on their work. Given how new many of the data practices are to leadership and teachers, co-creation of data application and transformations is critical for meaningfulness and validity. This issue addressed the question of 'what are we taking'. In the data journey, the data and its imperfections are being brought along. However, the knowledge and beliefs of stakeholders (as users and analysts) when interacting with data infrastructures will have a range of unanticipated effects on the journey and life of the data (e.g. Lingard & Sellar, 2013).

What are we making – and how?, In response to this question, we propose the need for future educational data journeys research to explore representations of evidence and data work practices. This is particularly critical in relation to in the large amount of data work that would need to occur at schools to provide evidence for school improvement, over four years (cf. Selwyn, 2021b). Over that range of time and with data covering a number of locations, there should be questions about who is doing that work, are there different people and what are their various understandings. While schools are provided with school dashboards to extract pre-processed data sets, once the data is at the school level and is transformed, over one to four years, it takes on meaning and intent from each user and their practices. Thus, what is 'made' at the end of the process and what is put forward as evidence is also a reflection of the data work at that location. Therefore, each school using NAPLAN data for the same purpose will produce different evidence. This introduces questions about how these are then assessed together or aggregated from the online reporting system. Again, without participation and collaboration at the stakeholder and data user level a high level of variation will exist in how educational data is used and valued in schools, who is even included in the representation of evidence and how their voice is heard in the story of school improvement (e.g. Williamson & Eynon, 2020).

Using the educational data journeys approach, we have demonstrated implications of data use in schools, based on existing expectations from policy. In the transformation of NAPLAN data from its origins as actual student performance and progression data to system-level data used as evidence for school improvement. There are a number of limitations in this analysis. The most pressing is our interpretation of the School Excellence policy and its implementation at schools. We stress that this is not an analysis of school and/or teaching practices. It is only an examination of an educational data journey through educational policy documents. It is one of several journeys that could be taken by school leaders and teachers, in school improvement work. Future research needs to study data journeys in relation to actual school and classroom practices. Until educational data journeys are examined beyond policy the full implications of data use will remain obscured. Without a better understanding of those practices, the knowledge differences, understandings, literacies and beliefs about data of each user will change what can be known and how data can be used. There is significant potential in educational data, but to improve the quality of data infrastructures and data practices to support AIED well, much more needs to be known about its reality.

7. **References**

Alhadad, S., Thompson, K., Knight, S., Lewis, M., & Lodge, J. (2018). Analytics-enabled Teaching As Design: Reconceptualisation and Call for Research. In S. Buckingham Shum, R. Ferguson, A. Merceron, & X. Ochoa (Eds.), *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 427–435). ACM. https://doi.org/10.1145/3170358.3170390

Almeda, M. (2020). Predicting Student Participation in STEM Careers: The Role of Affect and Engagement during Middle School. *Journal of Educational Data Mining, 12*(2), 33-47.

Aula, V. (2019) Institutions, infrastructures, and data friction – reforming secondary use of health data in Finland. *Big Data and Society, 6*(2). ISSN 2053-9517. Retrieved from http://eprints.lse.ac.uk/101454/3/Aula_Institutions_infrastructures_and_data_friction_2019.pdf

Baker, R. S., Berning, A. W., Gowda, S. M., Zhang, S., & Hawn, A. (2020). Predicting K-12 dropout. *Journal of Education for Students Placed at Risk, 25*(1), 28-54.

Ball, S., Maguire, M., Braun, A., Perryman, J., & Hoskins, K. (2012). Assessment technologies in schools: ‘deliverology’ and the ‘play of dominations.’ *Research Papers in Education*, *27*(5), 513–533. https://doi.org/10.1080/02671522.2010.550012

Barnes, N., Fives, H., & Dacey, C. M. (2017). U.S. teachers’ conceptions of the purposes of assessment. *Teaching and Teacher Education*, *65*, 107–116. https://doi.org/10.1016/j.tate.2017.02.017

Bates, J., Lin, Y.-W., & Goodale, P. (2016). Data journeys: Capturing the socio-material constitution of data objects and flows. *Big Data & Society*, *3*(2), 1–12. https://doi.org/10.1177/2053951716654502

Braman, S. (2006). Change of State: Information, Policy, and Power. MIT Press. https://books.google.com.au/books?id=vY36AQAAQBAJ

Carl, B., Richardson, J. T., Cheng, E., Kim, H., & Meyer, R. H. (2013). Theory and application of early warning systems for high school and beyond. *Journal of Education for Students Placed at Risk*, 18(1), 29-49.

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, *4*(5-6), 318-331.

Flick, U. (2018). *Doing triangulation and mixed methods* (2nd ed.). Sage.

Gewirtz, S., Maguire, M., Neumann, E., & Towers, E. (2021). What's wrong with 'deliverology'? Performance measurement, accountability and quality improvement in English secondary education. *Journal of Education Policy*, *36*(4), 504–529. https://doi.org/10.1080/02680939.2019.1706103

Gummer, E., & Mandinach, E. (2015). Building a Conceptual Framework for Data Literacy. *Teachers College Record*, *117*(4), 1–22.

Hallinan, M. T. (2006). *School Sector and Student Outcomes*. University of Notre Dame Press.

Hammersley, M. (2005). Is the evidence-based practice movement doing more good than harm? Reflections on Iain Chalmers' case for research-based policy making and practice. *Evidence & Policy: A Journal of Research, Debate and Practice, 1*(1), 85-100. doi:10.1332/1744264052703203

Jerrim, J., & Sims, S. (2021). School accountability and teacher stress: international evidence from the OECD TALIS study. Educational Assessment, Evaluation and Accountability. https://doi.org/10.1007/s11092-021-09360-0

Kitchin, R. 2014. *The data revolution: BigData, open data, data infrastructures and their consequences*. London: Sage.

Kitto, K., Whitmer, J., Silvers, A. E., & Webb, M. (2020). *Creating Data for Learning Analytics Ecosystems*. Position Paper. Society for Learning Analytics Research. http://solaresearch.org/wp-content/uploads/2020/09/SoLAR_Position-Paper_2020_09.pdf

Landri, P. (in press). To resist, or to align? The enactment of data-based school governance in Italy. Educational Assessment, Evaluation and Accountability. https://doi.org/10.1007/s11092-021-09367-7

Lawn, M. (2013). Introduction: The rise of data in education In M. Lawn (Ed.), The rise of data in education systems: Collection, visualisation and use (pp. 7-10). Oxford: Symposium.

Leonelli S. (2020) Learning from Data Journeys. In: Leonelli S., Tempini N. (eds) *Data Journeys in the Sciences*. Springer, Cham. https://doi.org/10.1007/978-3-030-37177-7_1

Light, B., Burgess, J., & Duguay, S. (2018). The walkthrough method: An approach to the study of apps. New Media & Society, 20(3), 881–900. https://doi.org/10.1177/1461444816675438

Lingard, B. & Lewis, S. (2016). Globalisation of the Anglo-American approach to top-down, test-based educational accountability. In G.T.L. Brown, L.R. Harris (Eds.) *Handbook of human and social conditions in assessment (1st ed.)*, 387-403. New York and London: Routledge

Luckin, R., Holmes, W., Griffiths, M., & Pearson, L. B. F. (2016). Intelligence Unleashed An argument for AI in Education.

Mandinach, E. B., & Gummer, E.S. (2016). What does it mean for teachers to be data literate: Laying out the skills, knowledge, and dispositions. *Teaching & Teacher Education, 60*, 366–376. https://doi.org/10.1016/j.tate.2016.07.011

Mandinach, E. B., & Jimerson, J. B. (2016). Teachers learning how to use data: A synthesis of the issues and what is known. *Teaching & Teacher Education, 60,* 452–457. https://doi.org/10.1016/j.tate.2016.07.009

Mertala, P. 2021. Data (il)literacy education as a hidden curriculum of the datafication of education. Journal of Media Literacy Education, 12(3), 30-42.

Mills, M., Mockler, N., Stacey, M., & Taylor, B. (2021). Teachers' orientations to educational research and data in England and Australia: Implications for teacher professionalism. *Teaching Education*, *32*(1), 77–98. https://doi.org/10.1080/10476210.2020.1843617

Mandinach, E. B., & Gummer, E. S. (2013). A Systemic View of Implementing Data Literacy in Educator Preparation. *Educational Researcher*, *42*(1), 30–37. https://doi.org/10.3102/0013189X12459803

Mahatody, T., Sagar, M., & Kolski, C. (2010). State of the Art on the Cognitive Walkthrough Method, Its Variants and Evolutions. *International Journal of Human–Computer Interaction*, *26*(8), 741–785. https://doi.org/10.1080/10447311003781409

Mumford, E. (2006). The story of socio-technical design: reflections on its successes, failures and potential. *Information Systems Journal 16*: 317-342.

NAP. (2016). NAPLAN. https://nap.edu.au/naplan

Nelson, J., & Campbell, C. (2017). Evidence-informed practice in education: Meanings and applications. Educational Research, 59(2), 127-135. doi:10.1080/00131881.2017.1314115

NSW DoE. (n.d.). School excellence and accountability.

NSW DoE. (2020a). Assessing impact using the Bands over Time report

NsW DoE. (2020b). Scout overview.

NSW DoE. (2021a). NSW Department of Education: Our outcomes and targets. NSW Government.

NSW DoE. (2021b). School Excellence.

NSW DoE. (2021c). HIPL School self-assessment tool.

Perrotta, C., Gulson, K. N., Williamson, B., & Witzenberger, K. (2021). Automation, APIs and the distributed labour of platform pedagogies in Google Classroom. *Critical Studies in Education*, *62*(1), 97–113. https://doi.org/10.1080/17508487.2020.1855597

Perrotta, C., & Selwyn, N. (2020). Deep learning goes to school: toward a relational understanding of AI in education. *Learning, Media and Technology*, *45*(3), 251–269. https://doi.org/10.1080/17439884.2020.1686017

Pasmore, W., Winby, S., Mohrman, S. A., & Vanasse, R. (2019). Reflections:

Sociotechnical Systems Design and Organization Change. *Journal of Change Management*, *19*(2), 67–85. https://doi.org/10.1080/14697017.2018.1553761

Peterson, K. D. (2000). Teacher Evaluation: A Comprehensive Guide to New Directions and Practices (2nd ed.). Thousand Oaks: Corwin Press.

Richards, C. E. (1988). A typology of educational monitoring systems. *Educational Evaluation and Policy Analysis*, *10*(2), 106–116. https://doi.org/10.3102/01623737010002106

Sales, A., Botelho, A. F., Patikorn, T., & Heffernan, N. T. (2018). Using big data to sharpen design-based inference in A/B tests. In *Proceedings of the Eleventh International Conference on Educational Data Mining* (pp. 479-485). Buffalo, NY: IEDMS

Sears, A. (1997). Heuristic Walkthroughs: Finding the Problems Without the Noise. *International Journal of Human–Computer Interaction*, *9*(3), 213–234. https://doi.org/10.1207/s15327590ijhc0903_2

Selwyn, N. (2021a). “There is a danger we get too robotic”: an investigation of institutional data logics within secondary schools. *Educational Review*, 1-17.

Selwyn, N. (2021b). The human labour of school data: exploring the production of digital data in schools. *Oxford Review of Education*, *47*(3), 353-368.

Selwyn, N., Pangrazio, L., & Cumbo, B. (2021b). Attending to data: Exploring the use of attendance data within the datafied school. Research in Education.

Selwyn, N., Pangrazio, L., & Cumbo, B. (2021c). Knowing the (datafied) student: The production of the student subject through school data. *British Journal of Educational Studies*, 1-17.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380-1400.

Spencer, T. D., Detrich, R., & Slocum, T. A. (2012). Evidence-based practice: A framework for making effective decisions. *Education and Treatment of Children*, *35*(2), 127-151.

Swist T, Collin P, Third A. (2019). Children’s data journeys beyond the ‘supply chain’: co-curating flows and frictions. *Media International Australia*, *170*(1), 68-77.

Timperley, H., & Earl, L. M. (2009). Using Conversations to Make Sense of Evidence: Possibilities and Pitfalls. In L. M. Earl & H. Timperley (Eds.), *Professional Learning Conversations: Challenges in Using Evidence for Improvement* (pp. 121–126). Springer Netherlands. https://doi.org/10.1007/978-1-4020-6917-8_10

Tripp, D. (2012). *Critical incidents in teaching: Developing professional judgement (2nd ed.).* Abingdon: Routledge.

Thompson, G. (2013). NAPLAN, MySchool and accountability: Teacher perceptions of the effects of testing. *The International Education Journal: Comparative Perspectives*, *12*(2), 62–84.

Thompson, G. (2017). Computer adaptive testing, big data and algorithmic approaches to education. *British Journal of Sociology of Education*, *38*(6), 827–840. https://doi.org/10.1080/01425692.2016.1158640 van Leeuwen A., van Wermeskerken M., Erkens G., & Rummel N. (2017). Measuring teacher sense making strategies of learning analytics: A case study. *Learning: Research & Practice, 3*(1), 42–58. https://doi.org/10.1080/23735082.2017.1284252

Wasson, B., & Hansen, C. (2016). Data literacy and use for teaching. In P. Reimann, S. Bull, M. D. Vatrap, R. Vatrapu, & B. Wasson (Eds.), *Measuring and Visualizing Learning in the Information-Rich Classroom* (p. 56). Oxford, UK: Routledge.

Williamson, B. (2017). Learning in the 'platform society': Disassembling an educational data assemblage. *Research in Education*, *98*(1), 59–82. https://doi.org/10.1177/0034523717723389

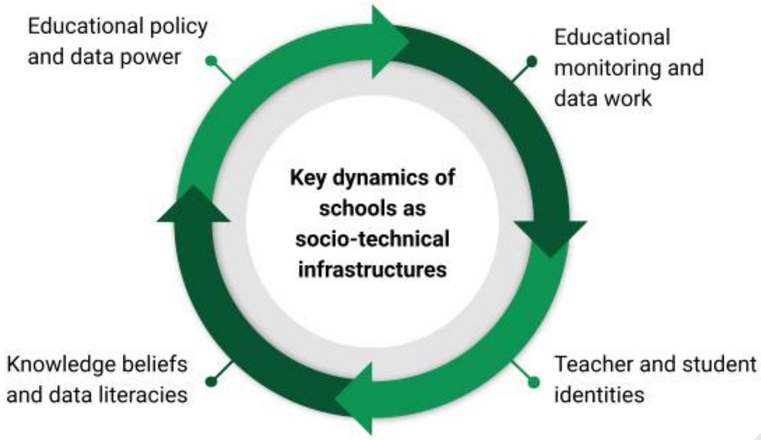
Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, *45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

Wilson, R., Piccoli, A., Hargreaves, A., Ng, P. T., & Sahlberg, P. (2021). *Putting Students First: Moving on from NAPLAN to a new educational assessment system* (The Gonski Institute Policy Paper #2-2021). Sydney: UNSW Gonski Institute.

Winne, P. H. (2017). Leveraging big data to help each learner and accelerate learning science. *Teacher College Record*, 119, 030304.

Wiseman, A. W. (2010). The use of evidence for educational policymaking: Global contexts and international trends. *Review of Research in Education, 34*(1), 1-24.

Figure 1. Key dynamics of educational data journeys: the interrelationship between data work, power, identities, and literacies



- Schools can be considered as socio-technical infrastructures that can influence data use
- Educational data practices can be contradictory and have effects over time
- Stakeholders' capacities need to be considered in data use
- Participatory approaches may ameliorate issues of contradictions and capacities

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: