UNLOCKING THE DATA DUNGEONS OF HIGHER EDUCATION (HE)

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Abstract

Higher Education in the United Kingdom (UK) operates under a regulatory framework, the Office for Students (OfS). The university sector need to report on a series of data metrics, where education has been quantified into measurable outcomes. These are focused on continuation and completion of studies, as well as readiness and ability to secure professional work. However, recent literature has documented the complexity of computing metrics in an environment in which universities are in constant transition and adaptation, and how these adaptive processes impact student transitions, including from university to graduate work. Thus collecting data with precision and fair statistical assessment of outcomes across the sector remain a challenge for the government and the sector alike.

Learning analytics is a highly contested field which is implemented and used in very different ways; in some cases, the collection of data places greater emphasis on institutional compliance for reputational protection and as a tool for data driven narrative creation. At its most effective, it places the learner at the centre of the process and as the primary audience for its output. Emerging trends point to how it is increasingly embedded within day-to-day activities that encompass learners, educators and the institution. The literature suggests three broad responses to data collection, collation and interpretations, where the institutional data gathered is actioned through very different strategic lenses. Best practice seeks to use this data to inform strategic and operational decisions; and to focus on the student experience, with a clear pedagogic rationale underpinning the sharing of data, that genuinely moves the student learning journey forward. The use and role of data can be characterised as a tool to defend the institution from external scrutiny; an intrinsic tool to inform course development or as instigator for dialogue (including self dialogue) by the learner. Our research indicates that it is most impactful when it supports data-informed pedagogic interventions.

The learning design that frames and encompasses learning analytics impacts significantly on the user. It can be cold, dehumanising and context free with the data stored in what we term as a ‘data dungeon’. It can be interpreted as a ‘data engine room’ driving forward the curricula and learning agenda; it can, we argue, at its cutting edge frame ‘data dialogues; shining the light into the data dungeon. This paper will draw upon these themes and suggest a maturity model to ensure the data collected has meaning, use and value and contributes to a greater understanding of the measurement and understanding of learning gain.

Keywords: Learning analytics, learner analytics, learning gain, data, pedagogy.

1 INTRODUCTION

The ever-increasing adoption of metricisation within almost every aspect of 21st century life is rapidly becoming an integral part of higher education with both positive and negative consequences and outcomes. Emerging trends in the Americas [1], Australia [2], South Africa [3], the United Kingdom [4] and cross-country [5][6] evidence how it is increasingly embedded within day-to-day activities that encompass learners, educators, institutions and policymakers. The adoption of learning analytics (LA) systems has been accelerated by rapid developments in educational software systems and the promise to senior teams of a fast, effective and efficient solution that simultaneously captures data for regulatory and monitoring purposes externally, while providing greater insights into student learning behaviours internally. However, questions remain around its key objective.

Policymakers are seeking a greater focus of the impact of LA in relation to learning gain [7]; holding institutions to account in terms of student outcomes and value for money. Institutions need to demonstrate to their funding bodies that these metrics reflect high level student outcomes and achievements; presented as homogenised trends and data sets that portray success at course and institutional level [8]. Educators, defined here as instructors, lecturers, tutors or equivalent, working directly with the learners, are seeking access to a rich data flow, that provides timely insights into how learners are engaging with their studies and their academic achievements, and pedagogically informed data insights which can be used to initiate an interaction or series of interventions with the learner, to stimulate a change in behaviour and learning [9].

There are competing perspectives at play; one set is around the broader set of expectations of staff in the institution, whereby engaging with the data collated is expected according to their role and responsibilities; the other perspective explores the ways in which individual learners have access to their own data, which they have given consent to be collected. Contemporary LA often fails to demonstrate meaningful outcomes to and for individual learners and their learning [10][11].

Used correctly, LA can enhance the efficacy of both the teaching and learning within an educational context and provide significant benefits to student learning gain, retention and success. LA can place the learner at the centre of the analytics process and ensures that their learning needs, as the primary goal of the implementation of LA, are met effectively. Best practice seeks to also use this data to inform strategic and operational decisions; and to focus on the student experience, with a clear pedagogic rationale underpinning the sharing of data, that genuinely moves the student learning journey forward. However, when poorly designed and deployed, it has the potential to generate confusion, inaccurate predictions of student success, and generate disengagement and a lack of self-confidence amongst individual students. LA is thus a highly contested field which is implemented and used in very different ways across the sector.

2 LITERATURE REVIEW

2.1 The evolution of learning analytics

Higher education institutions (HEIs) have historically been early adopters of highly complex student management information systems and virtual learning environments, and individual universities spend millions of pounds every year in licence fees for these specialist software applications and cloud-based services. In recent years, with increasing accountability, league tables and a more consumer-driven market place, senior management teams within universities across the world have been searching for new tools and techniques which offer the potential to improve student retention, increase student success and enhance learning gain, and thus provide a consequential enhancement to student satisfaction. External forces have also acted as drivers for LA. The onset of the COVID pandemic in early 2020, accelerated the momentum of investment in and adoption of digital learning within HEIs.

The successful introduction and application of learning analytics within a higher education environment requires a complex fusion of knowledge and understanding from the fields of both education and data science. Whilst recent advances in big data, cloud computing, artificial intelligence and high speed data networks facilitate the development of ever increasingly complex and sophisticated systems that generate and present vast amounts of data with greater accuracy and immediacy, the overarching requirement for LA should be to ‘add value’ and ‘enhance’ the student learning experience, with the primary focus being on increasing learning gain.

The field of LA field continues to embrace a range of researchers, academics and practitioners from a mixture of disciplines. During 2011, the international research community associated with learning analytics came together in Canada for the first International conference on Learning Analytics and Knowledge, and in the following 12 months, the highly esteemed Society for Learning Analytics Research (SoLAR) was formed, and has employed the following definition:

> ‘*Learning analytics* is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs’ [12]

This definition, created in 2011, has been widely adopted and used throughout a wide range of research that encompasses the fields of data science, computer science and education.

Literature on learning analytics has been themed and developed further to address the complexities of making data appropriate and contextual for use in LA. Having examined the common elements and processes associated with the implementation and operationalisation of learning analytics within HE institutions, we have been able to identify 6 core stages of what we term the Learning Analytics Process Chain; Collection, Collation, Interpretation, Cognition, Action and Reaction [11].

2.2 Stages in the learning analytics process chain

Figure 1 shows the six stages in the LA process chain.

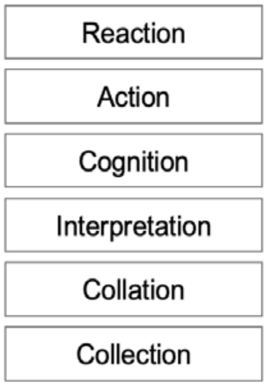

Figure 1. The LA Process Chain

1. Collection. In this stage data from learning applications and institutional systems are brought together in one place. The availability of data might emanate as a by-product of running an application or it might originate from a purpose-built data-capture system. As many institutions routinely and automatically collect data within learning or administrative applications, the collection is, for many, a simple process of data capture [13]. Examples include data from the virtual learning environment, a learner's library usage or their attendance [14].
2. Collation. Data from different sources will often use common field such as a student identification number or programme name. Collation involves the linking of disparate datasets into a coherent and consistent whole. This requires that the data is cleaned, linked by common fields, organised, protected, secured and stored using standardised data management processes.
3. Interpretation. Here, the datasets are summarised into metrics that can be disseminated around the institution [15]. Typically, this is achieved through the automatic production of reports, dashboards and alerts to educators and learners [16][17].
4. Cognition. Interpretation can be challenging to achieve without context. As an example, the interpretation stage may generate a number for a learner of 60% but it is context that gives meaning and understanding to the value. Cognition refers to the sense-making activities undertaken by educators and learners to interpret and contextualise data and turn it into meaningful and relevant information that can be used to provide insight [18]. The phases of interpretation and cognition can be influenced by culture and organisational norms [19], limited by an individual's capacity to make decisions [20] and circumscribed by different levels of data literacy on the part of the educator and learner [21].
5. Action. An action is the consequence of interpretation and cognition and can emanate from two main sources. First, an algorithm may generate an action, for example where an email may be sent to all learners who have not yet completed a quiz. This we term a data-driven intervention or DDI. DDI is typically undertaken on a large scale and possesses speed, efficiency, standardisation and depersonalisation characteristics [10]. Some institutions adopt this 'instrumentalist' approach to taking action deploying DDI in an attempt to address institutional challenges such as monitoring learner attendance [22]. Second, an action can be created by a human, for example where an educator wishes to discuss an aspect of a learner's performance or make changes to learning materials [23]. We refer to this as a data-informed intervention or DII. DII is not characterised by speed, efficiency or standardisation. Instead, DII is typically tailored to the learner, empathetic and context-aware. Whereas DDI is broad and shallow, DII is focused and deep. Learner-centred practices that result from DII typically empower and enable the learner [24], giving agency for their learning journey. This approach contrasts sharply with the context-free actions that are a consequence of DDI which can view learners that fall outside pre-set parameters as problems to be fixed. By contract, DII facilitates educators in supporting and stretching their learners, using their cognition of the situation to generate actions that are closely aligned with leaners' needs and aspirations.
6. Reaction. The intended outcome from stage 5 is a reaction from the educator or learner. For example, an educator may redesign their curriculum or a learner might change their pattern of attendance or engagement. This creates a more agile educator or 'more capable peer' [25]. However, not all actions result in a reaction. A learner may choose to ignore the suggested action or educator may not make changes to the curriculum. However, if a reaction is triggered, the changed behaviour will be recorded by the learning applications with the new data beginning the next cycle of the phases.

2.3 The learning analytics model

Building on the concept of the learning analytics process chain and a systematic review of academic literature to contextualize the model within broader theoretical and practical discussions, the review process involved the identification of relevant peer-reviewed articles, reports, and case studies. This analysis of this information allowed us to identify how the implementation of different combinations and sequences of the process chain stages result in different degrees of outcome, impact and value for different stakeholders. We have found that, in many instances, there are primarily two different, and often competing, 'lenses' on the learning analytics process chain.

The first focuses on the needs, aspirations and outcomes of the institution. This commonly operates using a lens focussed on homogenised course, year or departmental data – identifying trends, outcomes and opportunities for interventions targeted at groups of students. Our research suggests that this approach is quicker to implement across an institution, and can serve as defensive ammunition when challenged by external scrutiny, but yields a much lower level of benefit to individual learners and their learning gain. We have observed a common feature of this approach whereby access to the learning analytic data is heavily controlled – and often results in a 'data dungeon' where the opportunity to leverage learning gain is lost.

The second places the individual learner at the heart of the process, providing a more granular, personalised presentation of data that aims to motivate the learner, curate their learning journey and facilitate increased levels of learning gain. We have found that this approach requires a more comprehensive and time-consuming implementation plan, necessitates the buy-in of a wider range of stakeholders, and require a more open and transparent policy for data access. In organisations where this approach is adopted, we see the learner and their learning as the primary audience for real-time data storytelling conversations, interactions and learner reactions.

3 METHOD

This study employs a theoretical research design drawing on literature as the evidence base to explore the applicability of learning analytics process chain [11] to two distinct stakeholder groups: institutions and learners.

The study focuses on the learning analytics process chain, originally developed to identify and order the stages that exist in the application of learning analytics in HEIs and to assess its adaptability and relevance in two different contexts. A structured framework was used to analyse its key components, assumptions, and operational mechanisms. This involved the identification of core principles and an investigation of the links to the concept of maturity, examination of previous uses of LA in literature and the mapping of its components to the uses and needs of the two stakeholder groups.

This study is conceptual and does not include empirical testing of the proposed applications. The findings are based on theoretical reasoning and secondary data sources, and future research is planned to validate these propositions through empirical studies and stakeholder consultations.

4 RESULTS

The application of the method to the learning analytics process chain using the two lenses results in an institution-centric and a learner-centric view.

4.1 Institution-centric view of the process chain

Our research has shown that when looking through an 'Institution lens' on the Learning Analytics Process Chain, we often see an over-reliance on the use of automated, algorithm-driven interactions that place little value in the involvement of academics to provide learner context, preferring a simpler 'criteria met' threshold for action. We have identified that, whilst this implementation of learning analytics and data driven activity can be positive in terms of analysing and identifying trends in cohorts, courses and year groups, it has limited impact in terms of promoting and nurturing personalised learning gain.

Attendance monitoring is a frequently often used tool to analyse and report on engagement, and in many institutions, is a primary component of the learning analytic data set that drives interaction. Whilst such activity provides an efficient mechanism to create evidence of institutional monitoring of student engagement in terms of attending teaching, we would argue that this does not generate any evidence of learning taking place, and at best, could be considered an indication of 'intention to learn' on the part of the student. Mature, impactful learning analytics systems should aspire to monitor, measure and support learning and learning gain.

Our analysis of the implementation of the learning analytics process chain in such attendance monitoring scenarios, indicates a high degree of effective automation of data collection, collation and interpretation that, in most cases, trigger an automated email communication to the student based on a single institutionally-set threshold. Such actions are implemented as a result of student data meeting a single criteria, and provide little opportunity for contextualised knowledge of the student – such as a health issue, family emergency or wellbeing event that has impacted attendance. The institution-centric view exemplifies DDI.

The increasing regulation, monitoring and scrutiny of HEIs, for example by the OfS in the UK, has inevitably heightened the awareness of the importance of learning analytics and student datasets within the mindsets of university leadership teams. Public reporting of data comparing institutions across a range of criteria has accelerated the need for all institutions to develop more agile, dynamic data systems that can be used as a form of defence from external scrutiny.

We have identified examples of such defensive strategies in our research – and these are primarily associated with the creation of learning analytic data reports that provide evidence of monitoring attendance, engagement (through virtual learning environment access and interactions) and academic success (through end of unit/module assessments). We have observed that in the majority of these cases, there is very limited evidence of interaction with all students on a course or programme, with the primary focus and efforts directed on the minority of students whose data is interpreted as highlighting a 'cause for concern'. Whilst the automated interactions that these implementations of the learning analytics process chain provide to this subset of the student population can be shown to encourage and promote a change in learner behaviour and an increase in their ability to demonstrate a readiness or willingness to learn, they do not appear to demonstrate any direct correlation to an increase in learning gain across the student population.

Institution-centred implementations of the learning analytics process chains are commonly undertaken via a 'top down' strategic approach, have a narrow scope of action and result in the creation of homogenised data reports on cohorts, courses and year groups that are presented through a range of dashboard diagrams. Their primary audience is very often the institution's senior leadership team, and they are commonly used as the basis of risk management discussions and to inform strategic decision making. They rarely present data at the granular level of individual students, and almost never communicate learning gain. They have a place and function within the context of monitoring institutional performance, but have a relatively low ceiling on the axis of impact on learning gain.

4.2 Leaner-centric view of the process chain

Exploring the implementation of the learning analytics process chain through a learner-centric lens identifies the need for a more comprehensive use of all six stages, and highlights greater emphasis on the final three stages – cognition, action and reaction. The learner, their learning journey and their learning gain are clearly located at the heart of the process, and a transparent approach to data access is provided to all stakeholders. The overarching features of this approach highlight the need for personalised data storytelling conversations that engage, motivate and facilitate the learner to undertake positive reactions to communication, discussion and feedback.

Providing a learner-centric personalised, context-rich implementation of the learning analytic process chain is neither easy or quick to achieve, and requires a significant amount of input from all the professionals working with and supporting the learner. Whilst the automated interpretation algorithms that form a core part of commercial learning analytics software systems can provide a useful initial tool to identify patterns of behaviour or trends in academic achievements from large datasets, this is only the first stage of creating a personalised learning process.

We have seen that in order for learning analytic data to form the basis of insightful interactions with learners that then facilitates the opportunity for learner reactions that enhance learning, motivation and achievements, there is an essential need for nuanced contextualised knowledge of the learner to be considered when planning the actions. This reinforces our opinion that DIIs, whereby an academic or support worker adds human input to the action planning – giving due consideration to the contextual knowledge that they possess of the learner.

A good example of this would be where an educator is able to use the results of some formative assessment tests, along with their knowledge of the learners preferred learning style, to identify and guide the student through relevant revision and consolidation activities that address the poor understanding of concepts within the formative assessments. Knowing that the student struggles with text based learning, this would mean that the academic could direct the learner to video resources which are likely to be more productive in terms of enhancing learning gain.

Another example would be where an educator is able to combine attendance data and assessment marks to identify the most relevant way to interact and support an individual learner. In the event that a learner had high attendance levels, they would not be identified as ‘cause for concern’ from a DDI interpretation of the attendance data alone, but in the event that they had shared with their personal tutor that they had been experiencing a serious family emergency in the week prior to the assessment completion, then this combination of data analysis and learner context knowledge, would allow the personal tutor to adopt an interaction with the learner that showed compassion and awareness of events that are not within the scope of the learning analytics data set. Adopting a purely DDI approach in this example is likely to lead to a vulnerable student receiving an interaction that is not appropriate and that demonstrates little compassion or support.

One of the most evident challenges associated with implementing the learner-centric lens on the learning analytics process chain, is the need for all stakeholders to possess a good level of data literacy (understanding what the data shows) and graphical data literacy (knowing how best to present this to different audiences). Providing students with real-time access to a data dashboard showing a range of metrics related to attendance, engagement, achievement, library use etc, will only be effective and beneficial if the learner can read and interpret the data visualisations. Without a good level of data literacy, providing learning data to students, and some staff, can be counterproductive, and potentially erode confidence and motivation for learning. The Wonk HE survey [26] concludes that students are broadly supportive of the use of engagement data for analytics. However, students are more divided, 37% support notions of a student data dashboard, for example with cohort tracking and individual performance, yet 31% said this would make them even more anxious and stressed that they were not doing enough.

4.3 Defining learning gain

Learning gain is a highly contested term in the literature. In the United Kingdom, the Higher Education Funding Council (the precursor to the OfS) commissioned thirteen pilots from 2017 exploring learning gain from a number of perspectives, before concluding that institutions need to define their own stance on the subject. In this study, we characterise learning gain as a personalised and individual rise in a learner’s understanding and appreciation of their subject area. It is facilitated by human interpretation (DII) because it is nuanced and context-specific. Learning gain emanates from stage 6 of the process chain. How learners respond to the interventions they receive will determine their level of learning.

4.4 Retheorising maturity in learning analytics

A business definition of maturity is a measurement of the ability of an organisation for continuous improvement in a particular discipline. It is ‘the extent to which an organisation has explicitly and consistently deployed processes that are documented, managed, measured, controlled and continually improved’ [27]. Maturity is typically defined on a scale of 1 to 5. The higher the level of maturity, the better the organisational process. A maturity model is a framework for measuring an organisation's maturity. The term maturity model was first applied in the domain of software development in the 1980s but has broadened to encompass all sectors [28], including HE. In HE maturity continues to be viewed predominantly from a business perspective, as organisational processes that have levels of complexity or sophistication [29]. For this paper, we theorise maturity differently, in terms of learning gain. For example, an organisation may reach the highest maturity in the process of data ownership but unless that competence translates to benefit to the learner, we assess its leaning gain maturity at a much lower level. This conceptualisation of maturity places the learner at the centre of learning analytics and accordingly assesses maturity levels as the extent to which the dimensions impact the learner. This view of maturity in a learning analytics context is novel and will be the focus of future research by the team.

4.5 Fusing the process chains, a learner and learning-centric approach

Adopting an institution-centric and leaner-centric view of the process chain results in two very different perspectives. While both views appear to make use of all six stages, they can be differentiated by the impact they have on the learner. Institutions that collect large amounts of data but make limited use of it can be thought of as the keepers of a data dungeon. The DDIs that result are likely to have limited impact on the learner because they are often generic, automated and lacking in learner context. In our experience, learners often ignore automatically generated communications and thus they can sometimes have no effect on the learner. The effect may also be negative if the learner perceives the institution to have little regard for them as an individual.

Figure 2 visualises the two views and the extent to which they are likely to impact learning gain.

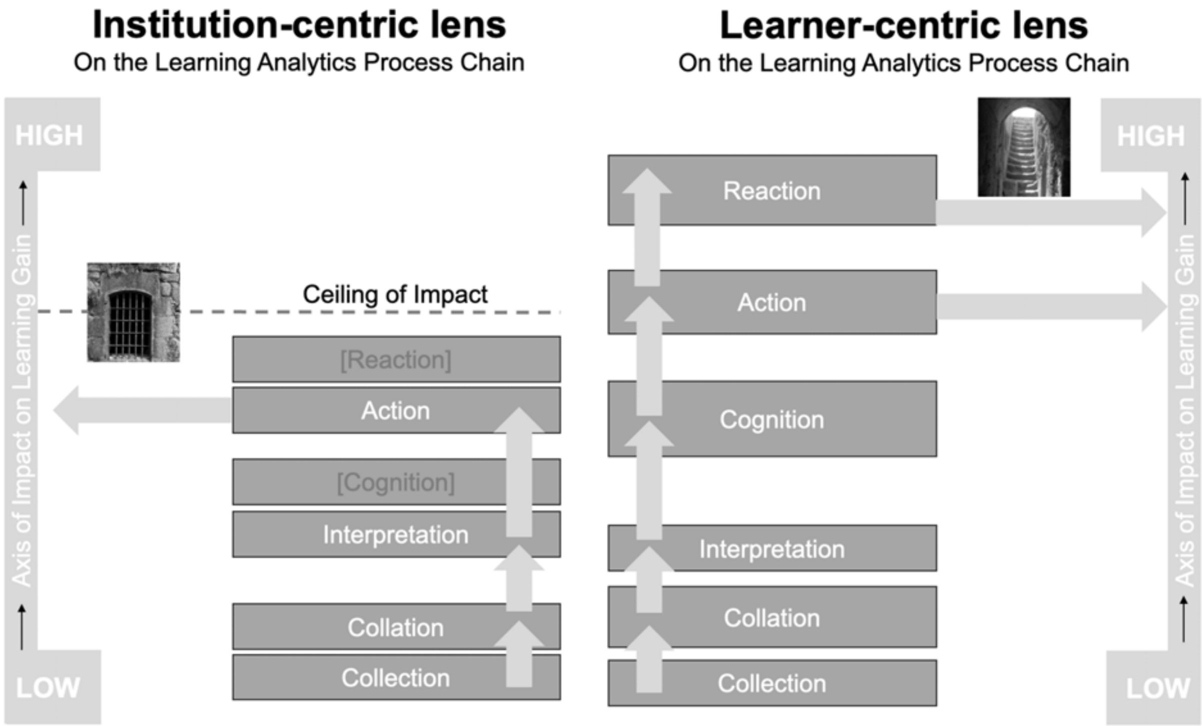

Figure 2. The two perspectives on the process chain and their link to learning gain

However, the DII approach is likely to have much greater impact on learning gain because the proposed actions will be relevant to the learner, recognise their learning style and needs, their past and current situation. In summary, DII demonstrate human knowledge and an awareness of emotion and thus communicate in a much more personalised manner; DII opens the data staircase that shines light on the learner and their learning journey. The learner's reaction to these proposed actions will have the highest probability of a positive outcome for the learner. The institution-centric view has a limited ceiling of impact for the learner whereas the learner-centric view has no ceiling on learning gain. It is an ascending staircase that illuminates and enriches the learning experience.

5 CONCLUSIONS

Demonstrating the significant potential and positive impact on student learning that adopting a learner-centric approach to learner analytics has within a HEI should, in our opinion, be a convincing proposal for institutional leaders. However, the current financial challenges faced by university leadership teams, coupled with the increasing level of external scrutiny and its inevitable requirement for homogenised data sets, results in a situation where the 'de facto' lens on learning analytics is most commonly focused on providing institutional defence and dungeons of unexploited learner data.

Our work has started to identify the emergence of a distinct third process chain that sits between the institution and the learner. This focuses on two core aspects of the teaching and learning process; the design and content of the curriculum (the 'what' is taught), and the pedagogies and delivery models (the 'how' the curriculum is structured and delivered). This third process chain fuses together data streams that identify and communicate the needs and expectations of the learner and the institutional delivery constraints such as staffing, timetabling, resources and regulatory compliance. We believe that this third process chain has the potential to lever greater discourse between senior leaders and teaching staff about the design and delivery of courses, and to support dialogues with learners about their views and experiences relating to specific modules/courses and programmes. These DIIs and discussions between all three core stakeholders within the higher education learning environment; institution, learner and educators, have the potential to result in improvements to all aspects of the learning experience, and provide positive outcomes for all parties.

Learning Analytics has a significant role to play in the ongoing evolution of higher education in the post-COVID era. The need to unlock the ever-increasing sized data dungeons that many institutions have been building over the last 5 years in order to ascend the data staircase to shine light on the untapped potential of this data, has never been more urgent.

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