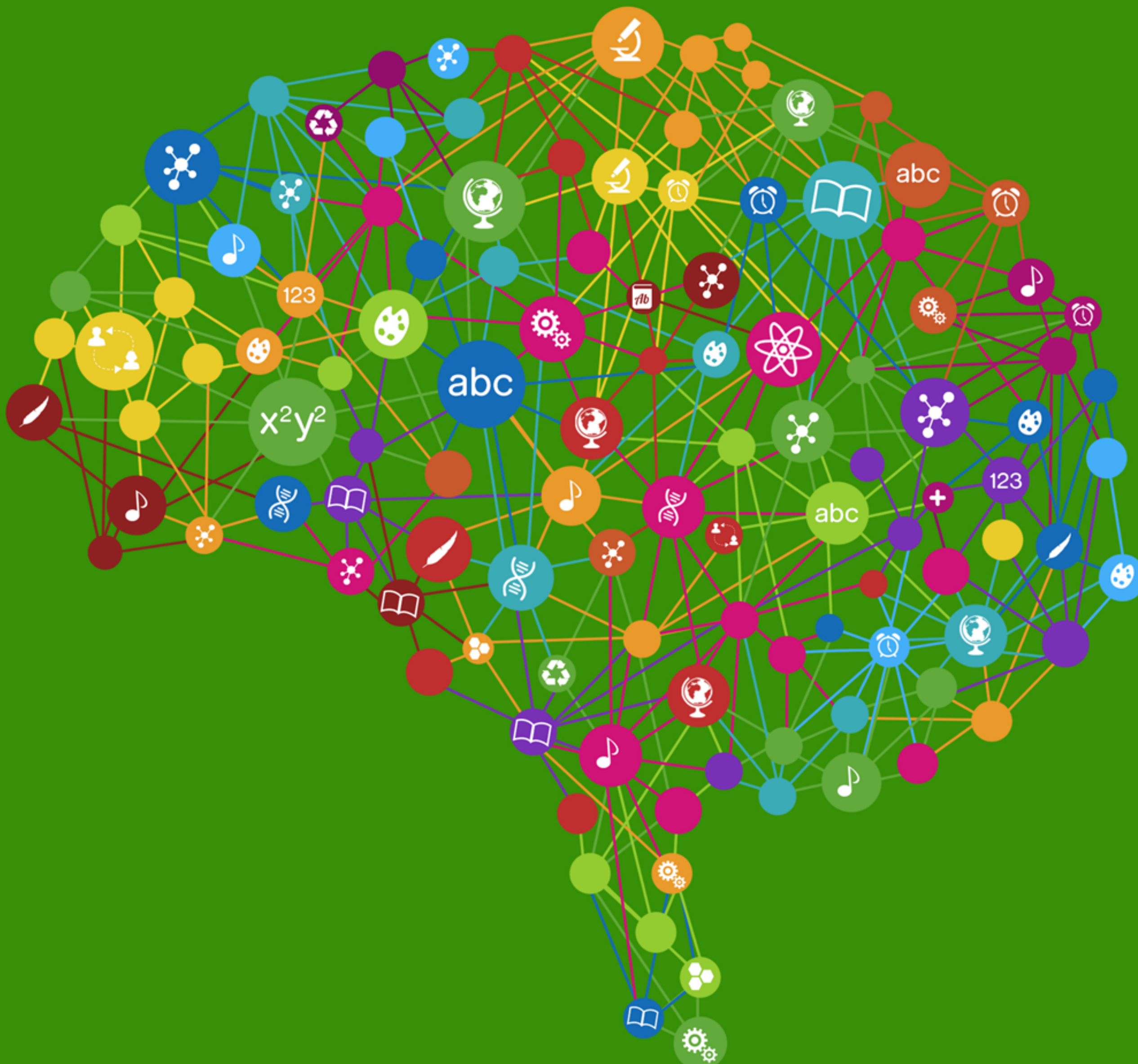
DL4D
DIGITAL LEARNING FOR DEVELOPMENT



Learning Analytics for the Global South

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ACRONYMS

AA	academic analytics
ADB	Asian Development Bank
APEC	Asia-Pacific Economic Cooperation
ASEAN	Association of Southeast Asian Nations
CLAToolkit	Connected Learning Analytics Toolkit
DFID	Department for International Development (United Kingdom)
DL4D	Digital Learning for Development
EDM	educational data mining
FIT-ED	Foundation for Information Technology Education and Development
GS	GroupScribbles
HEI	higher education institutions
IBRD	International Bank for Reconstruction and Development
ICT	information and communications technology
IDRC	International Development Research Centre
INASSA	Information and Networks in Asia and Sub-Saharan Africa
IT	information technology
ITU	International Telecommunication Union
MOOC	massive open online course
OAAI	Open Academic Analytics Initiative
OECD	Organisation for Economic Co-operation and Development
OLA	Open Learning Analytics
PISA	Programme for International Student Assessment
RCKI	Rapid Collaborative Knowledge Improvement
SEA	Southeast Asia
SEAMEO	Southeast Asian Ministers of Education Organization
SFC	Superintendencia Financiera de Colombia (Colombia Superintendency of Finance)
SIC	Superintendencia de Industria y Comercio (Superintendency of Industry and Commerce)
SoLAR	Society for Learning Analytics Research
UNDP	United Nations Development Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization

PREFACE

Learning Analytics for the Global South is a compilation of papers commissioned for the Digital Learning for Development (DL4D) project. DL4D is part of the Information Networks in Asia and Sub-Saharan Africa (INASSA) program funded jointly by the International Development Research Centre (IDRC) of Canada and the Department for International Development (DFID) of the United Kingdom, and administered by the Foundation for Information Technology Education and Development (FIT-ED) of the Philippines. DL4D aims to examine how digital learning could be used to address issues of equity, quality, and efficiency at all educational levels in developing countries.

Over the past two years, DL4D has brought together leading international and regional scholars and practitioners to critically assess the potentials, prospects, challenges, and future directions for the Global South in key areas of interest around digital learning. It commissioned discussion papers for each of these areas from leading experts in the field: Diana Laurillard of the University College London Knowledge Lab, for learning at scale; Chris Dede of Harvard University, for digital game-based learning; Charalambos Vrasidas of the Centre for the Advancement of Research and Development in Educational Technology, for cost-effective digital learning innovations; and for learning analytics, the subject of this compilation, Dragan Gašević of the University of Edinburgh Moray House School of Education and School of Informatics. Each discussion paper is complemented by responses from a developing country-perspective by regional experts in Asia, Latin America, Africa, and the Middle East.

Learning Analytics for the Global South considers how the collection, analysis, and use of data about learners and their contexts have the potential to broaden access to quality education and improve the efficiency of educational processes and systems in developing countries around the world. In his discussion paper, Prof. Gašević articulates these potentials and suggests how learning analytics could support critical digital learning and education imperatives such as quality learning at scale and the acquisition of 21st century skills. Experts from Africa (Paul Prinsloo of the University of South Africa), Mainland China (Bodong Chen of the University of Minnesota, USA and Yizhou Fan of Peking University, People's Republic of China), Southeast Asia (Ma. Mercedes T. Rodrigo of the Ateneo de Manila University, Philippines), and Latin America (Cristóbal Cobo and Cecilia Aguerrebere, both of the Ceibal Foundation, Uruguay) situate Prof. Gašević's proposals in their respective regional contexts, framing their responses around six key questions:

1. What are the main trends and challenges in education in your region?
2. How can learning analytics address these challenges?
3. What models of learning analytics adoption would be most effective in your region?
4. What are the barriers in adoption of learning analytics in your region and how could these be mitigated?
5. How do you envision ethical use and privacy protection in connection with learning analytics being addressed in your region?
6. How can the operationalization of learning analytics be futureproofed in your region?

We hope that this compilation will serve as a springboard for deeper conversations about the adoption and sustained use of learning analytics in developing countries – its potential benefits and risks for learners, educators, and educations systems, as well as the ways to move forward that are rigorous, context-appropriate, ethical, and accountable.

Cher Ping Lim and **Victoria L. Tinio**
Editors

DL4D
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Include us all! Directions for adoption of learning analytics in the global south

Dragan Gašević

ABSTRACT

The ever-growing use of technology in education has resulted in an unparalleled collection of data on various aspects of learning, teaching, and education systems. To address pressing challenges, education sectors across the world have recognized the potential of analyzing such data using advanced methods for data analytics. This interest in data in education resulted in the development of the field of learning analytics, which aims to understand and optimize learning and the environments in which learning occurs. While there have been many success stories about the use of learning analytics, such stories are predominantly from the Global North. This paper discusses opportunities for the adoption of learning analytics in the Global South in terms of the three main cornerstones of education – quality, equity, and efficiency. The paper suggests that the implementation of learning analytics in developing countries has significant potential to support learning at scale, to provide personalized feedback and learning experience, to increase the number of graduates, to identify biases affecting student success, to promote the development of 21st century skills, and to optimize the use of resources. The paper concludes by emphasizing the critical importance of the development of policies and codes of practice relating to the ethical use of learning analytics, privacy protection, and algorithmic accountability to support a healthy adoption of learning analytics.

1

INTRODUCTION

The adoption of learning analytics is viewed through the lens of three key challenges facing education systems in the Global South: quality, equity, and efficiency.

As their economies grow, countries in the Global South aim to become and remain competitive within the global market through, among others, the availability of a highly trained workforce. Education plays a key role in the development of the high-level skills required for the labor market. Opportunities for lifelong learning are essential for individuals to stay competitive on the job market and to attain higher incomes (UNESCO, 2015b). This has resulted in a continuously increasing demand for access to quality education and for scaling up educational opportunities (Kovanović, Joksimović, Gašević, Siemens, & Hatala, 2015). Technology is often seen as a possible means to address this growing educational need. However, the availability and deployment of technology offer no guarantee for productive learning if technology-enhanced learning opportunities are not closely integrated with curricula that can support learners and provide high quality learning experience (Evans & Popova, 2016). While there has been an increase in universal access to quality education in the Global South over the past two decades, the uneven distribution of economic wealth across class and geography has had a negative impact on the equitable distribution of educational gains among rich and poor, and among urban and rural regions (Asian Development Bank, 2012; UNESCO, 2015a). It is therefore important to find mechanisms to support educational systems in the Global South in their quest to scale up quality education in cost-effective and equitable ways.

This paper considers how the use of learning analytics can assist education systems in the Global South. A relatively new field of research and practice, learning analytics uses data about learners and the context in which learning occurs in order to advance understanding of and optimize learning (Siemens & Gašević, 2012). It also holds promise for addressing high priority issues in education (e.g., prediction of student retention, enrollments, and learning gains) (Dawson, Gašević, Siemens, & Joksimović, 2014). With the proliferation of the use of technology in education, the collection and analysis of such data can make a significant contribution to the provision of personalized and scalable support for learners which, in turn, can reduce gaps in the feedback loops inherently induced by large learner numbers and technology-mediated communication. However, an overwhelming majority of the current work on learning analytics originates from the Global North. Although many lessons learned are to some extent transferable, there are a number of specificities of the Global South context that need to be taken into account.

This paper provides direction for the adoption of learning analytics in the Global South by building on a framework that was created specifically to support analytics adoption in higher education (Gašević, Dawson & Pardo, 2016). Adoption is viewed through the lens of three key challenges facing education systems in the Global South: *quality*, *equity*, and *efficiency*. Here, quality refers to the extent to which educational systems and institutions provide learning experience and gains consistent with the specific needs of particular learners in particular situations (Ossiannilsson, Williams, Camilleri, , & Brown, 2015). Although traditionally linked to education access and general participation, equity is also related to education completion rates, to the transition from one educational level to another, and to overall educational achievement across different groups, based on factors such as gender, income, geographic location, minority status, and disabilities. Efficiency is an economic indicator of education and has internal and external dimensions: internal efficiency aims to enhance the effect on outputs (e.g., learning gains and employability) of resources invested in education, while external efficiency seeks to maximize the benefits of the outcomes of an educational system.

2

LEARNING ANALYTICS OVERVIEW

POLICY TAKEAWAYS 1

- Learning analytics is a field of research and practice that aims to make use of data about learners and learning contexts in order to understand and improve learning and learning environments.
- Learning analytics can predict which students are likely to be at risk of failing a course, detect learning tasks that offer the most effective learning gains, and identify differences in needs for tutorial support across a diverse range of students.
- Learning analytics in developing countries has the potential to support learning at scale, provide personalized feedback and learning experience, increase the number of graduates, identify biases affecting student success, promote the development of 21st century skills, and optimize the use of resources.

The field of learning analytics is recognized for its unprecedented collection of data about the technology-mediated interaction of learners with content, fellow learners, and teachers. It emerged through interaction between researchers and practitioners from different disciplines such as the learning sciences, education, psychology, sociology, data mining, statistics, information visualization, and human computer interaction (Dawson et al., 2014). According to the Society for Learning Analytics Research (SoLAR), learning analytics is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long, Siemens, Conole, & Gašević, 2011).

2.1 Key Activities in Learning Analytics

Generally, a learning analytics cycle covers four main interrelated stages, namely, data collection and pre-processing, data modeling, presentation of results, and interventions. Data collection is related to the acquistion of data about and measurement of different learning processes and learning outcomes.

Examples include data about learners' navigation through the resources available in a learning management system, text of discussion messages, student course registrations, geographic location of a school, and socio-economic and demographic data about students. Data predictive of academic achievement have been widely studied in learning analytics (Dawson et al., 2014). Recently, more attention has been paid to indicators of 21st century skills (Buckingham Shum & Deakin Crick, 2016), self-regulated learning (Roll & Winne, 2015) and learning dispositions (Buckingham Shum & Deakin Crick, 2012).

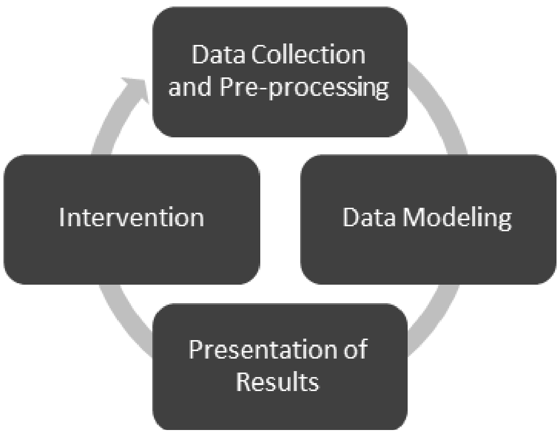

Figure 1. A model of key activities in a learning analytics process cycle

Data modeling is related to the processing of data collected with different statistical and machine learning methods in order to provide insights relevant to learning, teaching, and education. Examples of outcomes of data modeling may include prediction of student grades, identification of possible students at risk of failing a course, detection of learning tasks that promote the development of collaborative problem-solving skills, recognition of student satisfaction based on discussions, or prediction of the numbers of students who will enroll in a course in the future. Data modeling can create a foundation for the development of analytics tools that are used by students, teachers, and administrators; for instance, early warning systems (e.g., Krumm, Waddington, Teasley, & Lonn, 2014) can provide learners and instructors with insights into learning progression from the start of a course.

Presentation in learning analytics aims to show data collected and/or the results of data modeling to a wide range of stakeholders including students, teaching staff, and administrators (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). The purpose of presentation is to offer an accessible representation of the data in order to support stakeholders in making sense of the trends emerging from data as well as in decision-making about their future actions. Information visualization and dashboards are commonly associated with presentation in learning analytics. Other formats such as the generation of personalized feedback messages to students have demonstrated much promise recently (Pardo, Jovanović, Dawson, & Gašević, 2016; Wright, McKay, Hershock, Miller, & Tritz, 2014).

Interventions in learning analytics are actions informed by the data collected and modeled and that aim to enhance the learning environment and learning experience. Interventions can be related to academic processes (e.g., which courses to enroll in next to meet personal education goals most effectively) or course- and/or activity-specific processes (e.g., which study strategies would be most effective to follow). Recent developments in learning analytics explore approaches to using learning analytics-based interventions as an integral component of learning designs (Lockyer, Heathcote, & Dawson, 2013; Rienties & Toetenel, 2016; Wise, 2014). During the implementation of interventions, data are collected to evaluate the effects of the interventions through data modeling and to inform future decision-making.

2.2 Examples of Learning Analytics Practices

There are several well-known cases that demonstrate the potential benefits of the application of learning analytics in practice. Course Signals is a learning analytics system developed at Purdue University that makes use of indicators of students' learning progression extracted from institutional learning management and student information systems (Campbell, 2007). These indicators are analyzed to develop a predictive model that identifies students at risk. The three risk levels – high, medium, and no-risk – are shown to students and instructors. This process points instructors to those students who need urgent support. The process also prompts students to evaluate their learning progression. The findings of the use of the system showed considerable gains in student retention and degree program completion (Arnold & Pistilli, 2012).

The University of Michigan went a step further in the use of learning analytics when it developed a system named E²Coach to support learning in science courses (McKay, Miller, & Tritz, 2012). The system incorporates psychological principles to assist learners to develop the capacity to ascertain for themselves why a particular subject is important for their studies. The system also offers teaching guidance by building on the database on learning strategies that have been recommended by previous learners. The data models in E²Coach are constructed to compare the goals set by learners in order to personalize the advice a learner is given. Once the data modeling is complete, students receive advice that offers motivational and instructional guidance in the form of personalized email messages. The findings from the use of the E²Coach system indicated a significant improvement in grades for about 5% of students compared to when E²Couch was not used (Wright et al., 2014).

2.3 Policy Implications for the Global South

The use of learning analytics has the potential to address a number of existing challenges and future goals in the Global South. The following opportunities are highlighted as promising areas that could benefit the most from the use of learning analytics in developing countries.

- Support learning at scale through the use of learning analytics in order to improve the quality of learning experience and environments.
- Provide personalized feedback to learners at scale, with limited numbers of teaching staff, in order to improve learning outcomes and learning processes.
- Increase the number of graduates by identifying learners at risk of failure and/or withdrawal in the early stages of their studies.
- Identify biases affecting the success of under-supported and under-represented student sub-populations based on socio-economic and demographic factors.
- Optimize the use of resources by predicting future demands for learning and teaching support and by evaluating existing and future investments and programs.
- Promote the development of data literacy across a diverse range of stakeholder groups.

3

ADOPTION DIRECTION FOR LEARNING ANALYTICS IN THE GLOBAL SOUTH

To suggest directions for the adoption of learning analytics in the Global South, this paper builds on the learning analytics adoption model introduced by Gašević, Dawson, and Pardo (2016). The model is based on the approach used in business analytics and adapted to address the needs of higher education. It is designed to guide learning analytics adopters in the development of their understanding and vision of the approach. The model is based on three dinstic components – data, model, and transformation. Each of these three components is introduced in the following subsections and discussed with respect to the three critical dimensions of education in the Global South – quality, equity, and efficiency.

3.1 Data

POLICY TAKEAWAYS 2

- Creativity in data sourcing is critical. Even in regions with limited Internet access and electricity, data available in student records can offer much insight to inform decisions that promote the quality, equity, and efficiency of education.
- Support of and investment in information technology is necessary to enable the adoption of learning analytics. (Inter)national and regional partnerships and open source software initiatives can mitigate limitations in resources that are necessary for the adoption of learning analytics.
- Collection of data that support access to learning resources with mobile devices and social media inhibited by limited and intermittent bandwidth can also offer much value for quality and efficiency. Even the lack of some data is still data that can be of particular value for issues related to equity.

Although education systems have a long tradition of data collection for reporting to, for instance, funding and accreditation bodies, the use of data in day-to-day decision-making is less prevalent (Macfadyen &

Dawson, 2012; Siemens, Dawson, & Lynch, 2014). For this reason, many education systems need to be made aware of the potential benefits of the data regularly collected by their institutions.

3.1.1 Creative data sourcing

Creative data sourcing is the first key step in the learning analytics adoption model. It is particularly relevant for education systems in the Global South where the use of technology may be limited by low connectivity, bandwidth, and access to electricity. These kinds of factors can place significant constraints on providing support to learners in real-time. Nevertheless, even under such conditions, education systems usually collect data about students (e.g., socio-economic, demographic, and academic variables) in student information systems.

The use of data from student information systems can offer insights into learning experience and academic planning. For example, social networks can be identified from data on joint enrollments in the same class (Gašević, Zouaq, & Janzen, 2013). Such networks can reveal patterns behind decisions that students make regarding class enrollments (e.g., high-achieving students tend to take the same class together, as do low-achieving students). Moreover, the positions that students occupy in such networks can explain, to a large extent, students' academic success throughout the completion of their degrees. Finally, identification of students who occupy central roles in a rural region can be used as a foundation for creating peer teaching and support structures. The use of such data thus allows for making informed decisions about the formation of student cohorts and the provision of teaching support and academic counselling.

Efforts to address the challenge presented by the high use of mobile devices but with low bandwidth in the Global South have led to solutions that aim to provide opportunities for learners through the use of mainstream social media. For example, social media is recommended as a way of enriching learning experience in massive open online courses, which are designed specifically for developing countries (Patru & Balaji, 2016). The use of such data can offer insights into enhancing learner experience and advancing quality assurance – provided that the privacy of learners is protected, and that the terms of data collection and use are specified transparently.

3.1.2 Critical role of information technology support

For effective adoption of learning analytics, information technology (IT) support is of paramount importance. Although educational systems and institutions might have numerous relevant datasets, access to and use of these datasets needs to be provided and supported by IT units. Furthermore, many educational institutions are typically confronted by challenges such as insufficient support offered to providing data in a format suitable for analysis by all relevant stakeholders and for integrating data from different sources.

Specific needs for IT support for learning analytics in the Global South are related to opportunities to facilitate the collection of data from sources (such as social media) that can potentially improve learning experience (Patru & Balaji, 2016). The Connected Learning Analytics toolkit (CLAToolkit) is an open source software initiative that enables the collection of data for learning analytics outside of institutional learning management systems (Kitto et al., 2016). The CLAToolkit initiative stresses the importance of the development of standards for data collection and sharing (Viano, 2015) to boost the development and adoption of learning analytics (Bakharia, Kitto, Pardo, Gašević, & Dawson, 2016).

Involvement and cross-institutional collaboration in the development of open source software are also promising directions for the adoption of learning analytics in the Global South. Fortunately, the use of open educational resources and open source software has an established track record in the Global South. The benefits of the development of open source software for learning analytics include:

- reduction of costs for acquisition of learning analytics solutions;
- increase in prospects for cross-institutional exchange and collaboration;
- opportunities for customization to address specific needs for an educational system and/or institution; and
- transparency in the way certain data are used and algorithms executed.

The Open Learning Analytics (OLA) concept proposed by SoLAR (Siemens et al., 2011) could be used as a blueprint for the development of such an open learning analytics platform. In addition, the Apereo Learning Analytics Initiative could serve as a solid foundation for the future development of learning analytics and collaboration in the Global South (Apereo Foundation, 2016).

DATA SOURCES OF RELEVANCE TO THE GLOBAL SOUTH

For evaluating the quality of experience, highlighting inequities, and revealing efficiencies in the education system

Quality. Some of the original learning analytics initiatives aimed at addressing the limitations of existing quality assurance initiatives (Jovanovic et al., 2008). As quality in education is typically associated with addressing the particular needs of particular students in particular situations, approaches to quality assurance predominantly are based on student evaluations of teaching survey instruments. Event data about the availability of Internet access and electricity can be highly relevant to quality assurance in the Global South. While survey instruments can offer some insights into a learning experience, such data are only available once a course is finished (Jovanovic et al., 2008) and are not necessarily reflective of learning gains (Uttl, White, & Gonzalez, in press). Data extracted from student discourse and social networks are particularly valued by teaching staff for quality assurance purposes (Ali, Hatala, Gašević, & Jovanović, 2012). Recent developments in learning analytics suggest a strong integration of data collection with learning designs in use by education systems (Bakharia, Corrin, et al., 2016; Lockyer et al., 2013).

Equity. Socio-economic and demographic data, together with academic records, can be important sources of information pertaining to equity issues (even in education systems with minimal online delivery and social interaction among students). Thus, data such as geographic location, gender, minority status, and family education level can be useful in detecting biases relating to education access, learning outcomes, learning progression, or academic performance. The use of such data can inform the development of actions aimed at reducing – if not eliminating – some of these biases in the education system.

Efficiency. Many institutions, regardless of their level of connectivity, have various essential data systems in place, which relate to, for instance, student information (especially student records), the management of academic programs, institutional scheduling, and resource planning. Such data can be analyzed using different methods to understand the efficiency of and optimize planning in educational systems/institutions. Likewise, data collected from alternative models that facilitate course engagement via public social media and mobile technologies (Kitto, Cross, Waters, & Lupton, 2015; Patru & Balaji, 2016) can offer valuable insights into the factors that shape the academic success of learners in environments that promote learning at scale (Dowell et al., 2015).

3.2 Model

POLICY TAKEAWAYS 3

- Learning analytics makes use of data modeling methods to identify patterns, make predictions, or detect associations in data. Such models can inform the development of interventions that can reduce inequities and increase the number of graduates, enhance the quality of learning experience at scale, personalize feedback at scale, and optimize the use of resources.
- To avoid negative consequences of the careless use of data modeling, the application of question- and theory-driven approaches to data modeling is of critical importance in learning analytics. Learning analytics needs to account for relevant contextual, political, cultural, educational, and individual factors in order to produce actionable insights.
- Insights from postcolonial, socio-political, multicultural research can help inform research that may uncover strengths of the Global South for the implementation of learning analytics.

Methods from fields such as data mining, statistics, and natural language processing are employed for the analysis of data in learning analytics. The result of the analysis produced by the application of such methods is models that can identify patterns, make predictions, or detect associations in data. Although such models can be powerful sources for decision-making for a wide range of stakeholders in education, the models per se are not sufficient for learning analytics. Rather than committing to the promise of "data-driven" approaches to analytics, contemporary learning analytics suggests that models should be *question- and theory-driven* (Gašević, Dawson, & Pardo, 2016; Gašević, Dawson, & Siemens, 2015; Wise & Shaffer, 2015). Question-driven approaches stipulate that education systems and institutions first need to articulate questions of their strategic interest before investing in the use of data mining to address issues of relevance to quality, equity, and efficiency. Likewise, the choices of data that are fed into data mining algorithms, and the interpretations of patterns in data detected with the algorithms, are best done if they are informed by existing research on and theories of learning, teaching, and education.

The process of modeling in learning analytics needs to account for relevant contextual, political, cultural, educational, and individual factors in order to produce actionable insights for education. Some studies have shown that insufficient consideration of such factors may reduce the applicability of learning analytics. For example, a US-based study that applied models created in one institution for prediction of student retention in another did not produce satisfactory results (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014; Open Academic Analytics Initiative, 2014). Not only was the accuracy of such models reduced when applied in a different context, but contextual factors that were of relevance for decision-making were also missed. The reason for this is that a model created in one institution is based on specific characteristics (e.g., socio-economic, demographic, and cultural) of that student population, which might be very different from the student population at another institution. Such issues need to be critically interrogated especially when data modeling approaches from the Global North are considered for application in the Global South.

The fact that the one-size-fits-all approach does not work for data modeling has been accepted widely in learning analytics. For example, the predictor of learning success in one class may differ from that in other classes. This could be attributed to various factors such as differences in learning designs (Gašević, Dawson, Rogers, & Gasevic, 2016), individual differences among students enrolled in classes (Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015), and different classroom subject matter (Finnegan, Morris, & Lee, 2009). Therefore, given the pronounced inequities and the cultural, economic, and political specificities of education in the Global South, *the application of question- and theory-driven approaches to data modeling is of critical importance to learning analytics in order to provide value that can advance quality, equity, and efficiency.* Of particular relevance for the adoption of learning analytics could be insights from postcolonial, socio-political, multicultural research that can inform research that may uncover strengths of the Global South for the implementation of learning analytics.

DATA MODELING PROSPECTS AND CAUTIONS OF RELEVANCE TO THE GLOBAL SOUTH

For the use of data to assess the quality of experience, inform decision-making about inequities, and optimize the efficiency of education systems

Quality. Different data modeling methods can be employed to enhance the quality of learning experience. Predictive modeling methods can be used to identify factors that affect student learning experience based on their interactions with content, peers, and teaching staff. Such predictive models need to account for factors specific to learning design in order to provide actionable insights for teaching staff (Gašević, Dawson, Rogers, & Gasevic, 2016). Identification of such factors can be critical for meeting quality needs in learning at scale in the Global South. Methods for automated text analysis offer much promise related to quality of education in the Global South, such as in determining the quality of learning content for target learners (e.g., based on text readability) (Graesser, McNamara, & Kulikowich, 2011). Text analyses of this type can be particularly relevant in assessing the quality of open educational resources. It can also offer insights into the themes learners discuss as well as possible (negative or positive) sentiments voiced in social media as the learning unfolds (Ali et al., 2012).

Equity. The use of predictive models can be used to detect biases and inform the development of actions for addressing these. However, predictive modeling must be used with caution especially given the pronounced inequities in the Global South. If decision-making (e.g., admission of students to educational institutions) is based purely on predictive models, this can lead to the reinforcement of well-established biases rather than to their reduction (Custers, Calders, Schermer, & Zarsky, 2013; Pechenizkiy, 2015). This stems from the fact that the accuracy of predictive models depends on the discriminatory power of some variables. For example, in many countries, gender could emerge as a significant predictor of potential success of students in different science, technology, and engineering disciplines. Rather than reducing the chances of women enrolling in these disciplines, data modeling should be used to help institutions assess the effectiveness of different initiatives to promote greater inclusion into science, technology, and engineering education. Therefore, when using data modeling, decision-makers need to carefully consider the possible implications of different algorithms and the accountability associated with each.

Data modeling can also be used to identify other biases related to the quality of learning experience. For example, recent studies indicate that high-achieving students are twice more likely to submit end-of-course student evaluations of teaching than their peers with low achievement (Macfadyen, Dawson, Prest, & Gašević, 2016). Similarly, biases related to learning experience could be rooted in the differences in opportunities to access education between students from rural and urban regions. Therefore, if decisions about quality are made based purely on such evaluation surveys, the needs of some students (and especially those with greater needs for support) may easily be overlooked. Finally, education systems need to define the limitations of algorithms used for data modeling and consider issues of accountability that may emerge from the use of these methods (Buckingham Shum, 2016).

DATA MODELING PROSPECTS AND CAUTIONS OF RELEVANCE TO THE GLOBAL SOUTH

For the use of data to assess the quality of experience, inform decision-making about inequities, and optimize the efficiency of education systems

Efficiency. Data modeling can serve as a foundation for the identification of different factors that can improve the efficiency of education systems. Given the aims to scale learning in the Global South, increased student retention is one of the main issues to be addressed. Prediction of students at risk of failing a course is one of the most popular topics in data modeling as used in learning analytics (Dawson et al., 2014). Provided it takes into account relevant contextual factors, data modeling can inform the development of interventions that seek to support students (Arnold & Pistilli, 2012). Prediction of student completion of programs and learning gains is also critical in learning at scale in the Global South (Rosé et al., 2014). Data modeling can support the identification of bottlenecks in academic programs (Dawson & Hubball, 2014) and make predictions of relevance (e.g., numbers of student enrollments) for the utilization of resources (Ognjanovic, Gasevic, & Dawson, 2016).

3.3 Transformation

POLICY TAKEAWAYS 4

- Investment in the development of data literacy of all stakeholders in educational systems and institutions in order to maximize the benefits of learning analytics is critical. The development of strategic capabilities in analytics is the foremost step to facilitating the adoption of learning analytics.
- The development and/or acquisition of learning analytics tools need to be done through the active involvement of end users. Contextualization and localization of learning analytics tools for different parts of the Global South are crucial for effective adoption.
- Guidelines for the ethical use of learning analytics, privacy protection, and algorithmic accountability are necessary. They should recognize local culture, legislation, and context and should be informed by state-of-the-art standards and critical perspectives.
- Establishing links with communities of research and practice in the Global North can offer starting points for adoption, with the main goal of promoting the development of national, regional, and institutional capacity in the Global South.

Transformation assumes that a wide range of stakeholders can obtain analytics-based insights for their decision-making. Two critical challenges need to be addressed in the Global South to maximize the impact of analytics-based transformation. First, the underdeveloped culture for the use of data in decision-making in education is well-documented in the literature (Macfadyen & Dawson, 2012; Siemens et al., 2014). Second, the needs and concerns of relevant stakeholders involved in and affected by decisions informed by learning analytics must be addressed. To address these two challenges, the development of implementation capabilities should generally include four main foci:

- the development of strategic capability for learning analytics adoption;
- the development of data literacy among stakeholders;

- the development of policies for ethics, privacy protection, and algorithmic accountability; and
- the development of analytics-based tools with active stakeholder involvement.

The availability of *strategic capabilities* is the foremost prerequisite for an education system to embark on a successful analytics-based transformation (Colvin et al., 2015). Creating opportunities for the development of strategic capabilities in analytics is necessary for transformation in the Global South. Partnerships with professional organizations such as SoLAR can be an effective way to enable the development of strategic initiatives. Professional organizations have established infrastructures of development events delivered in blended formats (e.g., Learning Analytics Summer Institutes). Such events can be used to establish links, exchanges, and partnerships between leaders, researchers, and practitioners from the Global South and the global communities of research and practice. Potential partnerships can also open access to support from international development funds, banks, and agencies as well as national agencies and governments from the Global South. Access to such funding sources can enable the development of implementation capabilities in education systems and institutions.

The increase in data literacy and the ways in which the results of analytics can inform decision-making are highly relevant for all stakeholders, including students, teaching staff, and administrators (Wasson & Hansen, 2016; Wolff, Moore, Zdrahal, Hlosta, & Kuzilek, 2016). There are some cases where high levels of data literacy are not necessary and where external, easy-to-use solutions – such as Course Signals to address student retention – can be implemented without much (or any) data literacy development. In such cases, attention needs to be paid to the development of pedagogically sound interventions for students derived from insights obtained from analytics-based solutions. The development of data literacy will become essential when education institutions decide to grow their analytics capacity, promote innovation, and increase the quality of students and teaching staff's skills. If data literacy is not sufficiently developed, stakeholders may not be able to exploit the full potential of analytics and/or prevent cases in which the adoption of learning analytics may produce detrimental effects.

The development of policies for ethics, privacy protection, and algorithmic accountability (Buckingham Shum, 2016; Prinsloo & Slade, 2013, 2017; Sclater, 2016; Tsai & Gašević, 2017) is critical especially for those regions where relevant practices, guidelines, legislation, and norms are underdeveloped. Facilitating opportunities to build, interrogate, and share critical perspectives on learning analytics in the Global South is essential to enabling productive contributions through the implementation of learning analytics. Opportunities for the growth of critical perspectives may include the organization of events and publications that feature contributions by representatives of different stakeholder groups within a relevant region as well as thought leaders in the region and internationally. Such initiatives should lead to the production of codes of practice and policies that are specific to different regions of the Global South.

Active involvement of stakeholders in shaping learning analytics tools is essential to produce benefits for stakeholders and education systems. This is particularly important in order to develop new and adapt existing learning analytics tools that can recognize needs, culture, social norms, economic development, and infrastructural limitations in the Global South. A straightforward adoption of existing tools (even if they are free and open source) may not be possible without considerable investment in language and cultural adaptations of the user interfaces, and the ways in which the results of analytics are interpreted, communicated, and utilized.

[1] http://lasi.solaresearch.org/

For learning analytics to transform education, it is also necessary to remove barriers that are commonly reported to prevent adoption of educational innovation and technology. Although analytics should have the highest impact on learners, teaching staff should be the first group to whom support is provided in the adoption of learning analytics, owing to their critical role in shaping the learning experience. The lack of confidence, competence, and technical support are identified as key barriers for the adoption of IT by teaching staff in developing countries (Bingimlas, 2009). It is therefore vital to provide teaching staff with professional development opportunities to acquire the skills necessary to use analytics, which in turn should boost their confidence. Although the availability of contextualized and localized resources for professional development is essential, it is also important to identify local champions of learning analytics. According to the diffusion of innovation model (Rogers, 2010), local champions could include teaching staff in local communities who have created innovative localized practices and shared these practices with other members of their communities. Experience-sharing should happen by scheduling regular meetings within members of the same institution as well as via periodic events at the regional and national levels. However, without sufficient technical support (which requires infrastructural investment, as noted previously), the diffusion of learning analytics can be slowed down significantly. This can make it difficult for a critical mass of learning analytics users to be reached, which in turn may reduce the potential of learning analytics to make a systemic impact.

TRANSFORMATION PROSPECTS AND CAUTIONS OF RELEVANCE TO THE GLOBAL SOUTH

For the use of learning analytics to transform learning, teaching, and education processes across quality, equity, and efficiency dimensions

Quality. For education systems to unlock the full potential of analytics, especially in learning at scale, they need to provide sufficient opportunities for teaching staff to develop their learning analytics skills. Existing research demonstrates that the quality of teaching does not necessarily improve with the adoption of analytics-based tools alone (Tanes, Arnold, King, & Remnet, 2011). Instead, the skills required to embed analytics in teaching effectively are necessary. Growing availability of open and free resources in learning analytics increases access for academic development in the Global South. However, additional efforts are necessary to contextualize academic development and to account for the cultural specificities, infrastructural capacity, and economic development of different regions.

The introduction of analytics to curricula and teaching practice should also enhance the overall spectrum of graduate attributes of learners as another form of 21st century skills (Buckingham Shum & Deakin Crick, 2016). Present studies in the Global North indicate that even high-achieving students do not have sufficient skills to make informed decisions based on analytics (Corrin & de Barba, 2014). As the impact of the use of data on decision-making of people in different aspects of work and life will continue to grow, data literacy needs to be an important component of curricula to assure the competitiveness of the Global South in the globalized world.

Equity. For education systems to promote equity, policies regulating different aspects of the implementation and application of learning analytics need to be developed. Privacy protection, data ownership, informed consent, transparency, responsibility, and ethics are some of the critical aspects that need to be addressed as part of this process. There is an increasing number of guidelines for addressing issues of privacy and ethics in learning analytics (Ferguson, Hoel, Scheffel, & Drachsler, 2016; Sclater, 2016). However, guidelines specific to different regions of the Global South – consistent with local cultures, legislation, and practices – need to be developed. Moreover, to promote equity in the Global South, specific guidelines for the use of learning analytics need to be designed. These guidelines need to recognize possible threats resulting from the careless use of analytics that reinforce rather than eliminate biases. For the healthy adoption of learning analytics, limitations need to be acknowledged since no data model can explain or predict all things with absolute certainty.

TRANSFORMATION PROSPECTS AND CAUTIONS OF RELEVANCE TO THE GLOBAL SOUTH

For the use of learning analytics to transform learning, teaching, and education processes across quality, equity, and efficiency dimensions

Efficiency. Present work in learning analytics demonstrates the potential to provide personalized feedback to learners at scale (Wright et al., 2014). Moreover, learner experience can be increased with the analytics-based generation of personalized feedback at scale while reducing the workload of teaching staff (Pardo et al., 2016). Such improvement in efficiency of teaching, while maintaining or even improving the personal touch of teaching staff with their students, is critical for learning at scale. As with other aspects of learning analytics, analytics-based solutions need to take into account cultural and social norms in the communication of feedback specific to different regions of the Global South. Efficiency can also be improved by providing automated formative assessments of unstructured artifacts (e.g., essays) produced by learners (Landauer, Laham, & Foltz, 2003) as a foundation for the generation of personalized, formative, and real-time feedback.

Analytics approaches can also be used to systematically evaluate the effectiveness of certain pedagogical and technological interventions implemented in education in the Global South. As a field that bridges research and practice, learning analytics can be particularly effective in connecting evaluation with research-informed frameworks that warrant high rigor and validity (Reimann, 2016). As such, learning analytics can offer a continuous assessment of existing interventions and inform the development of new ones.

To demonstrate external efficiency, analytics can be used to analyze how different types of skills promoted by education institutions match those on demand in the labor market. To implement analytics of this type, which goes beyond the scope of learning analytics, education institutions need to develop partnerships with local governments and organizations promoting employment. Specific agreements on data privacy, sharing, and ownership need to be reached before analytics-based systems for external efficiency can be developed.

4

CONCLUDING REMARKS

As a point of departure, education systems in the Global South should engage in studies that will benchmark institutional readiness, existing practices, and stakeholder understanding of learning analytics and data.

This paper has outlined a range of benefits the Global South can derive from the use of learning analytics. Such benefits include support for learning at scale, the provision of personalized feedback at scale, increased numbers of graduates, the identification of biases affecting the success of under-represented and under-supported populations, optimization of the use of resources, and the development of data literacy. The paper also proposed directions for the adoption of learning analytics in the Global South. Although the Global South shares much in common with the Global North in terms of general adoption steps, there are some key specificities of the former that need to be recognized, in particular the pronounced social inequities, unequal access to education, constraints in resources, and limited access to the Internet and electricity. As a point of departure, it is recommended that education systems in the Global South engage in studies that will benchmark institutional readiness, existing practices, and stakeholder understanding of learning analytics and data in order to inform decision-making. Such benchmarking exercises will help education systems gauge the extent to which the existing findings about learning analytics adoption are applicable across different contexts in the Global South.

Although learning analytics offers many promising opportunities for education, the rhetoric of simple technological fixes in the adoption of this approach can be counterproductive especially in complex systems (Gašević, Dawson, & Pardo, 2016; Macfadyen, Dawson, Pardo, & Gasevic, 2014). The adoption of learning analytics needs to consider the cultural, political, economic, infrastructural, and social characteristics of different regions of the Global South if positive effects on quality, equity, and efficiency in education are to be achieved. It is also recommended that education systems encourage cross-institutional collaboration as a way of combining resources and promoting the sharing of experiences.

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DL4D
DIGITAL LEARNING FOR DEVELOPMENT

Responses from the Global South

CONTEXT MATTERS: AN AFRICAN PERSPECTIVE ON INSTITUTIONALIZING LEARNING ANALYTICS

Paul Prinsloo

1. Introduction

This paper is an invited response to Dragan Gašević's (2018) paper entitled, "Include us all! Directions for adoption of learning analytics in the global south." Gašević proposes that:

> the implementation of learning analytics in developing countries has significant potential to support *learning at scale*, to provide *personalized feedback* and learning *experience*, to *increase the number of graduates*, to *identify biases* affecting student success, to promote the development of *21st century skills*, and to *optimize the use of resources*. (p. 2; emphasis added)

He acknowledges that most of the current literature (both scholarly and popular) on learning analytics "originates from the Global North" and does not necessarily speak to "a number of specificities of the Global South" (p. 3).

"Making space" for a voice from the Global South recognizes, firstly, that some voices are excluded or absent from the discourses on learning analytics (for whatever reason) but also recognizes that this exclusion and/or absence points to a certain "invisibility" (Sheared & Sissel, 2001). Inviting voices from the Global South and "making space" for their voices to be heard also points to the fact that the one who offers the invitation has the power (or capital in the Bourdieusian sense) to invite, and thereby to include and exclude. We, therefore, need to recognize the invitation's terms and conditions that signify an asymmetrical power relationship between the one who invites and the one who accepts the invitation. Despite and in recognition of the fact that an invitation to contribute and respond is embedded in a range of issues of power, voice, silence, and opportunity; I hope I can both honor and do justice in my response to Gašević's invitation to "Include us all!"

The invitation to respond also needs to be seen as an invaluable opportunity to engage, to question and contest, to contribute, voice, disrupt, and amplify the explicit and implicit values embedded in the proposal. The title of the paper – "Include us all!" – therefore points not only to an invitation but also signifies a demand to be heard and to be recognized.

I acknowledge that I cannot speak on behalf of the Global South or even on behalf of the African continent. It is impossible to provide an *African* perspective on the adoption of learning analytics, considering that the African continent comprises 54 sovereign states, each with its unique regulatory framework, development agenda, information and communications technology (ICT) infrastructure, and state of adoption of online learning.

2. Why Context Matters

Gašević (2018) is *partly* correct when he states that the "ever-growing use of technology in education has resulted in an unparalleled collection of data on various aspects of learning, teaching, and education systems" (p. 2). As I will point out later on, claims such as these may disregard the specifics of a context, or even a continent. *The world is not flat*.

Castells (2009), for example, points out that what "characterises the global network society is the contraposition between the logic of the global net and the affirmation of a multiplicity of local selves" (p. 37). We, therefore, need to understand the collection of data in the context of attempts to articulate the links, overlaps, and contestations between the global and the local. We have to consider evidence that with the growing access to

> the Internet and to wireless communication, abysmal inequality in broadband access and educational gaps in the ability to operate a digital culture tend to reproduce and amplify the class, race, age, and gender structures of social domination between countries and within countries. (Castells, 2009, p. 57)

Networks, therefore, do not only include but also *exclude*, and "the cost of exclusion from networks increases faster than the benefits of inclusion in the networks" (Castells, 2009, p. 42).

In response to Gašević's (2018) proposal, I offer a number of counter-questions: What is the potential of learning analytics in data-poor environments where individual or institutional access to the Internet and wireless technologies may be non-existent, poor, intermittent and/or expensive? If we accept that models for understanding student success and retention may not be appropriate in contexts in the Global South (see Subotzky & Prinsloo, 2011), what are the implications of utilizing these models uncritically "as-is" in the Global South? What capacities, skills, infrastructure, and human resources are needed to not only institutionalize a context-appropriate, ethical approach to learning analytics but also to respond to identified needs and risks?

Gašević (2018) acknowledges the need for a process of modeling in learning analytics to "account for relevant contextual, political, cultural, educational, and individual factors in order to produce actionable insights for education" (p. 11). In light of the fact that data modeling approaches from the Global North may not be appropriate for application in the Global South, we have to welcome his proposal that models be critically interrogated:

> Of particular relevance for the adoption of learning analytics could be insights from postcolonial, socio-political, multicultural research that can inform research that may uncover strengths of the Global South for the implementation of learning analytics. (p. 12)

In support of Gašević's proposal, we have to ask:

> How do we collect, analyse and use student data recognising that their data are not indicators of their potential, merit or even necessarily engagement but the results of the inter-generational impact of the skewed allocation of value and resources based on race, gender and culture? (Prinsloo, 2016)

As Kitchen's (2014) asserts, data are "framed technically, economically, ethically, temporally, spatially and philosophically. Data do not exist independently of the ideas, instruments, practices, contexts, and knowledge used to generate, process and analyse them" (Kitchen, 2014, p. 2).

We, therefore, cannot disregard the uses of data during colonialism and in the South African context to "classify humans according to those worthy of humanity and dignity and those who were, somehow, less human, less worthy, and of lesser merit" (Prinsloo, 2016). In considering the proposed directions for the adoption of learning analytics in the Global South, we have to consider, as point of departure, that data collection, analysis, and use are "political acts and serve declared and hidden assumptions about the purpose of higher education and the masters it serves" (Prinsloo, 2016). (See also Apple, 2004, 2007; Grimmelman, 2013; Kitchen, 2014; Watters, 2015.)

Learning analytics, like all (educational) technology, must be "understood as a knot of social, political, economic and cultural agendas that is riddled with complications, contradictions and conflicts" (Selwyn, 2014, p. 6). We, therefore, have to map the current and future adoption of learning analytics as an integral part of "the complex ways that social, economic and political tensions are 'mediated' in educational settings" (Selwyn, 2014, p. 4). We should, therefore, guard against a certain "techno-romanticism" and claims of "truthiness" (Selwyn, 2014, p. 10) formulated in the Global North or in the corridors of venture capitalism and/or Silicon Valley (Selwyn, 2014; Watters, 2015). While a certain skepticism is not only in order but also necessary, we should also not be self-righteous in our questioning of any particular educational technology, including learning analytics, and critically and actively engage with its claims and proposals.

While the opportunities, challenges, and concerns regarding learning analytics are well-documented in scholarly and popular publications, it is noteworthy that the discourses surrounding learning analytics have originated and have been and continue to be shaped by mostly North Atlantic centers of knowledge production. Contemplating the current shape, scope, and content of the discourses on learning analytics, it would be disingenuous to discount the historical and persistent effects of the global asymmetries of knowledge production and dissemination (e.g., Epstein, Boden, Deem, Rizvi, & Wright, 2008; Hoppers, 2000; Stack, 2016). On the other hand, it would simplistic to blame such asymmetries entirely for the relative silence pertaining to indigenous learning analytics discourse on the African continent. Rather, we must also consider the effect of current homogenizing narratives regarding the potential of ICT in education (Selwyn, 2014); the role of Silicon Valley and venture capitalism (Watters, 2105) amid persisting and increasing global socio-economic inequalities (Piketty, 2014), and the impact of networks of inclusion/exclusion and resource allocation in African economies, and specifically in African higher education (Fosu, 2013; Jerven, 2015). We also cannot ignore the skewness of the digital revolution and the evidence that the majority of people in the Global South do not necessarily share the dividends of the digital age (World Bank, 2016).

Considering that we are "condemned to context" (Tessmer & Richey, 1997, p. 88), we simply cannot reflect on learning analytics' potential and challenges in the Global South without considering a range of deeply complex, often intergenerational and mutually constitutive and generative mechanisms indigenous to the Global South. The proposal of Jonassen that "[c]ontext is everything" (Jonassen, 1993, in Tessmer & Richey, 1997, p. 86) serves as a timely reminder to consider learning analytics – its potential, challenges, and paradoxes – in context.

3. Learning Analytics on the African Continent

Since the emergence and growth of learning analytics as a discipline, research focus, and institutional practice, there has been a distinction made between academic analytics and learning analytics. For purposes of this response, academic analytics refers to the collection, analysis, and use of aggregated student data by administrators, funders, marketers, governments, etc., at institutional, regional, national, and international levels for, inter alia, resource allocation, comparisons between systems, and quality assurance. Learning analytics, in contrast, focuses on the individual performance of students at the course and departmental levels, and is used by teachers, students, and support staff to inform teaching and learning (Siemens et al., 2011).

Most of the published research on the collection, analysis, and use of student data from the African context falls under the category of academic analytics and institutional research (Lemmens & Henn, 2016). There is, however, an increasing number of examples of the institutionalization of learning analytics, albeit mostly from South Africa. For example, Visser and Barnes (2016), as well as Muller, Sipho, and Philiswa (2016), report on learning analytics in the context of institutional research. Walji, Deacon, Small, and Czerniewicz (2016) report on learning analytics in the context of a massive open online course (MOOC) provided by the University of Cape Town, while Lourens and Bleazard (2016) report on the use of predictive learning analytics by the Cape Peninsula University of Technology.

At the time of writing of this response, only one example of published research could be found on the adoption or practice of learning analytics by an African university outside of South Africa. Oyerinde and Chia (2017) report on the use of predictive learning analytics in the Department of Computer Science at a Nigerian university. Other examples report on African students as part of a sample for research (e.g., Cohen & Shimony, 2016) but not specifically undertaken in an African context.

In setting the tone for this response, I will refer briefly to the overview and findings of Lemmens and Henn (2016) in regard to learning analytics in the *South African* context. The authors refer to the fact that "[s] everal South African higher education institutions (HEIs) have started to appropriate critically the notion of 'data-driven decisions', in the hope of using the insights from analytics to reduce potential risks" (p. 231). Most of the analytics in the South African higher education context still fall within the broader definition of academic analytics, with the emphasis on institutional reporting to the South African government and a range of regulatory and funding bodies, as well as for the purposes of, for example, marketing (Lemmens & Henn, 2016). Using student data for the sake of informing learners and faculty about student progress is "still in its infancy" (Lemmens & Henn, 2016, p. 236). Nonetheless, it is encouraging to find that learning analytics has been part of the institutional research discourse in South Africa since as early as 2013 (Lemmens and Henn, 2016), only two years after the first Learning Analytics and Knowledge Conference took place in Banff, Alberta (Canada) in 2011.[1]

Since South African HEIs do not have "a common framework that allows for the internal evaluation of their analytics systems nor for scientific comparison or replication among institutions" (Lemmens & Henn, 2016, p. 239), Lemmens and Henn (2016) used the Greller and Drachsler (2012) framework to map the state of learning analytics in six of the 25 HEIs in South Africa. While Lemmens and Henn's sample is not representative, it does provide a snapshot of the three types of South African HEIs – traditional universities, technology universities, and comprehensive universities (a hybrid of the first two types).

[1] https://tekri.athabascau.ca/analytics/

Of particular interest in writing this response to Gašević (2018) is Lemmens and Henn's (2016) finding that *students* as beneficiaries of the collection and analysis of data are positioned at the lowest rung in the ladder of stakeholders, below institutional planning departments, professional and support services, and faculty. They found that most of the current analytical practices support institutional reporting and reflection rather than prediction: "The system has not yet matured to include a predictive model that actively tracks and provides feedback to the stakeholders in a real-time fashion" (Lemmens & Henn, 2016, p. 248).

With regard to constraints, all six institutions reported "exhaustive" internal ethical frameworks and full compliance with the South African Protection of Personal Information legislation (Lemmens & Henn, 2016, p. 247). Access to data was not considered a constraint either; all the institutions reported "proxy access by user." In addition, two institutions reported "advanced analytical competence" (Lemmens & Henn, 2016, p. 247). It is important to note that survey respondents were limited to "senior management, managers and staff from Learning Technology and Institutional Planning departments" (Lemmens & Henn, 2016, p. 243) from "six institutions that presented papers at the 2013 SAHELA conference and two of the institutions that form part of The Kresge Foundation's Siyaphumelela (We succeed) project" (Lemmens & Henn, 2016, p. 242).

Despite the limitations of the Lemmens and Henn (2016) study in terms of the sampling of institutions and individual respondents, it does point to the relative immaturity of learning analytics in the South African higher education context.

4. Challenges in Learning Analytics Adoption in African Higher Education

There is ample evidence to suggest that Africa in general, and South Africa in particular, is not immune to the challenges faced by HEIs worldwide. According to Altbach, Reisberg, and Rumbley (2009), the most important trend in higher education in recent years has been massification. Various sources on higher education on the African continent refer to the impact of massification on resources and infrastructure, and underscore the need for data-informed decision-making (e.g., Badat, 2005; Baijnath & Butcher, 2015; Maasen & Cloete, 2006; Mohamedbhai, 2014; Teferra & Altbach; 2004). Despite considerable diversity among African HEIs, Teferra and Altbach (2004) point to several commonalities around issues such as access, funding, governance and autonomy, privatization, language, the "role of research and the problems of scholarly communication," and the "brain drain" (p. 21).

4.1 Collection, analysis, and use of student data

Subotzky and Prinsloo (2011), in the context of a mega distance education institution in South Africa, make the point that intergenerational inequalities and macro-societal factors (past and present) have severe negative impacts on students' preparedness for and engagement in higher education. These impacts often fall outside of the loci of control of students and institutions. Should learning analytics in the context of the Global South collect, combine, analyze, and use data regarding *who* students are (in terms of race, gender, culture, employment, marital status, home language, home address, etc.) and what they *do* (in terms of class attendance, submissions of assignments or the taking of exams, participation in online fora, etc.), there is a danger that the data may not necessarily be representative of the potential of students but rather serve as an indication of the intergenerational legacy of economic and political exclusion. This danger is even more acute where, as is the case with many African HEIs, student data is often fragmented, incomplete, of varying quality and integrity, governed by often competing rules and regulations, and stored in different formats that impact on its integration with other data sources.

The solution for Africa may not be to harvest more (or different) data (Prinsloo, Archer, Barnes, Chetty, & Van Zyl, 2015; Prinsloo, 2017a), or at least not without, as Gašević (2018) suggests, "policies and codes of practice relating to the ethical use of learning analytics, privacy protection, and algorithmic accountability to support a healthy adoption of learning analytics" (p. 2). The formulation of such policies and standards, and the institutional operationalization of learning analytics itself, would require political will and the allocation of resources, both of which may be in scarce supply owing to competing claims and needs.

As a way forward, Prinsloo (2017a, slides 45-46) suggests the need to consider the following:

1. What are our (management, administrative, faculty, and support staff's) beliefs about knowledge, learning, assessment, data, and evidence?
2. What student data do we already have, why was it collected, in which format is it stored, who has access to the data, how is the data used and by whom, and do students know this, have access to it, and know how it influences our and their choices?
3. What data do students currently have access to about their learning and about our choices pertaining to their learning?
4. What data don't students currently have access to, *but we have*, that will help them to plan their time and resources in order to maximize their chances of success?
5. What student data *don't we have* but need in order to teach better, allocate resources, and support students? Is this data available, under what conditions will we be able to access it, how will we govern its storage/combination with other sources of data, who will have access to it and under what conditions?

4.2 ICT access and technical skills

In light of the fact that much of the international learning analytics discourses (including elements in this paper) increasingly focus on student *online* engagement and the collection and analysis of student online and *digital data*, it is important to consider the unequal distribution of access to the affordances of ICT. A recent report by the World Bank (2016) points to evidence that increased access to digital technologies did not necessarily benefit those who most needed the affordances of access to digital technologies. More than 60% of the world's population is still offline, and "some of the perceived benefits of digital technologies are offset by emerging risks" such as "polarised labor markets and rising inequality" with technology "replacing routine jobs, forcing many workers to compete for low-paying jobs" (World Bank, 2016, p. 3). Those who benefit the most from having access to the Internet are "the better educated, well connected, and more capable... [thus] circumscribing the gains from the digital revolution" (World Bank, 2016, p. 3). While there is a commitment to make the Internet available and affordable, "[w] orldwide, some 4 billion people do not have any internet access, nearly 2 billion do not use a mobile phone, and almost half a billion live outside areas with a mobile signal" (World Bank, 2016, p. 4).

There are signs, however, that the connectivity landscape is changing. A report published by Pew Research Global shows an increase from 45% in 2013 to 54% in 2015 in the median percentage of the population, across 21 emerging and developing countries, who occasionally accessed the Internet or who owned a smartphone (Poushter, 2016). Increased access, however, is *not equally shared amongst genders*. The report notes that "…in 20 nations, men are more likely than women to use the internet. These differences are especially stark in African nations" (Poushter, 2016, p. 6). Only 39% of women in South Africa have access to the Internet compared to 46% of men (Poushter, 2016, p. 13).

There is also evidence of the correlation between per capita income, on the one hand, and Internet access and use, on the other, in emerging economies; only 22% of those in the lower income group have access to the Internet compared to 52% of those in a higher income group (Poushter, 2016, p. 11).

Gašević (2018) points to the possibilities of using social media both for student support and for collecting student data to inform institutional strategies in providing more effective and equitable support. While increasing numbers of students may have access to technology and use social media (World Bank, 2016), a huge issue, at least in the South African context, is the cost and sustainability of access to the Internet (Smillie, 2016). Students' use of social media will also depend on the extent to which social media are integrated into course design and assessment strategies. There are also several ethical considerations to account for when institutions harvest student data from disparate sources outside of the institutional fiduciary and operational domains (Prinsloo & Slade, 2015; Prinsloo & Slade, 2016).

Beyond the question of access to data, few African HEIs have the capacity to collect student data of the scope, variety, velocity, and volume necessary for fine-grained analysis. Thus, those keen to take up learning analytics are likely to invest in commercial providers and platforms (Prinsloo, 2017a) and may find themselves exposed to exactly the dangers Gašević (2018) points to in regard to the inappropriateness of models developed in the Global North.

4.3 Ethics and privacy protection

Considering the increasing attention awarded to issues of ethics and privacy in learning analytics (Prinsloo, 2016; Prinsloo & Slade, 2017; Slade & Prinsloo, 2013), it is clear that there are still a number of unresolved issues with regard to, for example, the role of institutional oversight on ethical considerations and unintended consequences in learning analytics (e.g., Willis, Slade & Prinsloo, 2016). In the context of this response to Gašević's proposal, we need to consider how ethical considerations in the Global South may differ or have different nuances from approaches and concerns in the Global North (See for example Callaway, 2017; Kukutai & Taylor, 2016; Prinsloo, 2017b).

In the Global South, we are and should be, more aware of how individuals' data were used during colonialism and apartheid to classify humans and award different individuals levels of dignity, resources, and humanity depending on criteria shaped by ideology. While it falls outside of the scope of this response to formulate what a Global South context-appropriate approach would be to address issues of ethics and privacy, the "agenda" proposed by several authors in Kukutai and Taylor (2016) may provide some tentative pointers for further consideration:

- Data subjects should determine which criteria and variables matter. Their data belong to them and they have vested interests in determining what data are collected and for what purposes (Morphy, 2016; Sinn, 2016).
- The data collected should, therefore, reflect "the interests, values, and priorities of native people" (Sinn, 2016, p. 52).
- Data subjects "must have the power to determine who has access to these data" (Sinn, 2016, p. 52).
- We should acknowledge how North Atlantic and colonial epistemologies underpin the determination of criteria and variables (Pool, 2016).
- Data collection and definitions should be based on how data subjects and their communities see themselves and not on how those who have the power to collect data define them (Pool, 2016).

- Indicators and categories flow from specific North Atlantic, commercial, and neoliberal assumptions and epistemologies. For example, taking "age" and "dependents" as proxies for indicators of socioeconomic class or potential to contribute to the economy stand in stark contrast to how individuals in the Global South see these categories (Morphy, 2016).
- Indicators and criteria simplify complex phenomena (e.g., "family" and "household"). These indicators "do not just shape the way the world is understood, but also contain embedded value judgments" (Morphy, 2016, p. 108). Often the categories used by institutions and those who collect and analyze data silence that which matters for those whose data is collected.
- "In intercultural contexts, seemingly objective data and their interpretation as information can become misguided political, policy and ideological instruments. For that reason, both the data and information may have limited validity or usefulness when externally imposed as constructions of indigenous behaviors and social formations" (Smith, 2016, p. 120).
- "In every society, there are cultural determinants of what constitutes leadership, decision-making, representation, group membership, participation, legitimacy, and accountability. And different behaviors, standards and measures may apply" (Smith, 2016, p. 128). Smith (2016) refers to this as "culture-smart information" that asks, "Whose voice is given priority in determining the meaning, validity, and values attached to data?" (p. 128).

The above may serve as an illustration of the hypothesis that ethics and privacy are about power – the power to define what is regarded private and ethical (Prinsloo, 2017b).

5. Towards the Operationalization of Learning Analytics: Policy and Practice

There is ample evidence that the main function of the collection, analysis, and use of student data on the African continent has been, until recently, for purposes of reporting to various stakeholders on student success and throughput, and as such, can be categorized as *academic* analytics. Considering the constant challenges in the African higher education context to offer high quality and well-supported educational opportunities at *scale*, it would be irresponsible to disregard the huge potential of *learning* analytics.

I propose the following broad principles for consideration in the operationalization of learning analytics in the Global South/Africa.

1. The first step towards institutionalizing learning analytics would be to establish the scope of political will and available resources. While many institutions in the Global South may have a sense of the potential of learning analytics, there is evidence that institutions lack the necessary data infrastructure and/or human resources, with the necessary skills and access to the necessary software and analytical tools, to implement learning analytics. It is in this aspect that institutions in the Global South/Africa may be the most vulnerable when they decide to make use of outsourced solutions. Outsourcing the collection, analysis, and use of student data raises a number of issues such as cost, sustainability of the outsourcing, licensing agreements, ownership of the data, and adherence to institutional and national frameworks for the protection of student privacy and data. On the other hand, we also have to consider the implications of developing in-house capacity and providing the necessary hardware and

software capability. While it falls outside the scope of this response to fully engage with the different aspects of this decision, it may be sufficient at this stage to point to the issues and potential dangers in both of these options.

2. Institutions' understanding of the potential of learning analytics is shaped by their conceptual understanding of the different variables impacting on student success. These understandings determine what data institutions will collect, analyze, and use. It is therefore very important that institutions reflect on their own understanding of student success. In considering the wide range of empirical and conceptual models for understanding student success (Prinsloo, 2009; Prinsloo, 2017b), institutions in the Global South/Africa should be mindful of the ontologies and epistemologies underpinning these models and to what extent these models are appropriate for their particular institutional character and geopolitical context (see, for example, Subotzky and Prinsloo, 2011).
3. It is crucial to determine what data an institution *currently* has access to, where the data is located, how the data is governed, the quality and formats of the data, how the current data sets are used to inform teaching and learning, who does the analysis, and who uses these data sets. Depending on the institutional and geopolitical context, the data (and learning) may be kept in digital or analogue form. All of these determine to what extent any institution can start to think about the potential of learning analytics to inform teaching and learning.
4. Depending on the level of maturity of the digitization of student information, as well as the digitization of teaching and learning, institutions may have to use whatever data they currently have to map and analyze student learning to inform teaching, the allocation of resources, and student support. Some institutions may already have access to rich data sets regarding students' learning journeys, while other institutions may be data-poor/poor-data environments.
5. Students need information and feedback on their progress in order to make informed decisions. Often the quality and granularity of feedback and institutional responsiveness are shaped by departmental and institutional resources. Institutions, therefore, have to consult with their students in order to determine what information and analysis students would need in order to make informed decisions regarding their choices. We should not forget that students' learning is the main focus of learning analytics and, therefore, it is impossible not to consider students' need for information and feedback as central to any institutionalization of learning analytics.

6. (In)conclusions

Gašević (2018) states that it is of great importance "to develop new and to adapt existing learning analytics tools that can recognize needs, culture, social norms, economic development, and infrastructural limitations in the Global South. A straightforward adoption of existing tools (even if they are free and open source) may not be possible without considerable investment in language and cultural adaptations of the user interfaces, and the ways in which the results of analytics are interpreted, communicated, and utilized" (p. 14). I cannot agree more.

While the statement by Tessmer and Richey (1997) that we are "condemned to context" (p. 88) may sound overly deterministic, we ignore the impact of context on the institutionalization of learning analytics on the African continent at our own peril. Despite and amid the contextual constraints, there are, however, some glimpses of how to realize the potential of learning analytics on the African continent. Operationalizing learning analytics will require African

HEIs to consider either using commercial providers/products or developing their own infrastructure and expertise. In either case, institutions should (re) consider their assumptions about and understanding of student retention and success, and the scope, characteristics, and quality of data they can and need to access given those assumptions and understanding. At the heart of learning analytics and underpinning institutional responses to constraints should be students – their learning, their aspirations, and their needs.

Acknowledgements

I am grateful for having had the opportunity to reflect on Gašević's (2018) proposal and consider the implications from the perspective of the Global South. As acknowledged earlier, the Global South and Africa are not homogenous and it is impossible to speak "on behalf of" either the Global South and/or Africa. I do, however, hope that some of my reflections may be of value for various stakeholders in the broader context of the Global South.

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LEARNING ANALYTICS: PERSPECTIVES FROM MAINLAND CHINA

Bodong Chen and Yizhou Fan

1. Introduction

Since the emergence of learning analytics as a scholarly field, it has been garnering significant interest among educational researchers in Mainland China (hereafter referred to as China). A search of the *China Academic Journals Full-text Database* shows that the term "learning analytics" entered Chinese scholarly discourse in 2012 with the publication of seven articles. By 2016, the number of published articles on learning analytics had grown to 88. Yet this increase only reflects a glimpse of growing interest in this area, motivated by emerging national big data agendas across all sectors of China. Since 2012, a dozen policy documents emphasizing "big data" have been published by the Chinese Central Government, covering important strategic areas including medicine, energy, manufacturing, and education.[1] In this brief paper, we discuss the nascent development of learning analytics in China in response to three cornerstones of education – quality, equity, and efficiency – highlighted in Gašević (2018). In the following sections, we situate our discussion in the Chinese context, highlight key opportunities, and discuss foreseeable barriers and coping strategies for implementing learning analytics in China.

2. Understanding the Chinese Context

In an analysis of educational reform in China, Zhou and Zhu (2007) identified four major challenges that remain applicable today, namely, the demand for relevant curricula in rural areas; the lack of diversified learning resources; the need for long-term teacher professional development; and prevalent examination-driven educational practices. Underpinning these challenges are complex historical, political, social, and cultural realities in China including nationwide unbalanced development, centralized educational administration, and staggering progress in technology integration in education. While these challenges and realities offer opportunities for learning analytics to make a difference, they also bound the development of learning analytics in the Chinese context and therefore need to be recognized in discussions of learning analytics' potential impact on the quality, equity, and efficiency of China's education systems.

2.1. A rising country with unbalanced development

Over the past four decades of Chinese economic reform, China has achieved remarkable economic

[1] See, for example, the State Council's Announcement Regarding the Program of Action for Big Data Development: http://www.gov.cn/zhengce/content/2015-09/05/%20content_10137.htm.
[2] https://www.chinainternetwatch.com/whitepaper/china-internet-statistics/#ixzz4jBqrQc9s

progress. In the technology sector, China's Internet users reached 731 million and an Internet penetration rate of 53.2% in late 2016; 95.1% of users could access the Internet through mobile devices. In education, the Nine-Year Compulsory Education Law has dramatically elevated China's literacy rate from 68% in 1980 to 94.3% in 2010 (Malik, 2013) while China's more recent expansion of higher education is driving college education mainstream (Zha, 2012). Overall, public education in China has greatly improved in terms of both access and quality over the past few decades.

However, incredible imbalance figures in China's economic, cultural, and educational development (Jahan, 2015). According to the National Bureau of Statistics of China, while its national average GDP per capita reached RMB 43,852 ($7,248) in 2013,[3] the highest GDP per capita among all metropolitan areas was 25 times more than the lowest; in terms of educational expenditure per student, Hebei Province spent the lowest at RMB 1,404 ($232) in comparison to RMB 4,727 ($782) by neighboring Beijing. On the one hand, regions with tremendous growth are demanding high-quality education – public or private, formal or informal, face-to-face or online – that is comparable to the Global North. On the other hand, many underdeveloped regions are still lacking necessary resources to attract qualified teachers, maintain relevant learning resources, and gain access to modern technologies. So far, various regional, national, and transnational efforts have been made to mitigate these imbalances between urban and rural areas, and between eastern and western provinces. Examples include the national *Western Development Campaign* (Goodman, 2004), the *Distance Education Program for Rural Areas* (Wang & Feng, 2012), and initiatives funded by international aid agencies, nonprofits, and transnational corporations (e.g., Robinson, 2016; Robinson & Yi, 2009; Wu & Li, 2003). New educational reforms in China need to operate within constraints set by the imbalance and inequity (Zhou & Zhu, 2007), and seek congruence with existing initiatives.

2.2. The top-down administration mode

In China, the government has tremendous power in shaping innovation in all sectors including education. For instance, the governance structure in Chinese universities, which pivots on the party secretary, gives little decision-making power to faculty members, in contrast to the faculty governance model in the Global North. In basic education, local administrative departments of education, instead of individual schools, dictate a range of activities such as resource allocation, exam administration, teacher professional development, and so on. Decentralization of these activities in schools, while not nonexistent, is rare especially in underdeveloped regions. Local administrations are more responsive to policies from the "top" or higher-level offices than to local schools. One example is that any change with the College Entrance Exam (the *Gaokao*) – which largely determines what is taught in classrooms – would spur intensive reactions from local administrations and schools (Rui, 2014).[4] This top-down administration mode is influencing how stakeholders in education, e.g., teachers and parents, respond to innovations. If a learning analytics innovation introduced from the "outside" is not considered consonant with current agendas from the top, it is less likely to be embraced by stakeholders. In contrast to this, if an innovation is channeled through the top and is shown to contribute to existing agendas, not only will it have a better chance of being adopted, it will also likely be implemented efficiently and at scale. This reality bounds the implementation of educational innovations, including learning analytics, and needs to be considered in any attempts to sustain changes.

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[3] See National Bureau of Statistics of China http://data.stats.gov.cn/easyquery.htm?cn=C01. The used exchange rate in 2013 was RMB ¥ 6.05 = US$1.00.

[4] See, for example, the latest attempt to adjust the weights of different subject areas in the 2017 College Entrance Exam: https://internationaleducation.gov.au/News/Latest-News/Pages/Gaokao.aspx

2.3. Technology integration: A work in progress

Technology integration in China's education systems provides an important context for the development of learning analytics. In its *National Mid- to Long-term Educational Reform and Development Plan* (*2010-2020*), technology integration is emphasized as a transformative force in educational reforms. In the past few decades, China has invested heavily in educational resources and ICT infrastructures, leading to substantial progress in technology integration in education at all levels. In light of the UNESCO model of ICT development in education (Zhou, Shinohara, & Lee, 2005), China is moving from the initial "emerging" and "applying" stages towards more advanced stages of "infusing" and "transforming" (Zhu, 2012). However, tensions exist in various aspects of planning, management, execution, and implementation of technology integration that have led to redundant, incoherent efforts and unclear governance in earlier initiatives (Yu, 2012). Technology integration in China has historically focused on the technology side and largely remains a work-in-progress in both developing and developed regions of the country. Development in learning analytics needs to build on and learn from prior and ongoing efforts in technology integration.

3. Opportunities for Learning Analytics

With these contextual factors in mind, we discuss below opportunities offered by learning analytics to address quality, equity, and efficiency issues in education highlighted in Gašević (2018).

3.1. Assessment regimes, learner agency, and 21st century competencies

Learning analytics has the potential to challenge exam-driven educational practices prevalent in China's K-12 education (Zhou & Zhu, 2007). Despite the high performance of Chinese educational regimes in international standardized tests such as the Programme for International Student Assessment (PISA) (Sellar & Lingard, 2013), China's exam-driven practices are facing intense criticism (Zhao, 2012). Chinese curriculum standards have also been criticized for a lack of emphasis on 21st century competencies and student agency in learning. The development of learning analytics in China is destined to be influenced by its current assessment regimes centering on high-stakes formal exams and rote learning (Knight, Buckingham Shum, & Littleton, 2014).

In this situation, learning analytics can be a tool for reforming educational assessment – to defy the traditional reliance on examinations and advocate for a fuller picture of learning. Indeed, exams as a form of summative assessment are narrow in scope and insufficient in capturing learning processes. In the face of demands for high-quality education, especially from China's increasingly well-educated families, the traditional test-and-drill practice falls short in meeting emerging needs for more authentic and holistic learning experiences. Richer data and conscientious use of learning analytics offer a new opportunity for assessments to become more formative, integrated, holistic, and personalized (Gašević, 2018; Pea, 2014).

With informal education on the rise in China, particularly in areas such as educational games, new media, and environmental education, learning analytics could help unveil emerging genres of learning in non-traditional spaces. For example, given the environmental problems facing the country, some parents are seeking learning opportunities for their children that are more participatory and engaged in environmental issues. Novel data collection and analytics design, in combination with the pervasive use of social media in China, could make such learning designs and settings more visible and thus raise awareness of alternatives to exam-driven learning experiences.

Finally, learning analytics provides researchers, practitioners, and stakeholders an opportunity to engage with learner agency – absent in current exam-driven practices – as a genuine concern in education (Buckingham Shum, 2015). When educators are exposed to fresh views of learning they are not used to – such as learners being capable of deciding for themselves with support from analytics (e.g., Chen & Zhang, 2016) – confidence in transforming the assessment regime in China could be instilled.

3.2. Learning at scale

The scale of China's education system is massive, raising challenges but also providing opportunities for learning analytics. The challenge of being large-scale manifests at different levels. First of all, large class sizes are common in classrooms at all levels in China. In many primary and secondary schools, the class size is usually between 40 and 70 students despite mandates to reduce class sizes; in college, large lectures are typical. Providing personalized feedback to learners in these settings remains a challenge. As Gašević (2018) highlights, learning analytics offers means to provide personalized feedback to learners at scale where student-teacher ratios are high. Examples of successful efforts in the West include E²Coach at the University of Michigan (McKay, Miller, & Tritz, 2012) and the Summit Public Schools that originated from California (Childress & Benson, 2014).

Given China's large population, there are ample opportunities for learning analytics to support learning at scale beyond individual classrooms. As a matter of fact, startups powered by learning analytics have emerged to offer learning solutions at scale. For example, Pigai (meaning the Marking Website)[5] offers formative feedback on English essays based on writing analytics (Yang & Dai, 2015). By 2017, Pigai had scored more than 300 million essays for almost 18 million teachers and students in China. Other startup companies relying on certain forms of learning analytics also include Mita (an intelligent teaching assistant with predictive analytics) and Yuantiku (an item bank with test-and-drill services).[6] But aside from these efforts directly related to learning analytics, there are many other companies providing online learning solutions at scale that are yet to harness learning analytics for personalized learning. Such companies include New Oriental Online (run by a Nasdaq company specializing in English training), 100 Education (an online tutoring service from technology giant Xiaomi), and various massive open online course (MOOC) platforms backed by major technology companies in China. The integration of learning analytics into these solutions, if well designed, could contribute to quality learning at scale.

Nevertheless, it needs to be noted that these initiatives and opportunities are substantially influenced by the exam-driven culture discussed earlier and are in some cases reinforcing existing paradigms. Using learning analytics to make transformative changes, as advocated by Gašević (2018), requires systematic and coordinated efforts among stakeholders.

3.3. Teacher professional development

The synergy between learning analytics and teacher inquiry, which has been explored in international settings (Mor, Ferguson, & Wasson, 2015), could be explored in China especially in its developed regions. In recent years, renowned universities have launched teaching centers to support the professional development of their teaching faculties. By integrating learning analytics into their current offerings, teachers at these universities could become better poised to inquire into their own teaching. Such work is conducive to the development of new literacies among teachers, such as assessment and data literacies (Bocala & Boudett, 2015; Fullan, 2000)

[5] http://www.pigai.org/
[6] Mita: http://mita.mycos.com/. Yuantiku: https://yuantiku.com/.

and cultural and global competencies (Zhao, 2010), if teachers are exposed to analytics addressing diverse student populations.

In contrast to universities in developed regions of the country, schools in underdeveloped areas are facing a shortage of qualified teachers (Liu, 2014). There has been a significant teacher education gap in Western provinces, which has attracted national and international investments (Crichton & Kopp, 2006). Teachers in these regions lack access to quality professional learning opportunities; if any opportunities are available to them at all, these are often "one-shot workshops" delivered by experts that often fail to inspire or sustain real-world changes in their practices (Wu, Qin, & Zhang, 2009). The role learning analytics could play here, together with other emerging approaches such as MOOCs catered to in-service teachers (e.g., Wang, Chen, Fan, & Zhang, 2017), is to facilitate teacher professional distance learning. Providing teachers with access to learning analytics in these MOOCs could potentially help them regulate their professional learning, a skill which they can in turn nurture in their students (Randi, 2004). In addition, devising learning analytics to help teachers stay connected in communities of practice, either organized by third-parties (e.g., the *Intel Teach to the Future* community) or self-organized on social media, could potentially make a lasting impact on teacher professional learning on a large scale.

4. Ethical Use of Educational Data: Challenges and Opportunities

Ethics and privacy protection are vital for the success of learning analytics applications. The ongoing dialogue and debate over ethical use of educational data has led to evolving understandings that represent the values and perspectives of a wide range of stakeholders (Boyd & Crawford, 2012; Ifenthaler & Schumacher, 2016; Willis, Slade, & Prinsloo, 2016).

The development of learning analytics in China is expected to face considerable challenges in this area. First of all, ethical review boards are rare, if not nonexistent, in Chinese institutions, a drastically different situation than many countries in the Global North. Existing ethics review bodies in China are focused on medical research; they reside in governmental agencies, hospitals, and universities with medical schools (Guan & Fan, 2007) and have yet to attend to social sciences research involving human subjects. Protection of human subjects in educational research relies on the researcher's own morality and self-checking. Intensive participation of the corporate world in learning analytics could make this situation even more complex, raising important challenges for ethics and privacy protection in learning analytics.

To mitigate the situation, professional societies need to play a role. For example, the Chinese Association of Educational Technology, a professional association established in 1991, has served as a platform for discussing and recommending policies, regulations, and capacity building strategies.[7] Its broad reach within China, in K-16 and the industry, and its outward-looking posture (i.e., towards international counterparts such as the Association for Educational Communications and Technology) makes it an important player in the formulation of ethics guidelines in learning analytics. If awareness of ethics concerns could be raised broadly among researchers and practitioners, similar to what happened in medical science years ago (Guan & Fan, 2007), fast-tracking the development of ethics review mechanisms in China would be possible.

5. Concluding Remarks: The Need for Novel Models in the Chinese Context

Many discussions of learning analytics, this paper included, could seem to be merely wishful thinking. To move towards real-world changes in China, consideration needs to be given to its authentic

[7] See http://www.caet.org.cn/page/regulations

contexts – local, regional, and national. As Fullan (2000) observes, "the main enemies of large-scale reform are overload and extreme fragmentation" (p. 8); sustained reforms depend on the reciprocity between "inside" (the school) and "outside" (external forces, policy infrastructures). (See also Cuban, 1990.)

The development of learning analytics in emerging economies needs to avoid these enemies and look for connectedness within local systems and across levels of a system. Investments in external policies, internal cultures of schools, capacity building at multiple levels, and ongoing support need to go hand in hand to sustain impacts of educational reforms (Fullan, 2000).

Given the Chinese context, we need to look for novel models of learning analytics implementation (Wise & Vytasek, 2017) that are responsive to those aforementioned conditions and also "defiant" enough to challenge the status quo. Given the education reform agendas in China to cultivate an innovation-driven society, learning analytics could and *should* be used to find novel ways to promote 21st century competencies, learner agency, and entrepreneurship (Zhao, Meyer, Meyer, & Benavot, 2013) and in so doing, challenge the current exam-driven culture.

Because of the uniqueness of the Chinese context, we cannot transplant a model of learning analytics implementation that works in a Global North setting to China and expect it to work naturally. As Selwyn (2013) asserts, educational technology solutions are packed with a variety of interests, values, agendas, and ideological viewpoints. Importing a "Silicon Valley narrative" into American schools (e.g., Facebook's Summit schools) could face hurdles; needless to say, packaging a learning analytics solution developed by a Silicon Valley startup to profit from Chinese schools is destined to fail. When devising learning analytics initiatives in China, important questions need to be asked: How can the protection of student privacy be ensured? How can the competencies of teachers who are used to exam-driven teaching practices be developed? How can the "top-down" administration model be leveraged to nurture decentralization for local schools to explore learning analytics innovations? For learning analytics efforts in China, there may be fewer lessons to learn from the Global North in this regard. Chinese scholars and practitioners need to build on prior work by colleagues from other countries and develop novel models for their own contexts, which could, in turn, become important contributions to the international field of learning analytics.

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A CRITICAL EXAMINATION OF THE PRE-CONDITIONS OF LEARNING ANALYTICS ADOPTION IN DEVELOPING COUNTRIES IN SOUTHEAST ASIA

Ma. Mercedes T. Rodrigo

1. Introduction

Big data analytics is a field of research that uses data analysis to make informed decisions (Daniel, 2015). It is characterized by large amounts of possibly ambiguous or noisy data collected at a high rate of speed from a variety of sources. The data is then analyzed to generate valuable insights about a specific domain.

When applied to educational contexts, big data analytics has at least three variants – academic analytics (AA), learning analytics, and educational data mining (EDM). AA usually has the coarsest grain size of the three, referring to data collected and processed at institutional levels for better administration, resource allocation, and management (Daniel, 2015). Both learning analytics and EDM, on the other hand, begin with finer-grained, transaction-level data and use them in subtly different ways. Baker and Siemens (2014) cite several differences that distinguish EDM from learning analytics:

- EDM focuses on automated methods for discovery within data while learning analytics makes use of more human-led methods;
- EDM emphasizes modeling of specific educational phenomena and their interactions while learning analytics emphasizes a more integrated, systems-based understanding of these same phenomena; and
- EDM seeks to build applications that will support personalized learning experiences while learning analytics seeks to inform and empower administrators, teachers, and learners.

For simplicity's sake and to remain consistent with the terminology of Gašević (2018), to which this paper responds, this paper will use "learning analytics" to refer to all these different forms of big data analysis in educational contexts.

In "Include us all! Directions for adoption of learning analytics in the global south," Gašević (2018) discusses learning analytics' potential to increase education quality, equity, and efficiency in the Global South. He and other researchers (e.g., Daniel, 2015; Romero & Ventura, 2010) argue that learning analytics can help improve educational management processes, upgrade learning and learning environments, support early identification and remediation of students-at-risk, provide personalized feedback and learning experiences, optimize resource use, evaluate courseware quality, and so on.

Before educational systems can use and benefit from learning analytics, however, an ecosystem capable of four key activities – data collection and pre-processing, modeling, presentation and visualization, and intervention – needs to be in place (Gašević, 2018; see Figure 1).

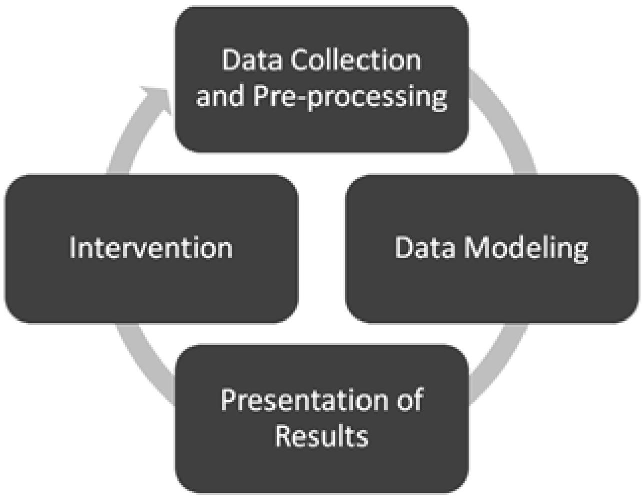

Figure 1. Key activities in the learning analytics process (Gašević, 2018).

1.1 Research questions

The questions arise: To what extent does Gašević's (2018) enabling ecosystem exist in the Global South? How ready is the Global South to embrace learning analytics and reap its benefits? Does the Global South collect enough data from enough sources at a fast enough rate to warrant the kinds of deep analyses for which learning analytics is known? Do these countries have the expertise to process the data, even if they had it? How data-driven are decision-makers when formulating policy?

1.2 Scope and limitations

This paper is an attempt to answer these questions in the context of developing countries in Southeast Asia (SEA), namely, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Thailand, Timor-Leste, and Vietnam ("ASEAN member states," n.d.; UNDP, 2016). It contrasts findings from these countries from the experiences of Singapore, a SEA country that is one of the most advanced in the world.

As learning analytics must be built on top of an ecosystem of educational policy, curriculum, pedagogy, infrastructure, and professional capabilities, this paper assesses the state of readiness of these environmental components. The organizing framework for this paper is drawn largely from a report by the Southeast Asian Ministers of Education Organization (SEAMEO, 2010) on the extent of information and communications technology (ICT) adoption in SEA educational systems. The report makes use of UNESCO's (2005 in SEAMEO, 2010) four stages of ICT Development: *emerging*, *applying*, *infusing*, and *transforming*. The SEAMEO (2010) report maps these stages along several dimensions of ICTs in education and describes how each stage would manifest. It then plots where each SEA country is within this matrix.

This paper's main discussion points, adapted from the SEAMEO (2010) matrix, are national-level education policies; ICT infrastructure and resources in schools; professional development for teachers and school leaders; ICT in education curriculum and pedagogy; assessment; and evaluation and research. These dimensions are the pre-conditions that determine the extent to which learning analytics can be applied to an educational system. The national-level policy is an articulation of a high level commitment to the use of ICTs in education. Commitment translates to the scale of ICT investments in schools. The ways in which these ICTs are used are determined by the curriculum, pedagogy, assessment styles, and teacher training. Teacher and administrator training also influence how data is analyzed. Coming full circle, plans for high-level evaluation and research determine what data is collected, how it is analyzed to assess policy effects, and how these results are used to influence subsequent decision-making.

This paper makes use of academic publications for theoretical grounding. Most of the inputs for this paper, however, were collected from reports from institutions such as the Asian Development Bank [ADB]; SEAMEO; UNESCO; and government sources. Findings from SEAMEO (2010) are used to start each discussion point, together with information from other, more recent reports and publications. This paper focuses primarily on basic education because source materials tended to limit their scope to primary and secondary school.

2. National-Level Education Policies

A national-level ICT in education vision and related education plans and policies articulate the government's recognition of the benefits of using ICTs in education and its commitment to supporting efforts to realize these benefits. These commitments have a direct bearing on ICT investments in schools, what educational data is collected, how it can be accessed and processed, by whom, and for what purposes. It also determines the extent to which interventions can be created and deployed.

SEAMEO (2010) categorizes Laos and Timor-Leste in the *emerging* stage of having formulated ICT in education policies, in that these countries have limited ICT-driven educational plans or policies. One possible reason for this limitation is that these countries may be prioritizing the establishment of basic ICT infrastructure at this time. For example, while Laos's *National ICT Policies Education Sector Development Framework 2009-2015* promotes the development of infrastructure and access as well as human resource development in general (UNESCO, 2013a), a recent government report does not cite education as a priority sector for the deployment of broadband services (Phissamay, 2016).

On its part, Timor-Leste is in the process of rebuilding after recent internal conflicts. Its national development plans cite ICT capability as a cornerstone of economic development (International Bank for Reconstruction and Development [IBRD]/The World Bank, 2013). Primary education is a key focus area, with projects dedicated to the rehabilitation of facilities and the provision of textbooks and other instructional materials. These plans, however, are silent on ICT education. Indeed, ICT education has not yet been identified as a learning goal at any educational level.

Cambodia and Myanmar are considered to be at the *applying* stage in which ICT is used to support or automate existing culture, policies, and practices (SEAMEO, 2010). Their national governments provide funding for hardware and software but ICT developments are led by specialists. Like countries in the *emerging* stage, countries in the *applying* stage seem to be focusing most efforts on deploying a critical mass of infrastructure as well as supporting current educational approaches. Cambodia's *Education Strategy Plan 2009-2013* and *ICT-in-Education Master Plan* prioritize equitable access to education services, improvement of education quality, and educational staff development, while Myanmar's *ICT Infrastructure Development Plan* and *ICT Master Plan 2011-2015* commit to upgrading their telephone networks and Internet backbone (UNESCO, 2013a). Some broad priority programs hint at the possible use of learning analytics. Cambodia's *Education Strategy Plan 2014-2018* includes a results-based management system that is supposed to develop the capacity for evidence- and outcomes-based planning (Cambodia Ministry of Education, Youth, and Sport, 2014) but it does not mention learning analytics explicitly.

Indonesia and the Philippines are squarely categorized as *infusing* (SEAMEO, 2010). ICT is envisioned as mediating changes in culture, policies, and practice. National-level funding is provided for hardware, software, and teacher professional development.

Indonesia's *Five-year Action Plan for the Development and Implementation of ICT in Indonesia* supports the development of ICT networks and the integration of ICTs in learning (UNESCO, 2013a). The Philippines's *Education for All Plan of Action* calls for ICT integration as well as the use of ICTs to enhance educational management at all levels (Philippines National Education for All Committee, 2014).

Thailand and Vietnam straddle the line between *infusing* and *transforming* (SEAMEO, 2010). Aside from envisioning ICT as a driver of change and providing support for infrastructure and human capacity building, they also show evidence of integrating ICTs in overall school development. Teachers and students are included in ICT-related plans, and funding is broadly available. In Vietnam, these commitments to education took root as far back as 2001 when they planned the improvement of student ICT training and teacher ICT usage (UNESCO, 2013a). In its *Master Plan on ICTs in Education 2007-2011*, Thailand continues its efforts to improve access to technology and indeed strives to become a creator of technology, not just a user (UNESCO, 2013a). A more recent OECD/UNESCO (2016) report confirms that ICT has been and continues to be one of Thailand's strategies for economic growth. It notes that Thai schools began offering computer courses as far back as 1984 and, by the 2000s, Thailand was already committed to integrating ICTs in subject areas as pedagogical tools.

Malaysia was the only developing SEA country categorized in the *transforming* stage (SEAMEO, 2010), i.e., possessing exemplary national-level vision and policies that other countries study and emulate. In keeping with this status, Malaysia's *Education Blueprint 2013-2025* commits to providing students with Internet access and virtual learning environments, augmenting online content, and creating more opportunities for distance and self-paced learning (UNESCO, 2013a).

While not directly related to education, SEA countries are in the process of developing legislation regarding data privacy and protection, which have implications on analytics in general. As far back as 2005, the Asia-Pacific Economic Cooperation (APEC) network—which includes Indonesia, Malaysia, the Philippines, Thailand, and Vietnam (APEC, 2017)—crafted a framework for the protection of personal information. Among the guiding principles of this framework were the prevention of harm, informed consent, the need for security and accountability, and the right to access and correction. Several SEA countries have since begun codifying these principles (Zicolaw, 2014). Thailand and Indonesia already have laws under consideration regarding the protection of individual data, while the Philippines and Malaysia have enacted data privacy laws that protect the right to privacy while ensuring the free flow of information. Cambodia, Laos, Myanmar, and Vietnam are still in the process of developing similar legislation.

What do these findings say about the readiness of developing countries in SEA to engage in learning analytics? The national-level policy seems compatible with the use of learning analytics. All countries have mandated investment in ICT-related infrastructure, curriculum, and skills, and they are formulating laws to protect personal data. Policies state the desire for evidence-based decision-making, which hints at learning analytics without explicitly mentioning it.

In contrast, Singapore began basic ICT skills and literacy training in the 1960s and, in 1997, began introducing a series of *ICT in Education Masterplans*. As described in Tan, Cheah, Chen and Choy (2017), the first masterplan established a strong ICT infrastructure and began intensive teacher training. The second empowered schools to make their own autonomous judgments about the use of ICTs while the third focused on strengthening and scaling in order to reach a transformational stage of ICT usage. Although the plans do not explicitly mention learning analytics, they "built-up a healthy IT-oriented mindset, familiarity with technologies, and a general belief in the value of ICT for Singapore's development" (p. 35). They also enable the next wave of development, which includes the use of analytics to track students and respond to individual needs.

In the succeeding sections, we shall examine other component parts that help triangulate the readiness of SEA educational systems in the use of learning analytics.

3. ICT Infrastructure and Resources in Schools

ICT infrastructure and resources in schools refer to the computers, the Internet, related peripherals, and courseware that are available in schools for the use of the students, teachers, and administrators. The availability of these resources and the ways in which they are used determine the volume and variety of the data captured and the speed at which it is captured, if at all. It also estimates how possible or probable it is to deploy educational interventions that are borne out of learning analytics' outputs.

SEAMEO (2010) characterizes Timor-Leste's ICT infrastructure as *emerging*. ICT resources are typically non-existent to very limited. If schools have ICTs at all, they are standalone computers with productivity tools for administrators, teachers, and students to use. Timor-Leste is taking steps to correct this situation. In 2010, the National University of Timor-Leste was linked to the *School on Internet Project* of UNESCO, which utilized satellite-based Internet to connect higher education and research institutions in SEA (UNESCO Bangkok, 2010).

Cambodia, Indonesia, and the Philippines are transitioning from the *emerging* to *applying* stages (SEAMEO, 2010). Aside from standalone computers and productivity tools, schools in these countries also have computer laboratories with a limited number of printers and other peripherals as well as Internet access. The presence of ICTs in schools, however, does not guarantee access. In Cambodian schools, there are over 400 to 500 secondary school students per computer (UNESCO, 2014). Seven percent of primary schools and less than 1% of secondary schools have Internet access. In the Philippines, over 400 primary school students share a single computer. Like Cambodia, only 7% of primary schools have Internet access. At the secondary school level, the situation is less dire with about 50 students per machine while about 40% of schools have Internet access. It is therefore unlikely that students in these countries are able to use school ICT resources in substantial ways.

Myanmar's ICT infrastructure is categorized as being in the *applying* stage (SEAMEO, 2010). In 2014, Myanmar reformed its telecommunications industry resulting in more affordable Internet access. UNESCO launched an ICT for education project in Myanmar in which teachers were trained to use mobile broadband services and ICT-based teaching in rural schools (Stenbock-Fermor, 2017).

Malaysia, Thailand, and Vietnam are moving from the *infusing* to *transforming* stage (SEAMEO, 2010). Schools are equipped with networked computers in both laboratories and classrooms. Students and teachers have access to a wide variety of peripherals and a rich variety of learning resources. In some cases, schools have access to web-based learning spaces, conferencing and collaboration tools, and self-management software. The availability of computers and the Internet in Malaysian and Thai schools bear this classification out. Malaysia and Thailand provide one computer for every 7 to 17 students (UNESCO, 2014). Over 90% of schools in these countries have Internet access.

Even if institutionally provided ICT access is limited, personal access is on the rise with young people leading the way. In developing countries, 67% of people aged 15–24 have access to the Internet, thanks in large part to the affordability of mobile broadband (ITU, 2017).

Following through on their policy commitments to provide schools with more ICT resources, countries have invested heavily in computers, the Internet, and peripheral devices. Like national-level policies, this development is friendly towards the use of learning analytics. However, the reality on the ground is much more constrained. Access to computers and the Internet is uneven both within and among countries. For every four broadband subscribers per 100 people in developed countries, there are two subscribers in developing countries and one in the least developed countries (ITU, 2017). Global mobile access is estimated at 84%, but only 67% of users are in rural areas (ITU, 2016). The youngest and oldest segments of the population, people living in rural areas, and women and girls are less likely to own mobile phones (ITU, 2016). Even Thailand, one of the more advanced SEA nations in terms of infrastructure, reports an internal digital divide in which learner-to-computer ratios are lower in urban schools than in rural schools (OECD/UNESCO, 2016). A study of the use of tablet computers in Thai schools (Office of the Basic Education Commission, 2012-13 in OECD/UNESCO, 2016) showed that hardware distributions needed to be accompanied by contextualized content and teacher support. At this stage, ICTs do not seem diffused enough in SEA schools to enable the collection of high-volume, fine-grained data for learning analytics.

As mentioned in the prior section, the Singapore experience is notably different (Tan et al, 2017). Many schools have already achieved a 1:1 student-to-computer ratio. Learning management systems and digital resources are common and broadband Internet access is widely available. Many of these environments collect fine-grained, student interaction-level data that is used to reach educational goals. This will be discussed in greater detail in Section 7.

4. Professional Development for Teachers and School Leaders

A skilled workforce is essential to the use of analytics, but it is also one of the most difficult resources to develop. It is estimated that the global public and private sector is only able to capture 30% of the value that big data offers (McKinsey Global Institute, 2016). Organizational inability to train, attract, and retain qualified analytics personnel is one of the major impediments to the success of analytics within organizations of all kinds – government, the private sector, and education.

Laos and Timor-Leste are at the *emerging* stages of professional development for teachers and school leaders (SEAMEO, 2010). They are aware of the need for professional development but have not yet formulated concrete plans to address this need. One impediment is a lack of internal capacity to support ICTs in education. In Timor-Leste, few tertiary institutions offer ICT-related courses, and they themselves lack qualified teachers and proper teaching and learning facilities (IBRD/The World Bank, 2013). Timor-Leste teachers often depend on private or religious organizations for ICT training. The situation in Laos is slightly more progressive. Teachers do receive ICT training, but it is generally limited to productivity tools and Internet searching, browsing, and communications (Utakrit, 2016).

Cambodia, Indonesia, and Myanmar are in the *applying* stage in which ICT training tends to be unplanned (SEAMEO, 2010). The training that teachers and school leaders do receive tends to be limited to ICT applications. The dearth of ICT-related training for teachers could be caused in part by the focus on other aspects of teacher training. For example, Indonesia shifted to a new basic education curriculum in 2013. It emphasized more interactive and team-based teaching to develop higher-order thinking skills (OECD/ADB, 2015). Hence, professional development efforts focus on developing these specific areas.

At the *infusing* stage are Malaysia, the Philippines, Thailand, and Vietnam (SEAMEO, 2010). Teachers and school leaders receive training in the use of ICTs to teach specific subject areas. Pre-service teachers in Malaysia and the Philippines take at least one course on educational assessment, measurement, and evaluation (SEAMEO, 2015). In-service teachers are offered classroom assessment training once a year in Malaysia and twice a year in the Philippines.

Of interest regarding this dimension is the absence of any mention of training for learning analytics. Based on the source documents surveyed, the current focus of teacher and administrator training in SEA is, at best, at the level of using ICTs for teaching specific subjects or for tracking inputs to schools. In the Philippines, training supposedly includes item analysis and test score analysis (SEAMEO, 2015), but learning analytics is not explicitly mentioned in pre-service or in-service training programs.

The same can be said of Singapore's teacher education and training programs (Tan et al, 2017). Singapore invests extensive resources in the development of teachers' ICT skills, their capacity for innovative ICT use, and the creation of ICT resources. Capacity building for learning analytics is not explicitly included among training goals. However, Singapore's National Institute for Education regularly engages teachers in their ICT development and deployment projects and shares the results of data analysis. This implies that teachers are kept informed of the effects and consequences of these various strategies, and they are literate enough to internalize and appreciate these findings.

Several authors identify the development of learning analytics expertise as a priority (e.g., Siemens, 2012) and warn that simplistic data processing may lead to its misinterpretation and misuse, leading to negative consequences on stakeholders (Karnad, 2014). If learning analytics is to be used correctly and effectively in SEA, teachers and administrators need training. The reports reviewed suggest, however, that this specific type of training is not widely available at the pre-service and in-service levels. Hence, the education workforce in developing countries in SEA is not well-poised to use learning analytics, even if the data were available.

Not all software captures for fine-grained, user-level data. Software has to be designed to collect user interactions. Computer-based learning environments must be built to log student data and to include other educationally relevant attributes such as learning contexts, correctness, and timing. Curriculum and pedagogy determine whether such environments exist in schools and the extent to which students use them.

5. ICT in Education Curriculum and Pedagogy

Curriculum can be described at three levels: the *intended* curriculum which refers to high-level articulations of educational goals; the *implemented* curriculum, referring to mid-level plans for content, time allocations, and instructional strategies; and the *achieved* curriculum, which refers to the competencies that students actually develop as a result of the educational interventions (Pelgrum, 1999). This and the succeeding section examine what developing countries in SEA state as their educational goals, how they implement these goals, and how they assess whether they have reached these goals.

Within the nationally-prescribed ICT in education curricula, *emerging* category countries Cambodia, Laos, and Timor-Leste mandate the development of ICT literacy skills (SEAMEO, 2010). The pedagogical strategies used by *emerging* category countries Laos and Timor-Leste are usually highly teacher-centered and didactic (SEAMEO, 2010). Several factors account for a reluctance to shift to student-centered methodologies. Teachers confront "… isolation, lack of collaboration, and limited support from administrators; the constraints of the official syllabus or curriculum and examinations that test memory instead of understanding; lack of time and resources, among others" (MacKinnon & Thepphasoulithone, 2014). These circumstances make innovation difficult and traditional teaching methods convenient.

Cambodia and Myanmar span the *emerging* to *applying* categories. They are still teacher-centered, didactic, and teach ICTs as a separate subject (SEAMEO, 2010). This is consistent with reports on limited student access to computers and the Internet: About 1% of primary school students and 15% of secondary school students in Myanmar are enrolled in classes with access to these resources and only 2% of teachers were trained to teach with ICTs (UNESCO, 2014).

Indonesia, Myanmar, the Philippines, and Thailand are categorized as *applying* (SEAMEO, 2010). Their national curricula stipulate the use of ICTs in specific subject areas but these uses are generally isolated from one another. At their best, Indonesian and Thai pedagogical practices are characterized as *infusing*, where they introduce more learner-centered and collaborative methods (SEAMEO, 2010). The categorization of Thailand, however, might be overly modest as all Thai students are reportedly enrolled in classes that make use of computers and the Internet, and 79% of trained Thai teachers teach using ICTs (UNESCO, 2014).

In contrast, the categorization of the Philippines as being in the *infusing* category (SEAMEO, 2010) might have been overstated. UNESCO's (2014) report showed that only 41% of primary school students and 87% of secondary school students were enrolled in classes that made use of computers, while 4% of primary school students and 28% of secondary school students had classes that made use of the Internet. Indeed, the same report showed that only 2% of teachers in the Philippines were trained to teach with ICTs.

In the *infusing* category, Malaysia and Vietnam have integrated learning systems that encourage students to solve problems in authentic contexts (SEAMEO, 2010). None of the intended curricula of developing countries in SEA have reached the *transforming* stage. Teaching and learning strategies in the schools in Malaysia and Vietnam are varied; hence, these countries span the *applying* to *transforming* categories (SEAMEO, 2010). There is evidence of both teacher-centered and student-centered pedagogies. ICTs are taught as separate subjects and they are used for experimentation and multi-sensory learning. Other data sources imply that Malaysia provides its schools with the resources to achieve transformation. All Malaysian primary and secondary students are reported to be enrolled in classes that use computers and the Internet, and 100% of teachers teach with ICTs (UNESCO, 2014).

In the search for information about ICT-based curricula and pedagogical practices, it was evident that there is a dearth of academic literature regarding innovative ways in which ICTs are being applied in SEA schools. The International Conference on Computers in Education is an annual meta-conference hosted by the Asia-Pacific Society for Computers in Education. Under this conference are tracks on artificial intelligence in education, advanced learning technologies, game-based learning, and others. A cursory inspection of the proceedings from 2014 (Liu, Ogata, Kong, & Kashihara, 2014), 2015 (Ogata, Chen, Kong, & Qiu, 2015), and 2016 (Chen, Yang, Murthy, Wong, & Iyer, 2016) showed few contributions from developing countries in SEA.

Learning analytics typically leverages on the use of highly interactive learning environments such as tutorials, games, simulations, and the like. These environments produce rich data streams that can be mined for interesting patterns. In Singapore, teachers are trained to make use of ICT-based pedagogies and are able to implement lessons with ICT components (Tan et al, 2017). Indeed, Singaporean teachers are so comfortable with ICTs that they are able to contribute to the development of ICT-based applications to help teach subjects such as Math and Physics. The same cannot be said of their counterparts in developing SEA countries. The data suggests that teachers in these countries are either unable or reluctant to make use of these formats; hence, students in SEA do not have much exposure to them. The ways in which ICTs are used in most SEA classrooms – primarily teacher-centric, with a focus on ICTs as subject matter in themselves – do not lend themselves to substantial data collection and, hence, use of learning analytics.

6. Assessment

Assessments are used to determine how much of the intended and the implemented curriculum is actually achieved. They are an indicator of the effectiveness of teaching and the readiness of learners to progress. They are also indicators of the quality of an educational system (SEAMEO, 2015). In SEA, assessments usually take place at three levels: the classroom level, where teachers give periodic tests to gauge student achievement; the national level, where high-stakes exams determine promotion from primary to secondary school or from secondary school to college; and the international level, where sample schools take standardized tests as a means of diagnosing the entire educational system to help formulate or adjust policy (Cambodia Ministry of Education, Youth, and Sport, n.d.).

At the classroom level, teachers in SEA have access to a variety of assessment tools: textbooks, workbooks, assessment toolkits, scoring rubrics, test item banks, and test item data (SEAMEO, 2015). Students in *emerging* countries Cambodia, Indonesia, Laos, Myanmar, Philippines, and Timor-Leste tend to be assessed for discrete subjects, using paper-and-pencil tests (SEAMEO, 2010). ICT use in assessment tends to be limited to the development, encoding, and recording of assessments, especially at the primary school level (SEAMEO, 2015).

Thailand and Vietnam fall into the *applying* stage where students are assessed for their skills but the overall format is still teacher-centered and subject-focused (SEAMEO, 2010). As with the *emerging*-stage countries, the use of ICTs for assessment is limited because teachers themselves lack confidence, and because ICTs are taught as subjects in themselves (OCED/UNESCO, 2016).

Malaysia is the sole entry in the *infusing* category (SEAMEO, 2010). The Malaysian school system designs what it views as holistic, authentic assessment that measures students' cognitive, affective, and psychomotor skills (SEAMEO, 2015). These assessments are designed to be taken in authentic situations as well as during coursework.

At the national level, all SEA countries give summative, high-stakes examinations. The main use of the test data is to determine student achievement levels against the prescribed curriculum (SEAMEO, 2015). There is, however, a certain level of mistrust of national-level tests. Test validity, sampling methods, and quality of test administration are all the subject of doubt (SEAMEO, 2013). In Indonesia, for example, the national-level examinations are supposed to assess learning, serve as criteria for graduation, rank students for competitive entry, evaluate the success of educational programs, provide information to improve teaching and learning, and so on (OECD/ADB, 2015). However, there is little confidence that the exam is able to satisfy any of these purposes.

At the classroom and national levels, it is clear that all developing SEA countries have massive stores of student-level assessment data. Much of it though is not digital and therefore not in a form that can be easily mined. ICT-based assessments are not commonly used. Furthermore, questions are raised about the validity of national-level tests. This is a challenging environment for learning analytics.

Finally, developing countries in SEA make use of large-scale international tests as tools to evaluate their educational systems. The Programme for International Student Assessment, Progress in International Reading Literacy Study, and Trends in International Mathematics and Science Study are examples of tests in which whole countries participate (Assessment, Curriculum, and Technology Research Center, 2015).

Countries generally claim to use test results for policymaking (Assessment, Curriculum, and Technology Research Center, 2015; UNESCO, 2017a). The Philippines, for example, uses results to rationalize capacity building and skills development among teachers. Thailand uses the results to review the curriculum and design student intervention programs. Like the Philippines, Myanmar uses results to design professional development programs. There is a sense, however, that large-scale assessment data is underutilized (UNESCO, 2017b). As mentioned in the section on professional development, teachers and administrators are not trained to process large data sets; hence, educational systems lack the human resources capable of performing the rigorous research needed to convert data into information.

7. Evaluation and Research

At first blush, evaluation and assessment appear synonymous. The two areas do overlap, but evaluation in this context differs from assessment in terms of focus. Evaluation examines the effects of broader ICT in education policies on the identified areas for improvement, while assessment, as discussed in Section 6, investigates the extent to which the goals of a curriculum were achieved.

Research, on the other hand, refers to scholarly inquiry into an educational problem. Evaluating the effects of policy is a research endeavor that can result in a cost-benefit analysis of ICT investments, refinement of educational theory, and identification of best practices (SEAMEO, 2010). It is here that learning analytics should be put to work.

At this point, many developing countries in SEA still lack the capacity for evaluation and research. *Emerging*-stage countries Cambodia, Laos, the Philippines, and Timor-Leste generally do not include evaluation and research in their national-level ICT plans (SEAMEO, 2010). There are, however, efforts that support the evaluation process. The Philippines, for example, has mounted substantial initiatives to collect a variety of data on the basic educational system in a comprehensive and timely manner (Read, 2017). These include enrollment, staffing, ICT resources such as computers and the Internet, health and nutrition, exit assessment results, and others. Data tends to be coarse-grained though. It includes all resource inputs – not just ICT – and has a limited indication of resource usage.

Indonesia, Thailand, and Myanmar are in the *applying* stage in which evaluations tend to be summative in nature and the capability to make evidence-based decisions is limited (SEAMEO, 2010). One of the issues surrounding Thailand's ICT in education plans is that the country lacks the capacity to monitor and assess ICT usage in schools (OECD/UNESCO, 2016). Despite the substantial investments that Thailand has made in this regard, it does not systematically collect data on inputs and outcomes; hence, it has limited data upon which to build policy.

In the *infusing* stage are Malaysia and Vietnam (SEAMEO, 2010). They make use of both summative and formative assessments and invest in research to provide the basis for data-driven policies. These claims are not undisputed though. A UNESCO (2013b) study pointed out that Malaysia has fallen behind its benchmarking countries because of a lack of policy formulation, monitoring, and feedback. In Vietnam, a survey of 32 key representatives from 20 public and private sector organizations involved in ICT in education ranked evaluation and research as a 7th priority among 10 ICT in education dimensions (VVOB Vietnam, n.d.). Highest among these dimensions are the deployment of infrastructure, teacher training, and curriculum. Key representatives agreed that research was essential for proper policy formulation but only for as long as it did not impede change and innovation.

Learning analytics is one of the tools of evaluation and research. At this point, however, developing countries in SEA lack a culture of evaluation and research, which leads to an underutilization of these tools.

In contrast, Singapore's Learning Sciences Lab within the National Institute for Education focuses on the use of learning analytics to develop "evidence-based claims about how people learn to derive practical, pedagogical, and theoretical implications" (Tan et al., 2017). To illustrate: The *Rapid Collaborative Knowledge Improvement (RCKI)* using *GroupScribbles (GS)* project refers to both a product and a practice that supports group participation and face-to-face collaboration. GS is a shared digital space in which students can share ideas in textual or graphical forms. Students scribble on a personal window and post their work to a shared window when they are ready. The analysis of RCKI using GS showed that GS classes performed better than non-GS classes because GS facilitated students' understanding of and attitude towards the subject matter. Since its introduction, over 300 RCKI lessons have been designed with the help of 15 teachers and 17 classes.

8. Conclusion

Within developing countries in SEA, there are massive opportunities to improve education with the use of learning analytics. As Gašević (2018) argues, learning analytics can be used to improve education quality, equity, and efficiency in many ways and at many levels. Rich sources of data such as social networking behaviors and discourse can augment formal assessments to come to better understandings of learners and their needs, and can help learning systems direct students to appropriate learning activities. Learning analytics can help overcome biases in education access by factoring in the effects of geography, gender, minority status, and so on to lead to more equitable learning environments. Finally, learning analytics can help policy makers and practitioners better manage educational programs and resource allocation.

The Singaporean experience provides a success story. Singapore proves that ICTs in general, and learning analytics in particular, have the potential to contribute positively to educational change (Tan et al, 2017). Examples of Singaporean projects such as the RCKI using GS and EduLab, point to increased quality, equity, and efficiency, with even greater promise ahead. Singaporean researchers anticipate that learning analytics will lead to more personalized learning environments capable of complex interactions and challenge educators to design, develop, and study such innovations.

However, the Singaporean experience is not universal. The goal of this paper was to determine the extent to which the enabling ecosystem of learning analytics existed in developing countries in SEA. The findings are somewhat grim. There is a national-level commitment to the use of ICTs in education, but the priority is on addressing internal digital divides through the improvement of telecommunications, increased technology deployment, and teacher training for ICT literacy and integration.
The computer-based learning environments in schools tend to consist of personal computers with productivity tools, with the possible exception of schools in *infusing* and *transforming* countries such as Malaysia. Even in these advanced countries, however, there is little evidence that learning systems

automatically collect the kind of fine-grained data that drives learning analytics. Rather, most testing still uses pen and paper. Even when digitized data is available, the teachers and administrative staff lack the culture of evaluation and research and the specialized training to convert the data into meaningful information.

At this time, none of the pre-conditions to making full use of learning analytics seem to be present in developing countries within SEA. Countries are still in the process of amassing policy, technology, and human resources, as well as developing the culture to leverage learning analytics for wide-scale educational improvements. Fortunately, efforts continue to bolster ICT in education and develop related expertise within these countries. It is therefore reasonable to expect that SEA will become an active participant in the learning analytics community in the years to come.

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BUILDING CAPACITY FOR LEARNING ANALYTICS IN LATIN AMERICA

Cristóbal Cobo and Cecilia Aguerrebere

1. Introduction

The rhetoric about big data in general, and learning analytics in particular, tends to highlight the opportunities and potential benefits that learning analytics might bring to education. Gašević (2018) goes even further suggesting that in the specific case of developing countries learning analytics can: support learning at scale, improve the quality of learning experience, provide personalized feedback to learners, increase numbers of graduates at risk of failure, optimize the use of resources, predict future demands, etc.

But not everybody agrees with that perspective. Boyd and Crawford (2012), among others, argue that this utopian perspective needs to be balanced with dystopian concerns. Boyd and Crawford highlight what they call six provocations: 1) big data changes the definition of knowledge; 2) objectivity and accuracy are misleading; 3) bigger data are not always better data; 4) when the context is taken out, big data loses its meaning; 5) just because data can be accessible, it does not make it ethical; and 6) limited access to big data creates new digital divides.

This report will discuss learning analytics with a special focus on the Latin American reality. This article identifies some of the advances in this field but also highlights what Boyd and Crawford called the emerging digital divide not only between the haves and the have-nots but also between the doers and the do-nots, and between the knowers and the know-nots. The development of learning analytic studies is still considered emergent in Latin America, but there are trends which make us think that this will be a topic of growing relevance in the years to come. In addition to building the necessary technical, financial, academic, and legal infrastructure for learning analytics, it will be relevant to develop and consolidate a dynamic Latin American research network in this field.

This article concludes with some of the challenges that need to be addressed for developing new capacities towards making educational data more actionable in this region.

2. Latin America's Background and Current Trends

Latin America includes a collection of countries with many similarities. It refers to a vast geographical region that comprises South America, Central America, a part of North America, and the Caribbean. Countries in this region share a common historical and cultural past, but they are highly diverse in many aspects including language, resources, and educational infrastructure including academic and research centers (Kalergis, Lacerda, Rabinovich & Rosenstein, 2016).

Latin America is a profoundly socially unequal sub-continent not only in terms of income distribution but also in terms of individual access to public services including education, health, water, and other utilities. The difference in average years of education for adults in the top and bottom income quintiles, for example, ranges from five to nine years in different countries. Available data, which extends back to 1950, suggests that Latin American countries have consistently been among the most unequal throughout the period.

Compared to international standards, much of Latin America can be said to suffer from a massive "secondary school deficit," with abnormally low proportions of the population achieving secondary education, directly impacting higher education achievement. The most obvious concern perhaps is that as much as three-quarters of the region's potential labor force possesses at most only a few years of basic primary education. In turn, unequal educational distribution clearly serves as an important channel for perpetuating inequality across generations.

It is fair to mention that there has been some progress at the quantitative level. Over the past two decades, for example, the average years of schooling for Latin America's adult population (25 and older) increased by 1.7 years (De Ferranti & Ody, 2006). Most Latin American countries are close to achieving universal participation in at least some primary schooling. Earlier gender gaps in school attendance were also narrowed or eliminated over the past decades. However, the substantial improvements in quality indicators have been more difficult to achieve than the quantitative increases in attendance.

Latin American higher education consists of close to 6,000 public and private postsecondary institutions, of which 15% qualify as universities. They serve almost 500 million inhabitants in 19 countries. It is important to mention that higher education systems in Latin America need a deep transformation to consistently assure quality in education (higher retention rates, well trained and employable professionals) and science (excellence, international presence, better funding schemes), support smarter diversification, and provide society with the knowledge-based resources needed (Knobel & Bernasconi, 2017).

Internet penetration in the Latin American region is at 59.6%, placing the sub-continent below the worldwide median ("Internet users," n.d.). This rate is expected to be higher among higher education institutions, where the Internet has played a key role in overcoming the isolation of scientific communities by facilitating exchanges among peers across the world and increasing access to scientific journals.

There is still a long way to go to increase the budget for R&D in order to address and overcome the main challenges that these societies face. Additional efforts are required to build new research centers and train young scientists.

3. Possible Scenarios for an Actionable Learning Analytics

In Latin America, one of the most vulnerable groups is those "out of school and out of work." Having a growing youth population divorced from activities that allow them to develop new skills and capacities, which affects their employability, not only undermines the future potential of this cohort but could also raise major challenges to society (D'Alessandre, 2013). While enrollment and graduation rates in Latin America increased and dropouts decreased between 1990 and 2010 (Bassi, Busso, & Muñoz, 2015), nearly 10 million Latin Americans between the ages of 15 and 18 are still neither studying nor working (Cárdenas, De Hoyos, & Székely, 2015).

Learning analytics can supply valuable information tools to work on this problem. For instance, it can provide relevant and actionable information by analyzing the impact of learner's socio-economic context, the school or college's quality, the learner's engagement, the effectiveness of the educational systems, among others (see, for example, Park, Denaro, Rodriguez, Smyth, & Warschauer, 2017 or McKay, Miller, & Tritz, 2012). One of the main differences between learning analytics and "traditional" studies of school disengagement is that with the increasing adoption of digital tools (i.e., smartphones, social networks, school management software or online educational resources), which generates an information-rich context, it is possible to have a much more updated (if not real-time) description of the learner's path. Additionally, proficient deployment of learning analytics can help to identify at a much more granular level when the learners are at risk of leaving the formal education.

As we move into an era of greater usage of online learning, an increasing number of online and blended interactive learning systems are expressing their interest in moving toward higher personalization. Evidence on the effectiveness of personalization is still preliminary (Baker, 2016). Nevertheless, vendors are increasingly offering "personalized" learning systems and analytics. Educational institutions should request evidence on these systems' effectiveness, as well as transparency on the developed algorithms.

Personalized learning is a popular buzzword symbolizing the potential for data use in education. As Bulger (2016) argues, personalized learning encompasses such a broad range of possibilities – from customized interfaces to adaptive tutors, from student-centered classrooms to learning management systems. Bulger emphasizes that since personalized learning systems are relatively new and largely untested, the impact on students' regulation of their learning remains unclear, creating tensions between promise and reality.

We argue that moving into the personalization of learning will require additional actions in terms of data privacy. In order to guarantee the quality and integrity of data management as well as user protection, ethical and legal guidelines in accordance with both national legislation and international standards should be followed.

In addition to privacy concerns, it is also necessary to better understand how learners interact with an ecosystem of educational platforms. Considering that more and more learners are learning on several platforms simultaneously (e.g., Moodle, YouTube, WhatsApp, Facebook, Elsevier), it is necessary to conduct analysis across multiple platforms. Several learning analytics studies (e.g., on massive open online courses or MOOCs, Khan Academy, Wikipedia) tend to analyze silos of information (individual online platforms), thereby losing perspective on the multi-platform online user's behavior.

This more holistic approach, although challenging, can contribute to building a much more comprehensive picture of the learning experience. This is considered a *conditio sine qua non* before moving towards more ambitious "personalized learning." As mentioned, adequately addressing ethical, legal, and societal concerns; handling student data responsibly; and adopting policies that protect privacy yet preserve data and ways to link student learning information are essential.

4. Effective Models of Learning Analytics for Latin America

Three major adoption models have been identified in learning analytics: predictors and indicators, visualization, and interventions (Brown, 2012; Gašević, Dawson, & Pardo, 2016):

- *Predictors and indicators* include solutions in which data obtained from learning contexts is analyzed, using statistical and data mining tools, to generate models capable of predicting variables of interest (e.g., performance, student engagement, dropout).

- *Visualization* tools are used to summarize and simplify large amounts of otherwise complex data, thus enabling more effective exploration and interpretation. These are particularly powerful tools for teachers and decision-makers assisting on educational policy formulation.
- *Interventions* concern the derivation of concrete initiatives to shape the learning environment to improve the learning experience.

Effective implementation of the three adoption models is crucial to mobilizing the full potential of learning analytics to tackle endemic problems in the education systems of Latin America such as student dropout, low performance, and disengagement. Predictive models of student dropout are essential to anticipate the problem and create early warnings, giving the education system the opportunity to make timely interventions (Tempelaar, Rienties, & Giesbers, 2015). Addressing different learning needs and interests through personalized learning can help improve the learning experience, thus increasing performance and student retention. Proficient use of learning analytics can support the design of more personalized strategies to detect and address school disengagement (e.g., context-based or personalized recommendations) (Papamitsiou & Economides, 2014).

There are some moderate initiatives towards learning analytics adoption in Latin America. The learning analytics research community in the region reflects what is observed in the international community. On a regular basis, research initiatives are conducted by universities addressing mainly higher education needs (e.g., studies of student behavior in MOOCs). However, the actual learning analytics adoption in the region is still very limited (e.g. limited participation of Latin American proposals during the last conference 'Learning Analytics & Knowledge 2017', at the Simon Fraser University, Vancouver, BC, Canada).

Today's main areas of research in the region are: *performance* (Ferreira, León, Yedra, Gutiérrez, & Ramos, 2015; Manhães, 2015; Costa, dos Santos Silva, de Brito, & do Rêgo, 2015), *engagement* (Santos, Bercht, & Wives, 2015; Santos, Bercht, Wives, & Cazella, 2015) and *dropout* (dos Santos, de Alburqueque Siebra, & Oliveira, 2014; Queiroga, Cechinel, Araújo, & da Costa Bretanha, 2016). Nonetheless, most of the academic production is still at an exploratory stage of "data crunching" and far from real interventions. There is yet a long way to go from academic research to actual learning analytics institutional adoption.

5. Ethics and Privacy Protection Experiences in Latin America

Pardo and Siemens (2014) define "personal digital information" as the information about persons captured by any means and then encoded in digital format. In the digital context, Pardo and Siemens (2014) define "ethics" as the systematization of correct and incorrect behavior in virtual spaces according to all stakeholders. They suggest four ethics and privacy principles for learning analytics: "transparency, student control over the data, security, and accountability and assessment" (p. 448).

According to Tobon, (2015) more than half of the countries in the Latin American region have adopted constitutional rights to privacy and/or comprehensive data protection regulation as mechanisms to protect privacy. For illustrative purposes, Table 1 describes the data protection laws and national data protection authorities in the seven most populous countries in Latin America (DLA Piper, 2017).

Table 1. Data protection laws and authorities in selected countries in Latin America (DLA Piper, 2017)

Country	Law/Authority	Description
Brazil	Data protection law	Brazil does not have a single statute establishing a data protection framework. However, the Brazilian Internet Act establishes general principles, rights, and obligations for the use of the Internet. It includes relevant provisions concerning the storage, use, treatment, and disclosure of data collected online.
	National data protection authority	The Brazilian Internet Steering Committee (*Comitê Gestor da Internet no Brasil*)
Mexico	Data protection law	The Federal Law on the Protection of Personal Data Held by Private Parties (2010)
	National data protection authority	The National Institute for Access to Information and Personal Data Protection (*Instituto Nacional de Acceso a la Información y Protección de Datos Personales*) and the Ministry of Economy (*Secretaría de Economía*)
Colombia	Data protection law	Law 1581 (2012) contains comprehensive personal data protection regulations. This law is intended to implement the constitutional right to know, update, and rectify personal information gathered in databases or files, as well as other rights, liberties, and constitutional guarantees referred to in the Constitution.
	National data protection authority	Two governmental authorities are designated as data protection authorities: the Superintendency of Industry and Commerce (*Superintendencia de Industria y Comercio* or SIC) and the Superintendency of Finance (*Superintendencia Financiera de Colombia* or SFC). The SIC is the data protection authority unless the administrator of the data is a company that performs financial or credit activities under the oversight of the SFC as set forth by applicable law, in which case the SFC will also serve as a data protection authority.
Argentina	Data protection law	Personal Data Protection Law (25,326) provides much broader protection of personal data closely following Spain's data protection law.
	National data protection authority	Argentine Personal Data Protection Agency (*Dirección Nacional de Protección de Datos Personales*)
Peru	Data protection law	Personal data protection is governed by the Personal Data Protection Law (29733) and the Security Policy on Information Managed by Databanks of Personal Data.
	National data protection authority	The General Agency on Data Protection (*Dirección General de Protección de Datos Personales*), part of the Ministry of Justice and Human Rights

Country	Law/Authority	Description
Venezuela	Data protection law	Venezuela does not have any general legislation regulating data protection. However, there are general principles established in the Constitution.
	National data protection authority	Venezuela does not have a national data protection authority. Various agencies (e.g., the Superintendency of Banks and the National Telecommunications Commission) have data protection authority within their specific jurisdictions.
Chile	Data protection law	Personal data protection is addressed by several specific laws and other legal authority. There are at least six main laws containing data protection provisions.
	National data protection authority	There is not one regulator who oversees matters relating to data protection. Such matters are resolved by the Chilean courts: The *Jueces de Letras* (territorial civil jurisdiction), the Appeal Courts (jurisdiction in the first instance in connection with constitutional actions) and the Supreme Court (for cases involving constitutional violations).

Díaz et al. (2015) conclude that in most Latin American countries this kind of personal information is regulated through *personal data protection* laws. Brazil, Colombia, Paraguay, Peru, Argentina, Ecuador, Panama, and Honduras have recognized *habeas data*[1] as a constitutional right. Argentina, Uruguay, Mexico, Peru, Costa Rica, and Colombia have enacted data protection laws based on the European Union Data Protection Directive of 1995. Chile and Paraguay have data protection laws, although they do not have a data protection authority.

6. Potential Barriers to Learning Analytics and Strategies to Overcome Them

The major barriers for learning analytics adoption can be associated with three main components: data, modeling, and transformation (Gašević, 2018). The first one concerns the information on learning activities, which is at the forefront of any learning analytics development. In this regard, data availability and data quality are two fundamental aspects (see, for example, Hazen, Boone, Ezell, & Jones-Farmer, 2014), which oftentimes present huge barriers to learning analytics adoption.

Data availability tends to be less of an issue in higher education since universities often record data on classroom and online courses. In contrast, primary and secondary education institutions frequently lack this kind of data because they do not have the means and resources to access and store it. Uruguay is a rare exception due to Plan Ceibal, a national policy program created to enable technology-enhanced learning in the country (Aguerrebere, Cobo, Gomez, & Mateu, 2017). Plan Ceibal provides a personal device (laptop or tablet) and Internet access to every child and teacher in K-12 education, as well as a comprehensive set of online educational platforms and contents. This governmental agency retrieves a significant volume of data generated from the student's online activities, creating an invaluable source of information about their learning process. During the last decade, Latin America has turned

[1] *Habeas data* is a remedy available to any person whose right to privacy in life, liberty or security is violated or threatened by an unlawful act or omission of a public official or employee, or of a private individual or entity engaged in the gathering, collecting, or storing of data or information regarding the person, family, home, and correspondence of the aggrieved party.

into one of the most proactive regions in the world regarding integration of ICT aimed at social inclusion and the democratization of education systems (Lugo & et al, 2016). In most Latin American countries, the telecommunications infrastructure that provides connectivity to educational institutions is decentralized, making it harder to overcome the data availability challenge. That being the case, it is imperative to deal with the legal and technical concerns of the various organizations involved (public and private), and only after these issues have been resolved would it be possible to start the discussion on technical interoperability and multi-platform data collection and integration. Although infrastructure and connectivity in Latin America have improved greatly in the last decade, the Internet penetration rate is still one of the lowest among the regions, making data availability even more challenging.

The second main component of learning analytics adoption concerns models, specifically the importance of developing correct modeling strategies. It has been proven that the "one-size-fits-all" approach does not work for learning analytics, and those models developed for other contexts, while potentially useful, need to be adapted to local realities (Gašević, 2018). It is essential to conduct learning analytics research using "question- and theory-driven approaches" (Gašević, 2018, p. 11) and not just "let data talk." In this regard, the limited number of experienced learning analytics research groups in the region may constitute an important barrier to field development and adoption. Despite the existence of regional initiatives to develop learning analytics,[2] with Brazil, Ecuador, Colombia, México, Argentina, and Chile at the forefront, scientific production is still limited (Nunes, 2015), and the connection with practitioners even more so. To mitigate the situation, it is important to, as Gašević (2018) suggests, promote participation in international initiatives (e.g., SoLAR) and cross-institutional collaborations.

Last but not least, an additional challenge of learning analytics is the development of data literacies among different communities, for instance: *data generators* (those with the skills to collect, select, clean, analyze, produce, visualize, and share quality information) and *data consumers* (those with the ability to interpret, use, and understand educational data without ignoring its limitations).

We would like to add that in Latin America learning analytics is still a new field for a large sector of the academic community, most likely for policymakers as well. Using Rogers' taxonomy (2010), we can say that learning analytics is only significant for a limited group of "innovators" and perhaps a few "early adopters." It is far from being adopted (or even sufficiently acknowledged) by an "early majority," much less the "late majority" and the "laggards."

The problem, therefore, is not that the potentials of learning analytics suggested by Gašević (2018) have not been reached yet but rather, that there is a worrying ignorance of the importance of developing a broader awareness and better understanding of learning analytics and related topics across all different groups in our increasingly data-driven society. It is time to discuss at the societal level how to find a balance between learning analytics research, on the one hand, and privacy and data protection issues, on the other, in order to comply with legal regulations as well as with a number of ethical challenges. For this reason, it is of utmost importance to promote the development of new data literacies among decision-makers, academics, and educators as well as key institutions to address the emerging challenges in this field: privacy; informed consent, transparency, location and interpretation of data; data ownership; obligation to act on knowledge (Steiner, Kickmeier-Rust, & Albert, 2015); and algorithmic accountability (Gašević, 2018).

[2] Examples of Latin American conferences include the Latin-American Conference on Learning Technologies (LACLO); *Congresso Brasileiro de Informática da Educação* (CBIE); and the Latin American Workshop on Learning Analytics (LALA) .

7. Conclusion

Proficient use of available digital information, enhanced by learning analytics techniques, is paramount to support early (re)actions of the different educational stakeholders (policymakers, educators or parents) to the major challenges facing education in Latin America. In the meantime, learning analytics adoption in the region can be considered emergent, where the main focus of studies is yet exploratory with limited intervention experiences. This trend will likely grow in the coming years, leading to broader and more effective adoption. The existing legal framework should be able to guarantee the first level of acknowledgement and regulation on fundamental ethical and privacy matters that emerge with learning analytics adoption (i.e., transparency, student control over the data, and security). Despite progress regarding legal concerns, there are still limitations and principles to be fulfilled when collecting, processing, storing, and analyzing personal data. Additional steps need to be taken, such as having a thorough treatment of ethical matters, pursuing the creation of national ethical committees, and promoting open discussions both regionally and internationally.

In conclusion, it is important to mention that while most of the analysis presented in this paper has been focused on infrastructure (scientific, legal, and technological), we would like to stress the need for a broader-based conversation about learning analytics involving all stakeholders. For this conversation to be fruitful, we need to foster the development of data literacy among different stakeholders while at the same time generating new R&D capabilities and grant programs in Latin America to facilitate the consolidation of a more dynamic academic community in this field.

A key challenge is how educators and other education stakeholders can be involved in the debates around big data to make sure that educational values are also part of how we use data. As we discussed in this paper, there are a number of problems and critical issues about learning analytics that need to be addressed – questions about the quality of data as well as the quantity and the nature of the tools and techniques used. But we also need more transparency to understand how generalizable the results are. Are we being reductive? Are we neglecting aspects of education that are important? This is not a conversation for experts alone. As Selwyn emphasizes (in Centro de Estudios Fundación Ceibal, 2016), an honest, open, and skeptical conversation about data should include everyone involved in education: students, teachers, parents, schools, employers, communities, and private companies. All those directly or indirectly affected should have a say in the way data are used in education.

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