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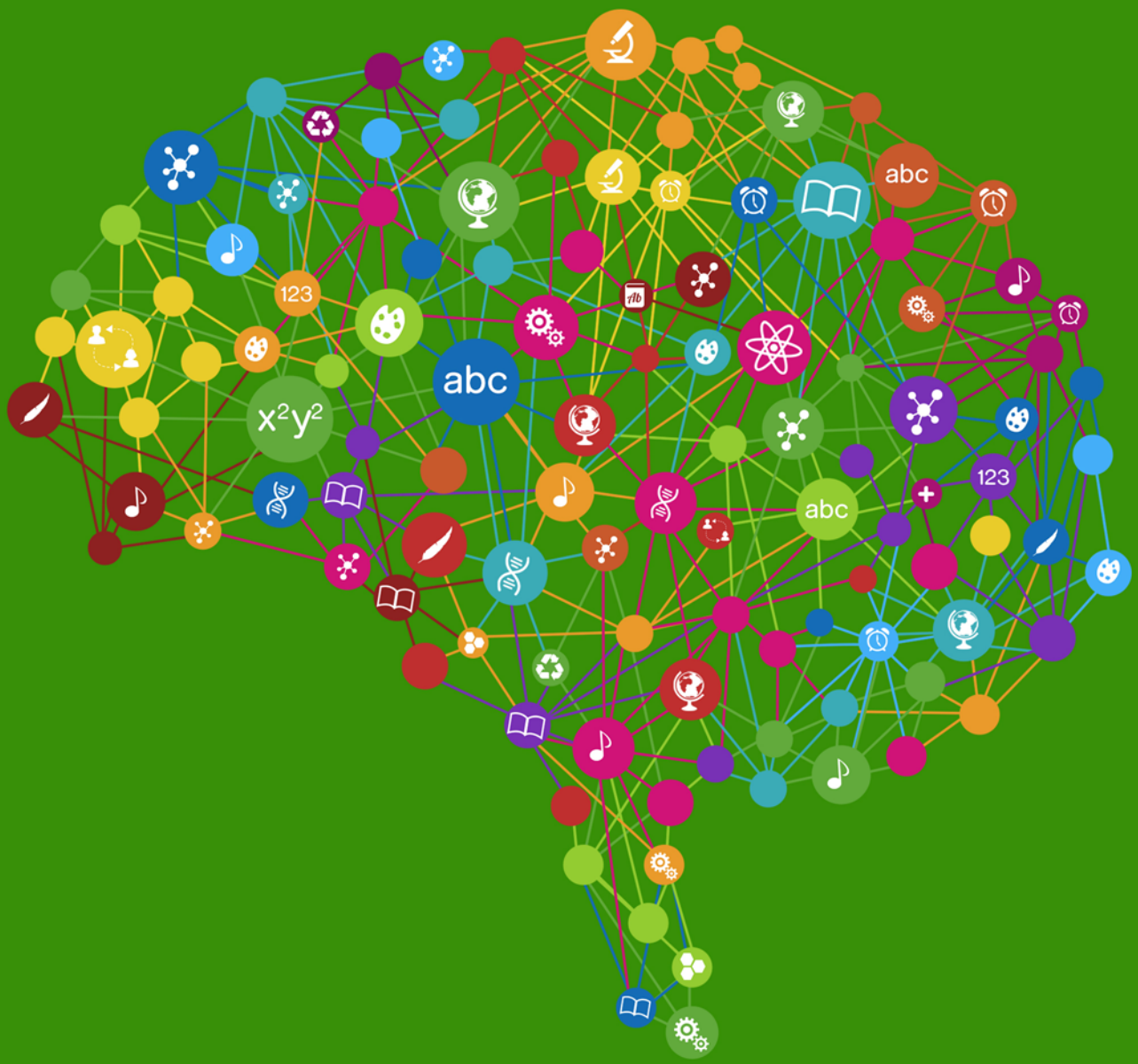
DIGITAL LEARNING FOR DEVELOPMENT



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
DIGITAL LEARNING FOR DEVELOPMENT

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).

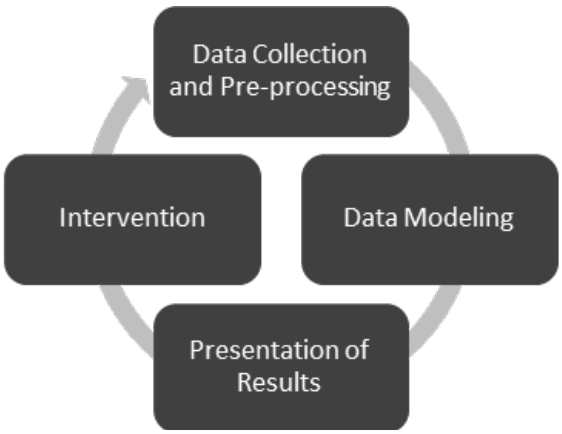

Figure 1. A model of key activities in a learning analytics process cycle

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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