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Thematic Working Group 6
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Putting Learning Back into Learning Analytics: Optimizing Learning Through Analyzing the Data

David Gibson, Curtin University, Australia (group leader)
Dirk Ifenthaler, University of Mannheim, Germany (group leader)
Jonathan San Diego, King's College London, UK (group leader)
Monique Baron, Sorbonne University, France
Jill Downie, Curtin University, Australia
Sandra Elliott, Global Grid for Learning, USA
Séverine Parent, University of Quebec at Rimouski, Canada
Doreen Prasse, The Schwyz University of Teacher Education, Switzerland
Atsushi Shimada, Kyushu University, Japan
Masanori Yamada, Kyushu University, Japan

Background

Learning analytics have been defined as the use of static and dynamic information about learners and learning environments, assessing, eliciting and analyzing it, for real-time modelling, prediction and optimization of learning processes, learning environments, as well as educational decision-making (Ifenthaler, 2015). To target the outcomes of data systems is a new challenge for computer scientists and engineers as well as educators. In addition, a large number of stakeholders draw on learning analytics, such as learners, teachers/educators, learning/instructional designers, institutional leaders, scientists, and public as well as private providers. For instance, learning analytics of student data sets can be used for formative and summative assessments, but issues related to privacy and usability are growing concerns. For example, with large data sets available to teachers and learners, who owns these data, which data are available, and which are private? Furthermore, who analyses these data and who is the data analyzed for? What can teachers do with all these data and what feedback and monitoring of learning might students expect from learning analytics? How can fair uses of techno-led or enabled assessment be ensured and what are the risks associated with data use for promoting students' achievements? This eBook report shares the results of an international discussion of these issues, which identified how learning analytics may influence policy and teaching practices.

The members of thematic working group 6 (TWG6), representing eight countries, spent six months in 2019 collecting, reviewing and synthesizing evidence from research publications, reports, correspondences, and practitioner conversations around learning analytics. The sources ranged from university research projects to articles based on practice and usage of learning analytics dashboards and applications. This background work enabled TWG6 to identify current and potential issues around the use of learning analytics. TWG6 report suggests strategies and actions, and recommendations for policy makers (PM), researchers (R) and practitioners (PR) to attempt to overcome the potential issues we foresee.

Alignment issues and challenges

In this section, five positions that highlight alignment issues and challenges due to a variety of problems, tensions, barriers and missed opportunities for effective use of learning analytics systems.

These consequently impedes on improvements in student learning and success at scale and their corresponding educational impacts on the whole of society. These five alignment issues and challenges are described below.

1. There is a widespread lack of knowledge and understanding about learning analytics and the concomitant need to select and use learning analytics systems for supporting learning, teaching and assessment; tracking progress; and, informing decision-making.

How should data inform practice? Who is prepared to analyze big data and who is the data analyzed for? Ethicists have pointed out that the purposes, actions and actors in an educational setting are a complex context of overlapping and sometimes competing interests (Ifenthaler & Schumacher, 2016; Roberts, Chang, & Gibson, 2017). This implies a need for a level of literacy to be achieved by all stakeholders in the system in order to support informed decision-making. What knowledge and skills are needed to understand the role of new data science methods and fit those with conventional qualitative and quantitative traditions of research? Some writers have called for a re-examination of the foundations of educational research in order to introduce data science methods into the open space that can potentially integrate qualitative and quantitative methods with AI-driven computational assistance and assistants. These writers have pointed out the current status and gaps in readiness of higher education to leverage learning analytics (Gibson & Ifenthaler, 2017). In particular what do students need to know to understand and be critical consumers of their own data and that of others? What can teachers do with all these data for their teaching activities and what feedback and monitoring of learning might students expect from learning analytics?

2. Guiding principles and policies need to be updated to help institutions make use of learning analytics.

Learning analytics can provide three kinds of information to students and teachers: summative, real-time or formative, and predictive insights from information prepared for decision-making and action (Ifenthaler, 2015). Today with the emerging potential to map sequences of the tools, communications and information utilized to solve a problem, the capability to build dynamic networks of the relationships of collaborating team members, and the computational resources to automatically classify and adapt curriculum materials in response to user interactions, the fields of learning design and analytics can be brought together as a new field of ‘learning analytics design.’ The new field integrates learning or instructional design informed by data analytics and the design of learning analytics interactive dashboards guided by learning design. Advancements in learning analytics design have the potential for mapping the cognitive, social and physical states of the learner and to optimize learning environments on the fly (Ifenthaler, Gibson, & Dobozy, 2018). Three analytics layers have been proposed for data-informed learning design (Hernández-Leo, Martinez-Maldonado, Pardo, Muñoz-Cristóbal, & Rodríguez-Triana, 2019): 1. analytics with a focus on learning decisions to be made by the learner (e.g., has the designed helped someone to learn), 2. analytics for decision-making by designers and teachers-as-designers (e.g. what aspects of the learning design were effective), and 3. analytics of the impact of community-based pedagogy for teachers (e.g., co-design of learning, peer learning).

3. Standards are needed for ethical design and use of learning analytics systems by educational data services providers and users for ensuring quality (e.g., auditing, transparency, reporting, security, privacy, compliance, sustainability, and scalability).

One of the main concerns of learning analytics applications is the handling of data privacy issues (Prinsloo & Slade, 2014). As almost every learning analytics feature collects and processes user data by default, learning analytics designers need to consider each country’s data privacy legislation, such as the European General Data Protection Regulation (EU-GDPR).

A principle of learning analytics developed by several authors is that a person will not be fully understood by their data trail, no matter how that data improves and broadens (Prinsloo & Slade, 2014). Such issues have been documented in recent research studies regarding privacy issues and ethical dilemmas in learning analytics (Ifenthaler & Schumacher, 2016; West, Huijser, & Heath, 2016).

However, it is also well understood that the improvement of automated decision-making, personalization of learning and adaptation of the curriculum requires a complex, multifaceted and distributed data model of the learner (Mislevy, Behrens, Dicerbo, Frezzo, & West, 2012). Many questions are implied and remain concerning the features of such a model, how to distribute relevant features as needed in different contexts and how to re-unite features into more complex and dynamic pictures of learning progress and achievement.

4. Flexible and user-centered designed tools are needed for different learning levels, ages and stakeholder groups in their unique educational contexts.

Real-time analytics are increasingly feasible for example as support systems for teaching. Research has reported on systems that track and analyze online readings as lecture system support services (Shimada, Konomi, & Ogata, 2018), student response systems for attention and engagement (Heaslip, Donovan, & Cullen, 2014) and dashboards that visualize student progress and achievement (Roberts, Howell, & Seaman, 2017; Schumacher & Ifenthaler, 2018).

In the context of game-based learning, learning analytics features often adopts a dashboard approach to achieve transparency in progress and to empower decision-making by the user. Dashboards can map skill acquisition, show the ratio of successful students who reached the learning objectives, and provide various kinds of feedback to teachers and students (Thille & Zimmaro, 2017). Dashboards can be powerful learning tool for both teachers and learners, if developed with user-centered design (e.g., the functions for teachers to interpret learning data before decision-making).

Adaptation can be machine-automated to some extent, but perhaps of equal importance, active decision-making by key actors such as students and teachers can be empowered by technology with more timely and targeted information such as critical feedback on performance and comparative standing in relationship to a cohort. Assessment that is self-sought, self-discovered and self-controlled suggests a strong role for technology as a disinterested but trustworthy provider of information; some have called this ‘quiet assessment’ (Webb & Gibson, 2015) recognizing the empowering position of self-determination and the role of AI and technology as a helpmate to a decision-maker (Ifenthaler, Greiff, & Gibson, 2018).

5. There is a need to apply and advance educationally relevant research-based knowledge to:
- *engage key stakeholders of learning (e.g. students, parents, teachers, school leaders)*
- *create and ethically use rich data models and methodologies to advance learning*
- *integrate instructional theory, design and delivery with analytics data and insights*
- *safeguard security, privacy and control of data*
- *understand the impacts of combining data types from all sectors (health, socio-emotional, SES, etc.) on interactions with the individual*
- *enhance data interoperability with standardized measures*
- *confirm the logic and research models used by technology companies developing educational software*

With large data sets becoming more available to teachers, learners and other stakeholders, some important issues are: who owns these data, which data are available to which users and for what purposes, as well as to the public and which are private?

Some teachers now use data to inform their practice. Their learners may have access to analytics performance information that may help them set their own pace and objectives. However, education institutions have different practices around data sharing and use. Whilst some institutions, for example, allow commercial providers to access data, the level of trusts in sharing data between institutions and providers, vary (Klein, Lester, Rangwala & Johri, 2019).

In a case study with 3,550 learners as well as linked follow-up studies (Ifenthaler, Gibson, & Zheng, 2018), navigational sequences and network graph analyses demonstrate the potential of learning analytics design by showing the most-used paths, characterizing path and learning affordance simplicity-to-complexity and the topological structure of the learning environment, and limiting the boundary of all possible paths of learning afforded by the problem space. Even with open-ended freedom of choice by learners in the initial study, only 608 sequences out of hundreds of millions of possible sequences were evidenced by learners. More recently, network analyses by the research team have led to new metrics of team collaboration by situating generic network measures in the specific context of collaborative teamwork in structured problem spaces.

Positive evidence has also been found on the use of learning analytics to support study success, but there is still a need for more evidence concerning the link between learning analytics and intervention measures to facilitate study success (Ifenthaler, Mah, & Yau, 2019).

It is also possible to automate certain features of the process of collection, identification of patterns, and creating options and adaptations. For example, in a game-like design, feedback can be nearly real-time by embedding response pathways and feedback about learner decisions into the digital code itself without resorting to deeper levels of analysis that require more time to collect and evaluate. What are the risks as well as the opportunities here?

Studies are also emerging that examine how instructors and students feel about various analytics opportunities, and find that people possess and base judgments on expectations concerning learning (e.g., one must remember and perform on one’s own without scaffolds) as well as teaching (e.g., too much scaffolding coddles learners) (Howell, Roberts, Seaman, & Gibson, 2018).

Possible actions to overcome misalignment

As new methods and models for data analysis and data representation (e.g., advanced statistics, dashboards, graphical visualizations for learner paths, semantic graphs or social networks, timing diagrams, etc.) continue to be elaborated and put to use, it is critical that stakeholders are enabled to understand the methods and models in order to know what is involved and to act consequently. To enable effective action, related literacies, in particular graphicacy and educational data literacy should be promoted. Educational data literacy is understood as the ethically responsible collection, management, analysis, comprehension, interpretation, and application of data from educational contexts (Sampson, et al., in press). Additional actions can be summarized as follows:

- Global differences in learning analytics impact uses, meanings, and methods.
- Advancing educational research is needed for analytics theory and methodology.
- Bridging data science and learning science requires improved frameworks as well as multidisciplinarity research and practice.
- Forms of collaboration and knowledge transfer with technology industry need to be proactively and critically developed and evaluated by the education sector.

Key insights from other TWGs

With reference to TWG4 (State of the art in thinking about machine learning – implications for education), learning analytics are closely linked to approaches of machine learning, as it is regarded as a way for computers to learn from data - for example detecting patterns, classifying data and making predictions. In addition, TWG10 (New paradigms for researching digital technologies: achieving scalability and sustainability) identified a need for research to identify how new research approaches are able to usefully inform sustainability and scalability of technological innovations, through continuous analysis and evaluation of what works for whom.

Strategies and actions

TWG6 recommends the following actions for policy makers (PM), researchers (R) and practitioners (PR) with each strategy linked to the corresponding challenges identified above (see Figure 1):

In order for evidence-based practice to be led by analytics:
• Develop learning analytics policy that focuses on leadership, professional learning, enabling mechanisms, and data governance. (PM, R)
• Ensure open access to resources and best practices is needed. (All)

To promote the adoption of learning analytics:
• Develop standards, guiding principles and policies as well as best practices for the use of learning analytics (PM)
• Enable organizational change to support stakeholders to utilize learning analytics for learning. (PR)

To inform and guide data services providers and users:
• Promote trustworthy, ethical quality assurance through mechanisms such as standards, accreditation processes, audits and recommendations and procurement requirements. (PM)
• Promote sustainability and scalability, for example via embedded and just-in-time services. ®

To impact learning via analytics tools:
• Ensure educationally relevant data literacy levels (knowledge, understanding and capacity for decision-making) of all stakeholders is raised. (All)
• Provide specific analytics tools for different stakeholders (user and age groups, learning levels), using evidence informed context and impact insights. (All)

To leverage the relationship between instructional design and learning analytics, and to extend to course and curriculum analytics, e.g. via AI:
• Use learning analytics to inform the advancement of instructional design for quality learning, teaching and assessment. (R, PR)
• Enable multidisciplinary and participatory research for quality assurance as well as for keeping pace with the technology lifecycle of enabled learning environments. (All)

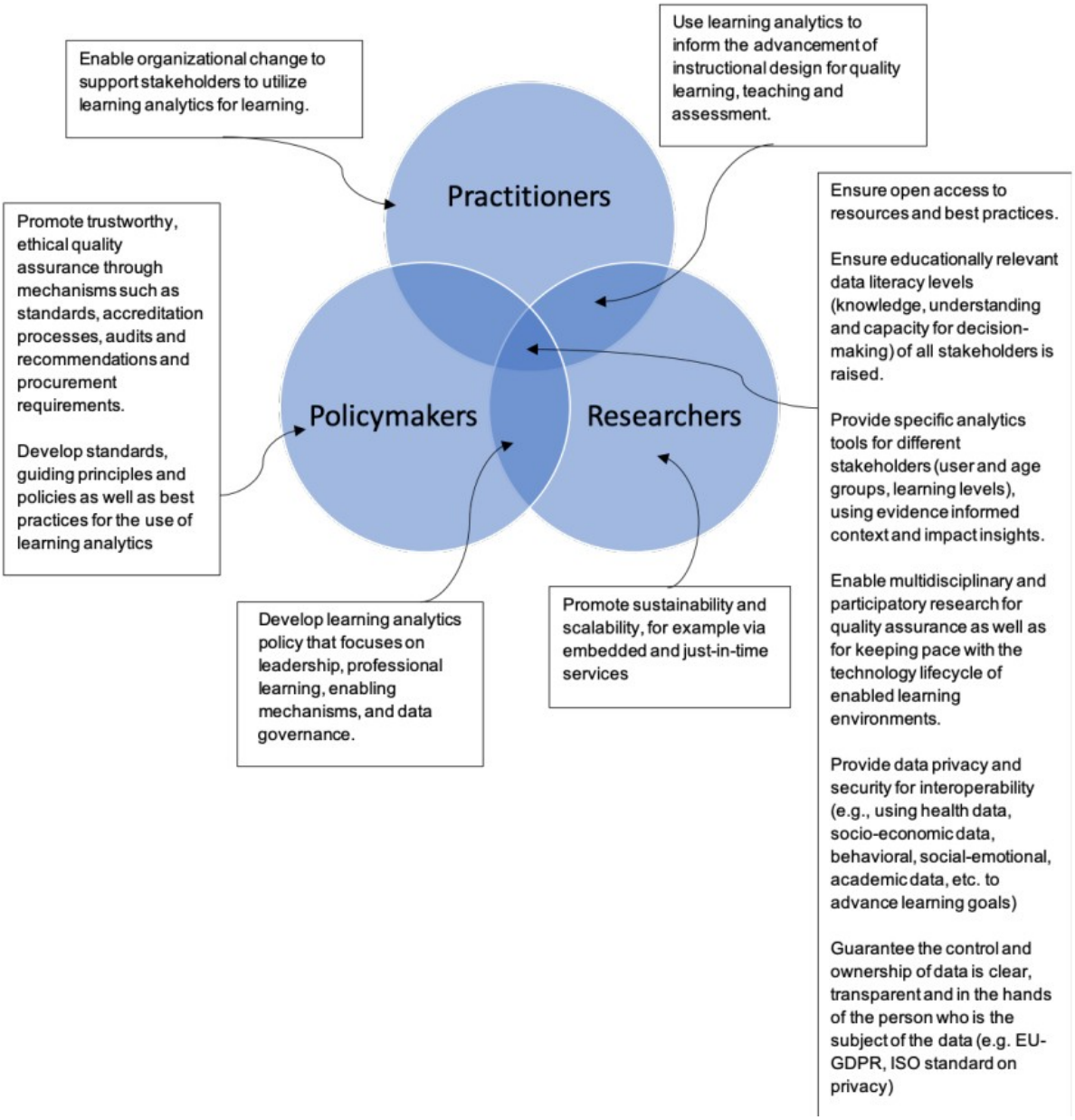

Figure 1. Actions for policy makers, researchers, and practitioners

To understand the impacts of combining data types from all sectors (health, socio-emotional, SES, etc.) on interactions with individuals; improving data models and leveraging AI and related technologies.

• Provide data privacy and security for interoperability (e.g., using health data, socio-economic data, behavioral, social-emotional, academic data, etc. to advance learning goals) (All)

• Guarantee the control and ownership of data is clear, transparent and in the hands of the person who is the subject of the data (e.g. EU-GDPR, ISO standard on privacy) (All)

Actions from the TWG

The members will be invited to co-author a journal-length article based on the group's process, deliberations and outcomes from EDUsummIT 2019. Members are invited to utilize the outcomes of the meeting at conferences and to make presentations that include the group's ideas. The group is planning a symposium at the EdMedia Conference (Amsterdam, June 2020) to disseminate the work linked to outcomes of other TWGs.

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