EDUsummIT 2019

Thematic Working Group 6

Putting learning back into learning analytics: optimizing learning through analysing the data

Group co-leaders

David Gibson (Curtin University), Dirk Ifenthaler (University of Mannheim and Curtin University), Jonathan San Diego (King's College London)

Contents

1. TWG6 Research Plan

TWG6: Putting learning back into learning analytics: optimizing learning through analysing the data

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Brief description of the theme’s focus, rationale and scope

To target the outcomes of data systems is a new challenge for computer scientists and engineers as well as educators. 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/enabled assessment (e.g. concept maps) be ensured and what are the risks associated with data use for promoting students’ achievements? The group will discuss how learning analytics can influence policy and teaching practices.

Objectives

1. To review recent research and innovations in learning analytics and their link to optimizing learning in order to identify key issues and trends in policy and practice.
2. Showcase best practice deployment of learning analytics in organisations.
3. To examine the potential for further development and innovation in learning analytics.
4. To make recommendations for policy, practice and research.

Expected Outputs

1. Discussion paper–background paper which will form the basis of discussion at the EDUSummIT 2019.
2. Develop/adapt an instrument focussing on the current state of learning analytics.
3. Article for Journal special issue.
4. Further articles and conference presentations after EDUSummIT 2019 to be decided.

Procedures and Means of communication within the group

Activity	**Timeline/ Deadline**
Group members to identify 5 trends *and/or* institutional practice related to learning analytics and circulate via email.	15 May 2019
Group co-leaders will collect the trends and build a priority list.	20 May 2019
Group members to provide 3 most relevant literature resources with brief resume of their focus and relevance.	10 June 2019
Group members to provide examples/cases/empirical studies focussing on the priority list	30 June 2019
Discussion of issues emerging from collected material and finalising the material into EDUsummIT discussion paper.	31 July 2019
Group co-leaders do final edit of EDUsummIT discussion paper.	01 August 2019

Suggested Reading

Gibson, D. C., & Ifenthaler, D. (2017). Preparing the next generation of education researchers for big data in higher education. In B. Kei Daniel (Ed.), *Big data and learning analytics: Current theory and practice in higher education* (pp. 29–42). New York, NY: Springer.

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 447–451). Thousand Oaks, CA: Sage.

Ifenthaler, D., Yau, J. Y.-K., & Mah, D.-K. (Eds.). (2019). *Utilizing learning analytics to support study success*. New York, NY: Springer.

2. TWG6 findings of activities

Priority list of trends identified by the group members

The following trends represent a priority list which have been identified by the TWG6 members.

- Dashboards and visualisation for learning and teaching; adaptive and real-time systems; assessment analytics
- Evidence-based practice through analytics; educational data literacy
- Relationship between instructional design and learning analytics; course and curriculum analytics; AI and learning analytics
- Combining different data types; data model; standardised variables; AI and methodology
- Role of vendors in analytics solutions; adoption of analytics systems

Resources based on the priority list of trends

The following resources represent a collection of identified papers focussing on the priority list of trends. For each resource, a citation and short description is listed below.

Atsushi Shimada, Shin'ichi Konomi, Hiroaki Ogata, (2018) "Real-time learning analytics system for improvement of on-site lectures", Interactive Technology and Smart Education, Vol. 15 Issue: 4, pp.314-331.

The purpose of this study is to propose a real-time lecture supporting system. The target of this study is on-site classrooms where teachers give lectures and a lot of students listen to teachers' explanations, conduct exercises, etc. The proposed system uses an e-learning system and an e-book system to collect teaching and learning activities from a teacher and students in real time. The collected data are immediately analyzed to provide feedback to the teacher just before the lecture starts and during the lecture. For example, the teacher can check which pages were well previewed and which pages were not previewed by students using the preview achievement graph. During the lecture, real-time analytics graphs are shown on the teacher's PC. The teacher can easily grasp students' status and whether or not students are following the teacher's explanation. Through the case study, the authors first confirmed the effectiveness of each tool developed in this study. Then, the authors conducted a large-scale experiment using a real-time analytics graph and investigated whether the proposed system could improve the teaching and learning in on-site classrooms. The results indicated that teachers could adjust the speed of their lecture based on the real-time feedback system, which also resulted in encouraging students to put bookmarks and highlights on keywords and sentences.

Xinyu Fu, Atsushi Shimada, Hiroaki Ogata, Yuta Taniguchi, Daiki Suehiro, (2017). "Real-time learning analytics for C programming language courses", 7th International Learning Analytics and Knowledge Conference, pp. 280-288.

The purpose of this research is to present a tool to help identify the weaknesses of novice programmers in order to improve teaching materials supporting C education in the classroom. Many universities choose the C programming language (C) as the first one they teach their students, early on in their program. Students often consider programming courses difficult, and these courses often have among the highest dropout rates of computer science courses offered. It is therefore critical to provide more effective instruction to help students understand the syntax of C and prevent them losing interest in programming. To facilitate teaching and learning of C, this paper proposes a system-LAPLE (Learning Analytics in Programming Language Education)-that provides a learning dashboard to capture the behavior of students in the classroom and identify the different difficulties faced by different students looking at different knowledge. With LAPLE, teachers may better grasp students' learning situation in real time and better improve educational materials using analysis results. The error type visualization allowed us to characterize students' weaknesses in their understanding of C material. The real-time analysis supported immediate feedback, so that teachers were able to provide effective and timely explanation when they noticed the students who were in trouble.

Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends, 61*, 366-371. DOI: 10.1007/s11528-016-0154-0

This research aims to investigate the perception of the benefits, staff, and systems for learning analytics-related issues for academic institutes, based on learning analytics benefits for stakeholders such as learning designer based on the previous research. The research findings revealed three points;
Learning data such as learning time, learner's previous knowledge are regarded as important for stakeholders
Learning facilitator, students, and learning designer are top three benefit receivers of learning analytics
LMS manager and learning designer are common staffs who use learning analytics data, but many institutions did not set learning analytics specialist.

The relationships between learning analytics and instructional design model (e.g., ARCS model) should be clear, in order to improve instruction and learning environments. This research pointed out important issue for the point above. Learning analytics and instructional design should be integrated, however, it is very difficult for instructional designer (including learning designer?) to analyze learning data for the improvement of the instruction. Learning analytics specialist is hopefully set in academic institute for effective instructional design. (In Japan, learning designer and instructional designer is not common staff in academic institution and company)

Hernández-Leo, D., Martinez-Maldonado, R., Pardo, A., Muñoz-Cristóbal, J. A., and Rodríguez-Triana, M.J. (2019). Analytics for learning design: A layered framework and tools, *British Journal of Educational Technology, 50*(1), 139-152. DOI: 10.1111/bjet.12645

This research proposed three learning analytics layers framework for learning design (AL4LD) integrated with learning analytics perspective, reviewing the previous research. This framework consists of three layers; learning analytics for learners (e.g., investigation for the effects of learning design), design analytics for learning design tools (e.g., investigation for design decision), community analytics for teachers (e.g., investigation for co-design for learning). Authors applied this framework to actual practices. The results revealed that data-driven framework is effective on learning design, but the relationships between elements of three layers and learning performance and satisfaction should be investigated.

This is practical research. This research suggested that practical model for organizational learning analytics, in order to improve learning environments. Many researches tend to focus on the first or second layers, but interesting point of this research is to suggest the third layer: community analytics for teachers. The findings of this research seem to be useful for many universities to apply learning analytics results to their educational practices.

Thille, C. and Zimmaro, D. (2017), Incorporating Learning Analytics in the Classroom. New Directions for Higher Education, 2017: 19-31. doi:10.1002/he.20240

This research introduced the Open Analytics Research Service (OARS), that developed and distributed learning analytics dashboard for the improvement of instruction and learning environments. The dashboard provides the information about learning and its visualization results to teachers, students and so on. The dashboard has skill-map data, show the ratio of successful students who reached the learning objectives, and feedback to teachers and students.

This paper focuses on the visualization of the accomplishment and feedback to education-related stakeholders. Skill-map is one of important factors for instructional design, because it relates to goal setting of the instruction. This paper is very interesting, and gives us the importance of goal settings in order to visualize the learning data, but less explanation about the relationship with instructional design. Reading this article, the relationships between instructional design and learning analytics should be more focused.

Wei, J., Cutler, F., Macfadyen, L.P., & Shirazi, S. (2019) Implementation of Learning Analytics to Optimize Learning and Learning Environments: Tertiary Instructor Perspectives. In

Companion Proceeding of the 9th International Conference on Learning Analytics & Knowledge (LAK'19) (pp. 56-61).

The evolution of learning analytics (LA) systems and tools offers unprecedented opportunities to make use of insights from learning data to promote effective teaching and learning practices. However, a significant gap still exists between what is possible, and what is being applied in practice. Little is known about instructors' interests and concerns in relation to implementing LA for supporting classroom practices. This study aims to address the gap by identifying tertiary teachers' interests and concerns regarding the implementation of LA in teaching and learning. Interviews and surveys were used to collect responses from faculty members of a large research-intensive university. Findings reveal tertiary instructors' degree of familiarity with LA, and their attitudes to, interest in and concerns about using LA tools in various contexts. Discussions about how to take actions to enhance teaching and learning practices with the implementation of LA are provided.

Clark, E., Fineman, D., Kaushik, P., & Aguilar, M. (2019, February 20). People analytics and learning: Driving workforce development by delivering the right solution to the right people at the right time. Retrieved from https://capitalhblog.deloitte.com/2019/02/20/people-analytics-and-learning-driving-workforce-development-by-delivering-the-right-solution-to-the-right-people-at-the-right-time/

Insights about learning come not just from identifying the before-and-after change in a given behavior, or observations between a test and control group, but also from combining learning data, business data, and behavioral data and conducting robust statistical analyses to provide a multi-layer view of the issue and/or individual. Extending traditional learning analytics to include multiple data points provides more precise solutions both for the user and the vendor who is seeking better business outcomes by using learning analytics. Revealing view of how businesses are using learning analytics and provides a discussion point for us as to how other industries view and use the analytics and the need to add contextual data.

Holstein, K., McLaren, B.M., & Aleven, V. (2018). Student learning benefits of a mixed-reality teacher awareness tool in AI-enhanced classrooms, presented at International Conference on Artificial Intelligence in Education, London, 2018. AIED 2018: Artificial Intelligence in Education. (pp 154-168).

When used in K-12 classrooms, intelligent tutoring systems (ITSs) can be highly effective in helping students learn. However, they might be even more effective if designed to work together with human teachers, to amplify their abilities and leverage their complementary strengths. In the present work, we designed a wearable, real-time teacher awareness tool: mixed-reality smart glasses that tune teachers in to the rich analytics generated by ITSs, alerting them to situations the ITS may be ill-suited to handle. A 3-condition experiment with 286 middle school students, across 18 classrooms and 8 teachers, found that presenting teachers with real-time analytics about student learning, metacognition, and behavior had a positive impact on student learning, compared with both business-as-usual and classroom monitoring support without advanced analytics. Our findings suggest that real-time teacher analytics can help to narrow the gap in learning outcomes across students of varying prior ability. This is the first experimental study showing that real-time teacher analytics can enhance student learning. This research illustrates the promise of AIED systems that integrate human and machine intelligence to support student learning.

Ifenthaler, D., Mah, D.-K., & Yau, J. Y.-K. (2019). Utilising learning analytics for study success. Reflections on current empirical findings. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 27–36). New York, NY: Springer.

The success of learning analytics in improving higher education students' learning has yet to be proven systematically and based on rigorous empirical findings. Only a few works have tried to address this but limited evidence is shown. This chapter aims to form a critical reflection on empirical evidence demonstrating how learning analytics have been successful in facilitating study success in continuation and completion of students' university courses. We present a critical reflection on empirical evidence linking study success and LA. Literature review contributions to learning analytics were first analysed, followed by individual experimental case studies containing research findings and empirical conclusions. Findings are reported focussing on positive evidence on the use of learning analytics to support study success, insufficient evidence on the use of learning analytics and link between learning analytics and intervention measures to facilitate study success.

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. doi:10.1016/j.chb.2017.06.030

More and more learning in higher education settings is being facilitated through online learning environments. Students' ability to self-regulate their learning is considered a key factor for success in higher education. Learning analytics offer a promising approach to better support and understand students' learning processes. The purpose of this study is to investigate students' expectations towards features of learning analytics systems and their willingness to use these features for learning. A total of 20 university students participated in an initial qualitative exploratory study. They were interviewed about their expectations of learning analytics features. The findings of the qualitative study were complemented by a quantitative study with 216 participating students. The findings show that students expect learning analytics features to support their planning and organization of learning processes, provide self-assessments, deliver adaptive recommendations, and produce personalized analyses of their learning activities.

Ifenthaler, D., Gibson, D. C., & Dobozy, E. (2018). Informing learning design through analytics: Applying network graph analysis. *Australasian Journal of Educational Technology, 34*(2), 117–132. doi:10.14742/ajet.3767

Learning design has traditionally been thought of as an activity occurring prior to the presentation of a learning experience or a description of that activity. With the advent of near real-time data and new opportunities of representing the decisions and actions of learners in digital learning environments, learning designers can now apply dynamic learning analytics information on the fly in order to evaluate learner characteristics, examine learning designs, analyse the effectiveness of learning materials and tasks, adjust difficulty levels, and measure the impact of interventions and feedback. In a case study with 3550 users, the navigation sequence and network graph analysis demonstrate a potential application of learning analytics design. Implications based on the case study show that integration of analytics data into the design of learning environments is a promising approach.

Tufte, E. R. (1988). The visual display of quantitative information. *IEEE Power Engineering Review*. https://doi.org/10.1109/MPER.1988.587534

Tufte presents the data-ink ratio idea "Data-ink is the non-erasable core of a graphic, the non-redundant ink arranged in response to variation in the numbers represented." The classic book on statistical graphics, charts, tables. Theory and practice in the design of data graphics, 250 illustrations of the best (and a few of the worst) statistical graphics, with detailed analysis of how to display data for precise, effective, quick analysis. Design of the high-resolution displays, small multiples. Editing and improving graphics. The data-ink ratio. Time-series, relational graphics, data maps, multivariate designs. Detection of graphical deception: design variation vs. data variation. Sources of deception. Aesthetics and data graphical displays.

Echeverria, V., Martinez-maldonado, R., Shum, S. B., & Conati, C. (2018). Exploratory versus Explanatory Visual Learning Analytics : Driving Teachers ’ Attention through Educational Data Storytelling. *Journal of Learning Analytics*, (August), 37.

From a human-centred computing perspective, supporting the interpretation of educational dashboards and visualisations by the people intended to use them exposes critical design challenges that may often be trivialised. Empirical evidence already shows that 'usable' and visually appealing visualisations, or even visualisations that invite users to explore data, are not necessarily effective from an educational perspective. Since an educator's interpretation of visualised data is essentially the construction of a narrative about student progress, in this paper, we propose the concept of "Educational Data Storytelling" as an approach for explaining student data by aligning educational visualisations with the intended learning design. We draw on the growing body of work on data storytelling as the inspiration for a set of enhancements that can be applied to data visualisations to improve their communicative power. We present a pilot study that explores the effectiveness of these data storytelling elements based on educators' responses to prototypes, by analysing the kinds of stories they articulate, their eye-tracking behaviour and their preferences after inspecting a series of student data visualisations. The dual purpose is understanding the contribution of each visual element for data storytelling, and the effectiveness of the enhancements when combined. 1 NOTES FOR PRACTICE • The learning analytics field, to effectively support teaching and learning visually, needs to move on from visual analytics that invite to explore the data, to visualisations that explain insights. • In this paper we propose the concept of "Educational Data Storytelling" as an approach to design visual learning analytics interfaces that explain student data by aligning educational visualisations with the learning design intended by the teacher. • We see the potential of learning design driven data storytelling elements to support sensemaking by guiding students and teachers to "one learning story per visualisation", given that learning is a complex task. 1 An earlier, shorter version of this paper (Echeverria et al. 2018) is the foundation for this article, which has been extended in light of the feedback and insights at LAK 2018.

Reimann, P. (2016). Connecting learning analytics with learning research: the role of design-based research. *Learning: Research and Practice*, *2*(2), 130–142. https://doi.org/10.1080/23735082.2016.1210198

The potential to advance learning research is explored along four dimensions: (1) data quantity, (2) longitudinal data, (3) data from multiple levels, and (4) data from multiple locations. This is followed by a description of how design-based research as practised in the learning sciences can serve as a bridge to LA, and how it would transform LA into a methodology that is also useful for advancing theories and models of learning.

Chai, K., & Gibson, D. (2015). Predicting the risk of attrition for undergraduate students with time based modelling. *Proceedings of the 12th International Conference on Cognition and Exploratory Learning in the Digital Age, CELDA 2015*, 109–116. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-84961786619&partnerID=tZOtx3y1

The study evaluated different models for predicting student attrition at four different time periods throughout a semester study period: pre-enrolment, enrolment, in-semester and end-of-semester models. A dataset of 23,291 students who enrolled in their first semester between 2011-2013 was extracted from various data sources. Three supervised machine learning techniques were tested to develop the predictive models: logistic regression, decision trees and random forests. The performance of these models was evaluated using the precision and recall metrics. The model achieved the best performance and user utility using logistic regression (67% precision, 29% recall).

Vieira, C., Parsons, P., & Byrd, V. (2018). Visual learning analytics of educational data: A systematic literature review and research agenda. *Computers & Education*, *122*, 119-135.

This literature review paper emphasize the role of visualisation of data as a way to make LA more effective. Also, the authors stress the importance of combining visual analytics with sound pedagogies. They actually made assessment rubric for assessing articles, that was interesting. Challenge seem to be the lack of good studies conducted in classroom settings and many of studies were rather simple, using only one data. The point was that visualisation provide support especially when using and combining different large data sets. The point is also the need for collaboration between educational researchers and information visualisation experts.

Ferguson, R., & Clow, D. (2017). Learning analytics: Avoiding failure. *Educause Review Online*, *31*.

Factors that need to be considered when integrating LA. Basically the role of managers, strategic level, capacity building and ethics align with all new pedagogical or technological integration ideas. Still, the paper provides a good background concerning the topics that need to be considered.

Vieira, C., Parsons, P., & Byrd, V. (2018). Visual learning analytics of educational data: A systematic literature review and research agenda. *Computers & Education*, *122*, 119-135.

This article presents a systematic literature review of the emerging field of visual learning analytics. They review existing work in this field from two perspectives: First, they analyze existing approaches, audiences, purposes, contexts, and data sources—both individually and in relation to one another— that designers and researchers have used to visualize educational data. Second, they examine how established literature in the fields of information visualization and education has been used to inform the design of visual learning analytics tools and to discuss research findings. They characterize the reviewed literature based on three dimensions: (a) connection with visualization background; (b) connection with educational theory; and (c) sophistication of visualization(s). The results from this systematic review suggest that: (1) little work has been done to bring visual learning analytics tools into classroom settings; (2) few studies consider background information from the students, such as demographics or prior performance; (3) traditional statistical visualization techniques, such as bar plots and scatter plots, are still the most commonly used in learning analytics contexts, while more advanced or novel techniques are rarely used; (4) while some studies employ sophisticated visualizations, and some engage deeply with educational theories, there is a lack of studies that both employ sophisticated visualizations and engage deeply with educational theories. Finally, we present a brief research agenda for the field of visual learning analytics based on the findings of our literature review.

3. TWG6 discussion paper

Putting learning back into learning analytics: optimizing learning through analysing data

Group co-leaders: David Gibson (Curtin University), Dirk Ifenthaler (University of Mannheim and Curtin University), Jonathan San Diego (King's College London)

Thematic Working Group 6 (TWG6) will examine how learning analytics tools, practices and policy can ensure a focus on the processes of learning. A focus on processes is critical because any summative information at any level of a dynamic education system (individual, classroom, school, region) will be a snapshot of more important ongoing progressions on a continuum of change. Change over time, not a static picture, is the living signature of adaptive behaviours of both individuals and organizations; so an emphasis on dynamics in a complex context is needed in order to ensure that emerging technology-enhanced capabilities and data science methods can be used to enhance without hindering learning.

TWG6 will also examine how researchers, practitioners and policy makers around the world can cope when inevitable conflicts arise between competing purposes of using big data and data science methods in an educational setting; for example to reward teachers, monitor learning progress, gain data needed for decision-making, or classify levels of achievement in balance with seeking to enhance learning. In addition, considering the many possibilities of using smart approaches with big data (e.g., artificial intelligence in educational operations, process automation, automated mentoring, teaching and analytics) the group aims to explore how to prioritize personalized learning at scale ahead of seeing what structures of schooling are needed to support any required transformation of educational systems.
The potential for conflict arises because the impacts of data systems and data science methods in education presents a relatively new, complex and multidisciplinary challenge that requires computer scientists, engineers, learning scientists and educators to work together to achieve outcomes for a wide variety of purposes (Gibson & Ifenthaler, 2017). However, in the key area of assessing students and taking actions, the impacts of some purposes interfere with the validation processes of others for example, classifying and ordering students versus helping them to learn. For instance, a summative judgment of a learner is a snapshot in time, yet the student may be continuously learning and improving. But not only can student datasets be used for both formative and summative assessments, entailing conflicts between helping and judging students, there are also issues of privacy and usability which are growing concerns, since informed consent and responsive inference and sensitive action on data requires both a level of awareness and a high level of smart-data literacy.

Furthermore, the decision makers of educational systems are found at many levels of position, awareness and capacity, from the classroom to the executive boardroom of governing bodies. At each level legitimate concerns and responsibilities also can interfere with each other. A striking example in many countries is the impact of ‘league tables’ on the behaviour of system administrators who seek to maximize their score with shortcuts such as tracking certain students into untested subgroups or telling some students to stay home on ‘test day’ instead of creating the conditions for the score to be a valid measure of an improving context. Access to more detailed data will not address this kind of bias in a representation system, so what is needed in the policy arena? Since the impacts of public data can lead to unintended negative consequences at every level, what principles are there for helping to minimize this risk?

Thematic Working Group 6 has developed five themes of interest to the members, which the group will pursue at EDUsummIT 2019. In each of these themes the central question will be "*What tools, practices and policy are there to help ensure that a focus remains on the processes of learning*?"

1. Dashboards and visualization for learning and teaching; adaptive and real-time systems; assessment analytics

The ground-breaking work of Edward Tufte (Tufte, 1988) pointed out that visual representation has an essential core of information communicating the variation in the numbers represented and he cautioned visual communicators to control for graphical deception as well as superfluous visual information. Now, with cloud-based online data, on-demand analysis and increased topological power (e.g. graphs as data structures, network analysis) the role of visualization in scientific inquiry has expanded beyond communication to include the data-exploratory power of interactive graphical displays. The two features of 'real-time' and 'interactive' can be combined with automated analytics to bring new affordances to learners and teachers via dashboards with interactive visualizations.

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; Shimada, Mouri, & Ogata, 2017), student response systems for attention and engagement (De Grez, Valcke, & Berings, 2010; Gauci, Dantas, Williams, & Kemm, 2009; Heaslip, Donovan, & Cullen, 2014) and dashboards that visualize student progress and achievement (de Freitas et al., 2017; Roberts, Howell, & Seaman, 2017; Schumacher & Ifenthaler, 2018a; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013).

Game-based learning often adopts a dashboard approach to achieve transparency in progress and to empower decision-making by the user (Schrier, 2018). 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).

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. (Lehmann, Hähnlein, & Ifenthaler, 2014; Webb & Gibson, 2015). 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).

2. Evidence-based practice through analytics; educational data literacy

How should data inform practice? Who is prepared to analyse big data and who is the data analysed 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 (Ferguson, Buckingham Shum, & Shum, 2012; Kozleski, Gibson, & Hynds, 2012; Ifenthaler & Schumacher, 2016; Roberts, Chang, & Gibson, 2017). This implies a need for a level of literacy to be achieved by all actors 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 (Blei & Smyth, 2017; Gibson, 2012) and 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 and what feedback and monitoring of learning might students expect from learning analytics?

3. Relationship between instructional design and learning analytics; course and curriculum analytics; AI and learning analytics

Learning analytics can provide three kinds of information to students and teachers: summative, real-time, 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*' that is, learning 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).

In a case study with 3,550 users as well as linked follow-up studies (Ifenthaler et al., 2018; Ifenthaler, Gibson, & Zheng, 2019; 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 (Kerrigan, Feng, Vuthularu, Ifenthaler, Gibson, in press).

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; Schumacher & Ifenthaler, 2018b; Roberts, Howell, Seaman, & Gibson, 2016).

4. Combining different data types; data model; standardized variables; AI and methodology

One of the principles 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 (Pardo & Siemens, 2014; Roberts, Chang, et al., 2017; Willis, Quick, & Hickey, 2015). 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 (Ifenthaler, Eseryel, & Ge, 2012; Mislevy, Behrens, Dicerbo, Frezzo, & West, 2012; Shute & Ke, 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 who to re-unite features into more complex and dynamic pictures of learning progress and achievement.

How can fair uses of technology-led and enabled assessment (e.g. using concept maps and portfolios of evidence) be ensured and what are the risks associated with data use for promoting students' achievements?

5. Role of vendors in analytics solutions; adoption of analytics systems

With large data sets becoming more available to teachers and learners, who owns these data, which data are available 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 (Sclater, Peasgood & Mullan, 2016). However, education institutions have different practices around data sharing and use (Ferguson et al., 2016). Whilst other 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).

The United Kingdom's Joint Information System Committee has identified a list of learning analytics vendors (see https://docs.analytics.alpha.jisc.ac.uk/docs/learning-analytics/Suppliers-in-the-Framework). With the increasing number of education technology vendors providing learning analytics tools (Ferguson et al., 2016; Sclater, Peasgood & Mullan, 2016), and different individuals and groups are given access to data, risks associated with learning analytics, may include: privacy, data sharing with third parties and data protection breaches. These risks suggest that policies, guidance and training on learning analytics data sharing; and training on data literacy skills may need to be provided to education institutions, analytics vendors, teachers and learners.

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