Are Higher Education Institutions Prepared for Learning Analytics?

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Learning analytics may provide multiple benefits for higher education institutions and for involved stakeholders by using different data analytics strategies to produce summative, real-time and predictive insights and recommendations. However, are institutions and academic as well as administrative staff prepared for learning analytics? Considering a learning analytics benefits matrix, this study investigates the current capabilities for learning analytics at higher education institutions, explores the importance of data sources for a valid learning analytics framework, and builds an understanding on how important insights from learning analytics are perceived. Findings revealed a lack of staff and technology being available for learning analytics projects. It is concluded that more empirical research focussing on the validity of learning analytics frameworks and on expected benefits for learning and instruction is required to confirm the high hopes this promising emerging technology is suggesting.

Keywords: learning analytics, benefits matrix, higher education, readiness

Introduction

The NMC Horizon Report: 2014 Higher Education Edition (Johnson, Adams Becker, Estrada, & Freeman, 2014) identified learning analytics as a mid-range trend driving changes in higher education within the next three to five years. Learning analytics (LA) uses dynamic information about learners and learning environments – assessing, eliciting and analysing them – for real-time modelling, prediction and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). Promising LA applications are being developed which use learner generated data and other relevant information in order to personalise and continuously adapt the learning environment (Long & Siemens, 2011). LA is expected to provide the pedagogical and technological background for producing real-time interventions at all times during the learning process. Students will benefit from LA through optimised learning pathways, personalised interventions and real-time scaffolds. LA will provide instructors detailed analysis and monitoring on the individual student level, allowing to identify particularly instable factors, like motivation or attention losses, before they occur. Instructional designers use LA information to evaluate learning materials, adjust difficulty levels and measure the impact of interventions (Lockyer, Heathcote, & Dawson, 2013). LA will further facilitate decision-making on institution level and help to analyse churn and identify gaps in curricular planning (Ifenthaler & Widanapathirana, 2014).

However, are institutions and academic as well as administrative staff prepared for LA? The vast amount of available educational data requires flexible data mining tools and new statistical methods (Ifenthaler & Widanapathirana, 2014). Further, institutions need to develop and implement interactive data visualisations which provide students, instructors, instructional designers and administrators an overview of relevant information (Greller & Drachsler, 2012). Therefore, the purpose of this research is to explore the current state of LA in higher education and to help to identify challenges and barriers for applying LA.

Benefits from learning analytics

From a holistic point of view, LA may provide multiple benefits for higher education institutions and for involved stakeholders. Additionally, different data analytics strategies can be applied to produce summative, real-time and predictive insights. Table 1 provides a matrix outlining the benefits of LA for stakeholders using three analytics perspectives (Ifenthaler & Widanapathirana, 2014). However, it is not required to implement all features of the presented LA benefits matrix. Institutions need to carefully decide which features a LA frameworks shall include and provide the necessary infrastructure for a successful implementation.

Purpose of the study and research questions

The implementation of a LA framework following the matrix of LA benefits (see Table 1) requires specialised staff and technological capabilities (d'Aquin, Dietze, Herder, Drachsler, & Taibi, 2014). Given the emerging field of LA, staff as well as technological solutions are scarce. Therefore, the purpose of this study was threefold: 1) to investigate the current capabilities for LA at higher education institutions, 2) to explore the importance of various data sources for a valid learning analytics framework, and 3) to build an understanding on how important insights from LA using a summative, real-time and predictive perspective are perceived.

Table 1: Learning analytics benefits matrix

	Perspective		
Stakeholder	Summative	Real-time	Predictive
Governance	• Apply cross-institutional comparisons • Develop benchmarks • Inform policy making • Inform quality assurance processes	• Increase productivity • Apply rapid response to critical incidents • Analyze performance	• Model impact of organizational decision-making • Plan for change management
Institution	• Analyze processes • Optimize resource allocation • Meet institutional standards • Compare units across programs and faculties	• Monitor processes • Evaluate resources • Track enrollments • Analyze churn	• Forecast processes • Project attrition • Model retention rates • Identify gaps
Learning design	• Analyze pedagogical models • Measure impact of interventions • Increase quality of curriculum	• Compare learning designs • Evaluate learning materials • Adjust difficulty levels • Provide resources required by learners	• Identify learning preferences • Plan for future interventions • Model difficulty levels • Model pathways
Facilitator	• Compare learners, cohorts and courses • Analyze teaching practices • Increase quality of teaching	• Monitor learning progression • Create meaningful interventions • Increase interaction • Modify content to meet cohorts' needs	• Identify learners at risk • Forecast learning progression • Plan interventions • Model success rates
Student	• Understand learning habits • Compare learning paths • Analyze learning outcomes • Track progress towards goals	• Receive automated interventions and scaffolds • Take assessments including just-in-time feedback	• Optimize learning paths • Adapt to recommendations • Increase engagement • Increase success rates

Method

Design

In order to reach a large number of international higher education institutions, the principle means of data collection was an online survey which was conducted between August and October 2013. The survey was implemented on the Qualtrics platform (www.qualtrics.com). International listservs, forums, and social media channels focussing on educational technology and learning analytics were used to disseminate the link to the online survey.

Participants

The initial dataset consisted of 176 responses. After removing incomplete responses, the final dataset included 153 valid responses (21% female, 78% male, 1% indeterminate/intersex/unspecified). The average age of the participants was 44.68 years (*SD* = 9.10). 30% worked in a research position, 28% were research and teaching staff, 7% reported to be in a teaching position, 4% were in a senior management role, 1% reported to work in IT services, and 1% worked as library staff. 29% worked in other roles such as data analyst, statistician, or instructional designer. The majority of participants were located in the United States (28%) and Australia (19%). Other countries included United Kingdom (5%), Canada (5%), and the Netherlands (4%). 31% of the participants reported that they were currently involved in a project focussing on LA.

Instrument

The survey instrument consisted of the following sections: 1. Staff capabilities for learning analytics (7 items, Cronbach's α = .89), 2. Available technology for learning analytics (13 items, Cronbach's α = .98), 3. Barriers for implementing learning analytics (13 items, Cronbach's α = .93), 4. Importance of student data (9 items, Cronbach's α = .81), 5. Importance of learning environment data (13 items, Cronbach's α = .85), 6. Benefits from learning analytics for the institution (20 items, Cronbach's α = .93), 7. Importance of summative learning analytics (17 items, Cronbach's α = .93), 8. Importance of real-time learning analytics (17 items, Cronbach's α = .94), 9. Importance of predictive learning analytics (18 items, Cronbach's α = .94), 10. Personal background (6 items). Most items were answered on a five-point Likert scale (e.g., 5 = very important; 4 = important; 3 = undecided; 2 = not very important; 1= not at all important). It took approximately 15 minutes to complete the survey.

Data analysis

All data stored on the Qualtrics platform was anonymised, exported, and analysed using SPSS V.22. Initial data checks showed that the distributions of ratings and scores satisfied the assumptions underlying the analysis procedures.

Results

Capabilities for learning analytics

When asked about staff capabilities available for LA projects, over half of the participants reported that their institution had at least one learning management specialist (62.7%) and at least one learning designer (68.6%). Other staff capabilities available for LA projects included database analyst (41.2%), statistician (38.5%), and information management architect (22.9%). Only 25% of the participants reported that they had staff in the role of a learning analytics specialist.

When asked about available technology for LA, only a small number of participants reported that their institution had a data warehouse in place (19.0%), used data visualisation capabilities (19.0%), and practised automated data reporting (21.6%) as well as predictive analytics (28.1%). One out of four participants indicated that their institution had interactive dashboards available for students and facilitators (25.5%). Interestingly, several institutions already utilised natural language processing (26.8), automated discussion board analytics (26.1), automated essay scoring (27.5%), and social network analysis (24.2%).

Importance of data sources

In order to implement a valid LA framework, participants reported that it is important to have data sources from students available: socio-demographic data (94.1%), educational background (97.4%), learning history (85.0%), personal interest (92,8%), prior knowledge (95.5%), preferred learning strategies (79.7%), and computer literacy (90.2%). Less important data sources included social media preferences (18.3%) and social ties (18.9%).

A valid LA framework also requires data sources from the learning environment (e.g., learning management system). Participants rated the importance of data sources as follows: use of learning materials (99.3%), discussion activity (92.1%), content navigation (92.2%), assessment results (98.7%), learning time (94.8%), use of external materials (89.6%), expected learning outcomes (98.1%), course difficulty level (94.7%), evaluation results (90.9%), expected learning paths (93.5%), and interaction of facilitators (96.1%). The location of learning was not regarded as being highly important (18.3%).

Perceptions of learning analytics insights

The three most important summative insights from LA reported by participants of the study were tracking student's progress towards goals (99.3%), understanding of student's learning habits (98.0%), and analyse student's learning outcomes (98.7%). The most important real-time insights from LA included modifying content to meet students' needs (96.7%), providing students with assessment including real-time feedback (98.0%), and creating meaningful interventions for students (98.0%). Participants rated the following insights from predictive LA being most important: increasing student's engagement (98.0%), increasing student's success rate (98.7%), and modelling student's success rate (98.0%). Overall, participants reported that facilitators (96.0%) would benefit most from LA at their institution followed by students (95.4%) and learning designers (95.1%). The least benefits were expected for finance (15.0%) and facilities services (9.2%).

Discussion and conclusions

LA draws on an eclectic set of methodologies and data to provide summative, real-time, and predictive insights for improving learning, teaching, organisational efficiency and decision making (Lockyer et al., 2013; Long & Siemens, 2011). While the field of LA is receiving much attention for its capacity to provide lead indicators of student failure, it has to date focused on individual courses in isolation of the capabilities of higher education institutions.

The findings of this work-in-progress study revealed a lack of staff being available for learning analytics projects. Specialised staff with a strong background in learning and teaching as well as data science are scarce. Similar, the findings clearly indicate that higher education institutions do not have the necessary technology available to implement valid LA frameworks. Accordingly, the high staff and technology requirements for LA frameworks can only be met by a small number of higher education institutions (Greller & Drachsler, 2012). Findings about the importance of data sources being relevant for a valid LA framework indicated that most of information from students and learning environments are perceived as equally important. Hence a current challenge for establishing LA frameworks is the interpretation of analysis results against the educational setting and its contextual idiosyncrasies (Coates, 2010). In other words, variables and indicators can carry different meanings and can therefore have different implications.

This work-in-progress study has its obvious limitations which need to addressed. The nature of self-report data and the small sample size from a LA-aware group need to be considered when interpreting the results. Accordingly, future research shall provide further empirical evidence regarding the capabilities of higher education institutions for implementing LA frameworks. More importantly, the effectiveness of LA frameworks for improving learning and teaching needs to be addressed by rigorous empirical research. Last, questions about ownership of data and data security need to be critically reflected on national and international scale (Pardo & Siemens, 2014).

To conclude, more educational data does not always make better educational data (Greller & Drachsler, 2012). LA has its obvious limitations and data collected from personal and educational sources (can) have multiple meanings. More importantly, empirical research focussing on the validity of LA frameworks and on expected benefits for learning and instruction is required to confirm the high hopes this promising emerging technology is suggesting.

References

Coates, H. (2010). Defining and monitoring standards in Australian higher education. *Higher Education Management and Policy, 22*(1), 41-58.

d'Aquin, M., Dietze, S., Herder, E., Drachsler, H., & Taibi, D. (2014). Using linked data in learning analytics. *eLearning Papers, 36*, 1-9.

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Educational Technology & Society, 15*(3), 42-57.

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

Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning, 19*(1-2), 221-240. doi: 10.1007/s10758-014-9226-4

Johnson, L., Adams Becker, S., Estrada, V., & Freeman, A. (2014). *NMC Horizon Report: 2014 Higher Education Edition*. Austin, TX: The New Media Consortium.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439–1459. doi: 10.1177/0002764213479367

Long, P. D., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 31-40.

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*. doi: 10.1111/bjet.12152

Ifenthaler, D. (2015). Are Higher Education Institutions Prepared for Learning Analytics? In T. Reiners, B.R. von Konsky, D. Gibson, V. Chang, L. Irving, & K. Clarke (Eds.), *Globally connected, digitally enabled*. Proceedings ascilite 2015 in Perth (pp. 471-475).

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