RISK MITIGATION IN THE AGE OF LEARNING ANALYTICS

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1. ABSTRACT

Despite rapid growth, the deployment of LA is still fragmented, and there is limited evidence of success available. This fragmentation decreases the visibility of results and experiences and amplifies possibilities for duplication in effort. Fragmentation and the bias of researchers to publish only successful studies increases the likelihood that we do not take into account lessons learned from failure and thus duplicate our efforts around mitigating actions. We should be highly motivated to decrease failure as it costs, the prime example being the Inbloom disaster, which impacted on many tens of thousands of students.

To structure this debate, we review the currently available frameworks that support the deployment of large-scale LA infrastructure and define a strategy of curation of a global risk mitigation matrix (risks vs mitigative actions). We show how a risk mitigation matrix can be attached to any deployment framework improving both the framework and the quality of the matrix. Finally, based on hackathons, to kick off curation, we suggest a series of interconnected workshops to facilitate the take-up this methodology to generate a periodic strategy document with associated top ten list of mitigations.

2. INTRODUCTION

The European Commission is convinced that within the next decade big data will have a remarkable impact on monitoring education (Berendt et al., 2017), on learning processes and the IT infrastructures that support teachers and students, specifically and through the means of Learning Analytics (LA). However, to balance expectations, Ferguson et al., (2016) noted that: "*The evidence shows that the use of learning analytics to improve and to innovate learning and teaching in Europe is still in its infancy. ... though the work across Europe on learning analytics is promising, it is currently fragmented" (p. 8).*

Deployment of complex systems, which not only include an IT aspect but also learning practices are complicated and at times risky. Fragmentation decreases visibility and we may not take into account lessons learned from failure. Failure comes with high costs, the prime example being the Inbloom disaster where a 120 million dollar project was shutdown due to the concerns of parents that Inbloom shared their children's data without consent with third parties (Inbloom shuts down, 2014).

On top of the problems of deploying large IT projects, three primary areas of concern exist specific to LA:

1. ***Organisational culture***: LA and the underlying notion of data driven education is a relatively new phenomenon, and it is not yet a stable building block of many educational organisation's culture. Ferguson, Macfadyen, Clow, Tynan, Alexander & Dawson (2014) noted that: *"institutions are stable systems, resistant to change"* (p. 120), which resistance is embedded in their organisational structure and culture. For instance at the University of Amsterdam, as many as sixteen stakeholder groups have the right to stop any central data warehouse project (Szorenyi, 2014). Teachers also have legitimate concerns, Griffiths (2013) noted that *"analytics techniques have the potential to disturb the balance*

between educational managers and the practice of teaching professionals, by extending the ability of the former to gather and process information about the latter" (p. 18). This power by its very nature empowers managers to score teachers and change the balance in their relationship. Various stakeholder groups' view on LA within an organisation should be facilitated by a common vision towards teaching and learning and driven by the organisational culture.

2. ***Learning practices should be in the focus and not technology***: There are concerns that we do not place learning sciences into leader positions in LA projects resulting in design and structures that are not relevant in the learning context. In their aptly named paper *Let's not forget:* ***Learning analytics is about learning****,* Gašević, Dawson & Siemens (2015) noted that "*the computational aspects of learning analytics must be well integrated within the existing educational research*" (p. 64). The risk to the field is that researchers focus on developing Machine Learning strategies for analysing data without understanding the theory and impact of the intervention strategies and their effect on the learner. Gašević, Dawson, Rogers & Gašević, (2016) in their study of nine undergraduate courses noted that "*it is imperative for learning analytics research to account for the diverse ways technology is adopted and applied in course-specific contexts*". However, at the architectural level, if we take into account only the IT-specific requirements we will doom students to complex systems out of the context of their learning experience.
3. ***Privacy and ethical and legal issues***: Privacy, legal and ethical issues have slowed the rate of large-scale deployments of LA. Even though the field is working its way through the legal and ethical issues around the use of personal data (see the ethics and privacy workshop series of LAK18, and LSAC2017 (Drachsler et al (2015), Kismihók et al (2017)), major risks arising from poor management of user expectations. The prime example being the above mentioned Inbloom disaster (sharing children's data without consent with third parties (Inbloom shuts down, 2014)). Therefore, given the backdrop of interest, researchers having spent considerable effort developing frameworks and discussing at workshops the issues to establish codes of practice (Drachsler, & Greller, 2016; Slade, & Prinsloo, 2013; Sclater, 2016; Ferguson, Hoel, Scheffel, & Drachsler, 2016; Engelfriet, Manderveld & Jeunink, 2015). Furthermore, at the time of writing (early 2018) the European Data Protection (GDPR) law is about to be enforced and is impacting on the way (not only) universities view the risk and benefit of campus-wide applications that involve Personally Identifiable Information[1]. Hoel, Griffiths & Chen (2017) described a multitude of impacts of the GDPR legal framework on the design of LA infrastructures. They described the design implications of governance processes associated with the rights of students with relation to their data. Their rights include the right to be informed, to access, to rectification, to erasure, to restrict processing, to data portability, to object. Thus, universities are required to design in accountability and governance including, breach notifications, control over where the data is transferred. Clearly, these ethical constraints will result in an intimate entanglement with the architecture required to govern the data processing.

Based on the authors' experience within the UvAInform program[2], an interlocked set of LA pilots aimed at delivering consensus around LA at the University of Amsterdam, the work on the Apereo Learning Analytics[3] Initiative and organising LA hackathons (Cooper, Berg, Sclater, Dorey-Elias, & Kitto, 2017; Berg, 2018), there are three main approaches to deployment of LA projects:

1. **Bottom-up:** The organisation allows projects to grow based on bottom-up demand organically. For example, different faculties at a university build tools and when a particular tool is found to be useful it is scaled at the campus level. Project teams learn by doing, and the results are inconsistent in quality with risks such as addiction to a particular commercial product followed by lockin or increased failure levels. This approach is the

[1] For a thorough introduction consider reading the Information Commissioner's Office GDPR Overview. (2017).

[2] https://lasiutrecht.files.wordpress.com/2014/06/uvainform-presentation-lasi-utrecht-2014.pdf

[3] https://www.apereo.org/communities/learning-analytics-initiative

riskiest, but the easiest to initiate. There is little need for leadership, and the initial resourcing is limited.

2. **Top Down:** Listen to the organisation's needs and apply an existing framework relevant to those needs. Focus resources on the areas that the framework consider essential. This approach is the least risky. However, this top-down approach will most likely to work in organisations that have strong leadership, well-established communication channels across the different entities within the organisation, and stakeholders that are not too numerous and do not have conflicting interests. Due to these preconditions, the risks are already to a significant degree mitigated.
3. **Up and Down:** The middle ground is a set of interlocking proof of concept projects at different faculties within a university. This approach allows staff to train up and leadership to feel there way into the priorities. However, due to a large number of stakeholders, the program may fall into conflict, a cultural problem avoided by stronger leadership and clear goals.

Guiding frameworks for LA deployment are helpful mostly within the context of top down management. These frameworks help organisations to become aware of their strengths and weaknesses and from this awareness accurately target resources. However, to be usable in a number of different contexts, frameworks often cover only general issues and lack specificity. For an example of the general nature of the advice, consider reviewing the Delicate framework by Drachsler & Greller (2016).

Ferguson, Macfadyen, Clow, Tynan, Alexander & Dawson (2014) described the experiences of the Open University (OU) UK with real uses with real data and placed the process of large scale deployment within the ROMA framework (Young & Mendizabal, 2009), that structures the effort into seven broad themes:

1. Define policy objectives
2. Map the context
3. Stakeholder analysis
4. Define the purpose of Learning Analytics
5. Create an articulated strategy
6. Analyze capacity and then develop the human resources necessary for the mission.
7. Evaluate through the means of monitoring and learning system

In case an organisation knows that it will deploy a data-driven process that it is vital to develop human capital, (process 6) and involve that capital in defining policy objectives, (process 1). Without direct feedback between the definition of policy with the staff that are trained, the organisation is at risk of outsourcing their decision making to those who do not understand the educational context of new LA services.

In recognition of the holistic nature of the technical and cultural aspects of universities resistance to the large scale deployment of LA, Arnold, Lonn and Pistilli (2014) developed the Learning Analytics Readiness Instrument. The instrument is a survey of 90 questions split into five areas'; (1) Ability, (2) Data, (3) Culture and Process, (4) Governance and Infrastructure, and, (5) Overall Readiness Perception. By making the organisation aware of its strengths and weaknesses via visual and textual feedback based on the survey, the organisation can better focus resources and plan to mitigate weak points. Also, at the level of individual tools, Scheffel (2017) has developed an evaluation framework based on concept mapping structured feedback from LA domain experts.

Due to the rapid expansion in LA investments, the co-related expectations and the maturity of the field, umbrella educational authorities should invest in the understanding and mitigation of reproducible risk in relation to LA. The debate around failure has already begun but needs more structure: Failathon workshops are organised at the LAK conferences (Clow et al., 2016; Clow et al., 2017). The stated aim of these failathons is to discuss individual experiences of failure in LA and explore how the field can improve, particularly regarding the creation and use of evidence[4].

Despite the complexity and lack of publication of a universal set of failure paths, practitioners have made great strides in standardising, benchmarking and scaling infrastructure. Examples are Course Signals (Arnold & Pistilli, 2012), Analytics4Action (Rienties et al., 2016), PAR framework (Ice et al., 2012) and the JISC National Infrastructure (Sclater, Berg & Webb, 2016). The JISC infrastructure is maturing rapidly, becoming well documented and has included substantial elements from the open Apereo Learning Analytics Initiative (Apereo, 2017), which is available to all to review, re-use and co-development by anyone interested. SoLAR's Open Learning Analytics framework, OLA (2014) profoundly influenced the design of Apereo LAI and thus JISC. SoLAR's design strives towards the enlightened goal of an open and modularised platform to enable plug and play with many LA related sources of services.

As part of the deployment of large-scale LA infrastructures to help focus organisations, JISC consultants provide services to inform awareness and collect risks and their mitigations. Using their methodology to manage risks a general pool of risks can be clustered into a pool and shared across the LA community. This pool will not only provide practical examples of mitigations for practitioners but also increase the quality of the mitigative actions and would also highlight gaps in current research. Therefore in this paper we want to shed light on 1) How can we link risk mitigation to existing LA deployment frameworks? And 2) How can we systematically limit the number of risks associated with the deployment of LA?

In the next section, we will discuss the risk mitigation matrices, followed by results from exercises at 12 Universities and colleges within the UK as part of the implementation of the JISC national LA infrastructure, which is supported by PhD research on the deployment of LA by the principal author.

3. RISK MITIGATION MATRICES

Risk matrices are simple methods to define and ranks risks associated with a structured process. They are widely used in management (usually in the area of supply chain management) or in areas where hazard is often occur, like in military, natural hazards, chemical production or health care. As defined by Markowski and Mannan, (2008, p152) *"A risk matrix is a mechanism to characterize and rank process risks that are typically identified through one or more multifunctional reviews (e.g., process hazard analysis, audits, or incident investigation)"*. A risk mitigation matrices are also commonly used within large scale IT projects to make aware and rank risks (Xiaosong et al., 2009).

Garvey and Lansdowne (1998, p18) describe the original risk matrix with seven properties: 1, Requirements, 2, Technology, 3, Risks, 4, Impact, 5, Probability of Occurrence, 6, Risk rating and 7, Manage/Mitigate. In their paper they also introduce a voting method for deciding on ranking of critical risks and also a tracking method for risk mitigations. The original risk matrix approach methodology has several variations according to disciplines and also extensions were introduced in the past (Ni et al, 2010).

Within the context of LA, some researchers and experts develop frameworks for deployments, and there are many LA related projects with little communication of risk between them however internal to their projects generate the raw material such as output from workshops from stakeholders. To create a global risk matrix requires methods to increase the visibility of the catalogues of risks being inventoried by consultants during the deployment of LA projects and their linking to frameworks. We should also be interested in the priorities of risk mitigation, not at any individual organisation, instead, as the collective preferences from all the institutions. One would naturally expect the global and continental top risks to evolve as rapidly as the field itself.

[4] The fact that failathon's exist is evidence enough that there is an acknowledged bias in research against publishing failures.

We, therefore, have two main aspects to address; the first is the workflow around connecting risks collected by consultants as LA projects are deployed to a set of researched risk mitigation strategies and two the process of advertisement of a Global risk matrix, and it's curation.

For this paper, we follow Xiaosong et al., (2009) approach, as this has been implemented in IT environments. In this variation risk, project management includes; the identification of risks, the analysis of the probabilities and impact of the risks, and the planning and management of those risks. We argue that a comprehensive risk matrix curated by a wide range of participants would significantly increase the actionable value of current LA frameworks.

4. PROCESS FOR THE DEVELOPMENT OF A MATRIX

In this section, we review how to move hard evidence created by consultants within a largescale project to a more refined table with mitigative actions and then link the second table to an LA deployment framework for dashboards. This process is a full end to end example where frameworks get feedback from projects and projects from frameworks. We ignore specific columns for the percentage chance of risk, impact and level as they are at this level organisational specific. We can collect risk, impact and level within a publically available place anonymously and then aggregate across all projects creating a top list of risks and mitigations. In this section we look at an abbreviated set of raw results based on JISC's consultants records from 12 universities and colleges. We then take a concrete example and process it into an extra row in table 2, which links the feedback to evidence from previous research. Finally, in this section, we will link the risk to a LA framework.

Table 1 is a typically raw input, in this case from the JISC consultancies in which were conducted workshops with key institutional staff around various themes, e.g. student support, technical issues etc.. Staff generated a list of challenges within their institution. They then looked at the likelihood of the risks occurring and the impact and went on to consider mitigation. The list presented is a short selection of the most common threats identified. It isn't intended to be exhaustive but does represent risks identified by most institutions.

Note that the '***risk identified***' column is not a specific risk, but a broad theme. To make actionable, we need to increase the detail of the risk. Consider the *example* column as a list of anti-patterns, things you should not do. The s*uggested mitigative actions* column delivers mostly general advice. If we wish to relate to research and generalise into a pool of mitigative actions, then we need to expand the list of suggested mitigations and a link to study and LA practice. Furthermore, we will need to complete the circle by linking back to specific clusters within a LA deployment framework.

To convert the raw data to mitigative action occurs by review either in the Institution involved in deployment or via experts who look at the raw material possibly as part of interrelated workshops at LA themed conferences. As an example, from table 1 (presented in **bold** in table 1 and 2): "Create a shared understanding and vocabulary for LA at the institution – don't expect everyone to share the same understanding of terminology as it refers to your implementation". If you generalise across higher education, you can add mitigative actions such as the use of common glossary of terms so that everyone is talking the same language (Van Barneveld, Arnold & Campbell, 2012) or common introductory training material and syllabus as was considered in a workshop at the LAK18 conference[5]. The mitigative actions relate to products that have not yet been produced at a sector level and is an advertisement for further investment.

Table 1: Risk Mitigation notes (raw material)

Risk identified	Examples	Suggested mitigating actions

[5] http://blogs.cuit.columbia.edu/cl3584/

Planning	No named authority. Poor/no decision making. Another project! Organisational politics getting in the way. Unfinished projects. No formal project management processes.	Accountabilities, ownership and responsibilities made clear Core group to make decisions – don't spread too wide, gather perspectives to inform the group's plan Consider where LA underpins existing work, this may not be another project, but a tool to support other work already in train Ensure senior leadership are aligned and involved in the project to cut through departmental divisions. Have a clear vision for the project with SMART objectives. Tie to institutional strategy/goals. What will success look like? Create a sense of urgency have clear deadlines for progress. Develop the business case and intended benefits.
Clarity of purpose for LA	Not knowing what LA means to our institution. Unclear purpose results in wasted effort.	Have a clear vision for the project with SMART objectives. Tie to institutional strategy/goals. Communicate. Senior leader drives the vision. Review supporting policies/processes and practices to ensure alignment and reinforcement of the purpose. Consider rolling up policies into one for student support and retention. **Create a shared understanding and vocabulary for LA at the institution – don't expect everyone to share the same understanding of terminology as it refers to your implementation.**
Resource availability	Skills. Knowledge. Technical. Staff spread too thinly. Money.	Consider LA as part of the underpinning infrastructure. What other work in progress would LA enable/support? Adopt agile approach – don't aim to provide everything at once – low hanging fruit – MVP. Is more investment needed? Buy in skills either to do the work or free those who have the knowledge. Learn from others. There are generally a limited number of SIS and VLEs in use do you need to reinvent the wheel? What other resources within the organisation might be mobilised? How could students contribute, for example?

Table 2 is a partial risk mitigation matrix what is missing are specific columns for the percentage chance of risk, impact and level. The partial matrix is generic across organisations whereas **the full matrix needs an evaluation relative to a specific organisation**. The first two values percentage chance of the risk and impact are context specific to a particular structure and are estimated by an expert as part of the evaluation process. The level is calculated by combining the percentage risk and impact. The level defines the priority of the issue, the monetary cost of the mitigation and level delivering a clear indication of the cost-benefit ratio of any given mitigation.

Table 2: LA Risk Mitigation Matrix

Risk	**Mitigation**	**Reference**
We don't talk the same language	**Use of common glossary of terms.** **Training based on a common curriculum**[6]	**Van Barneveld, Arnold & Campbell, 2012**

[6] http://blogs.cuit.columbia.edu/cl3584/

Build services that students don't want	Involve the student in the co-development of the LA service, for example through the means of grading exercises for software engineers Discuss issues in a conference setting at the university deploying LA	Berg, Bloeme & Dekkers, 2013 Berg & Kerman, 2017
We don't scale successful pilots	Warn resource owners early that they have to plan for success. Make sure that resource owners understand their responsibilities	UvAInform project[7]
Solution does not optimally support Learning practices	Involve the teacher in the co-development of the workflow built into the application. Practices to be developed through for example, hackathons.	Berg, 2018
Waiting on access to data scattered across many systems with many stakeholders	Initially, apply synthetic data. Create data structures from a curate open source synthetic data generator	Berg,Mol, Kismihók & Sclater, 2016 Berg, Mol, Kismihok & Sclater, 2016b
Duplication of already failed practices for deployment of projects	Review, structured, curated and published evidence such as from LACE	Ferguson & Clow, 2016
Duplication of already failed practices for teaching	Train the trainers and sharing training materials[8]	
Duplication of features from already existing dashboards	Collaborate on an open dashboard that is easily extendable	Hackathon at LAK15, Cooper et al., 2017
Reinvent the infrastructure wheel	Collaborate on an Open Learning Analytics framework Share Standards recipes Use an already existing National Framework	OLA, 2014 Berg, Scheffel, Drachsler,Ternier & Specht, 2016b Sclater, Berg, & Webb 2015
Not invented here syndrome	Collaborate with other Universities where similar requirements generate different solutions	Apereo, 2017
Failure to consistently apply best practices	Define curated best practices through the means of workshops and hackathons	Berg, 2018
Product chosen because of eye candy (nice visualisations without much purpose).	Multidisciplinary team reviews the product, e.g. not only the resource manager.	
Failure to comply with legal, ethical privacy and data minimisation requirements.	Long list of actions here such as data minimisation practices, roles within the system with least privileges, a generic consistent system, Privacy Impact Assessments, etc.	Drachsler & Greller, 2016; Hoel, Griffiths & Chen, 2017 Khalil & Ebner, 2016; Gursoy, M. E., Inan, A.,

[7] https://lasiutrecht.files.wordpress.com/2014/06/uvainform-presentation-lasi-utrecht-2014.pdf

[8] Unpublished material based on development of an online course on LA at the University of Amsterdam

		Nergiz, M. E., & Saygin, Y. (2017)
Too many stakeholders involved in decisions for LA deployment	Stakeholder analysis and stakeholder responsibility realignment	Szorenyi, 2014
Lack of visibility to the student on what is intended with their data.	Clearly Communicate your intentions to all stakeholders Use a standard package of documents that have been generated by the LA community that explains to the student the risks, benefits and rights.	Sclater, N. (2016)
Lack of support for data portability, as enshrined in GDPR	Use standard for capturing student digital traces. Use a community infrastructure that takes care of portability. For example, such at the JISC or PAR infrastructures.	Berg, Scheffel, Drachsler, Ternier, & Specht, 2016 Ice et al., 2012
Lack of data per student	When designing a model to identify new students at risk, the lack of data about each student's behaviour is a problem that may be addressed by modelling across cohorts.	Sclater, N., Peasgood, A., & Mullan, J. (2016, p. 23)

What is noticeable is that many of the mitigative actions have existing evidence and the evidence is waiting for a unifying structure to help focus into action.

A significant benefit of the risk matrix is that it can exist outside the context of a particular LA framework and post hoc cluster the risks and mitigations to the same structure. Both the LA framework and the matrix can suggest content for the other. Take for example Maren Scheffel's (2017) work on an Evaluation Framework for LA from concept mapping (Appendix B, page 177); experts expressed concern about data portability (point 8). The matrix reflects this with a mitigative action of standardisation, and of course, we can expand the mitigative action into more detailed sets. At a particular institute, local experts will then measure the priority of the risk, from the percentage chance, impact and level of the risk. If any locally developed mitigation is missing we should feedback to into the central pool.

In this section, we have shown that we can link feedback from consultancy to a risk mitigation matrix and from the risk mitigation matrix provides feedback to a framework and also from a framework suggest feedback into the matrix.

In the next section we discuss the implications and suggest how to advertise and maintain a global risk matrix.

5. DISCUSSION AND CONCLUSIONS

In this paper, we prepare the ground for a more comprehensive review and curation by the broader LA practitioner community of a general risk matrix in the hope of motivating broad participation.

Large, highly deployed LA infrastructure at scale needs to be generalisable. We require that the infrastructure adapts to a wide range of data sources, legal ethical and privacy concerns, teaching practices and a rapidly evolving understanding of what digital traces means in the context of learning. Therefore, there are significantly more risks and mitigative actions necessary than for an average educational IT project. We need to avoid repeating common error patterns such as the lack of user-friendliness, providing eye candy in dashboards that is not particularly relevant to teaching practices, etc. One method to diminish risk is to coherently publicise the dangers as our understanding evolves and attach the risk matrix to actionable frameworks designed for the deployment of LA infrastructure within educational organisations such as universities. Through this means we emphasise the practical motivations for collaboration and publication of best practices and methods. The communities of interested parties can achieve this by involving the student and teacher and educational specialist through the development cycle, creating evidence hubs such as LACE (Ferguson & Clow, 2016) and strengthening common infrastructural patterns such as the Apereo Learning Analytics Framework. We can amplify the message by planning interlocking events at domain-specific conferences such as through LAK hackathons (Berg, 2018) or workshops orchestrated by an evidence hub such as by LACE on privacy and ethics[9].

By deploying an accepted and curated risk matrix and evaluating, an organisation can define a detailed set of deliverables, prioritise and then plan. By prioritising mitigative actions, we can place a (monetary, priority) value within a project on the clusters within a framework and thus help decide where the research community focuses further research effort. We can also spot gaps in research by area's that are missing suggested actions.

To help structure further the debate, we have reviewed the currently available frameworks for the deployment of Learning Analytics (LA) infrastructure combined with practice and defines a strategy of curation of a global risk mitigation matrix. By this method, we communicate to practitioners in the field common errors and thus structure broader dissemination of avoidance strategies. This methodology is with precedent. LA has a lot in common with cybersecurity. The fields are changing rapidly and the risk profiles also. In acknowledgement of the pace of change, OWASP keeps a yearly updated list of attack vectors[10].

To increase the quality and consitency of risk mitigation, the authors recommend the systematic public curation of a risk mitigation matrix through the following actions:

1. The creation of open space for a standard risk mitigation matrix organised by a trusted party such as a Special Interest group at an organisation such as IEEE, SoLAR or the Apereo Foundation.
2. The ability to anonymously vote on the priority, scope and level of the risk.
3. Curation of the risks through an interrelated set of conference events such as hackathons and other types of workshops and SIG meetings.
4. Creation of a periodically updated strategy document that highlights common risks, mitigations and where necessary the gaps in research.
5. Creation of a top list of risks sorted by priority and mitigations that is updated yearly.

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7. COPYRIGHT NOTICE

8. REFERENCES

Apereo. (2017). Retrieved from https://www.apereo.org/content/projects-communities

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge - LAK '12 (p. 267). New York, New York, USA: ACM Press. https://doi.org/10.1145/2330601.2330666

[9] http://www.laceproject.eu/ethics-privacy-learning-analytics/

[10] https://www.owasp.org/index.php/Category:OWASP_Top_Ten_Project

Berendt, B., Littlejohn, A., Kern, P., Mitros, P., Shacklock, X., & Blakemore, M. (2017). Big Data for monitoring educational systems. https://doi.org/10.2766/3855

Berg, A., Scheffel, M., Drachsler, H., Ternier, S., & Specht, M. (2016). Dutch Cooking with xAPI Recipes: The Good, the Bad, and the Consistent. In *2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT)* (pp. 234-236). IEEE.

Berg, A., Scheffel, M., Drachsler, H., Ternier, S., & Specht, M. (2016b). The dutch xAPI experience. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16* (pp. 544–545). New York, New York, USA: ACM Press. https://doi.org/10.1145/2883851.2883968

Berg, A. (2018). Hacking the Hackathon. Unpublished work. In Proceedings of the 8th International Conference on Learning Analytics and Knowledge.

Berg, A., Bloeme, T., & Dekkers, H. (2013). *Teaching With Sakai Innovation Award*. Retrieved from https://www.sakaiproject.org/sites/default/files/content/2013 TWSIA Project Winner_University Amsterdam.pdf

Berg, A. M., Mol, S. T., Kismihók, G., & Sclater, N. (2016). The role of a reference synthetic data generator within the field of learning analytics. *Journal of Learning Analytics*, *3*, 107–128. https://doi.org/10.18608/jla.2016.31.7

Scaling Learning Analytics: The practical application of synthetic data. In *Proceedings of the 9th European Distance and E-Learning Network Research Workshop* (pp. p264-269).

Berg, A. M., & Kerman, S. (2017). *Should students have a right to analytics? LSAC 2017*. Amsterdam: Amsterdam Business School, University of Amsterdam. Pages 25-27

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. International Journal of Technology Enhanced Learning, 4(5/6), 318. https://doi.org/10.1504/IJTEL.2012.051815

Clow, D., Ferguson, R., Kitto, K., Cho, Y.-S., Sharkey, M., & Aguerrebere, C. (2017). Beyond failure. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference on - LAK '17 (pp. 504-505). New York, New York, USA: ACM Press. https://doi.org/10.1145/3027385.3029429

Clow, D., Ferguson, R., Macfadyen, L., Prinsloo, P., & Slade, S. (2016). LAK failathon. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16 (pp. 509-511). New York, New York, USA: ACM Press. https://doi.org/10.1145/2883851.2883918

Cooper, A., Berg, A., Sclater, N., Dorey-Elias, T., & Kitto, K. (2017). LAK17 hackathon. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference on - LAK '17* (pp. 514–515). New York, New York, USA: ACM Press. https://doi.org/10.1145/3027385.3029435

Drachsler, H., Hoel, T., Cooper, A., Kismihók, G., Berg, A., Scheffel, M., … Ferguson, R. (2016). Ethical and Privacy Issues in the Design of Learning Analytics Applications. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge (pp. 492–493). New York, NY, USA: ACM. https://doi.org/10.1145/2883851.2883933

Drachsler, H., & Greller, W. (2016). Privacy and analytics - It's a DELICATE issue. A Checklist to establish trusted Learning Analytics. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16 (pp. 89-98). New York, New York, USA: ACM Press. https://doi.org/10.1145/2883851.2883893

Engelfriet, A., Manderveld, J., & Jeunink, E. (2015). Learning Analytics under the (Dutch) Personal Data Protection Act. Policy paper. SURFnet. Retrieved from https://www.surf.nl/en/knowledge-base/2015/guide-to-learning-analytics-under-the-personal-data-protection-act.html

Ferguson, R., Hoel, T., Scheffel, M., & Drachsler, H. (2016). Guest editorial: Ethics and privacy in learning analytics. Journal of Learning Analytics, 3(1), 5-15. https://doi.org/10.18608/jla.2016.31.2

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., Ullmann, T., and Vuorikari, R. (2016). Research Evidence on the Use of Learning Analytics - Implications for Education Policy. Joint research centre for policy report. European Union. DOI: 10.2791/955210

Ferguson, R., Macfadyen, L.P., Clow, D., Tynan, B., Alexander, S. & Dawson, S. (2014). Setting Learning Analytics in Context: Overcoming the Barriers to LargeScale Adoption. Journal of Learning Analytics, 1(3), 120-144.

Ferguson, R., & Clow, D. (2016). Learning analytics community exchange. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16 (pp. 520-521). New York, New York, USA: ACM Press. https://doi.org/10.1145/2883851.2883878

Garvey, P. R., & Lansdowne, Z. F. (1998). Risk matrix: an approach for identifying, assessing, and ranking program risks. Air Force Journal of Logistics, 22(1), 18-21.

Gašević, D., Dawson, S., Rogers, T., & Gašević, D. (2016). Learning analytics should not promote one size fits all. The Effects of Instructional Conditions in Predicating Academic Success, 28, 68-84. https://doi.org/10.1016/j.iheduc.2015.10.002

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64-71. https://doi.org/10.1007/s11528-014-0822-x

GDPR Overview. (2017) Retrieved from https://en.wikipedia.org/wiki/General_Data_Protection_Regulation

Hoel, T., Griffiths, D., & Chen, W. (2017). The influence of data protection and privacy frameworks on the design of learning analytics systems. In LAK (pp. 243-252).

Griffiths, D. (2013). The implications of analytics for teaching practice in higher education analytics series (Vol. 1:10). Bolton, UK: JISC CETIS (Centre for Educational Technology, Interoperability and Standards of the Joint Information Systems Committee [UK]). Retrieved from http://publications.cetis.org.uk/wp-content/uploads/2013/02/Analytics-for-Teaching-Practice-Vol-1-No-10.pdf

Griffiths, D., Hoel, T. (2016). Comparing xAPI and Caliper. Learning Analytics Review, no. 7, January 2016, ISSN: 2057-7494. http://www.laceproject.eu/learning-analytics-review/lace-review-7_comparing-xapi-caliper/

Gursoy, M. E., Inan, A., Nergiz, M. E., & Saygin, Y. (2017). Privacy-Preserving Learning Analytics: Challenges and Techniques. *IEEE Transactions on Learning Technologies*, *10*(1), 68–81. https://doi.org/10.1109/TLT.2016.2607747

Ice, P., Díaz, S., Swan, K., Burgess, M., Sharkey, M., Sherrill, J., … Okimoto, H. (2012). The par framework proof of concept: Initial findings from a multi- institutional analysis of federated postsecondary data. Journal of Asynchronous Learning Network, 16(3), 63-86.

Inbloom shuts down. (2014). Retrieved from https://www.bloomberg.com/news/articles/2014-05-01/inbloom-shuts-down-amid-privacy-fears-over-student-data-tracking

Kismihók, G., Cornelisz, I., Klaveren, C. van, Berg, A. M., & Mol, S. T. (Eds.). (2017). Learning & Student Analytics Conference (LSAC) 2017: Implementation, Institutional Barriers and New Developments - Book of Abstracts. Amsterdam.

Khalil, M., & Ebner, M. (2016). De-identification in learning analytics. Journal of Learning Analytics, 129–138. https://doi.org/10.18608/jla.2016.31.8

Lang, C., Siemens, G., Wise, A., & Gasevic, D. (Eds.). (2017). Handbook of Learning Analytics. Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17

Markowski, A. S., & Mannan, M. S. (2008). Fuzzy risk matrix. Journal of Hazardous Materials, 159(1), 152–157. https://doi.org/10.1016/j.jhazmat.2008.03.055

Ni, H., Chen, A., & Chen, N. (2010). Some extensions on risk matrix approach. Safety Science, 48(10), 1269–1278. https://doi.org/10.1016/j.ssci.2010.04.005

OLA. (2014). Open Learning Analytics Press release, Retrieved from http://solaresearch.org/wp-content/uploads/2014/04/OLAPressReleaseFINALv2.pdf

Rienties, B., & Toetenel, L. (2016). The impact of 151 learning designs on student satisfaction and performance: social learning (analytics) matters. In LAK `16 Conference Proceedings: The Sixth International Learning Analytics & Knowledge Conference, (pp. 339-343). https://doi.org/10.1145/2883851.2883875

Sclater, N. (2016). Developing a code of practice for learning analytics. Journal of Learning Analytics, 16–42. https://doi.org/10.18608/jla.2016.31.3

Sclater, N. (2017). Learning Analytics Explained. ISBN: 978-1138931732. Routledge.
Sclater, N., Berg, A., & Webb, M. (2015). Developing an open architecture for learning analytics. Proceedings of the EUNIS 2015 Congress. https://doi.org/ISSN: 2409-1340

Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. London: Jisc. Accessed February, 8, 2017.

Scheffel, M. (2017, 22 September). The Evaluation Framework for Learning Analytics. Doctoral thesis. Heerlen, The Netherlands: Open Universiteit (Welten Institute, Research Centre for Learning, Teaching and Technology). http://hdl.handle.net/1820/8259

Siemens, G., & Long, P. (2011). Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE Review, 46, 30-32.

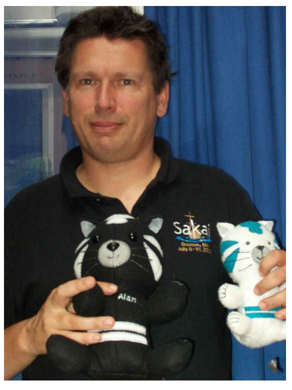
Straumsheim, C. (2013). Mixed Signals. Retrieved from https://www.insidehighered.com/news/2013/11/06/researchers-cast-doubt-about-early-warning-systems-effect-retention
Suthers, D., & Verbert, K. (2013). Learning analytics as a "middle space." In Proceedings of the Third International Conference on Learning Analytics and Knowledge - LAK '13 (p. 1). New York, New York, USA: ACM Press. https://doi.org/10.1145/2460296.2460298

Szorenyi, D. (2014). Contribution of normative stakeholder theory to the improvement of factors affecting data warehousing implementation success. University of Amsterdam. Retrieved from http://arno.uva.nl/document/544693

Van Barneveld, A., Arnold, K. E., & Campbell, J. P. (2012). Analytics in higher education: Establishing a common language. *EDUCAUSE learning initiative*, *1*(1), l-ll.

Xiaosong, L., Shushi, L., Wenjun, C., & Songjiang, F. (2009). The Application of Risk Matrix to Software Project Risk Management. In 2009 International Forum on Information Technology and Applications (Vol. 2, pp. 480-483). IEEE. https://doi.org/10.1109/IFITA.2009.542

9. AUTHORS' BIOGRAPHIES



Alan Mark Berg, BSc, MSc, PGCE, has been the lead developer at Central Computer Services at the University of Amsterdam since 1998. In his famously scarce spare time, he writes, consults and is currently a PhD candidate in Learning Analytics. Alan has a bachelor's degree, two master's degrees, a teaching qualification, and quality assurance certifications. He has also coauthored two Packt Publishing books about Sakai (http://sakaiproject.org), a highly successful open source learning management platform used by millions of students around the world. Alan has also written two Books on continuous delivery. He has won a couple of awards, including the Sakai Fellowship and Teaching With Sakai Innovation Award (TWSIA).

Alan enjoys working with talent; this forces him to improve his own competencies. This motivation is why Alan enjoys working in energetic, open source communities of interest and with researchers in the field of LA.

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Patrick Lynch is a Teaching Enhancement Adviser at the University of Hull. Patrick has BA (Hons), PGCert Teaching & Learning in H.E, and a PGCert Coaching. He is also the Community Officer for the Learning Analytics Initiative of the Apereo open source organisation. Patrick has worked in UK Higher Education for over 25 years in various roles.Patrick has recently worked within the Jisc Effective Learning Analytics project providing Readiness consultation with organisations across the UK. Patrick conducted this work for Jisc whilst employed as a consultant for Unicon Inc. alongside Lindsay Pineda, Senior Implementation Consultant at Unicon. Patrick's current work is around Learning Design and Learning Analytics developing more data informed approaches to teaching and learning. Patrick has many years of teaching experience in a number of disciplines and currently teaches on the Postgraduate Certificate in Academic Practice at Hull University.