The Promise of Learning Analytics and the Search for Evidence

Dirk Ifenthaler

Chair of Learning, Design and Technology
UNESCO Deputy Chair of Data Science in Higher Education Learning and Teaching
www.ifenthaler.info • dirk@ifenthaler.info

@ifenthaler

Learning analytics evolved from the increased opportunities to collect and make use of data about learning and learning contexts

2

Gašević, D., Jovanović, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: links with self-reported measures and academic performance. *Journal of Learning Analytics, 4*(2), 113–128. doi:jla.2017.42.10

Academic

Assessment

Games

Education

LEARNING ANALYTICS

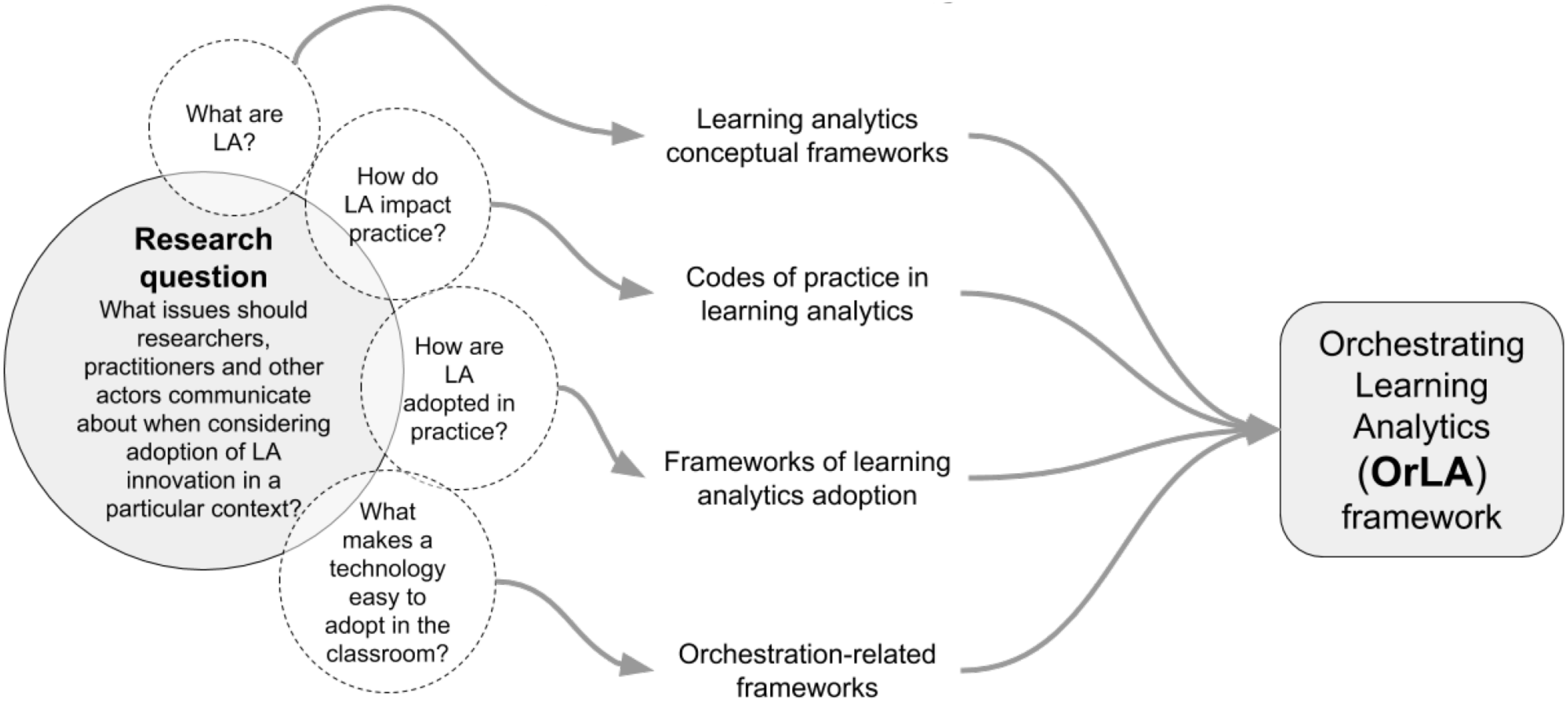
Measurement

Retention

School

Teacher

Ifenthaler, D. (2020). Change management for learning analytics. In N. Pinkwart & S. Liu (Eds.), *Artificial intelligence supported educational technologies*. Cham: Springer.



Prieto, L. P., Rodríguez-Triana, M. J., Martínez-Maldonado, R., Dimitriadis, Y., & Gašević, D. (2019). Orchestrating learning analytics (OrLA): Supporting inter-stakeholder communication about adoption of learning analytics at the classroom level. *Australasian Journal of Educational Technology, 35*(4), 14–33. doi:10.14742/ajet.4314

EDM AA LA

Educational Data Mining.

Educational data mining (EDM) refers to the process of extracting useful information out of a large collection of complex educational datasets

Romero, C., Ventura, S., Pechenizkiy, M., & Baker, R. S. (Eds.). (2011). *Handbook of educational data mining*. Boca Raton, FL: CRC Press.

Academic Analytics.

Academic analytics (AA) is the identification of meaningful patterns in educational data in order to inform academic issues (e.g., retention, success rates) and produce actionable strategies (e.g., budgeting, human resources)

Campbell, J. P., DeBlois, P. B., & Oblinger, D. (2010). Academic analytics: a new tool for a new era. *EDUCAUSE Review, 42*(4), 40-57.

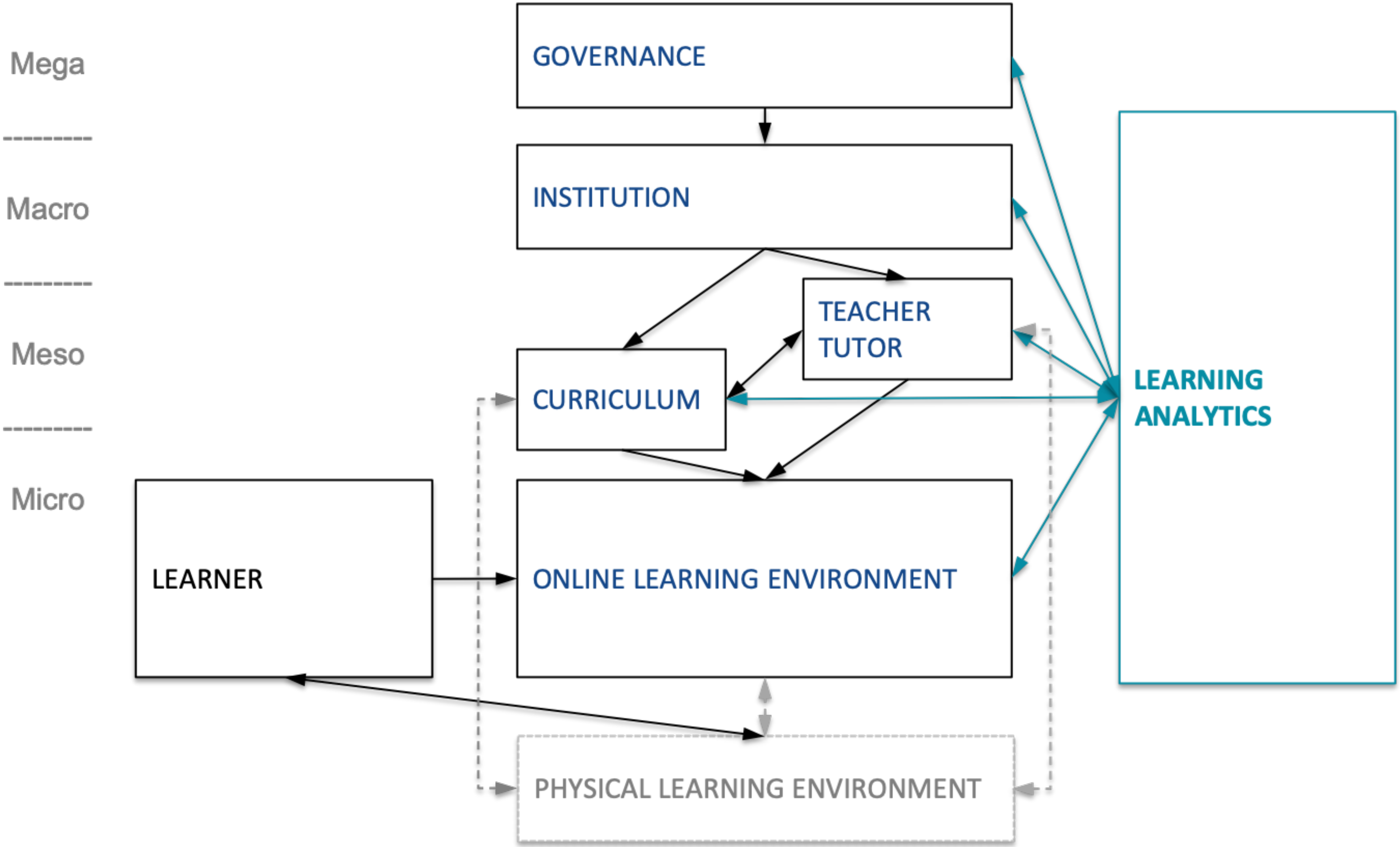
Learning Analytics.

Learning analytics (LA) are the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs

Siemens, G., & Baker, R. S. (2012). *Learning analytics and educational data mining: Towards communication and collaboration*. Paper presented at the 2nd International Conference on Learning Analytics and Knowledge, New York, NY.

Analytics for learning **use static and dynamic information about learners and learning environments – assessing, eliciting, and analysing it – for real-time modelling, prediction, and support of learning processes, learning environments, as well as educational decision making**

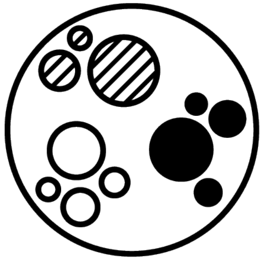
Ifenthaler, D. (2017). Learning analytics. In K. Peppler (Ed.), The SAGE encyclopedia of out-of-school learning (pp. 417–420). Thousand Oaks, CA: SAGE Publications.



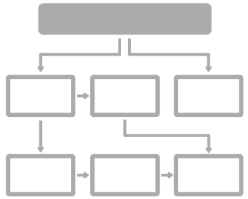
Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 447–451). Thousand Oaks, CA: Sage.

	Summative	Real-time/ Formative	Predictive/ Prescriptive
Governance	• Apply cross-institutional comparisons • Develop benchmarks • Inform policy making • Inform quality assurance processes	• Increase productivity • Apply rapid response to critical incidents • Analyse performance	• Model impact of organisational decision-making • Plan for change management
Organisation	• Analyse processes • Optimise resource allocation • Meet institutional standards • Compare units across programs and faculties	• Monitor processes • Evaluate resources • Track enrolments • Analyse churn	• Forecast processes • Project attrition • Model retention rates • Identify gaps
Learning design	• Analyse 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
Teacher	• Compare learners, cohorts and courses • Analyse teaching practises • 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 • Analyse learning outcomes • Track progress towards goals	• Receive automated interventions and scaffolds • Take assessments including just-in-time feedback	• Optimise learning paths • Adapt to recommendations • Increase engagement • Increase success rates

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.



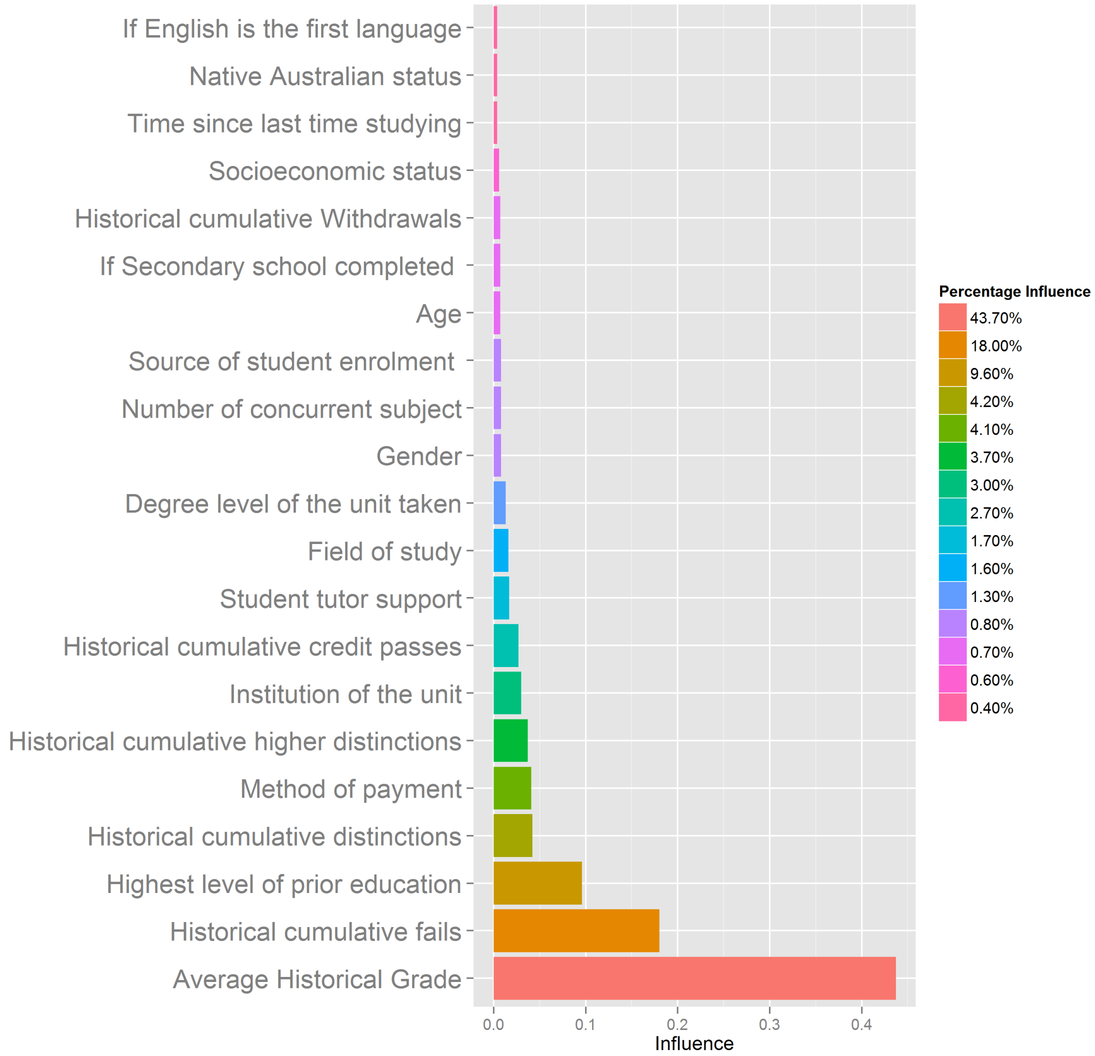
There is a lack of rigorous empirical research findings demonstrating the effectiveness of learning analytics to support study success



(So far) no wide-scale organisational implementation of learning analytics exist

FIGURE 10.2 Students' frequency of use of the different resources in the learning management system for each week of the semester

Schumacher, C., Klasen, D., & Ifenthaler, D. (2019). Implementation of a learning analytics system in a productive higher education environment In M. S. Khine (Ed.), *Emerging trends in learning analytics* (pp. 177–199). Leiden, NL: Brill.



N = 1,030,778 enrolments

Table 1 Model descriptions for student profile

Model 1	Student background and demographic data
Model 2	Student background and demographic data Student's and parent's historical education background
Model 3	Student background and demographic data Student's and parent's historical education background Study unit related information
Model 4	Student background and demographic data Student's and parent's historical education background Study unit related information Historical education record with institution
Model 5	Student background and demographic data Student's and parent's historical education background Study unit related information Historical education record with institution Average historical grade within institution
Model 6	Most important parameters identified from previous models

Table 2 Student profile model performance comparison

	R^2	Adjusted R^2	R^2-SVR	Predictive accuracy (SVM) (%)
Model 1	.057	.057***	.059	58.63
Model 2	.128	.128***	.130	63.80
Model 3	.187	.187***	.192	67.50
Model 4	.361	.361***	.424	79.52
Model 5	.441	.446***	.438	79.69
Model 6	.444	.435***	.451	80.03

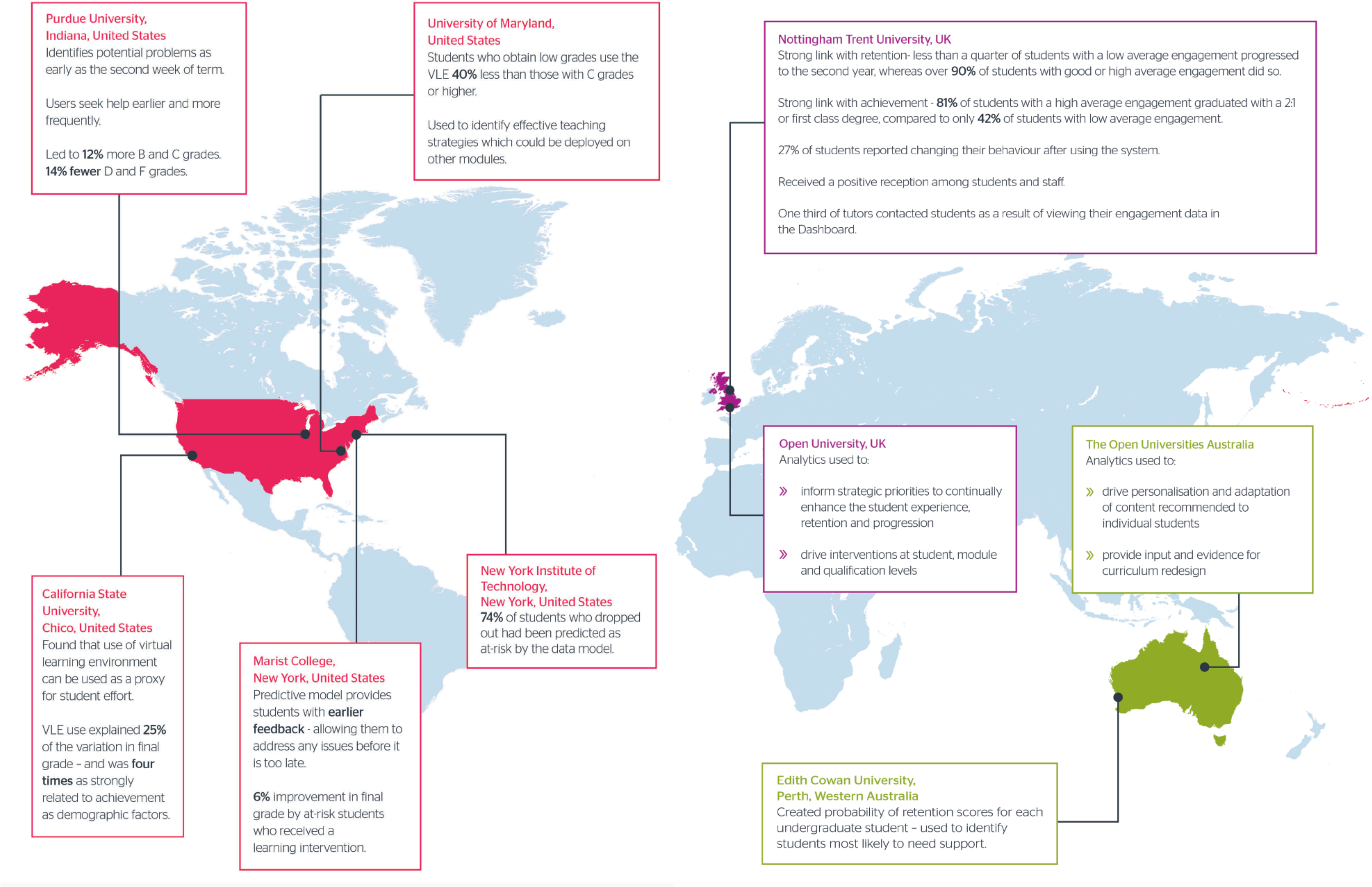
*** $p < .001$; *SVR* support vector regression, *SVM* support vector machines

Table 3 Student profile model performance comparison for higher education institutions

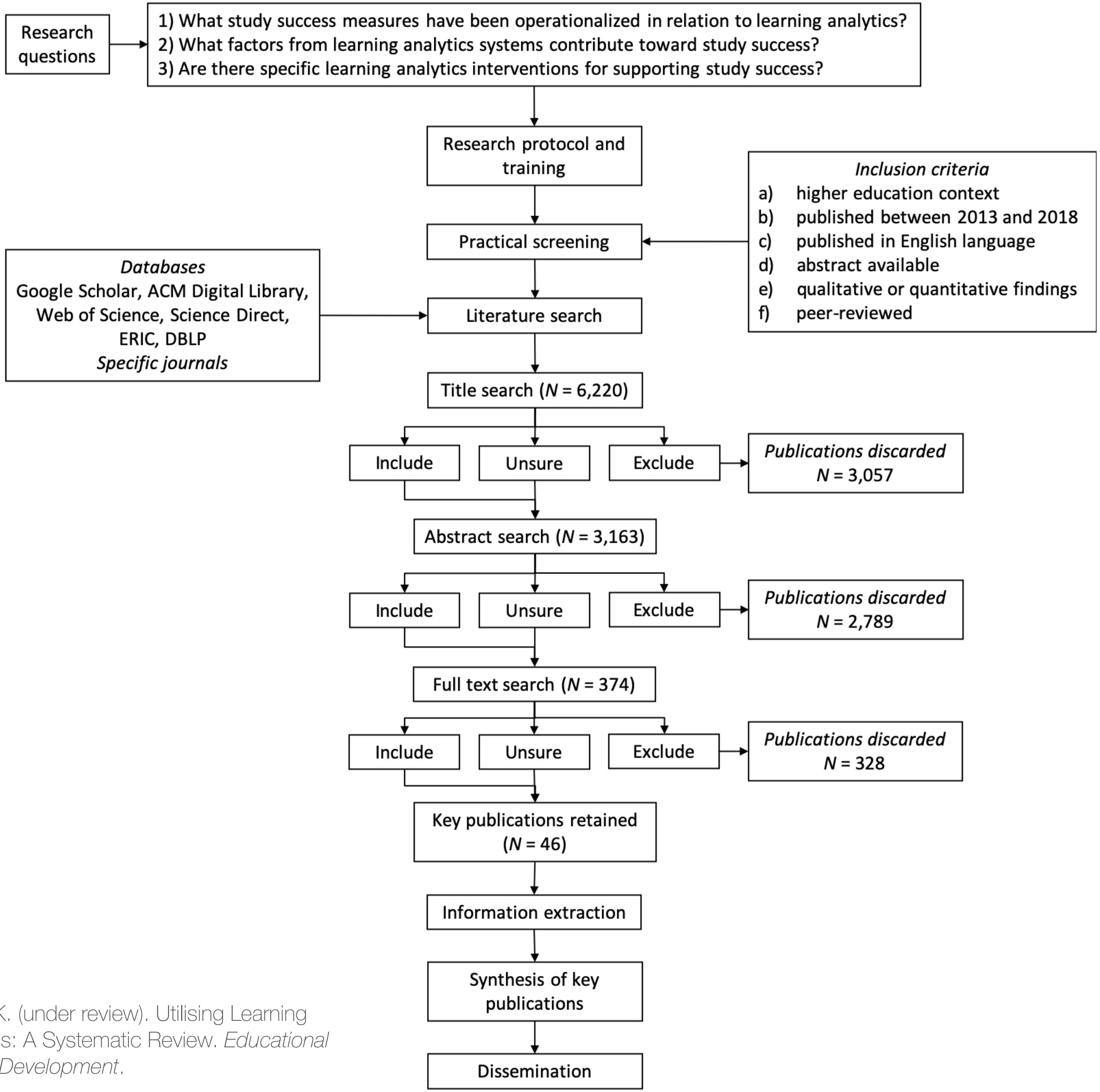
Higher Education Institution	R^2	Adjusted R^2	R^2-SVR	Predictive accuracy (SVM)
UniC	.464	.463***	.489	81.69 %
UniG	.453	.453***	.460	79.65 %
UniS	.431	.431***	.460	79.64 %
UniA	.372	.372***	.381	76.57 %
UniM	.438	.437***	.443	80.71 %
UniR	.364	.364***	.353	76.31 %
UniO	.434	.433***	.460	80.28 %
UniU	.372	.371***	.356	78.25 %
SD	.096	.096	.126	.024

*** $p < .001$; *SVR* support vector regression, *SVM* support vector machines

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



Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education: A review of UK and international practice. Bristol: JISC.



Ifenthaler, D., & Yau, J. Y.-K. (under review). Utilising Learning Analytics for Study Success: A Systematic Review. *Educational Technology Research and Development*.

Table 1. Summary of key publications focusing on learning analytics for supporting study success

Author	**Country**	**Sample (*N*)**	**Demographic background**	**Key purpose of the study**	**Variables**	**Operationalized study success measure**	**Interventions**	**Research rigor**
Aguiar, et al. (2014)	USA	29	First-year Engineering students	Identification of retained and dropout students	ePortfolio logins; hits; submissions	Engagement from students' electronic portfolios	N/A	weak
Andersson, et al. (2016)	Sweden	66	Online 3d-graphics students	Prediction of course completion	Number and frequency of posts; lengths of posts	Mention of predicting course performance via activities posted on online forum	N/A	weak
Aulck, et al. (2017)	USA	24,341	First-year STEM students	Prediction of course completion	Demographics; pre-college entry information (standardized test scores, high school grades, parents' educational attainment, and application zip code); complete transcript records	No mention of measuring study success, only the prediction of dropout	N/A	weak
Bukralia, et al. (2014)	USA	1,376	First-year students	Prediction of student dropout	Academic ability; financial support; academic goals; technology preparedness; demographics; course engagement and motivation; course characteristics	No operationalisation of study success measure	N/A	weak
Bydzovska, & Popelinsky (2014)	Czech Republic	7,457	Informatics students	Prediction of pass/ fail in courses in relation to social behaviour	Study-related data; social behaviour data; data about previously passed courses	No operationalisation of study success measure	N/A	weak
Cambruzzi, et al. (2015)	Brazil	2,491	Online Mathematics students	Prediction of student dropout	Interactions between students in forum	Adequate pedagogical actions that need to be taken if at-risk students are located	Set of pedagogical actions which are individualised depending on each of the students' weekly reports	moderate
Carroll & White (2017)	Ireland	524	First-year students	Prediction of learning behaviour	Lecture, tutorial, online scheduled attendance; print, online access to learning materials	No operationalisation of study success measure	Rigorous attendance requirements, assessment prompted engagement	weak
Carter, et al. (2017)	USA	140	Informatics students	Prediction of student performance	Programming activities; students' grades on individual assignments; students' overall assignment average; students' final grades	Programming behaviour	N/A	moderate
Casey & Azcona (2017)	Ireland	111	Computer science students	Prediction of low performing students	No. of successful or failed compilations; no. of connections; time spent; slides coverage	No operationalisation of study success measure	Structure students learning so that students can front-load their online work	moderate

Ifenthaler, D., & Yau, J. Y.-K. (under review). Utilising Learning Analytics for Study Success: A Systematic Review. *Educational Technology Research and Development*.

Institutional recommendations

01

Education leadership.

Develop, support and sustain models of education leadership that embrace the interdisciplinary nature of learning analytics requiring a combination of teams with skills from computer science, psychology, cognitive science, education, etc.

02

Idiosyncrasies.

Develop practices that are appropriate and fitting to the needs of an individual institution (with different sizes of student groups, courses, staff numbers, etc.). Support educators and staff to enhance learning and teaching using learning analytics.

03

Assessment.

Develop assessment practices, which are aligned with learning analytics in the institution including perspectives of assessment for learning as well as feedback for learning.

04

Organisational structure.

Develop organisational structures to support the use of learning analytics and help educational leaders (stakeholders in general) to implement these changes including capacity building (professional learning), support, credentials, etc.

05

Quality assurance.

Develop a robust quality assurance process to ensure the validity and reliability of learning analytics tools as well as evaluation checklists. Creating an accreditation body for learning analytics.

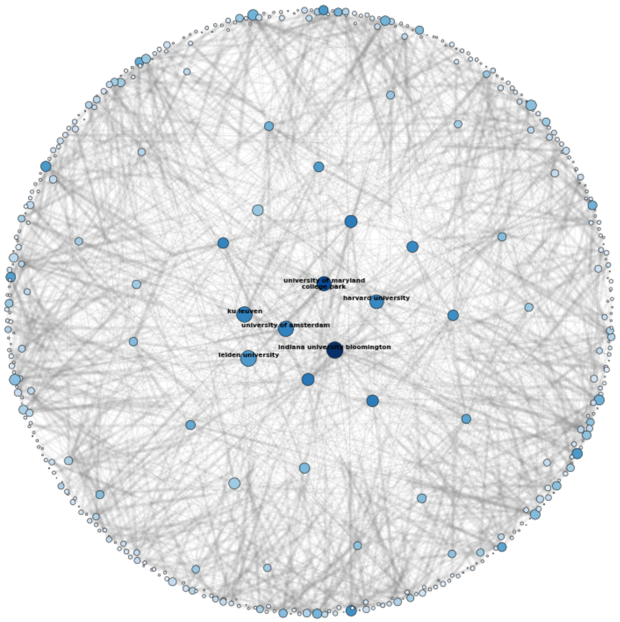
06

Data protection.

Continuation in the monitoring and adherence to ethics, data protection and privacy, which may infringe on individuals as well as the institution(s) involved.

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.

Cross-institutional recommendations



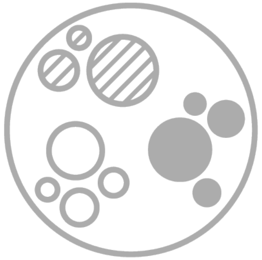
01 **Exchange.**
Enable institutional, cross institution and government discussions of learning analytics and its capacity to inform arising challenges from different perspectives: educational, administrative, financial, staff and technological constraints etc.

02 **National board.**
Develop a national learning analytics (ethical) board to stipulate that the ethics of each individual institution is met.

03 **Framework solution.**
Provide a learning analytics solution which can be adaptive to the needs of individual institutions but is also transferrable for increased ease of use state or nationwide. Develop technologies to enable learning analytics deployment.

04 **Collaboration.**
Support collaboration among higher education institutions, government and with other types of organisation such as commercial/industrial partners.

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.



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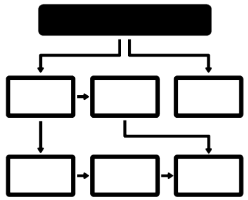

(So far) no wide-scale organisational implementation of learning analytics exist

Challenges for establishing learning analytics systems are the interaction and fragmentation of information as well as their contextual idiosyncrasies

Gašević, D., Dawson, S., Rogers, T., & Gašević, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *Internet and Higher Education, 28*, 68–84.

Understanding of learning analytics

If you collect enough data, one can probably **observe patterns of some things that can be improved**. It is a type of data analysis, where one can see some practices, which relate to **better results of the students** in the end or some practices, which may lead to poorer results.

The **more data one collects**, the better it would be for the learning analytics. However, it might imply possible **administering several surveys and questionnaires** during the course and may **conflict with the dynamics of the course** and some teaching staff may not be willing to do so easily.

N = 34 participants agreed and emphasised that the first, large obstacle to learning analytics implementation was data protection

Ifenthaler, D., & Yau, J. (2019). Higher education stakeholders' views on learning analytics policy recommendations for supporting study success. *International Journal of Learning Analytics and Artificial Intelligence for Education, 1*(1), 28–42. doi:10.3991/ijai.v1i1.10978

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STELA

There are currently staff and technological **resources required** by the institution before they can go ahead and adopt learning analytics.

The institution is mentally ready to adopt learning analytics as the **benefits for study success outweigh the costs**.

There is a **lack of learner's personal data** relating to their learning processes, exam grades and so on, which makes valid predictions for study success very difficult.

N = 30 participants mentioned that there were not any learning analytics projects currently operating at their institution

Readiness to adopt learning analytics

Ifenthaler, D., & Yau, J. (2019). Higher education stakeholders' views on learning analytics policy recommendations for supporting study success. *International Journal of Learning Analytics and Artificial Intelligence for Education, 1*(1), 28–42. doi:10.3991/ijai.v1i1.10978

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STELA

Current challenges in successful learning analytics implementation are widely known within the higher education community

Implementation guidelines

Experimental 'playgrounds' are required to understand, discuss, debate, test out all learning analytics ideas and put them into practice and learn from these good/bad experiences and studies.

It is also very important that learning analytics stakeholders **understand fully** what learning analytics adaptive teaching entails and how personalised learning works.

Professional learning and **guidelines for the implementation** of learning analytics and **policy standards** linked to EU-GDPR are needed.

Ifenthaler, D., & Yau, J. (2019). Higher education stakeholders' views on learning analytics policy recommendations for supporting study success. *International Journal of Learning Analytics and Artificial Intelligence for Education, 1*(1), 28–42. doi:10.3991/ijai.v1i1.10978

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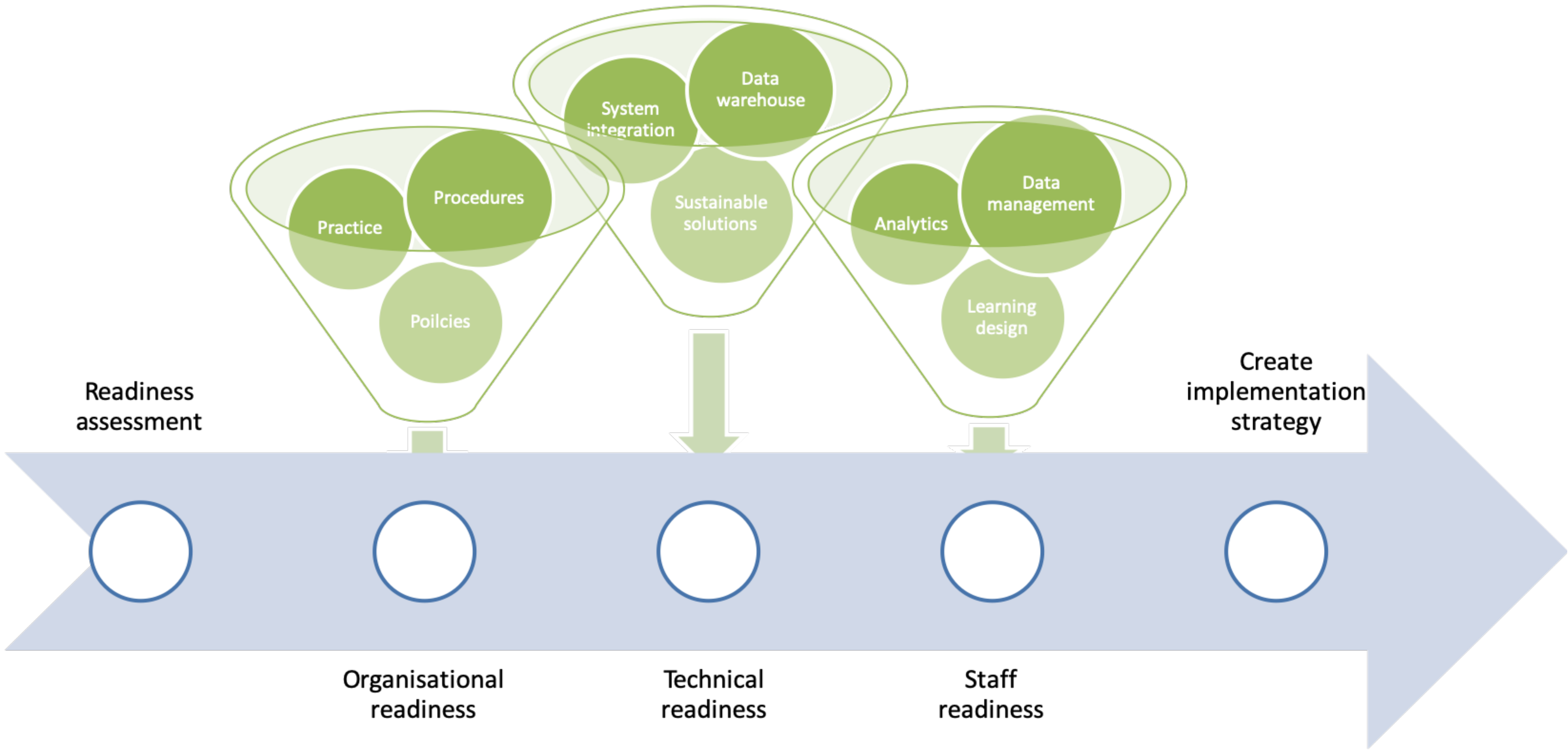

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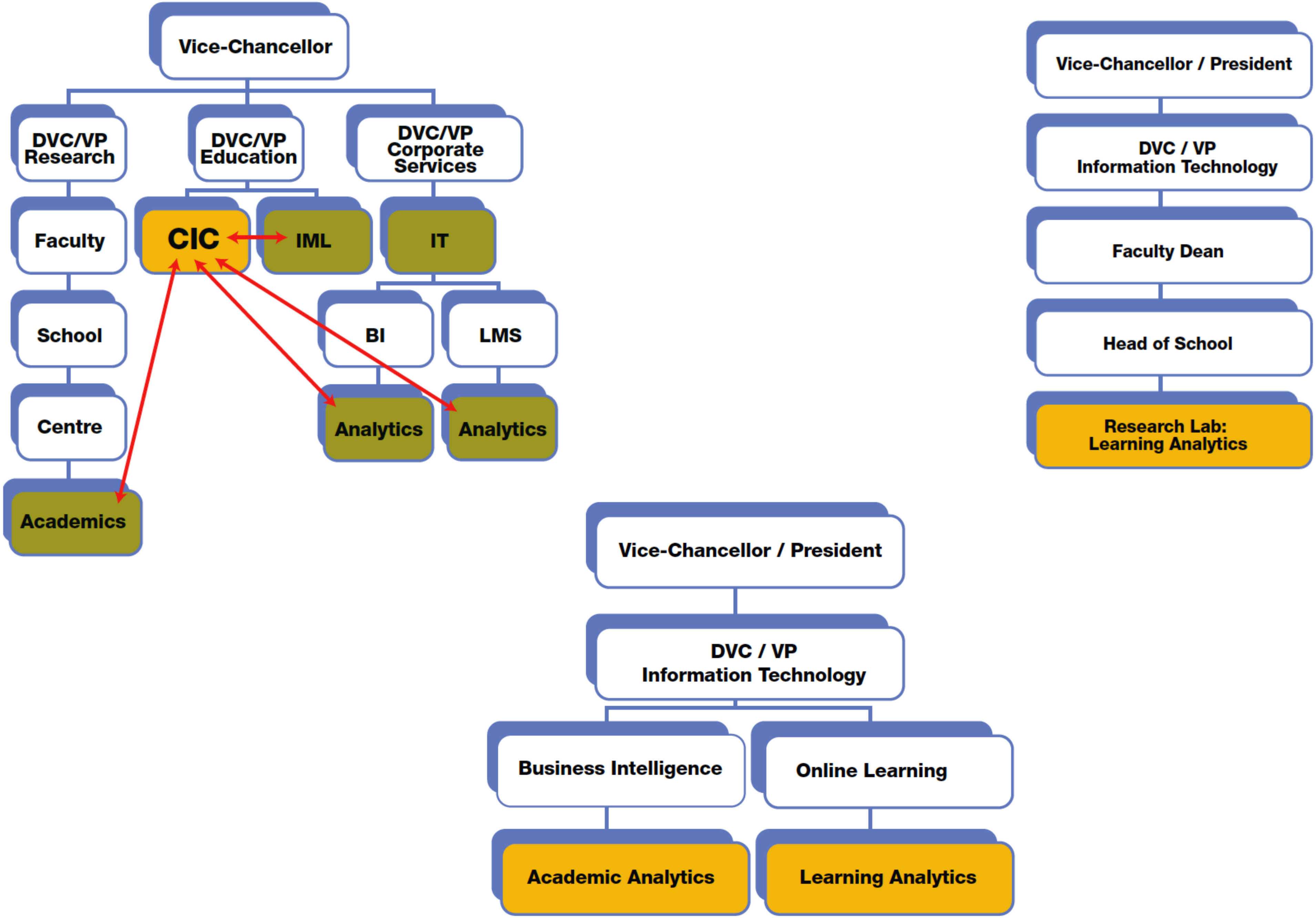
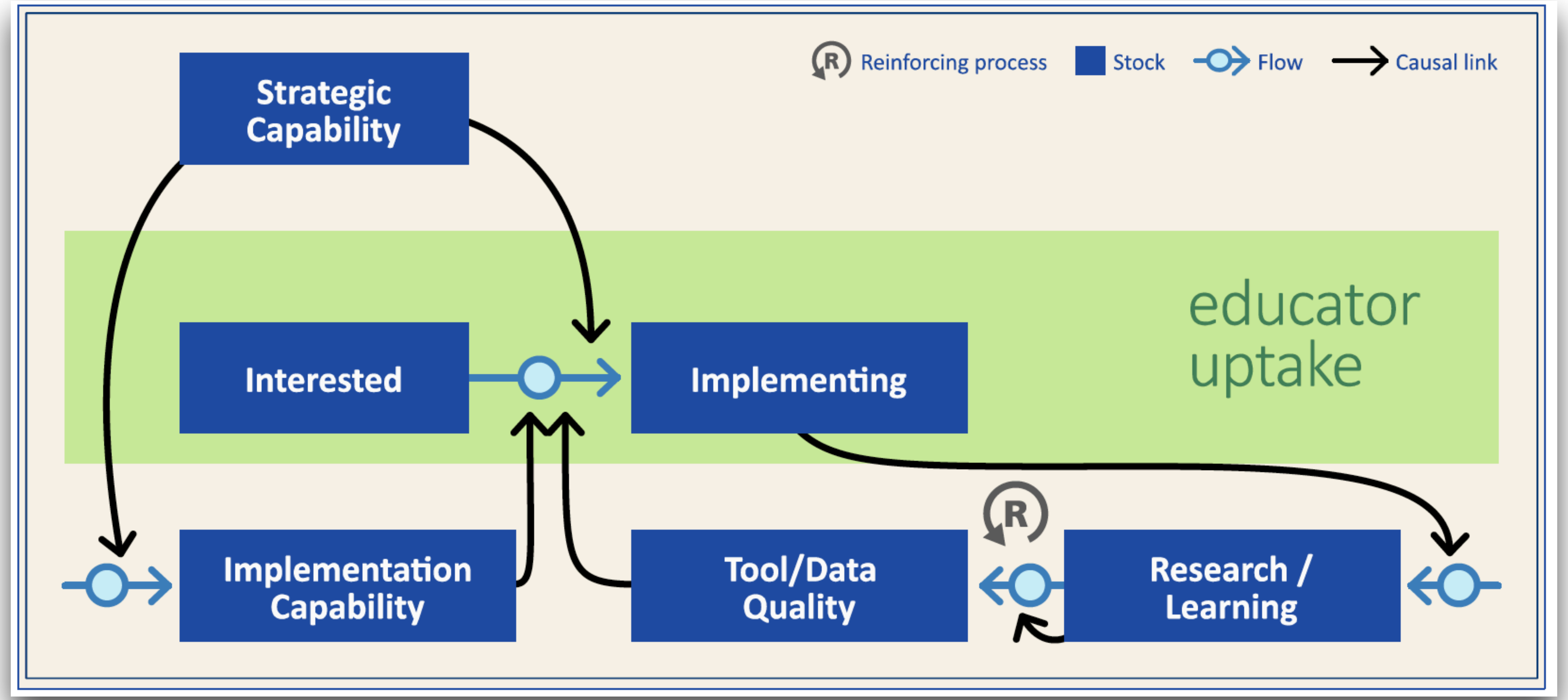


Buckingham Shum, S., & McKay, T. A. (2018). Architecting for learning analytics. Innovating for sustainable impact. *EDUCAUSE Review, 53*(2), 25–37.



Colvin, C., Rodgers, T., Wade, A., Dawson, S., Gasevic, D., Buckingham Shum, S., . . . Fisher, J. (2015). Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement. Canberra, ACT: Australian Government Office for Learning and Teaching.

Organisational guidelines

01 Developing **flexible learning analytics systems** which cater for the needs of individual institutions, i.e., their learning culture, requirements of specific study programmes, students and lecturers dispositions, technical and administrative specifications as well as the broader context of the institution.

02 Defining **requirements for data and algorithms** of learning analytics systems.

03 **Involving all higher education stakeholders** in the development of a learning analytics system.

04 Establishing **organisational, technological and pedagogical structures and process** for the application of learning analytics systems as well as providing support for all involved stakeholders for a sustainable operation.

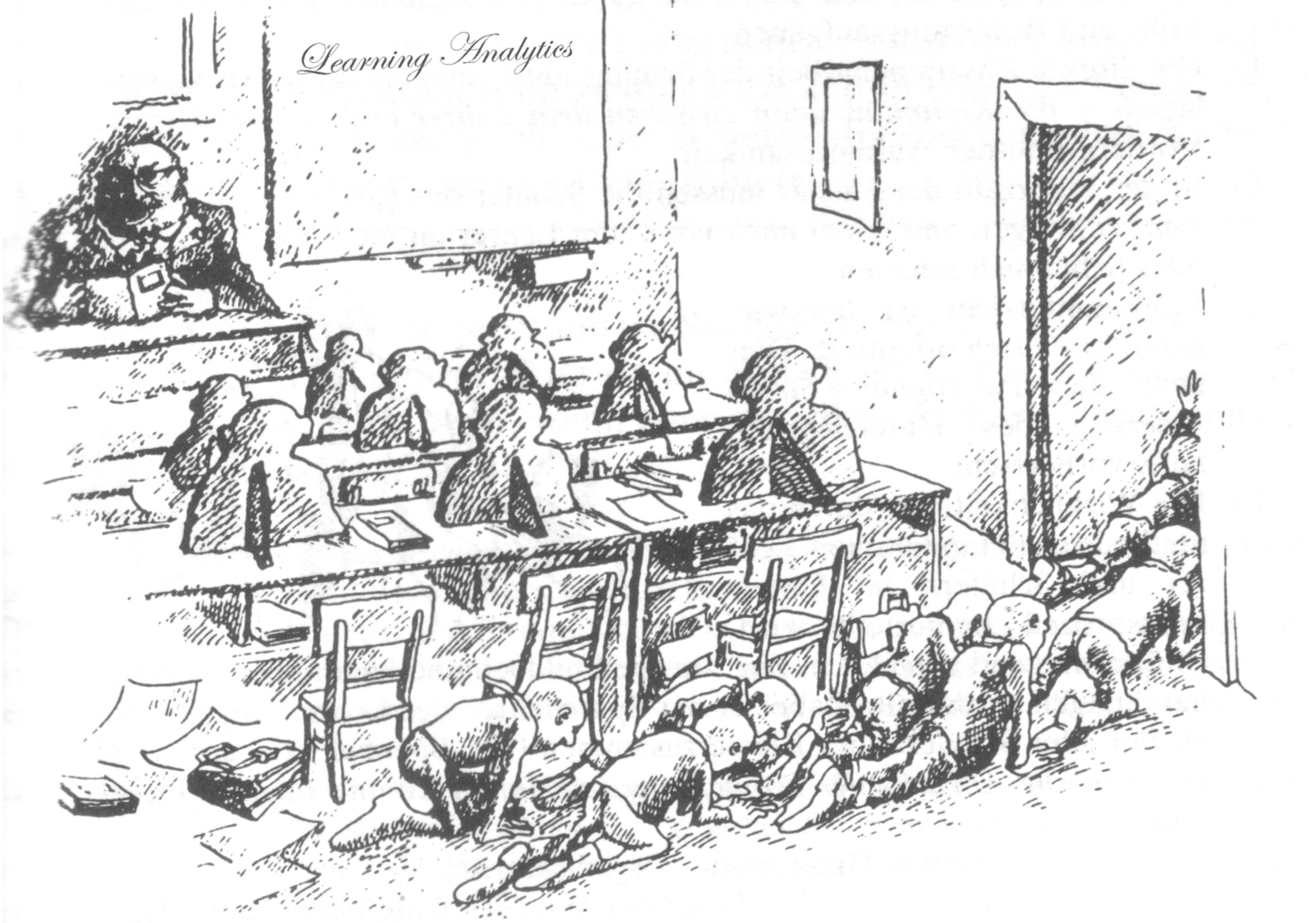
05 Informing all stakeholders with regard to **ethical issues and data privacy regulations** including professional learning opportunities.

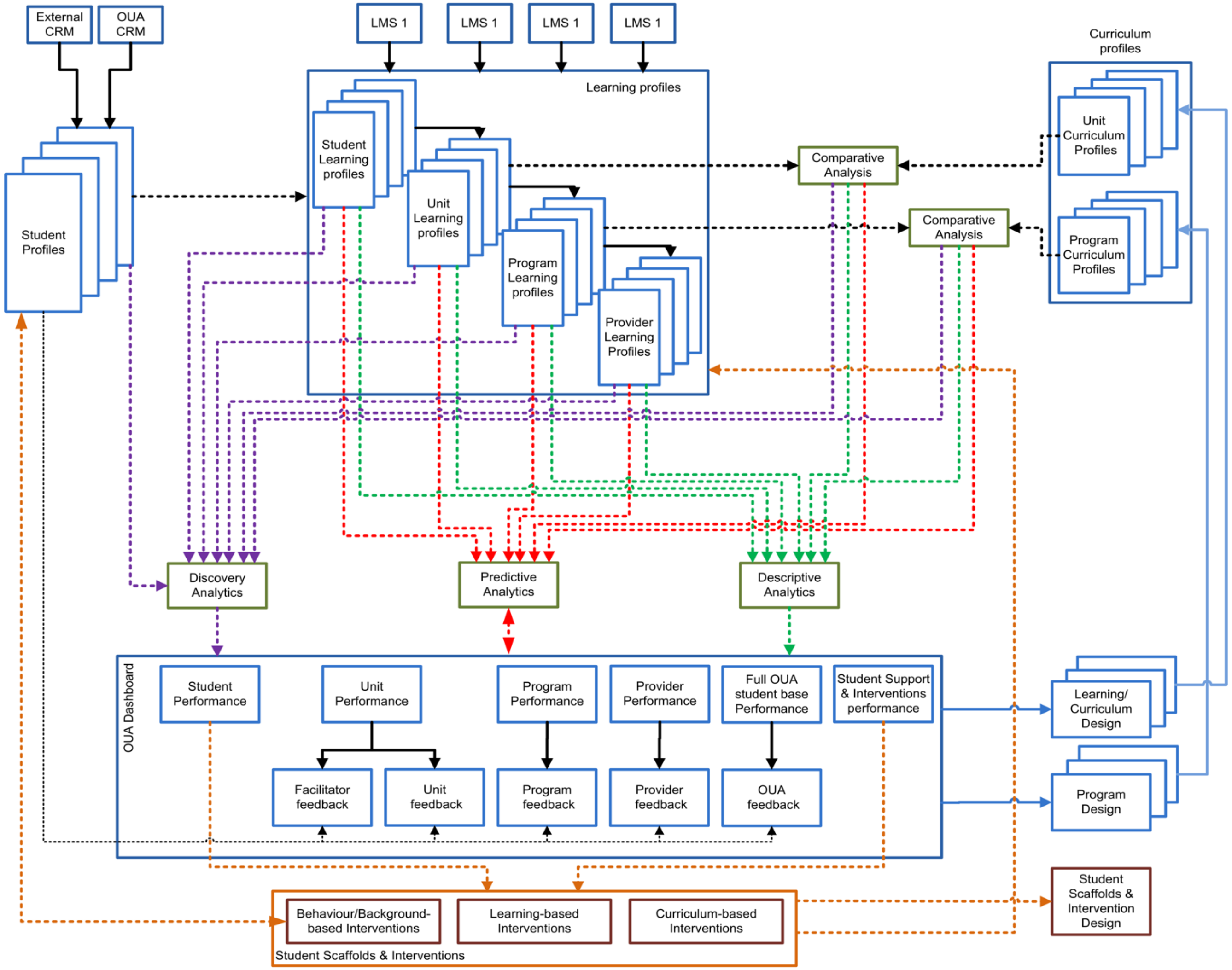
06 Building a robust **quality assurance process** focussing on the validity and veracity of learning analytics systems, data, algorithms and interventions.

07 **Funding of research** regarding questions on learning analytics within single institutions, research associations and national schemes.

08 Constituting local, regional and national **learning analytics committees** including stakeholders from science, economy and politics with a focus on adequate development and implementation (and **accreditation**) of learning analytics systems.

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*. New York, NY: Springer.


Learning Analytics



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01

Implementation.

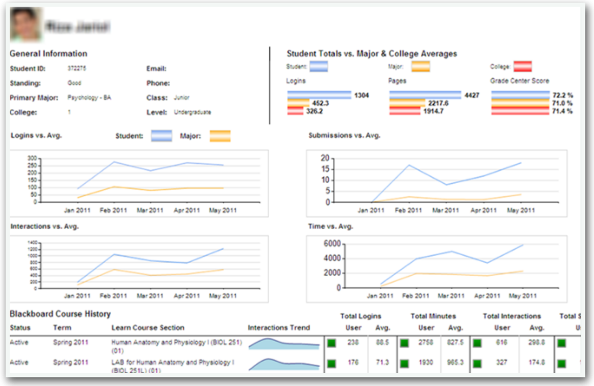
#	Feature	Willingness	Learning	Techno Cost	Orga Cost	Priority
14	**reminder for deadlines**	**3**	**2**	**3**	**3**	**54**
7	**prompts for self-assessments**	**3**	**3**	**2**	**2**	**36**
5	**timeline showing current status and goal**	**2**	**3**	**2**	**2**	**24**
13	feedback for assignments	3	2	1	3	18
11	newsfeed with relevant news matching the learning content	2	1	2	3	12
1	time spent online	1	2	3	2	12
3/8	learning recommendations	3	3	1	1	9
4	rating scales for provided learning material	1	1	3	3	9
12	revision of former learning content	3	3	1	1	9
6	time needed to complete a task or read a text	1	1	3	2	6
9	comparison with fellow students	1	1	2	2	4
2	suggestion of learning partners	1	2	1	1	2
15	term scheduler, recommending relevant courses	2	1	1	1	2

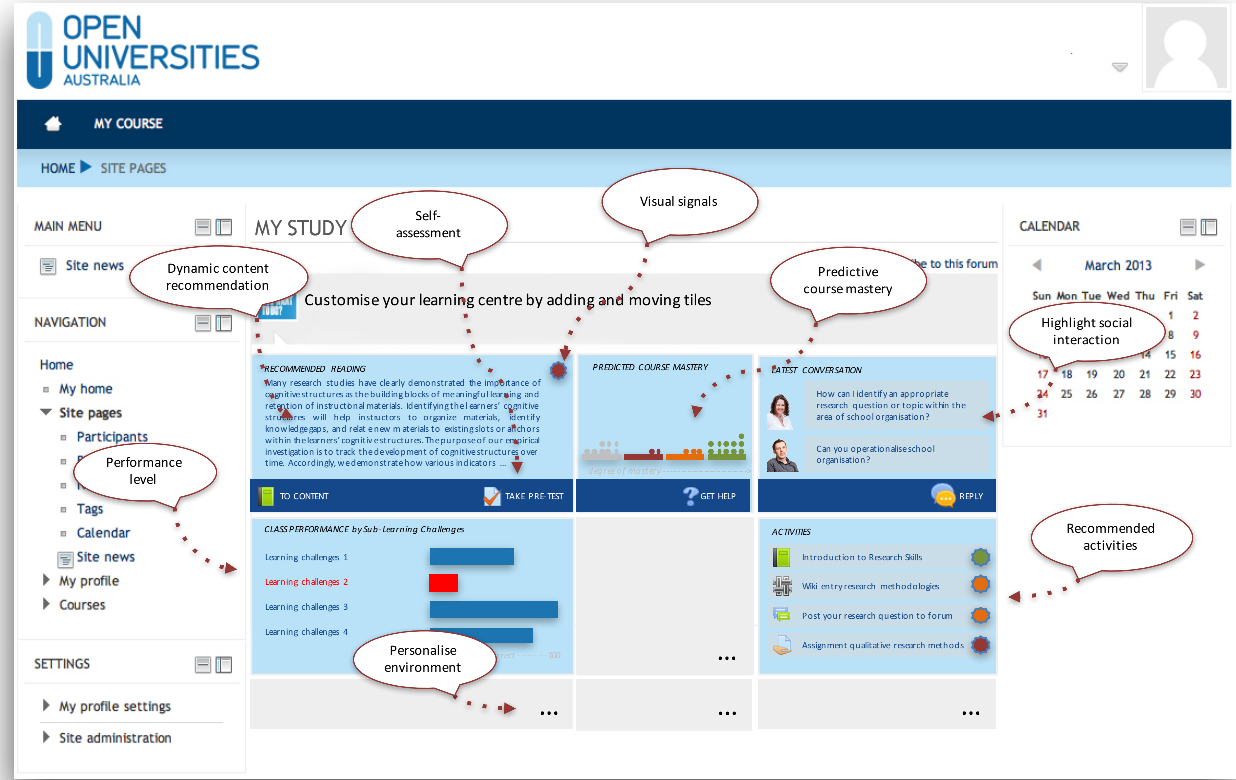
$$\mathrm{weight(n)} = \prod_{k=1}^{4} value_k(n)$$

Schumacher, C., Schön, D., & Ifenthaler, D. (2017). Implementing learning analytics features: At the intersection of pedagogical and information technological perspectives. Paper presented at the AECT International Convention, Jacksonville, FL, USA, 2017-11-06.

02

Dashboard.

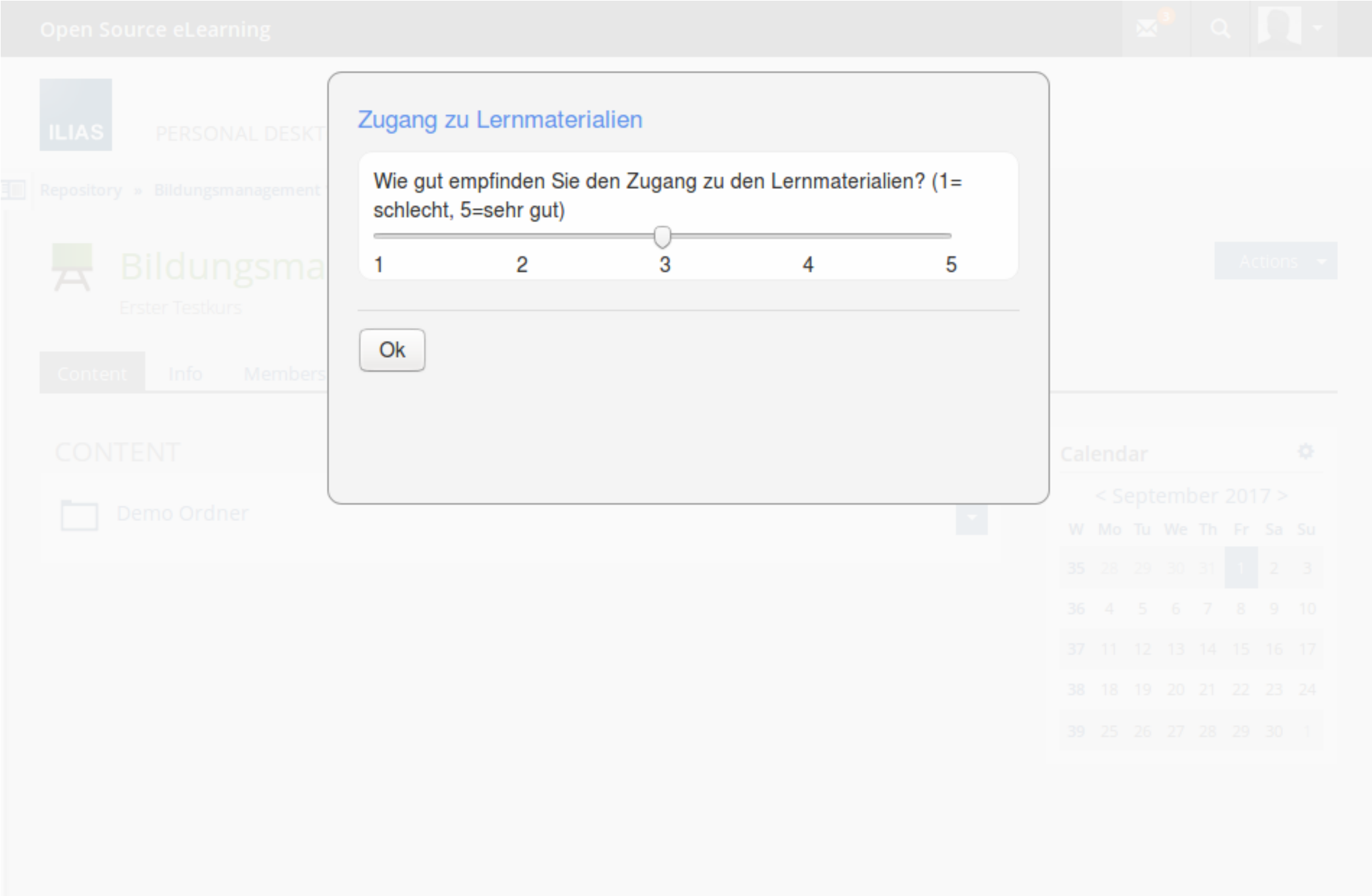




Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. doi:10.1016/j.chb.2017.06.030

LeAP

Klasen, D., & Ifenthaler, D. (2019). Implementing learning analytics into existing higher education legacy systems. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 61–72). New York, NY: Springer.



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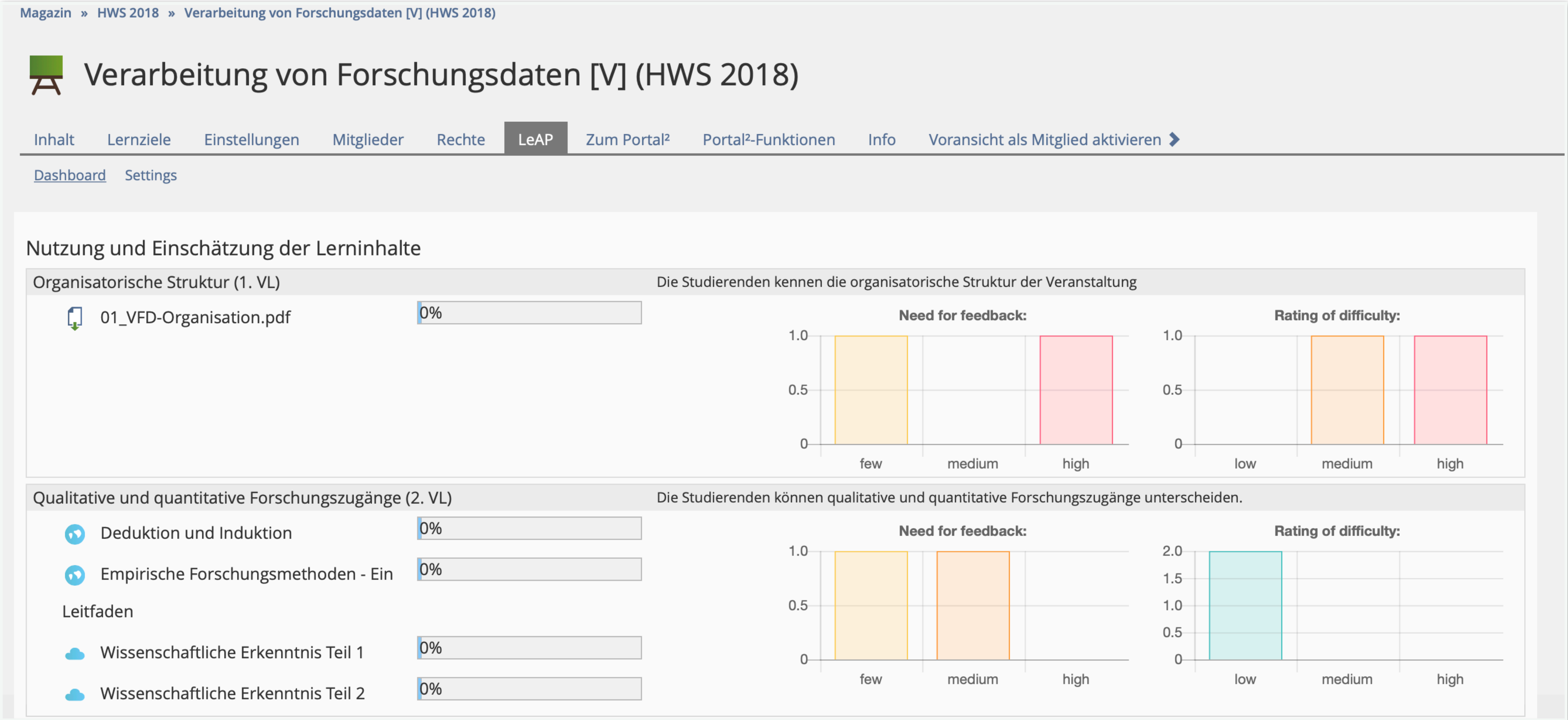

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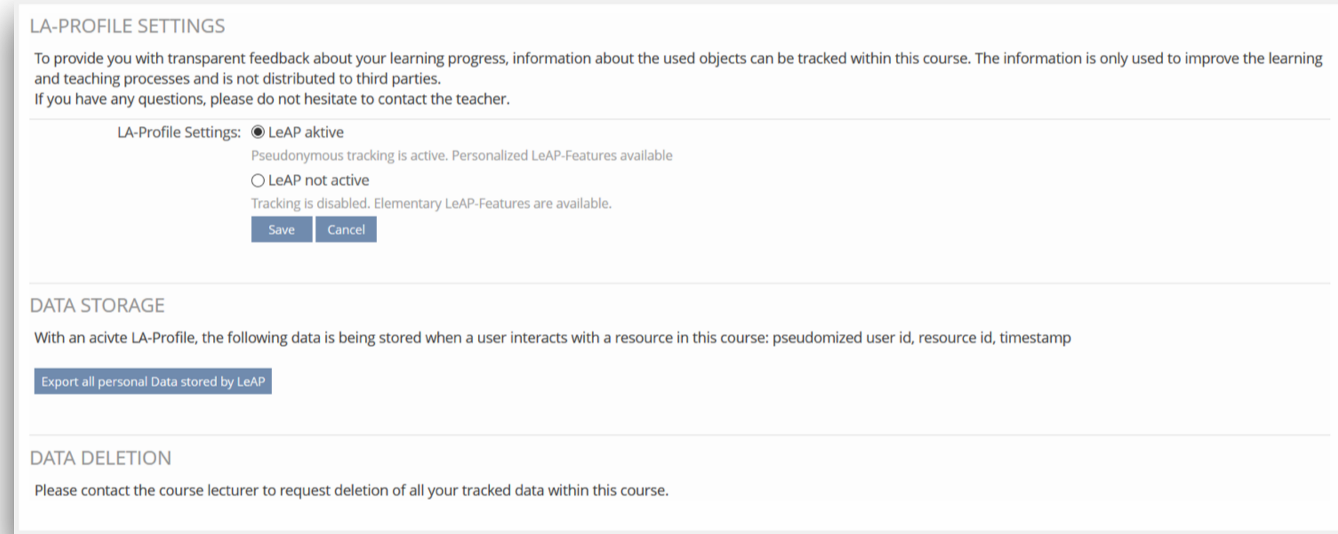
General
Data
Protection
Regulation

03

Data Protection.



LA-PROFILE SETTINGS

To provide you with transparent feedback about your learning progress, information about the used objects can be tracked within this course. The information is only used to improve the learning and teaching processes and is not distributed to third parties.
If you have any questions, please do not hesitate to contact the teacher.

LA-Profile Settings: ◉ LeAP aktive
Pseudonymous tracking is active. Personalized LeAP-Features available
○ LeAP not active
Tracking is disabled. Elementary LeAP-Features are available.
Save | Cancel

DATA STORAGE

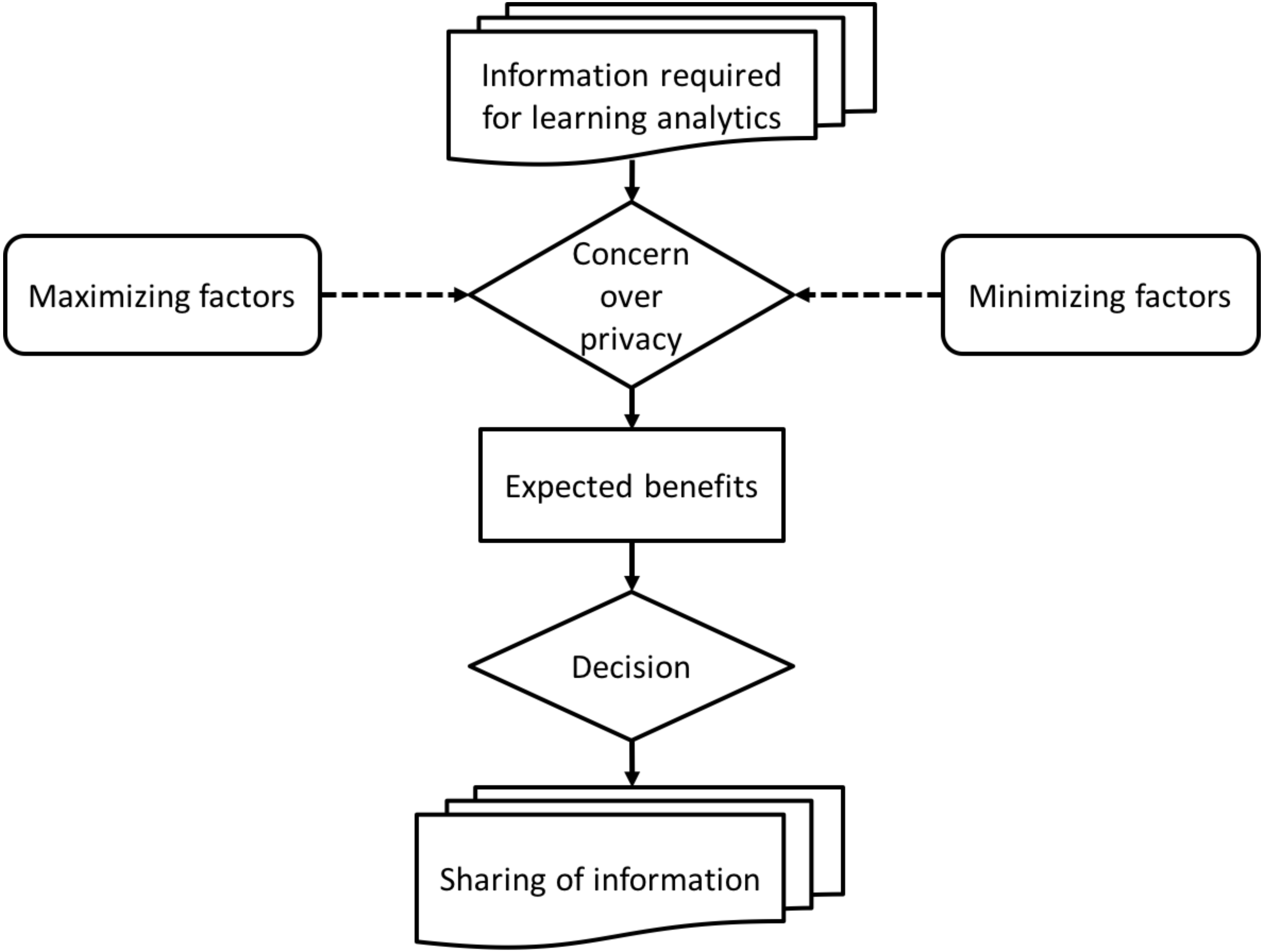
With an acivte LA-Profile, the following data is being stored when a user interacts with a resource in this course: pseudomized user id, resource id, timestamp

Export all personal Data stored by LeAP

DATA DELETION

Please contact the course lecturer to request deletion of all your tracked data within this course.

Klasen, D., & Ifenthaler, D. (2019). Implementing learning analytics into existing higher education legacy systems. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 61–72). New York, NY: Springer.



Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938. doi:10.1007/s11423-016-9477-y

04

Acceptance.

< 35 >

D

DETERMINATION – Begründung
- Was ist der Mehrwert (Organisatorisch und für das Individuum)?
- Welche Datenschutzrechte hat das Individuum? (e.g., EU Direktive 95/46/EC, General Data Processing Regulation ab 2018)

E

EXPLAIN – Erklärung
- Welche Daten werden zu welchem Zweck gesammelt?
- Wie lange werden diese Daten bewahrt?
- Wer hat Zugang zu diesen Daten?

L

LEGITIMATE – Legimitation
- Welche Daten bestehen schon und sind diese *nicht* ausreichend?
- Warum sind Sie legimitiert die Daten zu sammeln?

I

INVOLVE – Einbeziehung
- Seien Sie offen bezgl. Datenschutzbedenken
- Bieten Sie persönlichen Zugang zu den gesammelten Daten
- Trainieren Sie Beteiligte und Mitarbeiter

C

CONSENT – Einverständnis
- Fragen Sie nach dem Einverständnis des Individuums (Ja / Nein Antworten)
- Bieten Sie die Möglichkeit jederzeit aus der Datensammlung auszusteigen und dennoch dem Bildungsangebot zu folgen

A

ANONYMISE – Anonymisierung
- Anonymisieren Sie die Daten so weit wie möglich
- Aggregieren Sie die Daten, um ein abstraktes Datenmodel zu generieren (Ein solches Model fällt nicht mehr unter Datenschutzrecht)

T

TECHNICAL – Technisch und Organisatorisch
- Analysieren Sie regelmäßig, wer Zugang zu den Daten hat
- Bei Veränderungen der Analytics, fragen Sie erneut nach Einverständnis
- Daten müssen nach geltenden Sicherheitsstandards gespeichert werden

E

EXTERNAL – Externe Mitarbeiter oder Organisationen
- Vergewissern Sie sich, dass Externe sich ebenfalls an lokale Gesetze halten
- Regeln Sie vertraglich, wer für die Datensicherheit verantwortlich ist
- Stellen Sie sicher, dass die Daten nur für bestimmte Zwecke genutzt werden

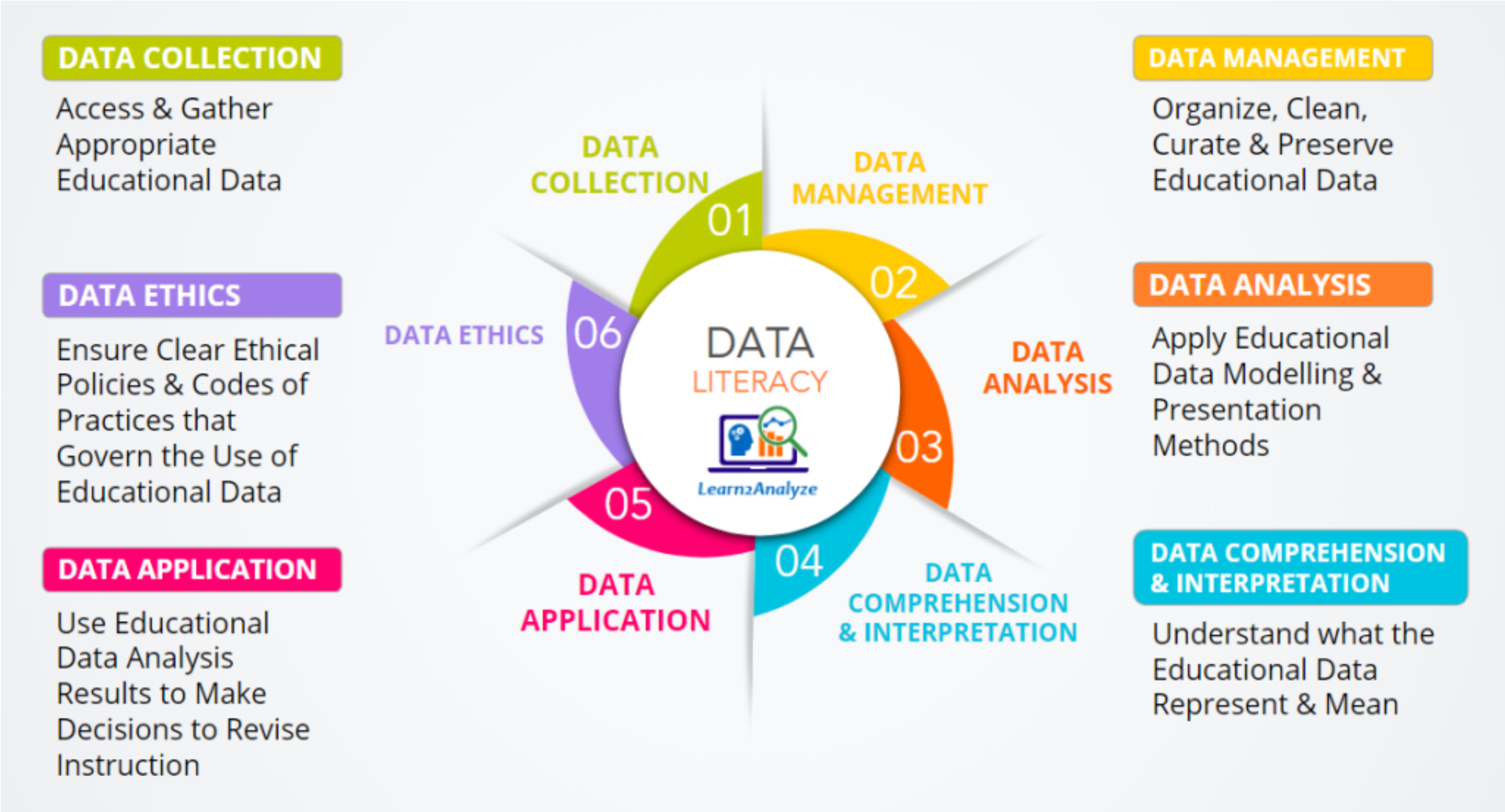
Ifenthaler, D., & Drachsler, H. (2018). Learning Analytics. In H. M. Niegemann & A. Weinberger (Eds.), *Lernen mit Bildungstechnologien* (pp. 1–20). Heidelberg: Springer.

Educational Data Literacy (EDL) is the ethically responsible collection, management, analysis, comprehension, interpretation, and application of data from educational contexts

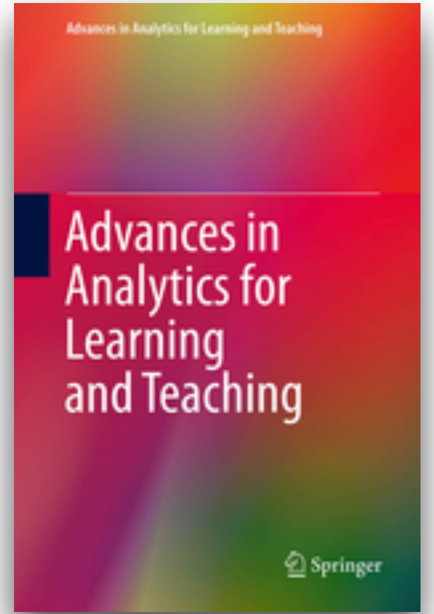
Learn2Analyze

Erasmus+

Ifenthaler, D. (2020). Change management for learning analytics. In N. Pinkwart & S. Liu (Eds.), *Artificial intelligence supported educational technologies*. Cham: Springer.



Sampson, D. G., Papamitsiou, Z., Ifenthaler, D., & Giannakos, M. (in press). *Educational data analytics literacy*. Cham: Springer.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The Promise of Learning Analytics and the Search for Evidence

Dirk Ifenthaler

Chair of Learning, Design and Technology
UNESCO Deputy Chair of Data Science in Higher Education Learning and Teaching
www.ifenthaler.info • dirk@ifenthaler.info

@ifenthaler