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https://towardsdatascience.com/10-machine-learning-algorithms-you-need-to-know-77fb0055fe0

Learning Analytics

Potentiale und Herausforderungen in der digital unterstützten Lehre

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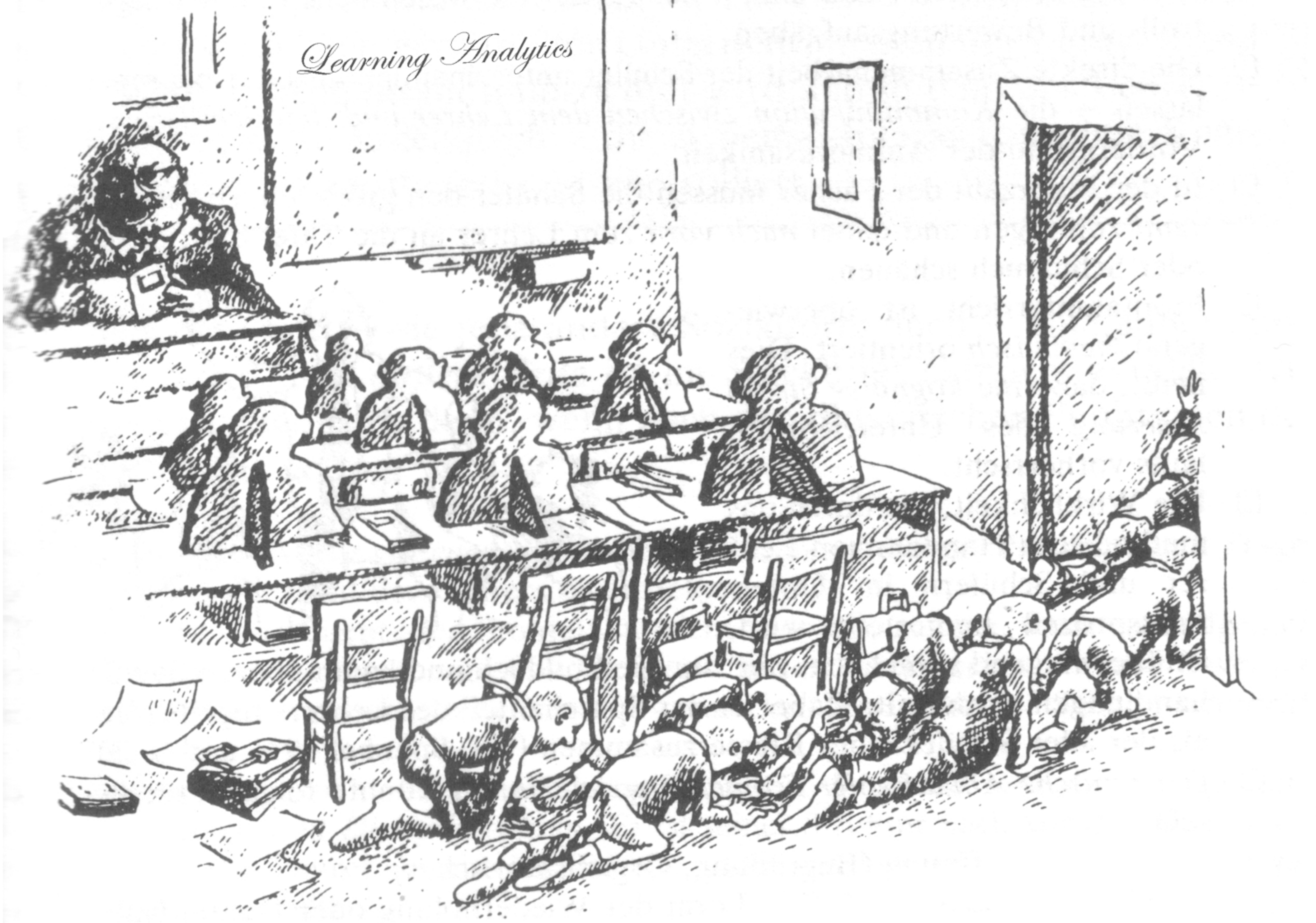
IN OMNIBUS VERITAS UNIVERSITÄT MANNHEIM

Curtin University


Learning Analytics

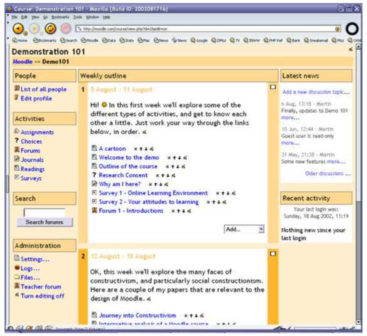
01	02	03	04
Status Quo Learning Analytics	Unterstützung von Lehr-Lern-Prozessen	Umgang mit Learning Analytics Daten	Ausblick

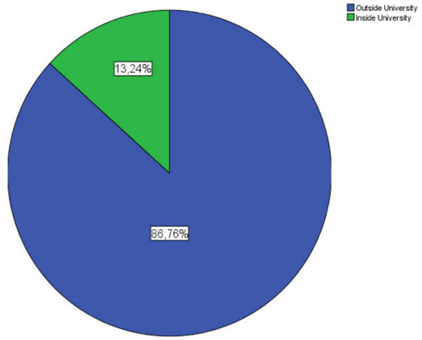
01 **Status Quo Learning Analytics**

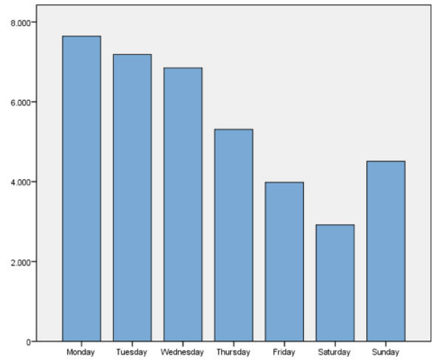
02 Unterstützung von Lehr-Lern-Prozessen

03 Umgang mit Learning Analytics Daten

04 Ausblick

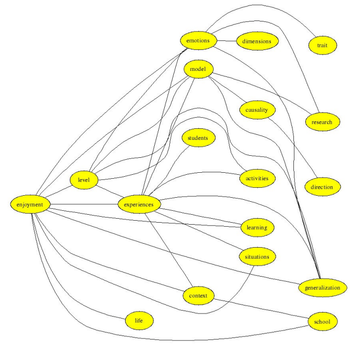


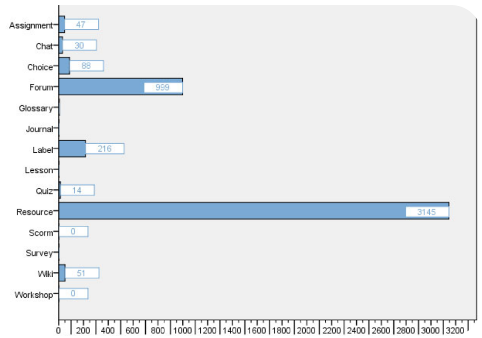




Learning analytics in 2003?

Over 86% of all hits to the LMS during the six semesters of the bachelor program occurred from outside the university





Promising learning analytics applications are being developed which use learner generated data and other relevant information in order to personalise and continuously adapt the learning environment

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

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

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

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.

Learning Analytics verwenden statische Daten von Lernenden und dynamische, in Lernumgebungen gesammelte, Daten über Aktivitäten (und den Kontext) des Lernenden, um diese in nahezu Echtzeit zu analysieren und zu visualisieren, mit dem Ziel der Modellierung, Unterstützung und Optimierung von Lehr-Lernprozessen und Lernumgebungen

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.

Purdue University, Indiana, United States
Identifies potential problems as early as the second week of term.

Users seek help earlier and more frequently.

Led to **12%** more B and C grades.
14% fewer D and F grades.

University of Maryland, United States
Students who obtain low grades use the VLE **40%** less than those with C grades or higher.

Used to identify effective teaching strategies which could be deployed on other modules.

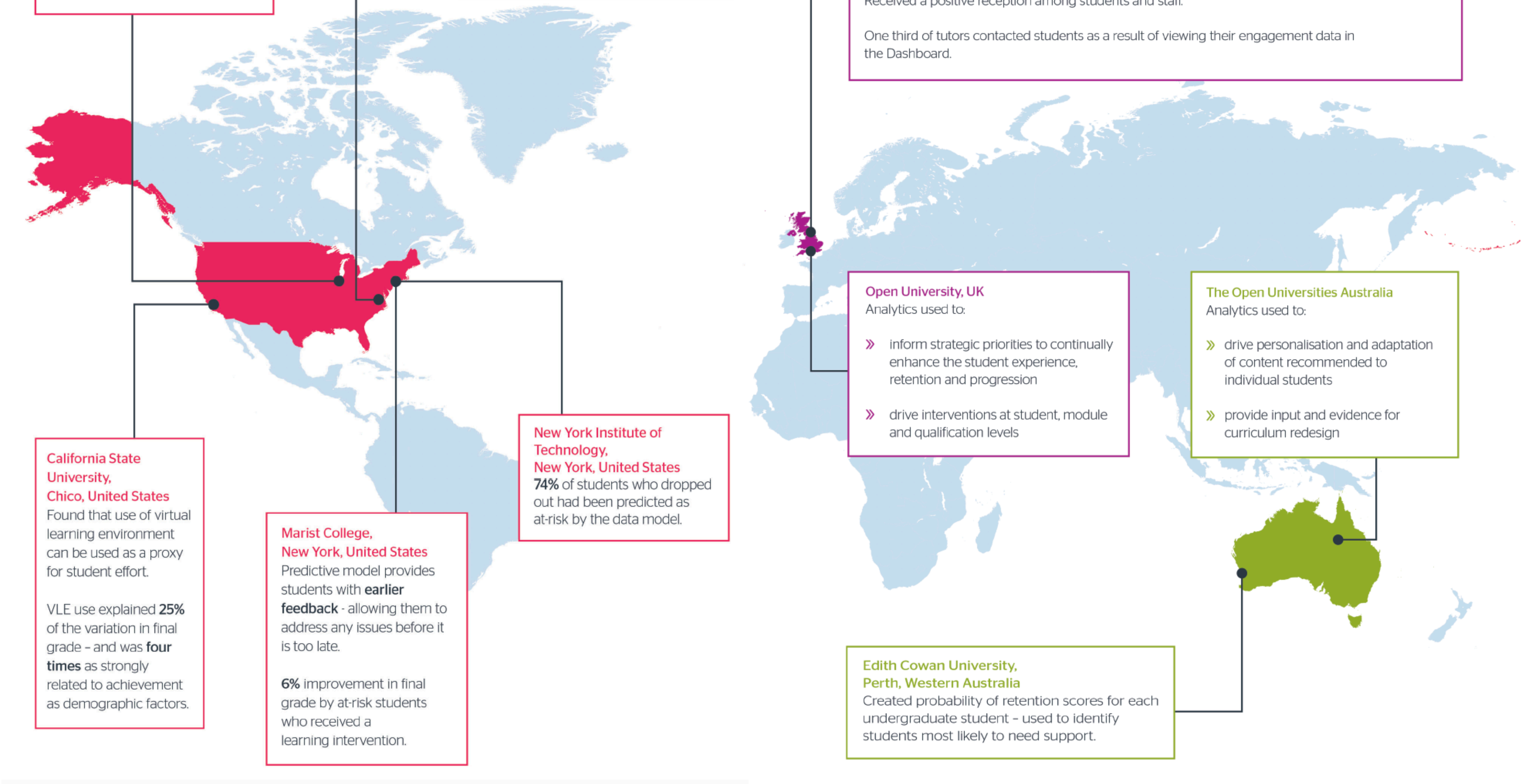
Nottingham Trent University, UK
Strong link with retention- less than a quarter of students with a low average engagement progressed to the second year, whereas over **90%** of students with good or high average engagement did so.

Strong link with achievement - **81%** of students with a high average engagement graduated with a 2:1 or first class degree, compared to only **42%** of students with low average engagement.

27% of students reported changing their behaviour after using the system.

Received a positive reception among students and staff.

One third of tutors contacted students as a result of viewing their engagement data in the Dashboard.



California State University, Chico, United States
Found that use of virtual learning environment can be used as a proxy for student effort.

VLE use explained **25%** of the variation in final grade – and was **four times** as strongly related to achievement as demographic factors.

Marist College, New York, United States
Predictive model provides students with **earlier feedback** - allowing them to address any issues before it is too late.

6% improvement in final grade by at-risk students who received a learning intervention.

New York Institute of Technology, New York, United States
74% of students who dropped out had been predicted as at-risk by the data model.

Open University, UK
Analytics used to:

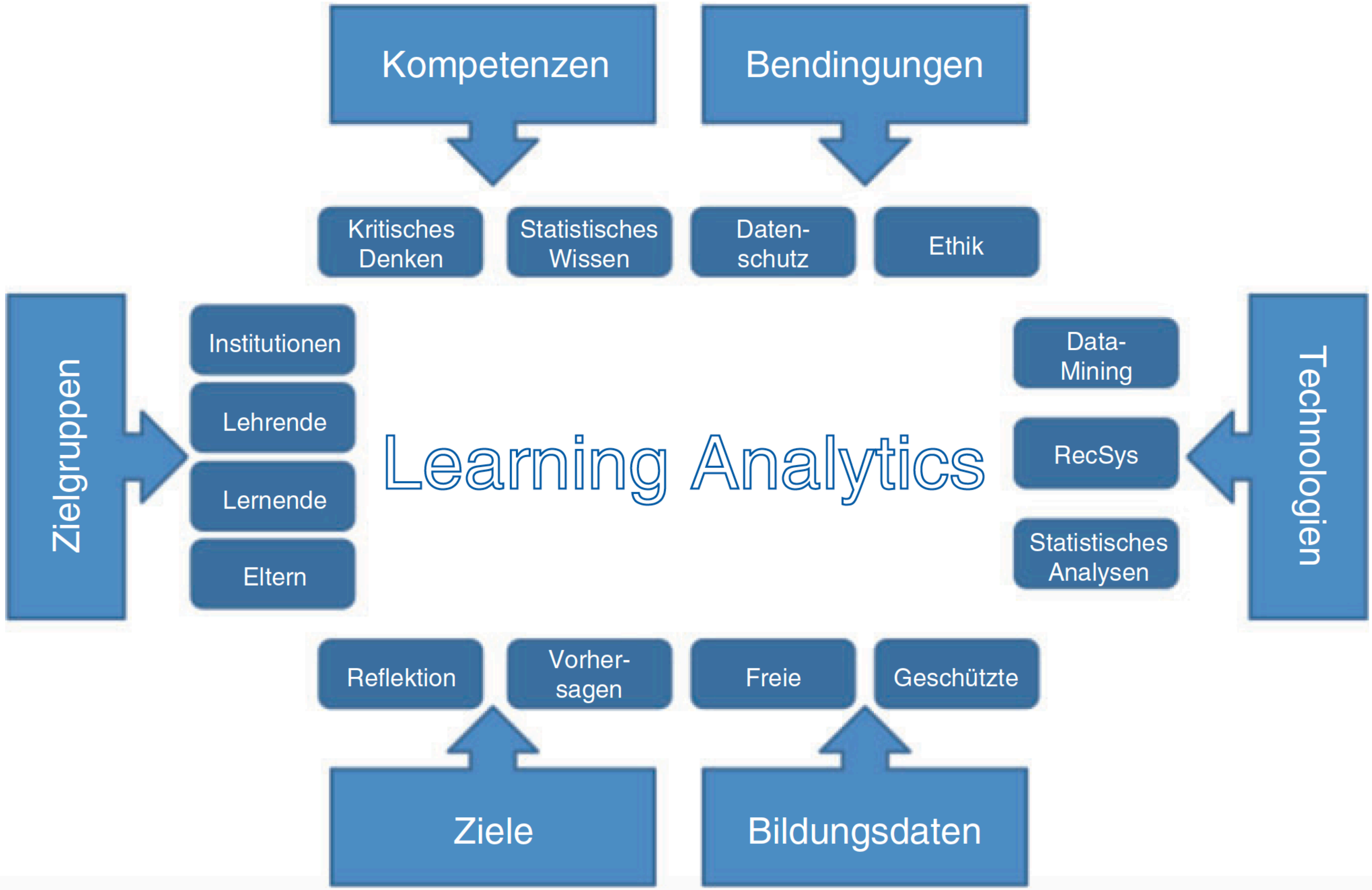
- inform strategic priorities to continually enhance the student experience, retention and progression
- drive interventions at student, module and qualification levels

The Open Universities Australia
Analytics used to:

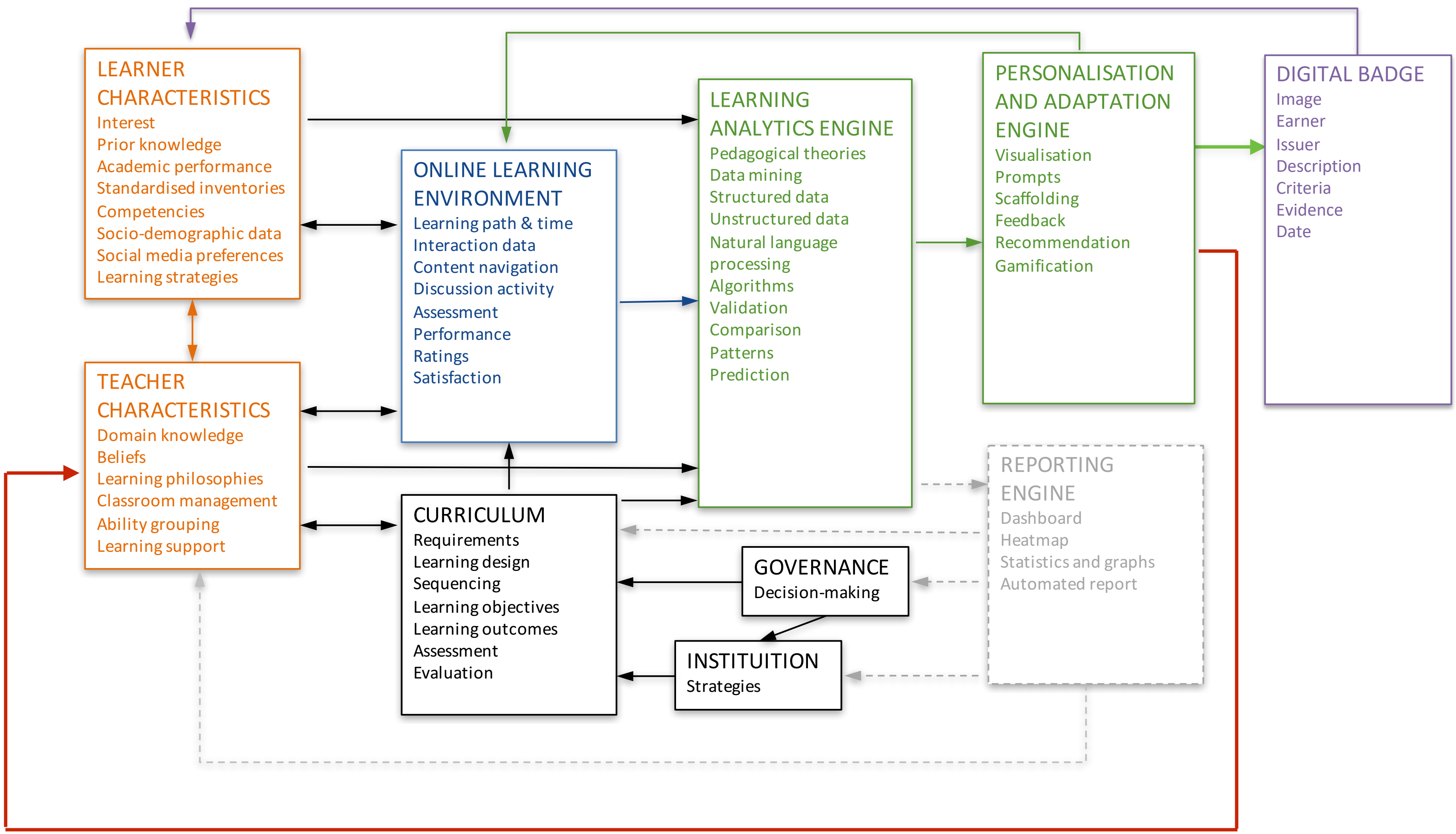
- drive personalisation and adaptation of content recommended to individual students
- provide input and evidence for curriculum redesign

Edith Cowan University, Perth, Western Australia
Created probability of retention scores for each undergraduate student – used to identify students most likely to need support.

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



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



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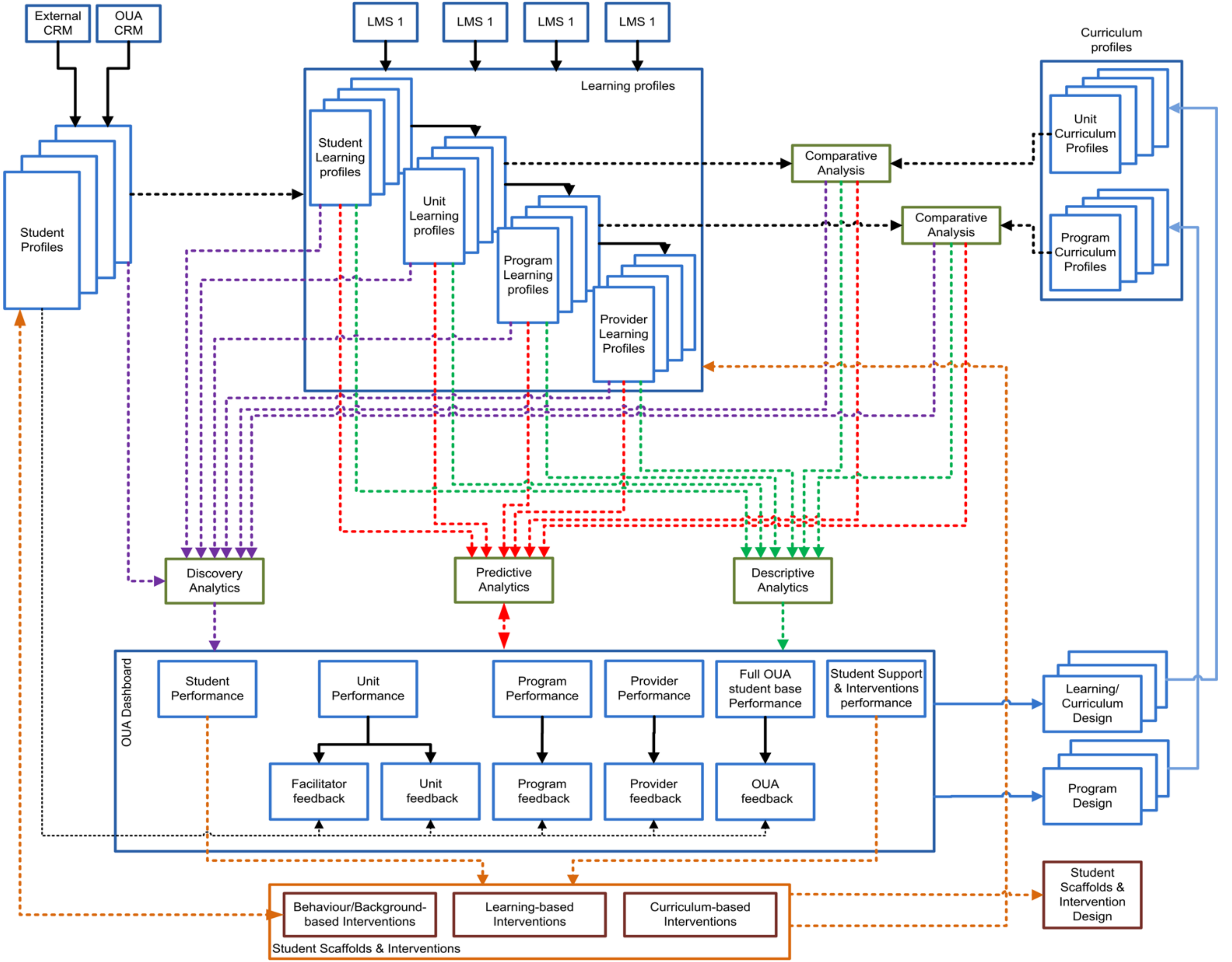
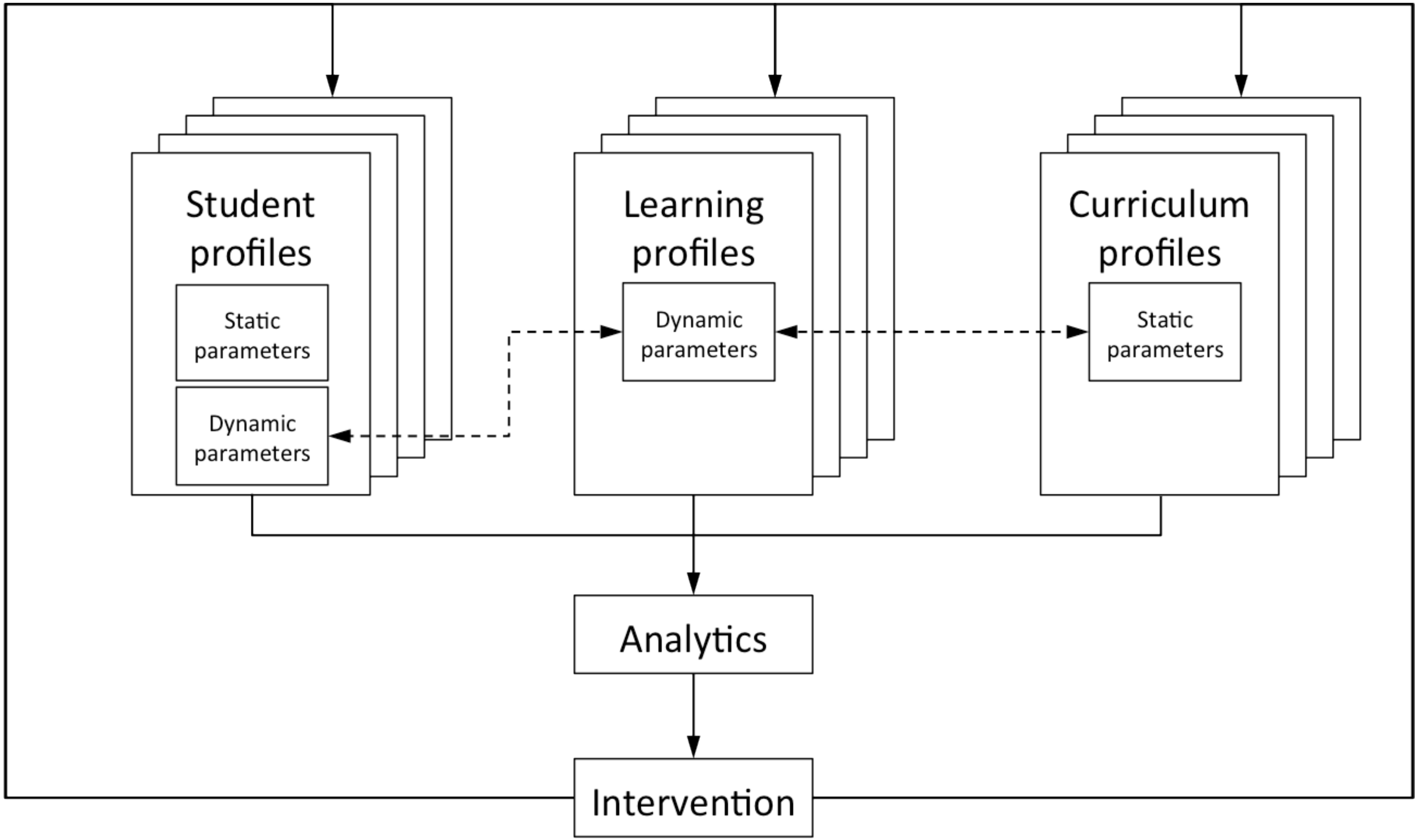
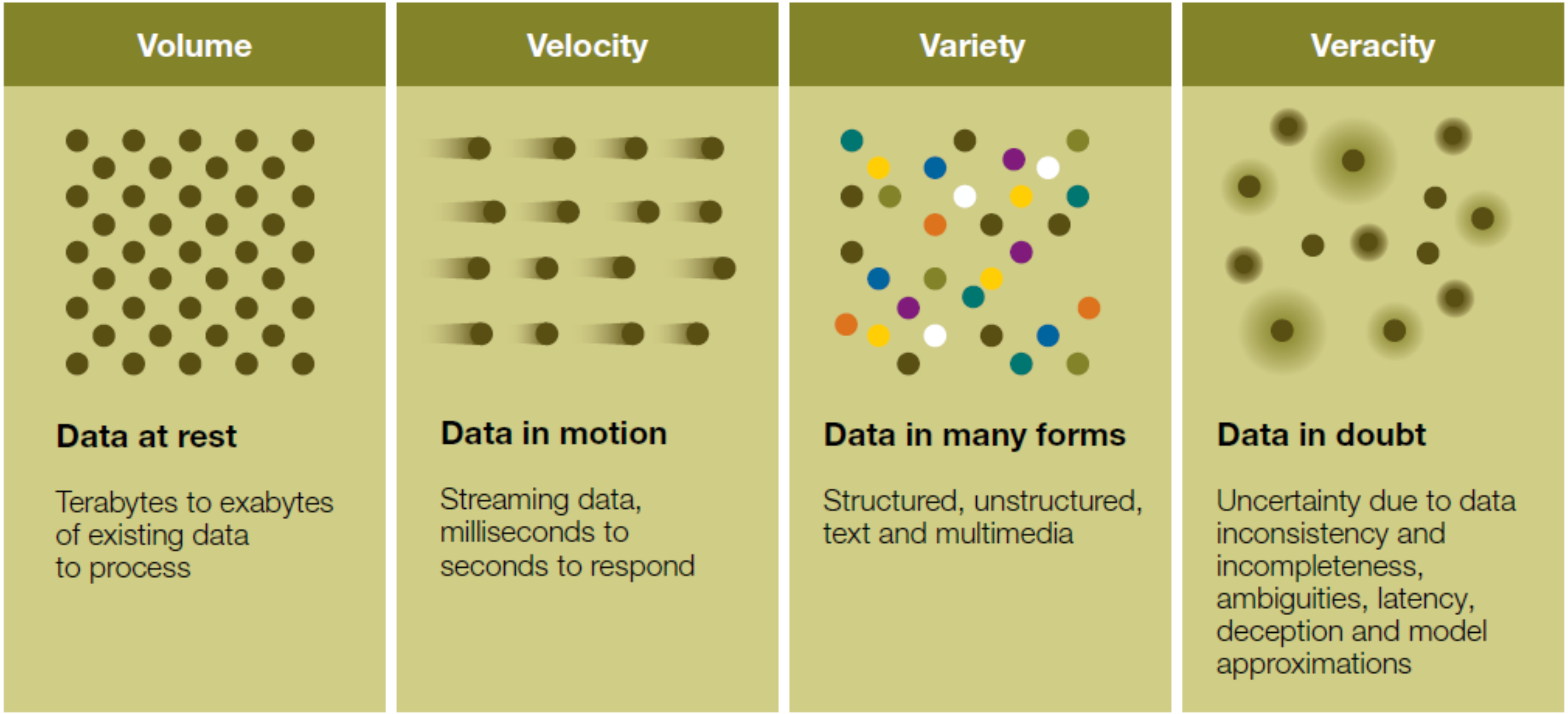
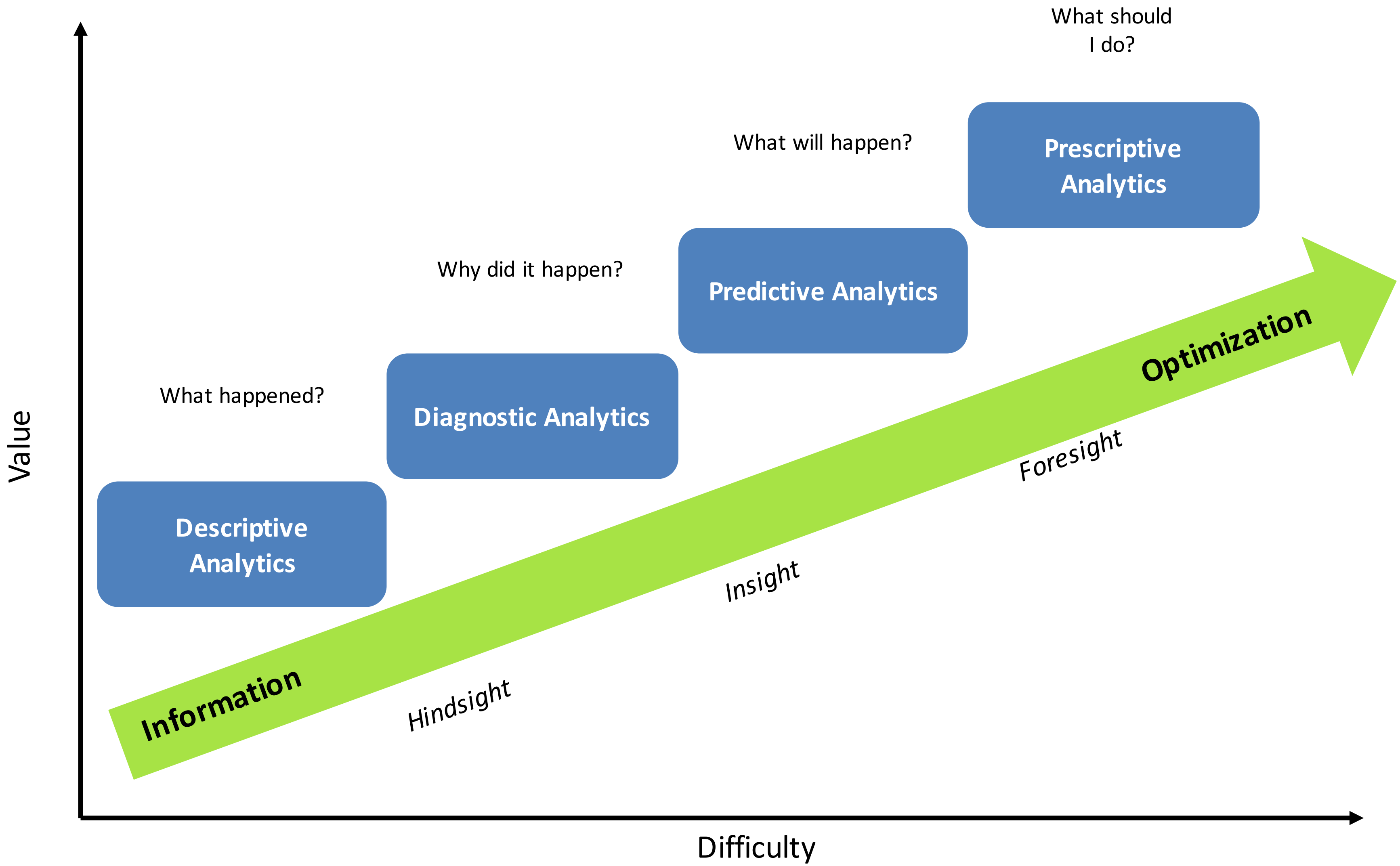

External CRM
OUA CRM
LMS 1
LMS 1
LMS 1
LMS 1
Learning profiles
Curriculum profiles
Student Profiles
Student Learning profiles
Unit Learning profiles
Program Learning profiles
Provider Learning Profiles
Comparative Analysis
Comparative Analysis
Unit Curriculum Profiles
Program Curriculum Profiles
Discovery Analytics
Predictive Analytics
Descriptive Analytics
OUA Dashboard
Student Performance
Unit Performance
Program Performance
Provider Performance
Full OUA student base Performance
Student Support & Interventions performance
Facilitator feedback
Unit feedback
Program feedback
Provider feedback
OUA feedback
Learning/ Curriculum Design
Program Design
Student Scaffolds & Intervention Design
Behaviour/Background-based Interventions
Learning-based Interventions
Curriculum-based Interventions
Student Scaffolds & Interventions



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



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.



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Mehrwerte durch Learning Analytics können aus summativer, formativer (Echtzeit) und prädikativer Perspektive erzielt werden

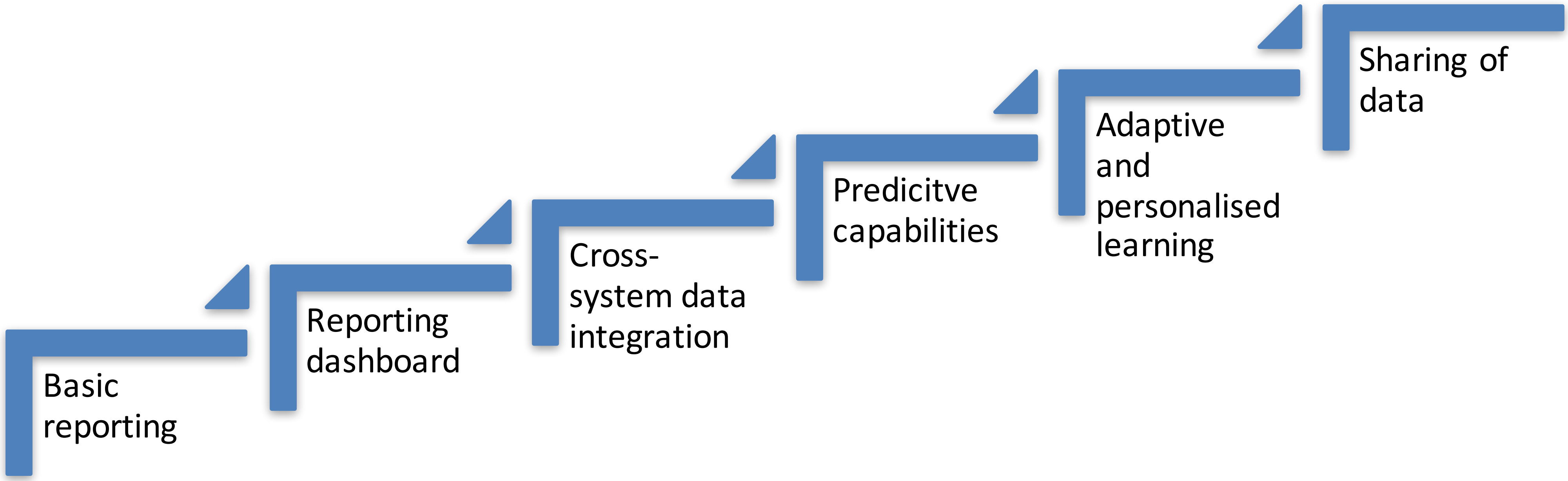
Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 447–451). Thousand Oaks, CA: Sage.

	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.

Bis heute existiert keine organisationsweite Implementation von Learning Analytics

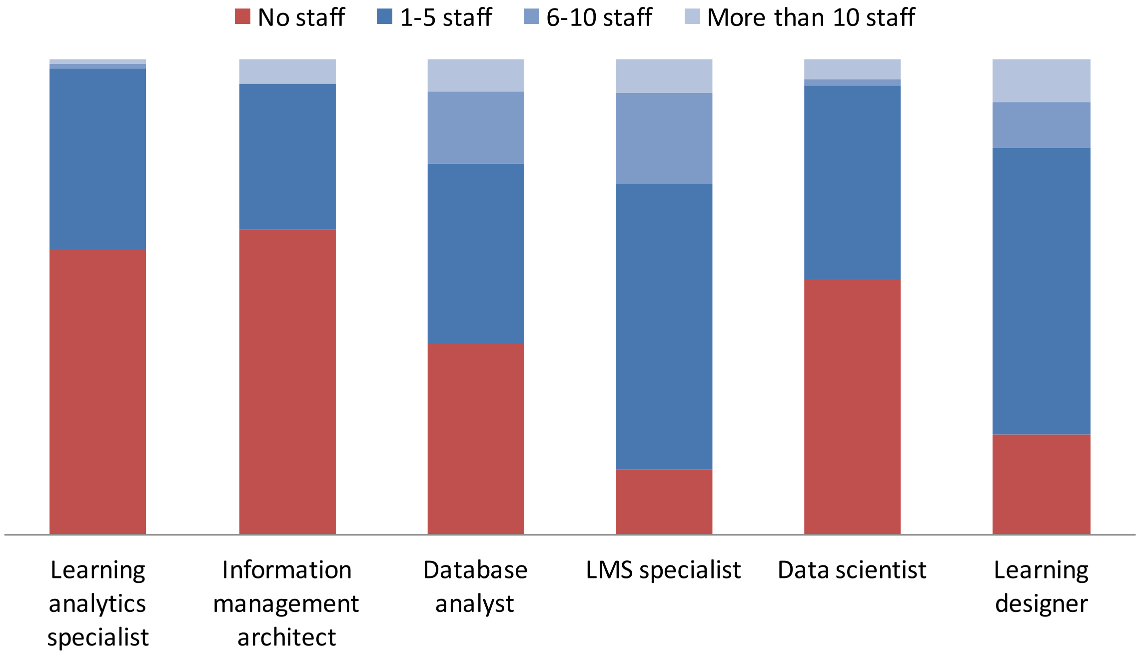
Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends, 61*(4), 366–371. doi:10.1007/s11528-016-0154-0

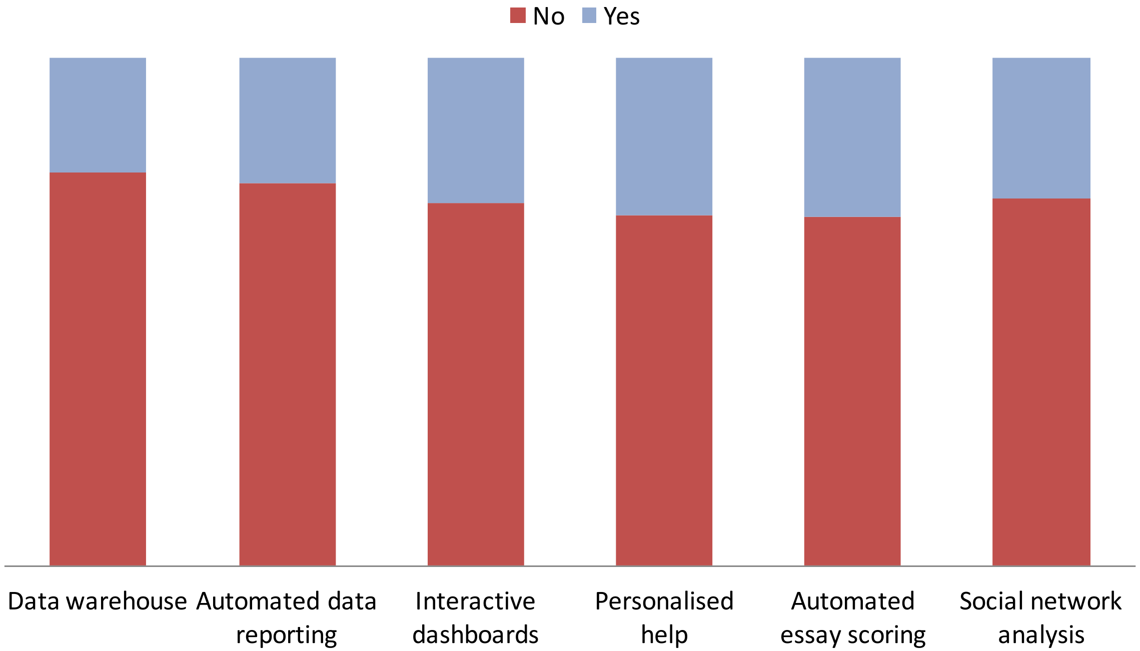


Gibson, D. C., & Ifenthaler, D. (2017). Preparing the next generation of education researchers for big data in higher education. In B. Kei Daniel (Ed.), *Big data and learning analytics: Current theory and practice in higher education* (pp. 29–42). New York, NY: Springer.

Die Implementation von Learning Analytics Systemen erfordert eine Weiterentwicklung von universitären Systemen, Prozessen und Personal

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





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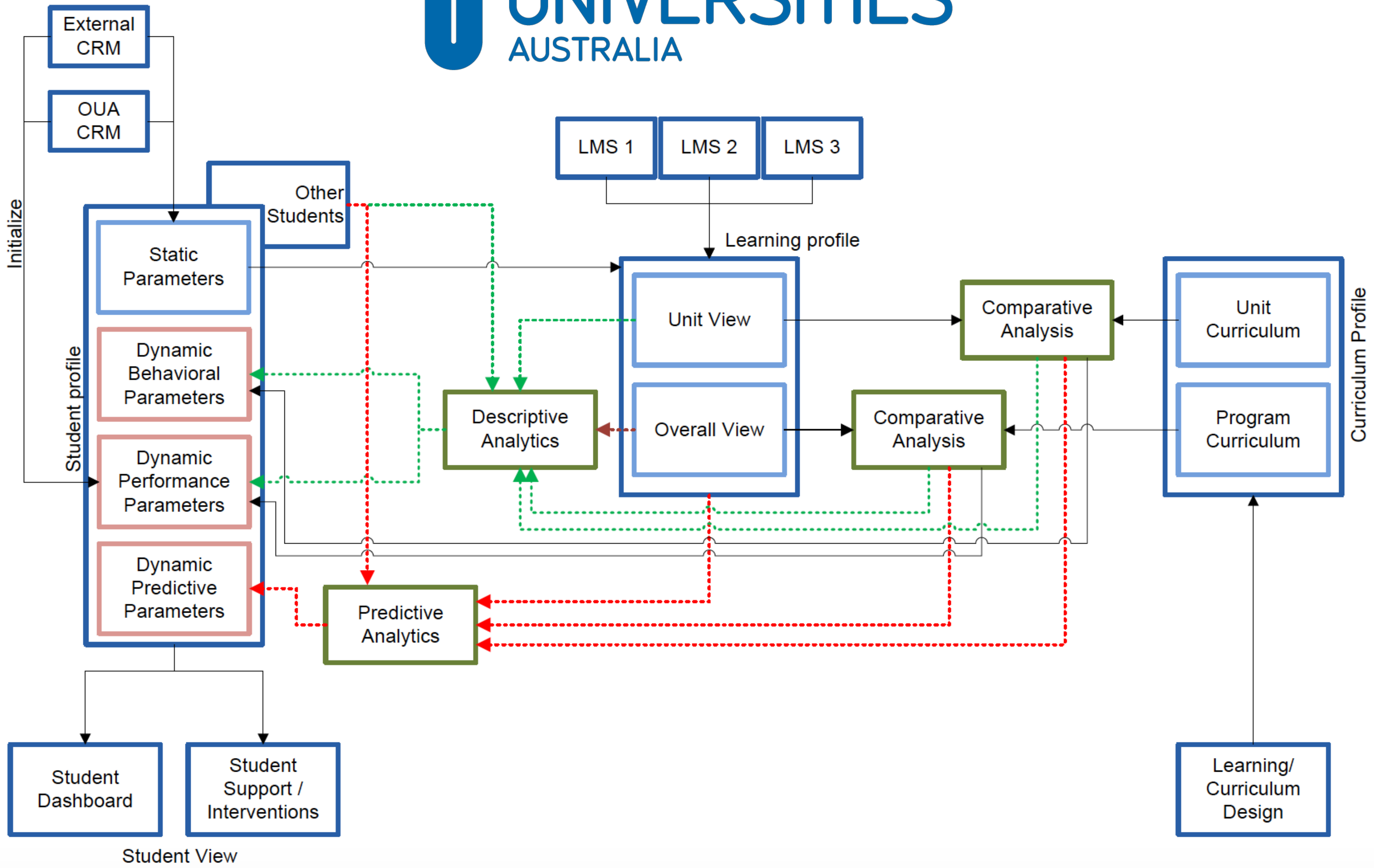
Capabilities deficit.



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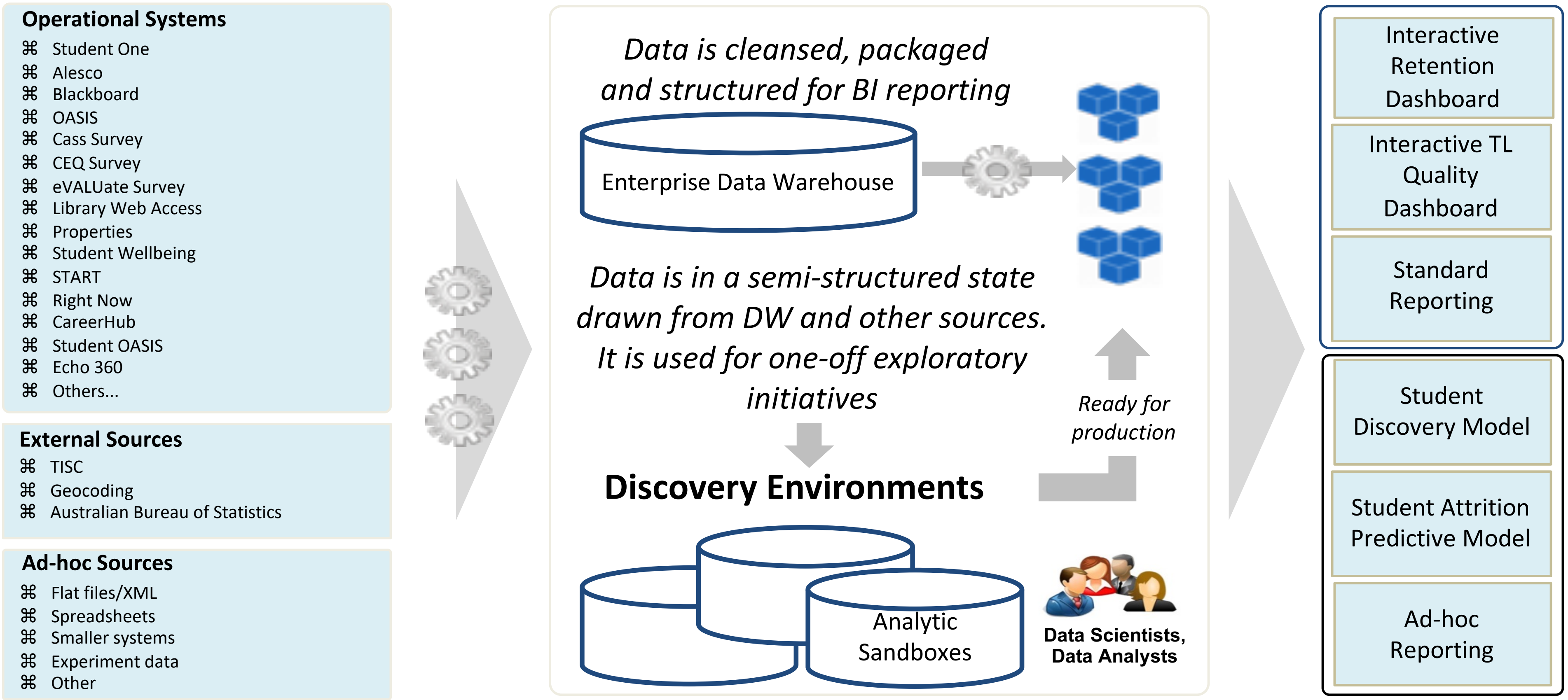
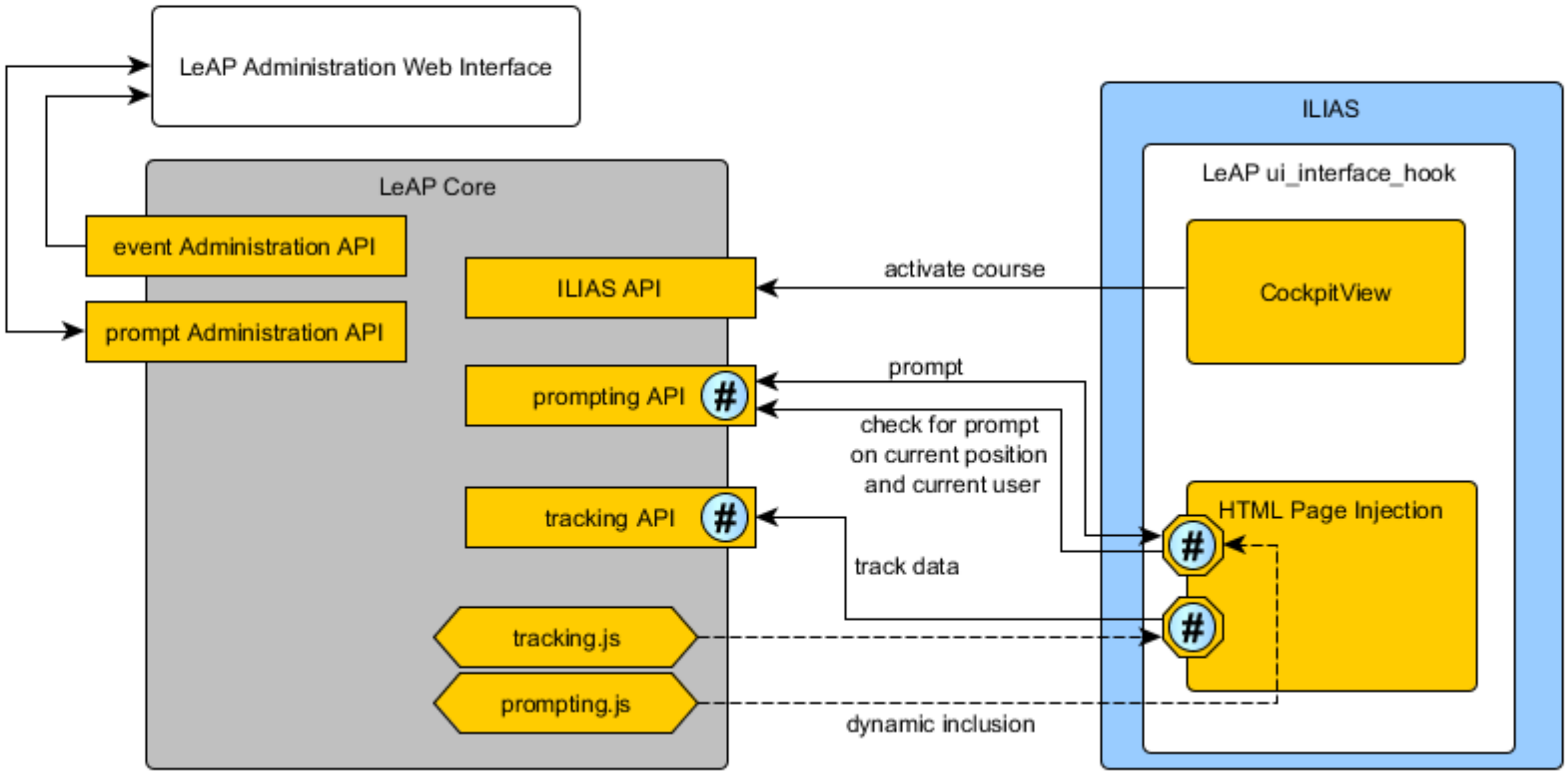
Curtin University



Gibson, D. C., Huband, S., Ifenthaler, D., & Parkin, E. (2018). Return on investment in higher education retention: Systematic focus on actionable information from data analytics. Paper presented at the ascilite Conference, Geelong, VIC, Australia, 25-11-2018.



Schön, D., & Ifenthaler, D. (2018). Prompting in pseudonymised learning analytics - implementing learner centric prompts in legacy systems with high privacy requirements. Paper presented at the International Conference on Computer Supported Education, Funchal, Madeira, Portugal, 15-03-2018.

Events

back to Courses

reset choice

Export Students

Exp. Resources

Export Events

Bildungsmanagement II : Weiterbildung [V] [1. PG] (FSS 2018)

Students - 160

Filter active students

StudentId	Account	Status	last update	Events
1	anonym745463	unknown	19.02.2018 17:06:23	7
2	student	unknown	19.02.2018 17:07:08	0
3	student	unknown	19.02.2018 17:07:08	2
4	student	unknown	19.02.2018 17:07:08	0
5	student	unknown	19.02.2018 17:07:09	0
6	student	unknown	19.02.2018 17:07:09	0
7	student	unknown	19.02.2018 17:07:09	5
8	student	unknown	19.02.2018 17:07:09	0
9	student	unknown	19.02.2018 17:07:09	0
10	student	unknown	19.02.2018 17:07:09	0
11	student	unknown	19.02.2018 17:07:09	0
12	student	unknown	19.02.2018 17:07:09	0
13	student	unknown	19.02.2018 17:07:09	0

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*. New York, NY: Springer.

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.

Table 1. Student profile – comparison of institutions predicting pass/fail rates

Institution	*N*	R^2	Adjusted R^2	R^2-SVR	Predictive accuracy (SVM)
UNI1	244494	0.4635	**0.4633*** **	0.4889	**0.817**
UNI2	217039	0.4528	0.4526***	0.4603	0.796
UNI3	127218	0.431	0.4306***	0.4595	0.796
UNI4	114432	0.372	0.3716***	0.3807	0.766
UNI5	88026	0.4379	0.4374***	0.4430	0.807
UNI6	84510	0.3641	**0.3635*** **	0.3530	**0.763**
UNI7	76278	0.434	0.4334***	0.4604	0.803
UNI8	73043	0.3718	0.3711***	0.3562	0.783
SD		0.096	0.097	0.126	0.024

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

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

Table 2. Student profile – comparison of areas of study predicting pass/fail rates

Areas of study	*N*	R^2	Adjusted R^2	R^2-SVR	Predictive accuracy (SVM)
Arts & Humanities	386059	0.4299	0.4297	0.45039	0.799
Business	269410	0.4054	0.4053	0.4360	0.780
Education	157693	0.4887	0.4885	0.5049	0.824
Law & Justice	84663	0.4900	**0.4896**	0.5166	**0.827**
IT	57371	0.3732	**0.3726**	0.3586	**0.776**
Science & Engineering	57234	0.4228	0.422	0.4234	0.800
SD		0.107	0.107	0.129	0.027

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

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

Table 3. Learning profile - change of predictors (pass/fail) over the semester (16 weeks)

	Week 1-4	Week 5-8	Week 9-12	Week 13-16
	Adjusted R^2			
Course A	0.4673	0.7613	0.8366	0.8592
Course B	0.4971	0.7572	0.8206	0.8359
Combined	0.4880***	0.7593***	**0.8273*** **	**0.8439*** **
	R^2-SVR			
Course A	0.4972	0.7571	0.8403	0.8563
Course B	0.5423	0.7856	0.8449	0.869
Combined	0.5284	0.7841	0.8602	0.8777
	Predictive accuracy (SVM)			
Course A	0.7498	0.8754	0.9326	0.9467
Course B	0.7694	0.8807	0.9351	0.9433
Combined	0.7644	**0.8879**	**0.9383**	**0.9463**

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

Aggregation of student produced information, uncontrolled relations to existing educational data, and simplistic algorithms increase the chance of critical biases

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.

01

Status Quo
Learning Analytics

02

**Unterstützung von
Lehr-Lern-Prozessen**

03

Umgang mit Learning
Analytics Daten

04

Ausblick

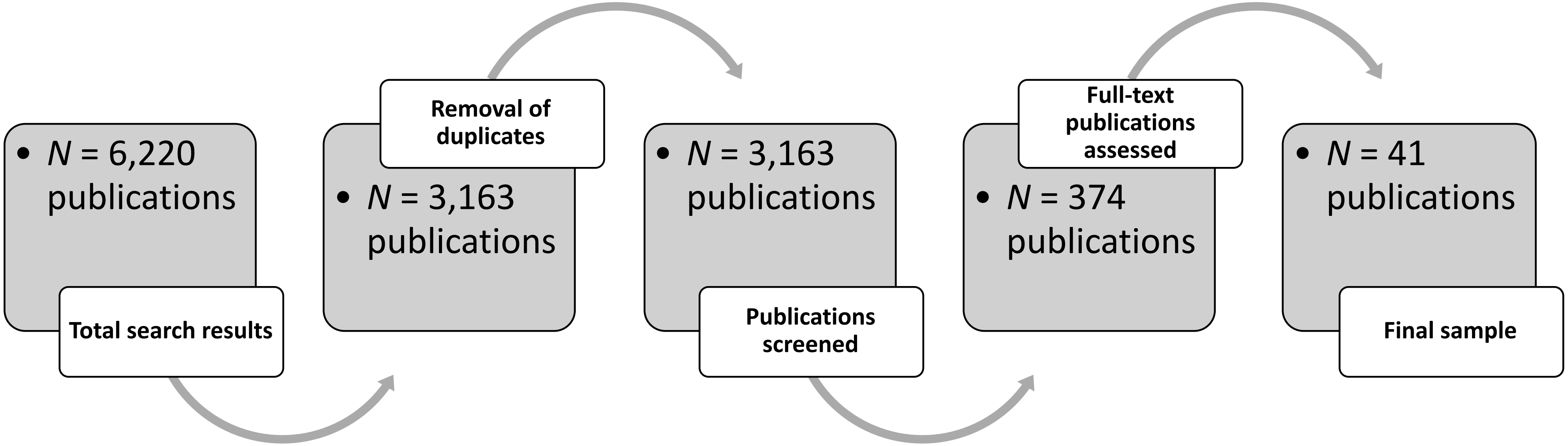
Learning analytics show promise to enhance study success in higher education

Pistilli, M. D., & Arnold, K. E. (2010). Purdue Signals: Mining real-time academic data to enhance student success. *About campus: Enriching the student learning experience*, 15(3), 22–24.

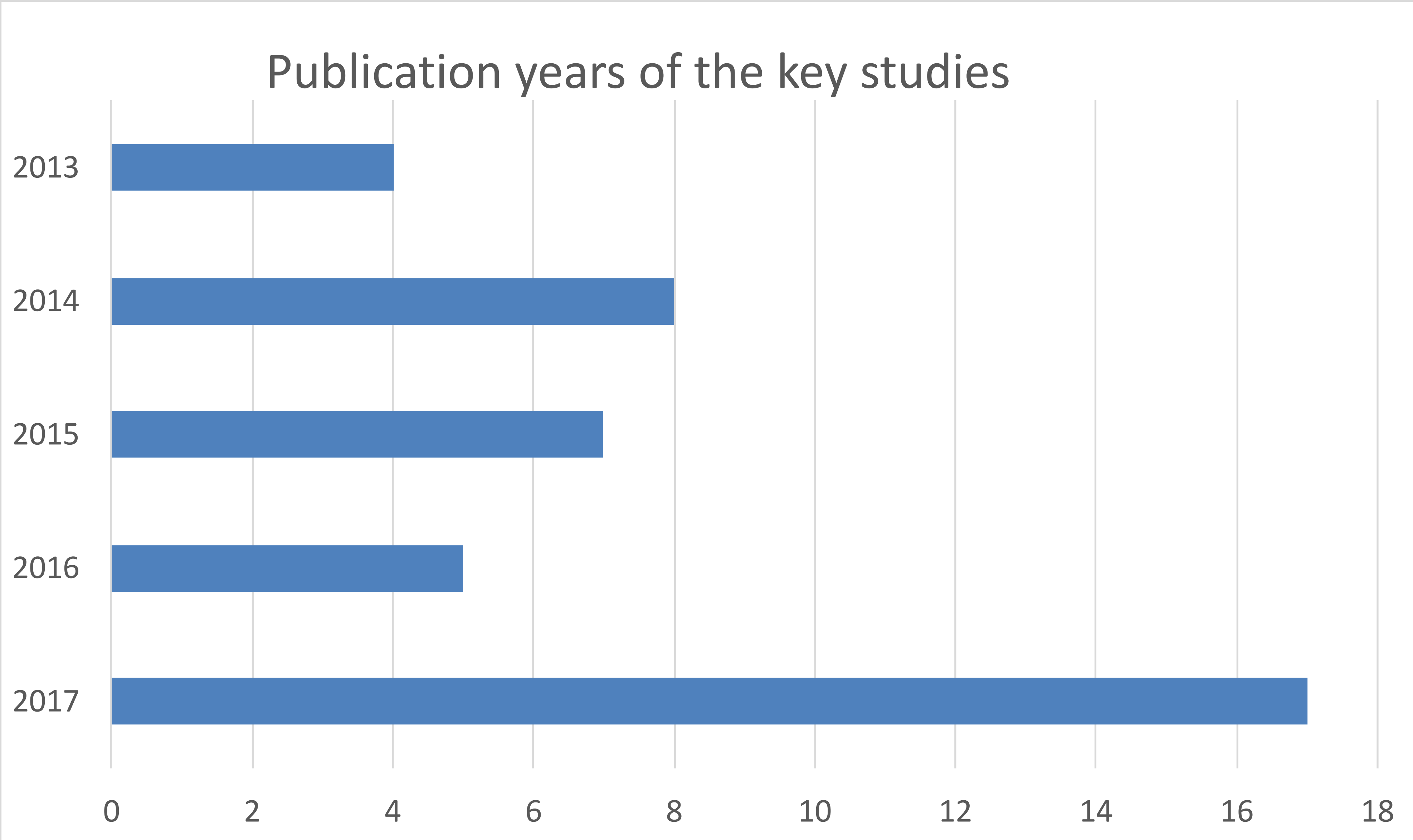
There exists the difficulty to isolate the influence of the use of learning analytics, as often they are used in addition to wider initiatives to improve student retention and academic achievement

Sclater, N., & Mullan, J. (2017). *Learning analytics and student success – assessing the evidence*. Bristol: JISC.

Systematic Review Process



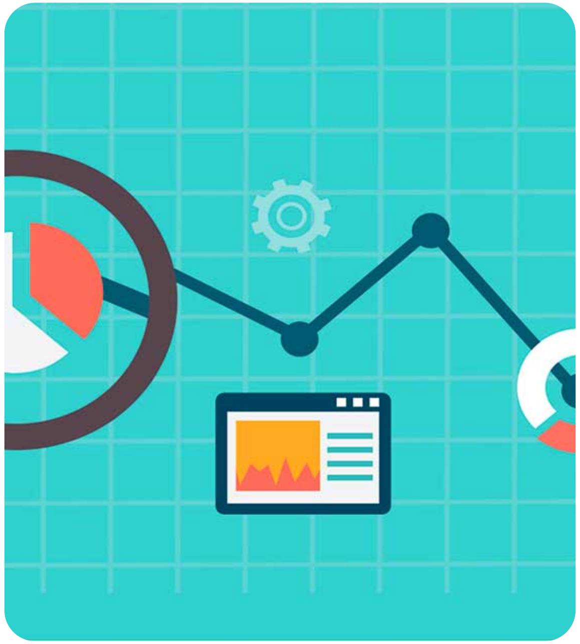
Ifenthaler, D., Mah, D.-K., & Yau, J. Y.-K. (2019). Utilising learning analytics for study success. Reflections on current empirical findings. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success*. New York, NY: Springer.


Publication years of the key studies
2013
2014
2015
2016
2017
0
2
4
6
8
10
12
14
16
18

Author/Year	Country	Sample size	Demographic background (age, study year)	Data collection/ sources	Data analytics methods	Key aim	Key indicators	Intervention (used as specified LA tool, Intervention)	Study success/ retention/dropout/ withdrawal non-completion/failure rate
Aulck, Aras, Li, L'Heureux, Lu, & West (2017)	USA	66,060	First year/freshman. Age not specified.	University databases (demographic, pre-college entry (e.g. standardized test scores, high school grades, parents' educational attainment) & transcript records)	Machine learning experiments	Prediction of course completion.	Demographic, pre-college entry information (standardized test scores, high school grades, parents' educational attainment, and application zip code), complete transcript records.	Not specified.	30% increase in prediction accuracy
Bukralia, Deokar, & Sarnikar, (2014)	USA	1,376	28% - freshman, 4% - remedial, remaining unspecified. Age not specified.	Variables from Student Information Systems and Course Management System	Binary classification problem, descriptive statistics, data mining techniques	Prediction of student dropout	Academic ability, financial support, academic goals, technology preparedness, demographics, course engagement and motivation, course characteristics	Not specified.	90.97% prediction accuracy
Bydzovska, & Popelinsky, (2014)	Czech Republic	7457	Not specified.	Datasets: Study-related, social behavior and data about previously passed courses	Social network analysis	Predict student social behaviour	Study-related data, social behaviour data, data about previously passed courses.	Not specified.	The accuracy of predicting student social behaviour increased by 3%.
Cambruzzi, Rigo, & Barbosa (2015)	Brazil	2491	Not specified.	Datasets	Case study	Prediction of student dropout	Interactions between students in forum	Set of pedagogical actions which are individualised depending on each of the students' weekly reports	87% accuracy, reduction of 11% in dropout rate
Carroll, & White (2017)	Ireland	524	On average 19.1 years, early stage students (87% entering directly from secondary school)	Datasets: lecture attendance, tutorial attendance, online scheduled access, print access, online full access	Latent class analysis	Predict student learner behaviour	Lecture/tutorial/ online scheduled attendance, print, online access to learning materials	Rigorous attendance requirements, assessment prompted engagement	Results showed that students were able to transition successfully to self-directed learners.
Carter, Hundhausen, & Adesope, (2017)	USA	140	Not specified.	Programming log data and course grades	Statistical analysis and machine learning	Predict student performance-1)grades on individual assignment, 2)students' overall assignment average, 3)students' final grades	Programming activities-(1) students' grades on individual assignments; (2) students' overall assignment average, and (3) students' final grades	Not specified.	28% of the variance of the final grade can be explained.
Casey (2017); Casey, & Azcona (2017)	Ireland	111	Not specified (dataset).	Datasets	Basic and extended Pass-fail classifier, linking keystroke metrics	Prediction of low-performing students.	No. of successful/ failed compilations, no. of connections, time spent, slides coverage	Structure students learning so that students can front-load their online work	Average week-by-week improvement is 0.028.
Chai, & Gibson (2015)	Australia	23,291	First semester, Age not specified.	Datasets	Cross-validation technique	Prediction of at-risk dropout	Logins for materials access/submit assignment, course average, participation in	Not specified.	An interactive model shows students' attrition risk and factors. Study success not

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.

Positive evidence



https://www.iadlearning.com/wp-content/uploads/2016/11/blog_e-Learning-analytics.jpg

01 Interventions.
Study success can be achieved by students who utilised learning analytics interventions.

02 Engagement.
Engagement of students is a predictor of study success.

03 Recommender system.
Recommender systems produce positive effects toward study success.

04 Data quality.
Prediction accuracy for study success increases over time (80% from week 12 of a semester)

05 Dropouts.
Reduction of dropout rates and prognosis of dropouts can be based on the specific courses attended.

06 Indexing.
Indexing methods can be utilised which produce accurate predictions of dropout and study success.

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.

Insufficient evidence

http://www.unglobalpulse.org/sites/default/files/UNGP_Privacy.jpg

01 Early stage adoption.
Most LA studies are in early stage and lack deep concrete empirical evidence

02 Geographical spread.
Use of LA concentrated in US, Australia and UK as well as lack of attention to LA cycle.

03 National policies.
National policies of LA exist in Denmark, Netherlands, Norway and some UK universities

04 Concerns.
Temporary character of data, incompleteness of data, ethics, data privacy.

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.

Evidence of learning analytics for supporting study success

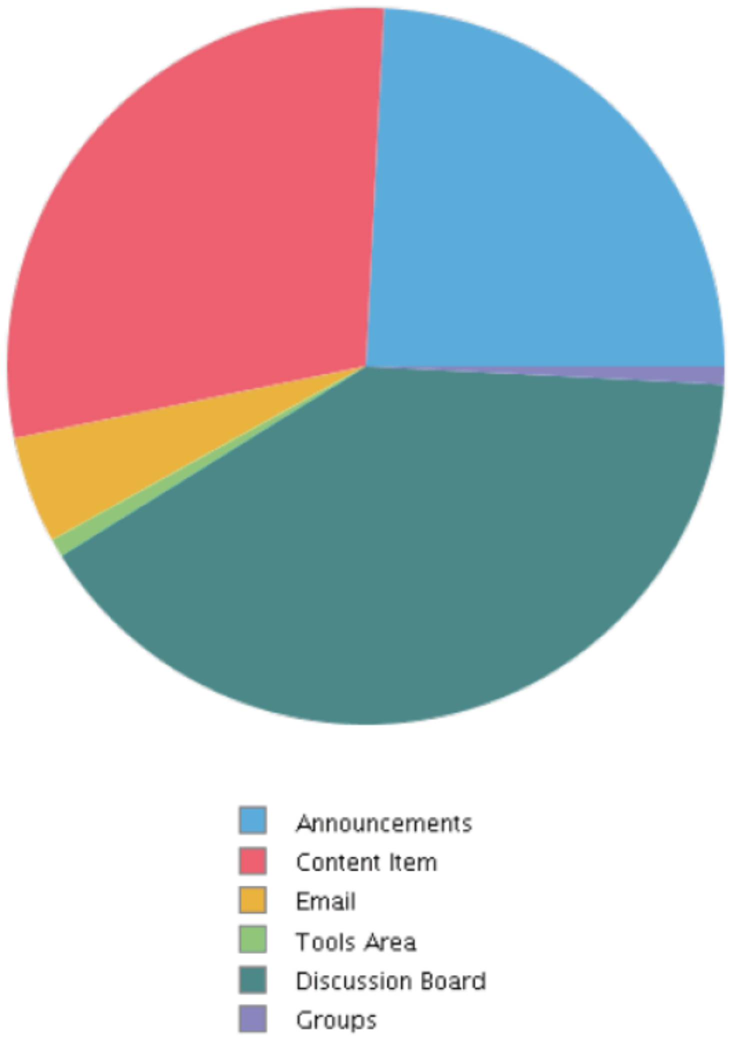
1. Study success **can be achieved by students who utilised learning analytics** interventions.
2. *Engagement* of students is a predictor of study success.
3. **Recommender systems** produce positive effects toward study success.
4. *GPA* and *financial status* characterise study success.
5. Predictive power / **prediction accuracy can be manifested and increased** through data on course completion, dropouts, achievement level, study achievement, total study time, interaction with colleagues, frequency of regular learning intervals, and number of downloads from the learning environment.
6. **Prediction accuracy** for study success increases over time (80% from week 12 of a semester).
7. Reduction of dropout rates and prognosis of dropouts can be based on the *specific courses attended*.
8. Strong correlation between CGPA and pre-set grades. CGPA serves as a study success indicator.
9. Small positive relationship between *student satisfaction* with the use of the **learning analytics dashboard** and their study success.
10. Students who completed a course expected better *performance feedback*.
11. Various online learning systems are reliable and can produce **solid predictions** for study success.
12. **Indexing methods** can be utilised which produce accurate predictions of dropout and study success.

Learning analytics dashboards with features for students are still on an initial level and therewith the research on learning analytics features and students' expectations

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

Access / Application

Area ID	Hits	Percent
Access WebAssign	0	0.00%
Announcements	30	24.19%
Bb FSU Grade Upload Tool	0	0.00%
Blackboard Scholar	0	0.00%
C-Labs BB	0	0.00%
Calendar	0	0.00%
Cengage Learning MindLinks™ Tools	0	0.00%
Chalk Title Management	0	0.00%
Collaboration	0	0.00%
Content Area	36	29.03%
Discussion Board	50	40.32%
Easy Group Managment	0	0.00%
Email	6	4.84%
EvaluationKIT Course Evaluations	0	0.00%
ExamSoft Registration	0	0.00%
ExamityFSUSSO	0	0.00%
FSU Guest User management	0	0.00%
Featured Stories	0	0.00%
First Day Attendance Tool	0	0.00%
Glossary	0	0.00%
Gradebook	0	0.00%
Groups	1	0.81%
Kaltura Mashup	0	0.00%
Kaltura My Media	0	0.00%
Link Checker	0	0.00%
LiveText Mashup URL Link	0	0.00%
LiveText SSO Tool	0	0.00%
LonCAPA Grade Loader	0	0.00%
Manual	0	0.00%
McGraw-Hill Campus	0	0.00%
McGraw-Hill Higher Education	0	0.00%
Media Gallery	0	0.00%
Messages	0	0.00%



1 / 8 Powered by Blackboard Learn™ 6/2/2016

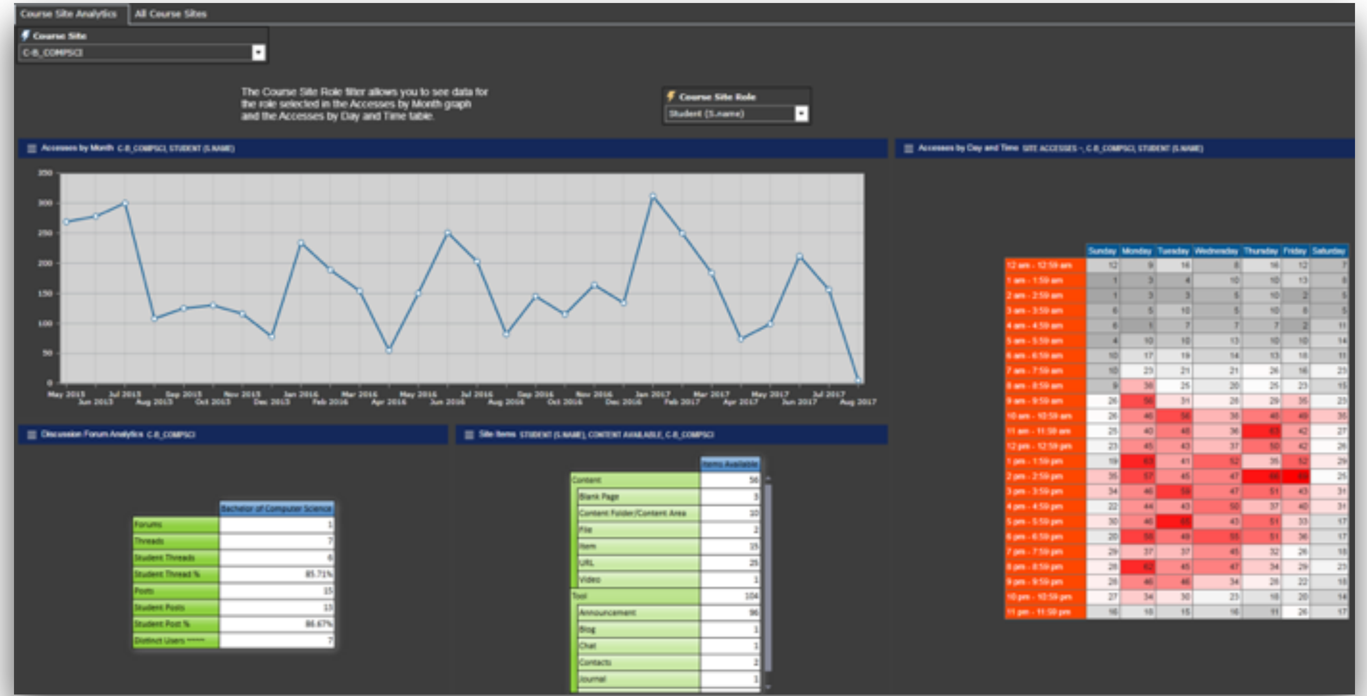
https://www.fsu.edu

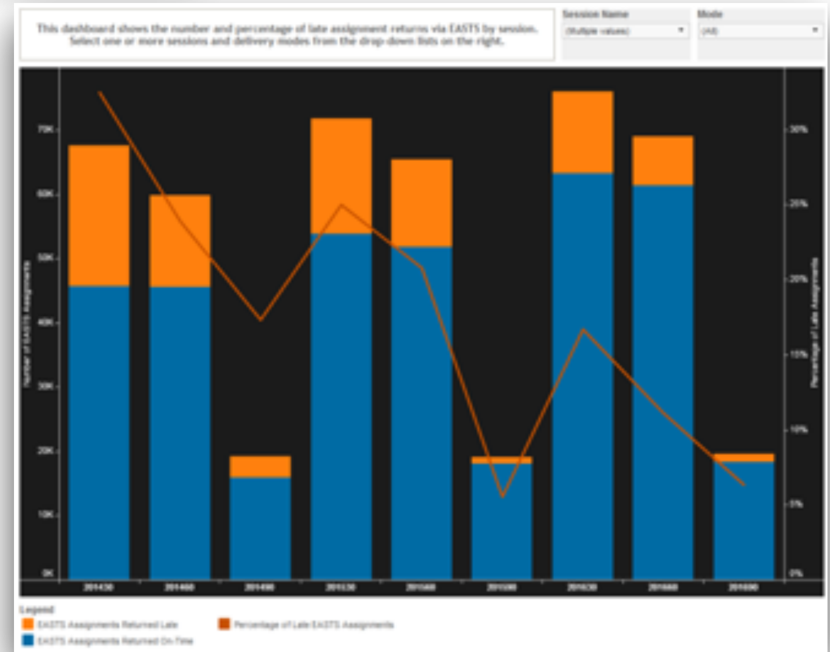
All Students Activity Report

Click the header to sort.

Name	Total Views	Sessions	Online Time	Viewed Resources	Initial Threads	Total Posts
Average	357.69	60.28	7:15:36	36.54		
	568	89	15:11:04	47		
	293	49	9:04:52	36		
	504	71	12:54:14	39		
	390	64	11:59:50	47		
	269	52	5:36:38	27	1	1
	290	47	10:24:45	32		
	260	41	1:42:18	33		
	776	103	13:34:17	47		
	372	73	5:57:26	49		

https://www.ucsb.edu





https://www.csu.edu.au

Learning Analytics Funktionen sollen Studierende während deren Lernprozessen unterstützen und Hilfestellungen zur Planung von Lernaktivitäten bieten

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

"That the system considers my personal schedule. I wouldn't mind if the system knows 'watching soccer with friends at 9 p.m.' and advices me to work for another hour." (interviewee 4)

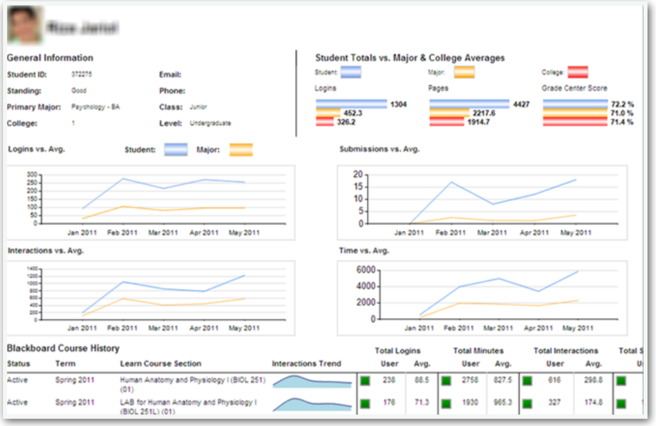
"… connected to my smartphone for receiving prompts 'you haven't done anything the last three days, how about starting now?' Might be problematic for persons who are not able to learn under pressure, for me it would be great." (interviewee 6)

"If the system would recognise other students dealing with the same content and suggests to connect to each other for exchanging ideas and for testing or even meeting in person." (interviewee 20)

"that exercises are offered for self-monitoring and that I am learning during the semester instead of delaying it to the end of the semester." (interviewee 14)

"… that the dashboard contains all programs available and everyone can arrange his own dashboard functions and structure… and that I can choose a wallpaper." (interviewee 6)

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



01 Learning history.

02 Activity time.

03 Recommendation.

04 Goal setting.

05 Study buddy.

06 Self assessment.

07 Content rating.

08 Visual signals.

09 Newsfeed.

10 Study planer.

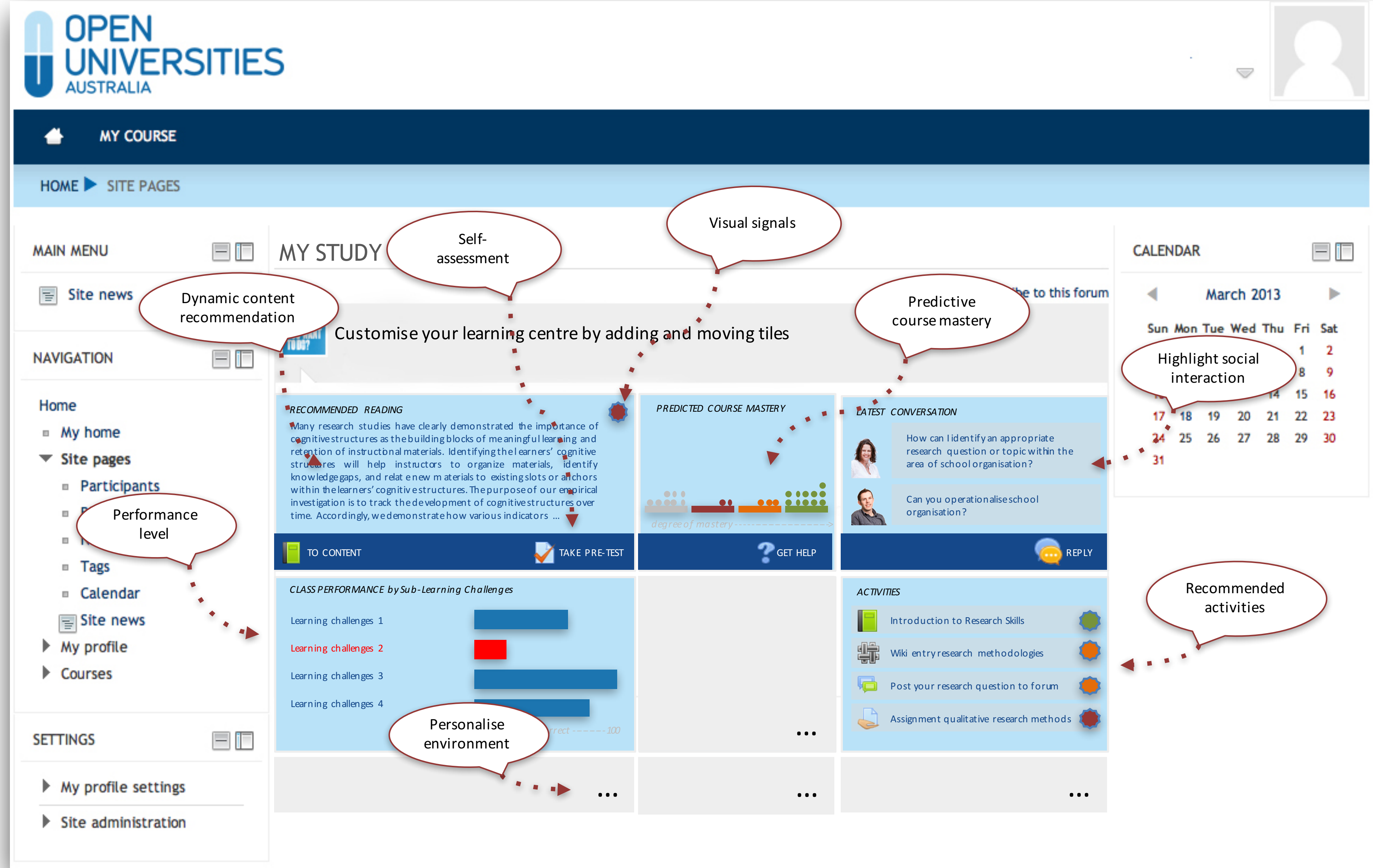
11 Feedback.

. . .

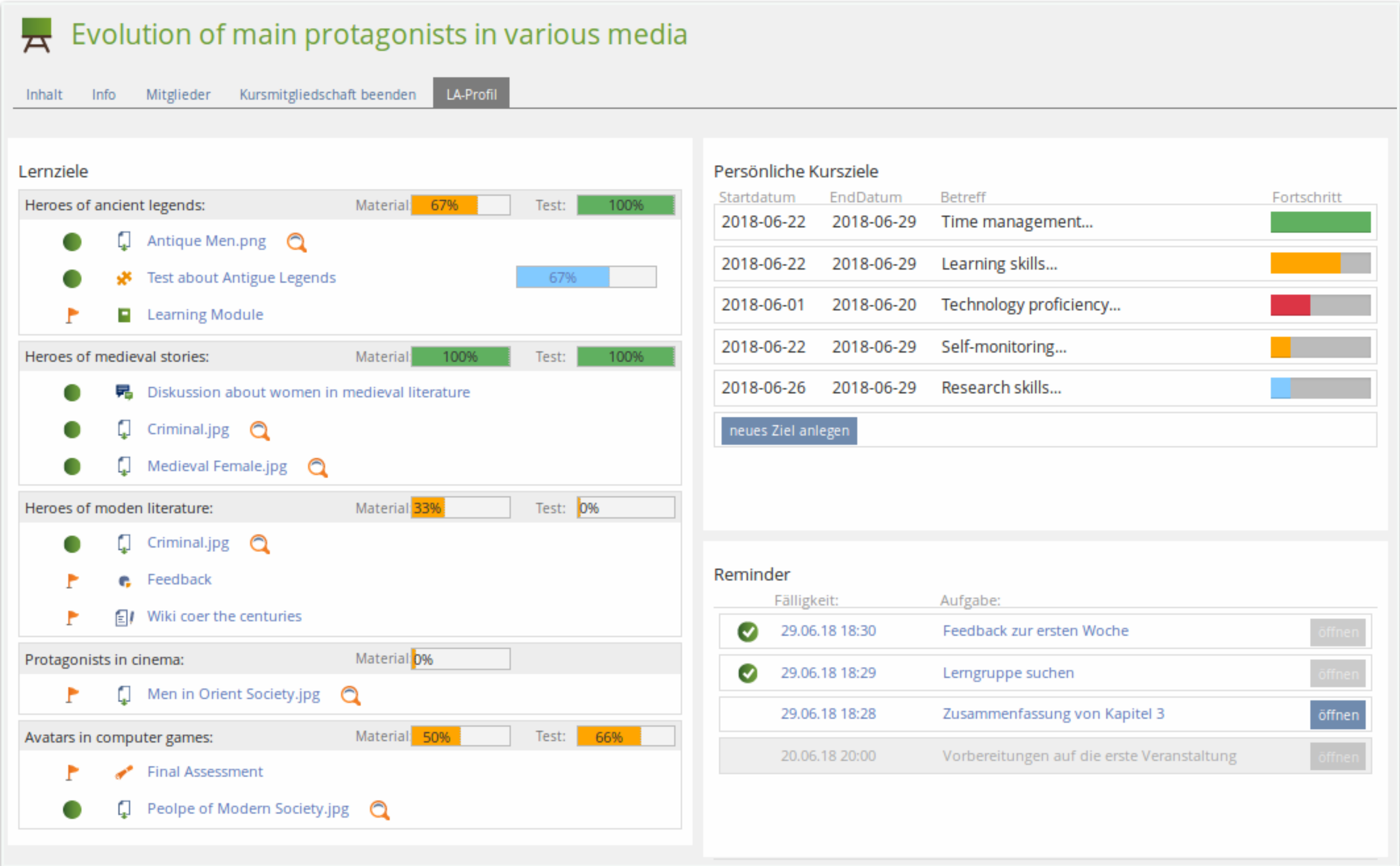
Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. doi:10.1016/j.chb.2017.06.030

Feature	Willingness to use			Evaluation in terms of learning		
	rank	**MD**	**SD**	**rank**	**MD**	**SD**
1) time spent online	13	3.125	1.192	10	2.989	.80
2) suggestion of learning partners	12	3.301	1.127	8	3.127	754
3) learning recommendations for successful course completion	5	3.981	1.011	2	3.696	.67
4) rating scales for provided learning material	11	3.306	1.346	12	2.797	906
5) timeline showing current status and goal	6	3.778	1.179	3	3.638	759
6) time needed to complete a task or read a text	**15**	**2.324**	**1.359**	**15**	**2.4**	**944**
7) prompts for self-assessments	3	4.074	999	**1**	**3.728**	**696**
8) further learning recommendations	7	3.685	999	5	3.484	737
9) comparison with fellow students	14	2.491	1.318	14	2.604	893
10) considering students' personal calendar for appropriate learning recommendations	9	3.5	1.301	7	3.227	846
11) newsfeed with relevant news matching the learning content	10	3.421	1.392	11	2.797	901
12) revision of former learning content	2	4.12	937	4	3.573	705
13) feedback for assignments	4	4.069	1.178	6	3.391	875
14) reminder for deadlines	**1**	**4.199**	**1.066**	9	3.088	.88
15) term scheduler, recommending relevant courses	8	3.667	1.339	13	2.788	927

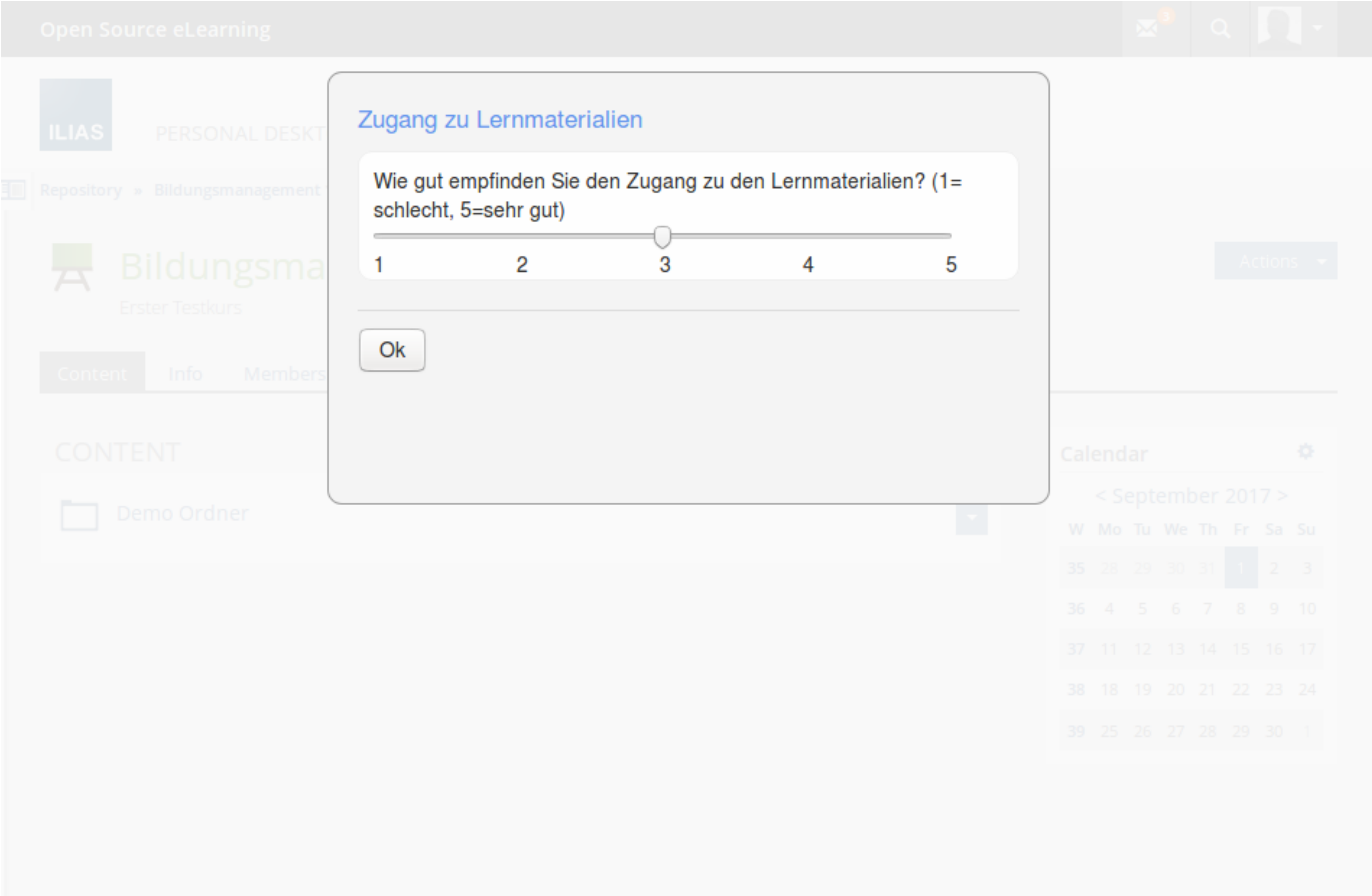
Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. doi:10.1016/j.chb.2017.06.030



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



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*. New York, NY: Springer.



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*. New York, NY: Springer.

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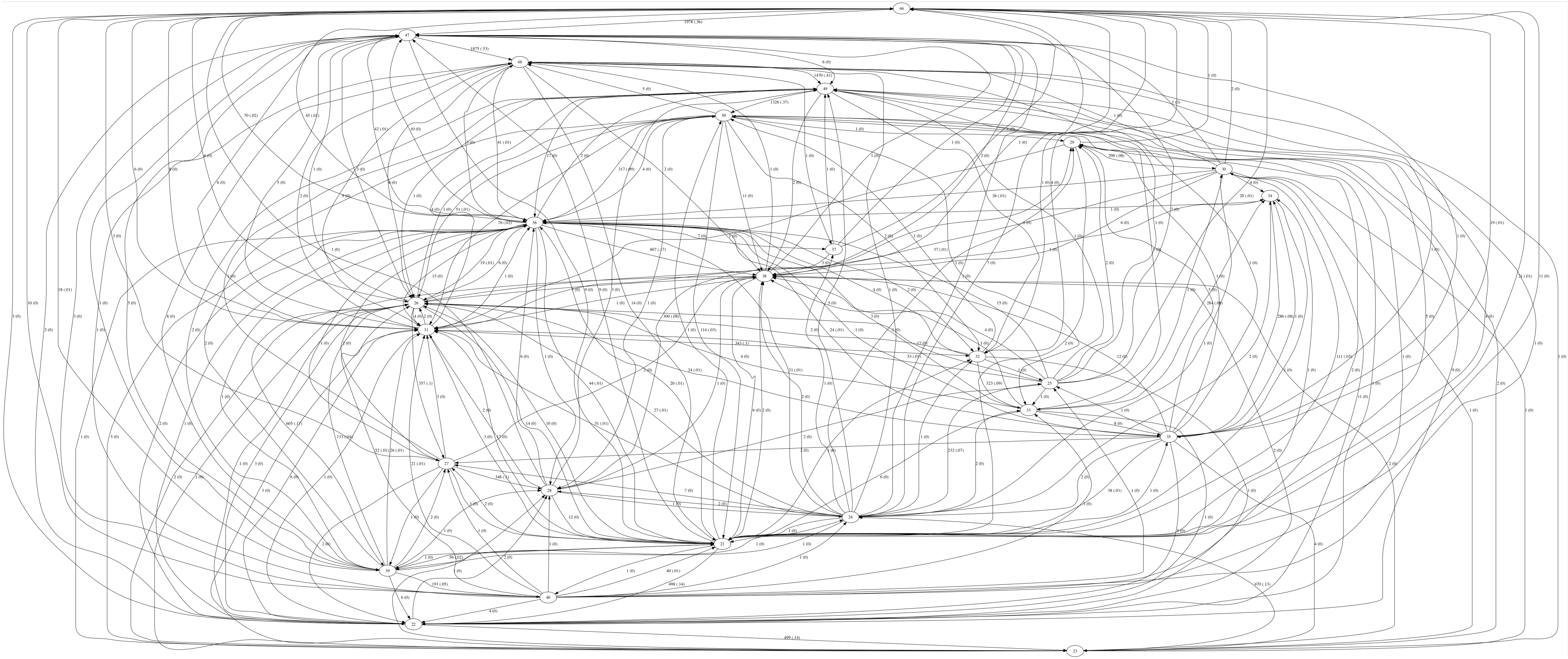
#	Feature	Willingness	Learning	Techno Cost	Orga Cost	Priority
14	**reminder for deadlines**	**3**	**2**	**3**	**3**	**54**
7	**prompts for self-assessments**	**3**	**3**	**2**	**2**	**36**
5	**timeline showing current status and goal**	**2**	**3**	**2**	**2**	**24**
13	feedback for assignments	3	2	1	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

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

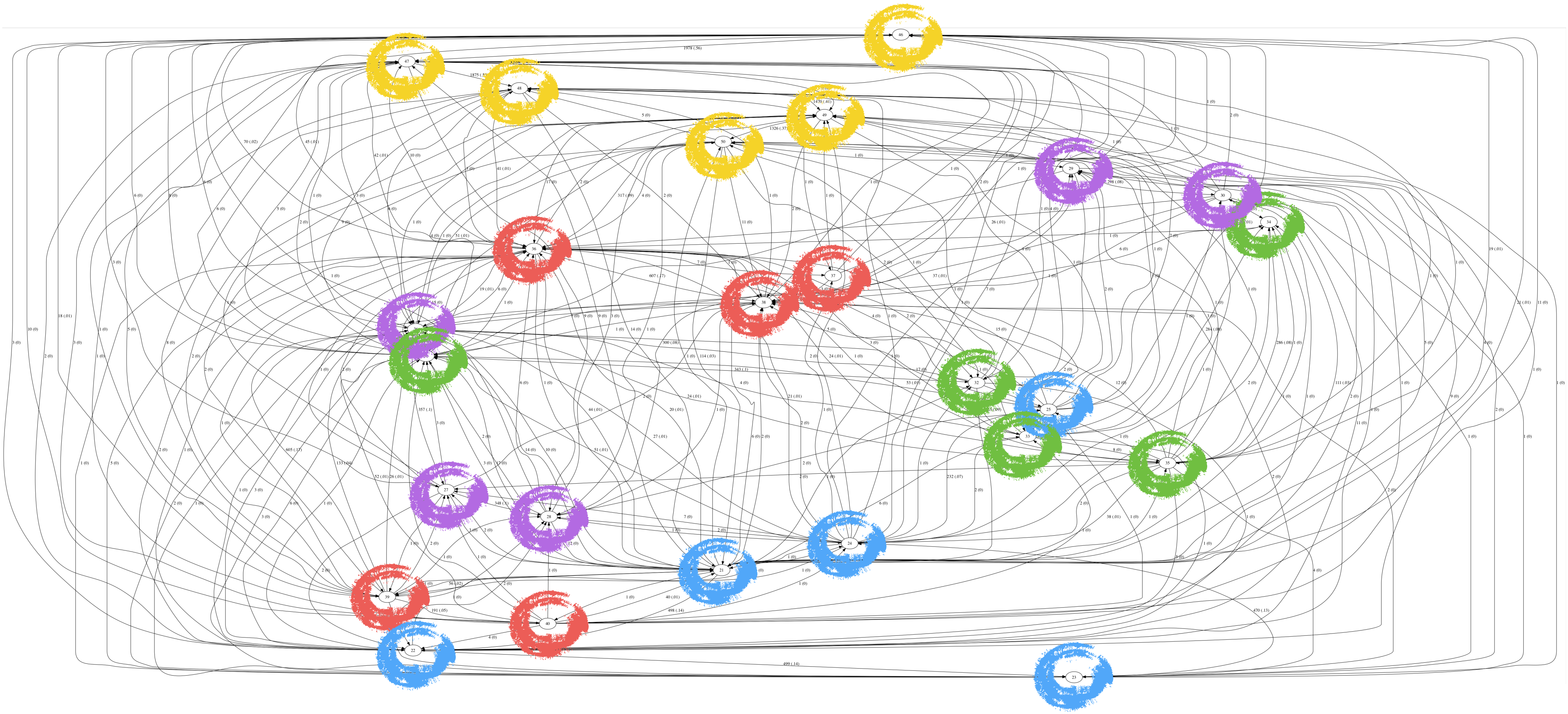
Schumacher, C., Schön, D., & Ifenthaler, D. (2017). implementing learning analytics features: At the intersection of pedagogical and information technological perspectives. Paper presented at the AECT International Convention, Jacksonville, FL, USA, 2017-11-06.

The network graph analysis identifies user paths within the learning environment and visualises them as a graph *on-the-fly*

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



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



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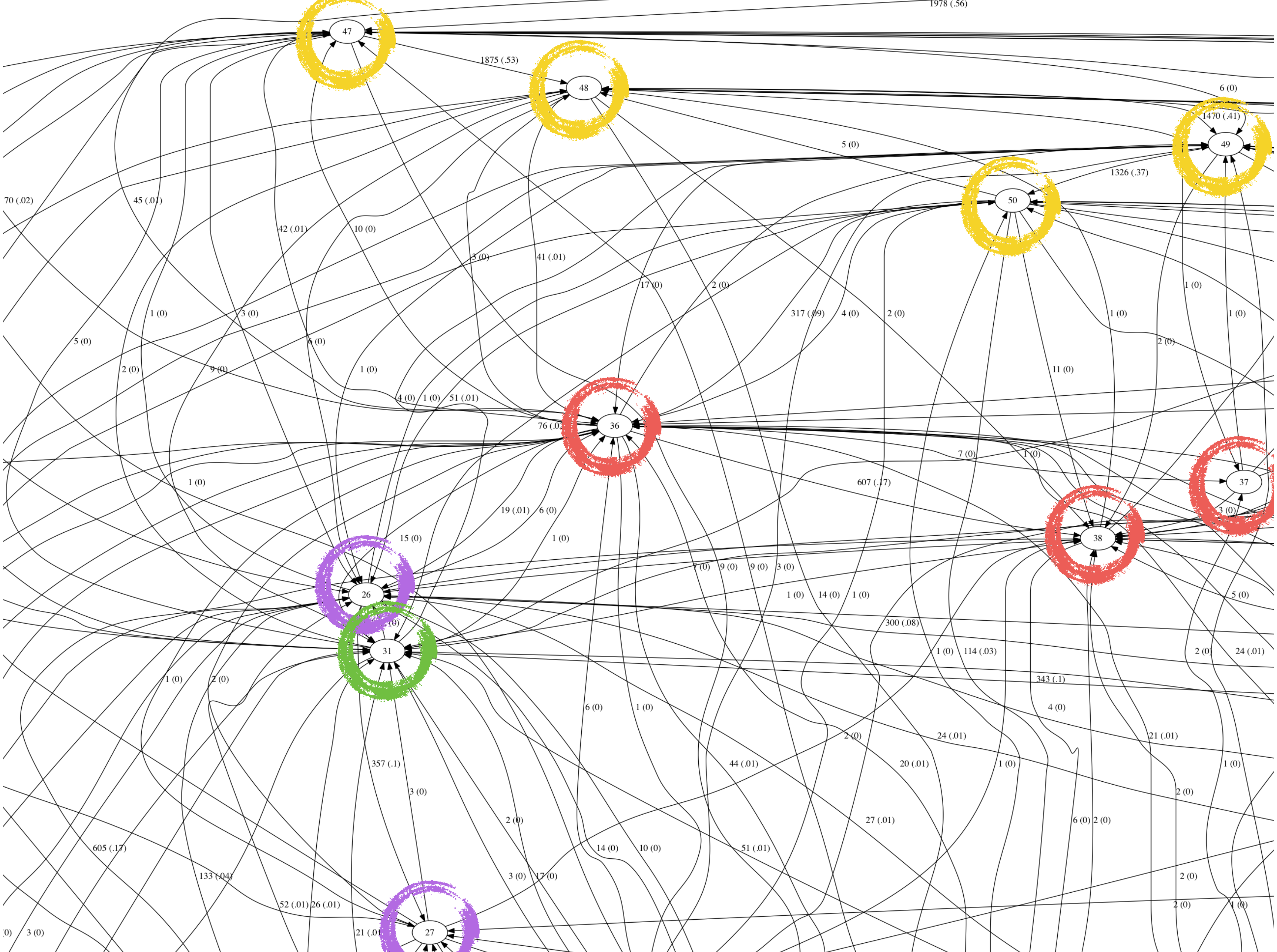
1978 (.56)
47
1875 (.53)
48
6 (0)
1470 (.41)
49
5 (0)
1326 (.37)
50
70 (.02)
45 (.01)
42 (.01)
10 (0)
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7 (0)
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1 (0)
114 (.03)
2 (0)
24 (.01)
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343 (.1)
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357 (.1)
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20 (.01)
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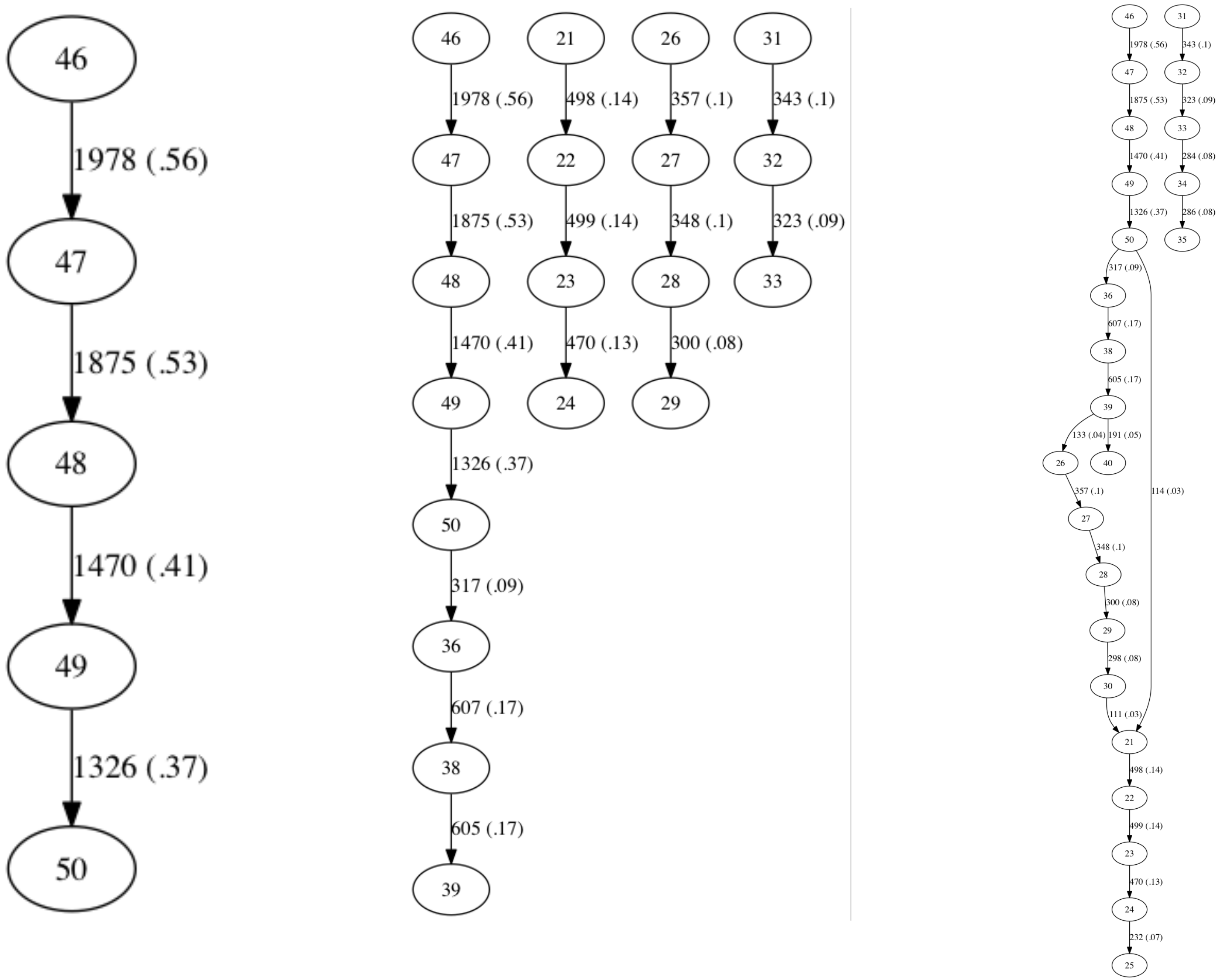
3 (0)
2 (0)
2 (0)
27 (.01)
6 (0)
2 (0)
605 (.17)
14 (0)
10 (0)
51 (.01)
133 (.04)
3 (0)
17 (0)
2 (0)
52 (.01)
26 (.01)
2 (0)
1 (0)
3 (0)
27

More than 1.000 students

More than 300 students

More than 100 students



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

01

Status Quo
Learning Analytics

02

Unterstützung von
Lehr-Lern-Prozessen

03

**Umgang mit Learning
Analytics Daten**

04

Ausblick

General
Data
Protection
Regulation

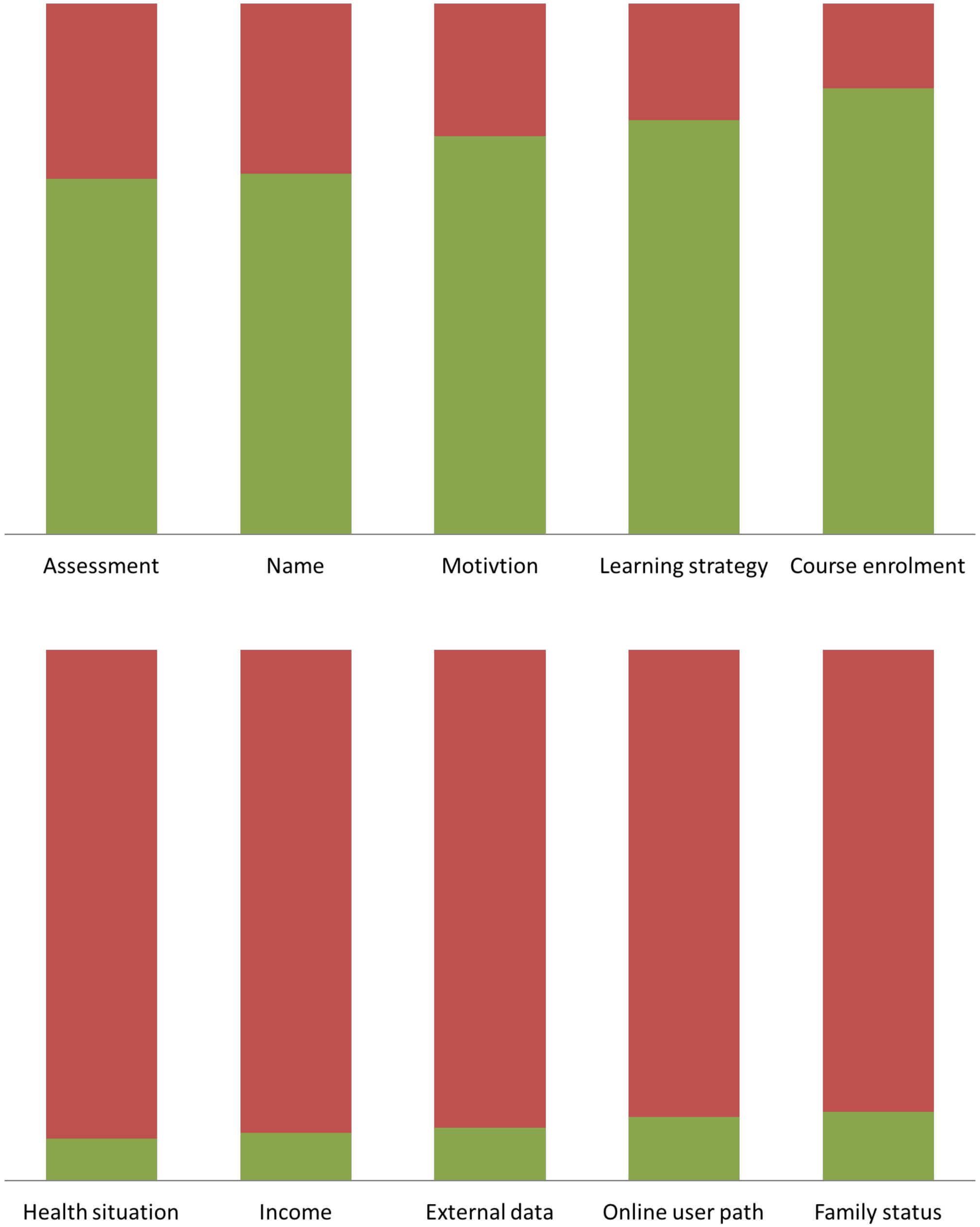
- Recht auf Information über Daten
- Recht auf Zugang zu Daten
- Recht auf Berichtigung von Daten
- Recht auf Löschung von Daten
- Recht auf Beschränkung von Datenverarbeitung
- Recht auf Übertragung von Daten
- Recht auf Widerspruch bei automatisierten Entscheidungssystemen

Sollten für Learning Analytics und deren Algorithmen keine zureichenden Informationen verfügbar gemacht werden, können auch keine Mehrwerte für Lernen und Lehren erzeugt werden

Ifenthaler, D., & Tracey, M. W. (2016). Exploring the relationship of ethics and privacy in learning analytics and design: implications for the field of educational technology. *Educational Technology Research and Development, 64*(5), 877–880. doi: 10.1007/s11423-016-9480-3

Studierende sind die Produzenten von umfangreichen Daten, welche für Learning Analytics verwendet werden - jedoch passive Rezipienten von Informationen aus simplifizierten Systemen

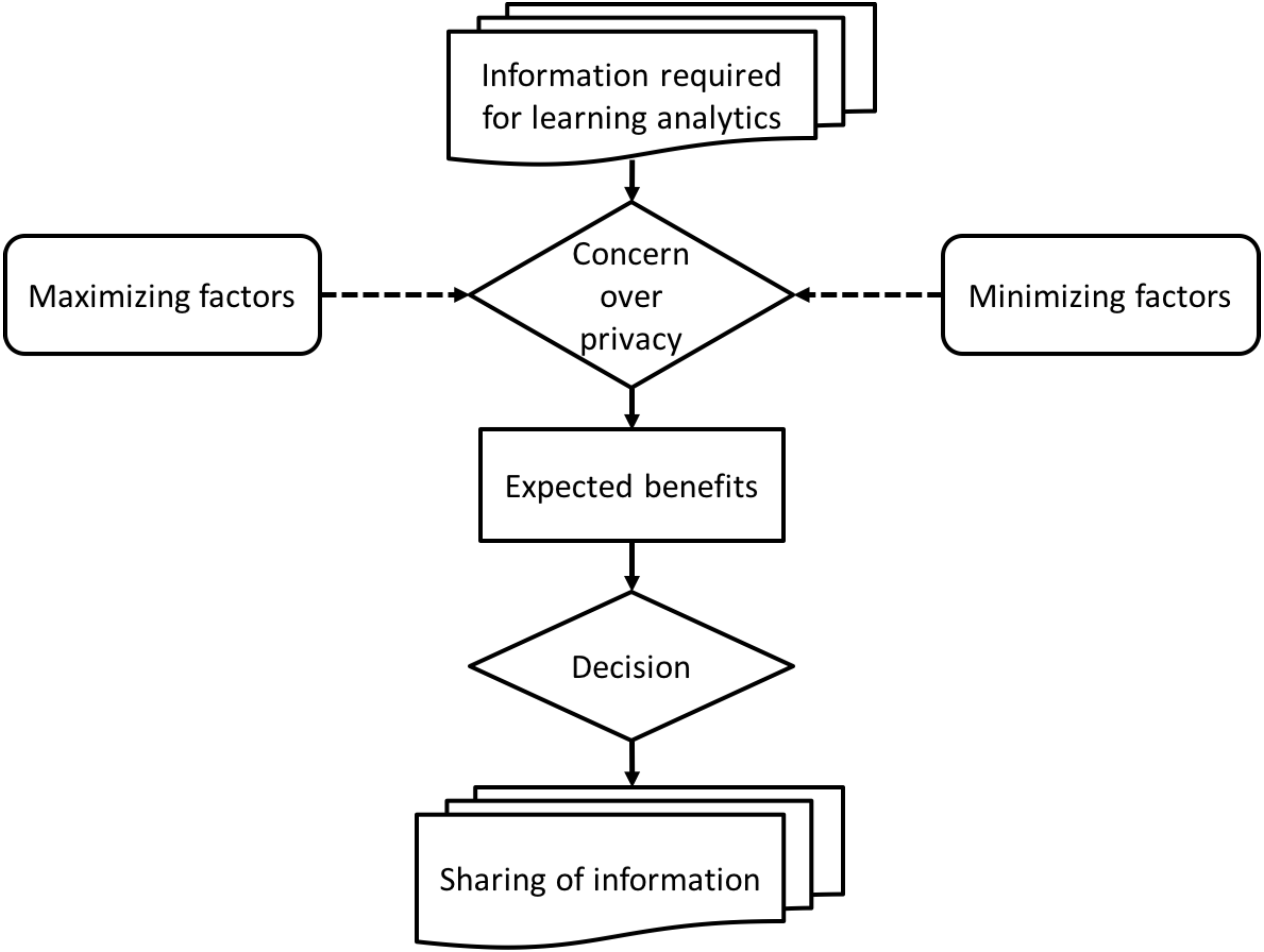
Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology, 45*(3), 438–450. doi:10.1111/bjet.12152



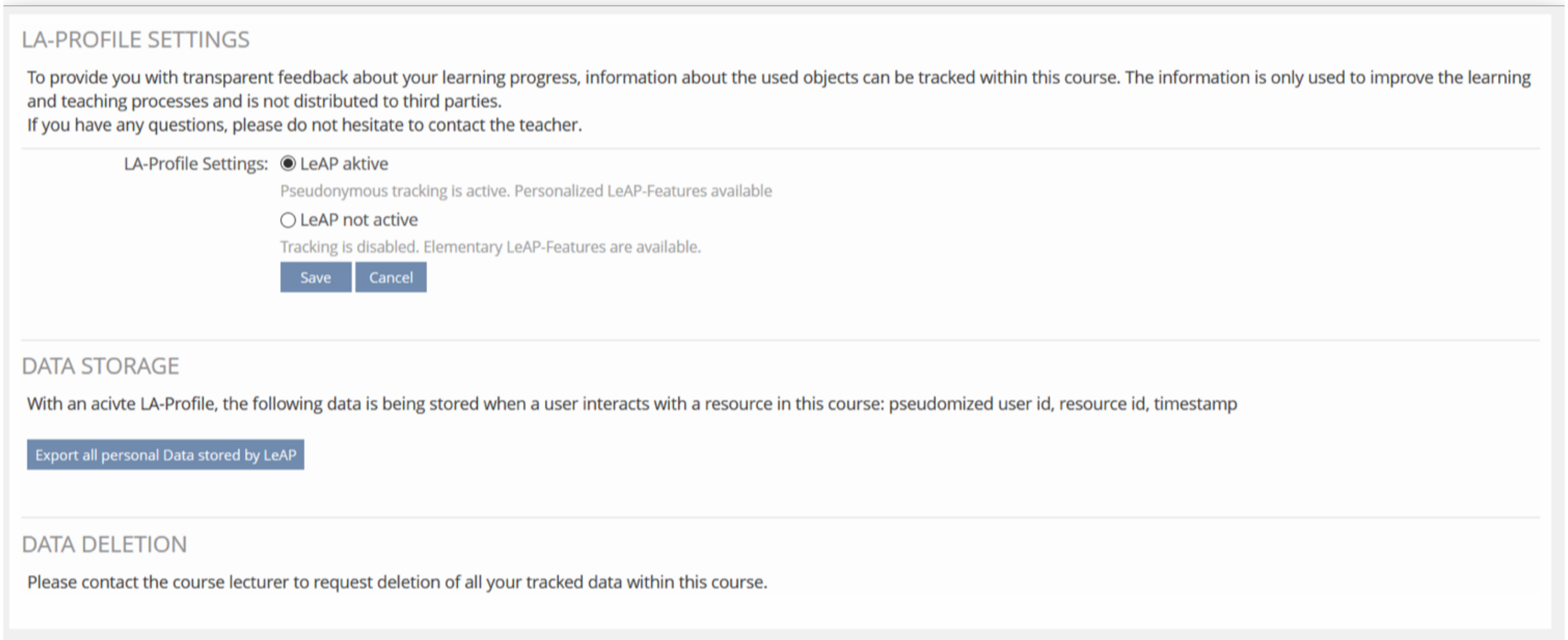
SD

Sharing of data.

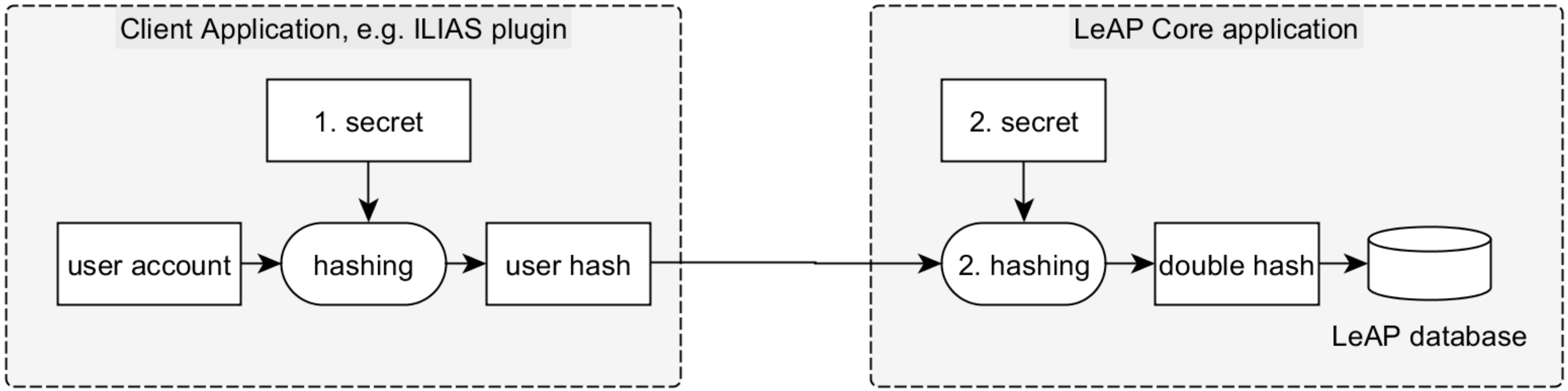
Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938. doi:10.1007/s11423-016-9477-y



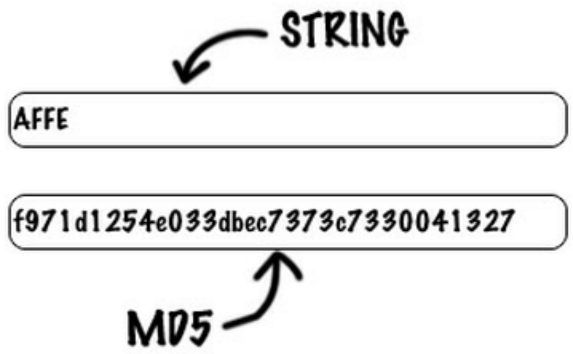
Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938. doi:10.1007/s11423-016-9477-y



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*. New York, NY: Springer.

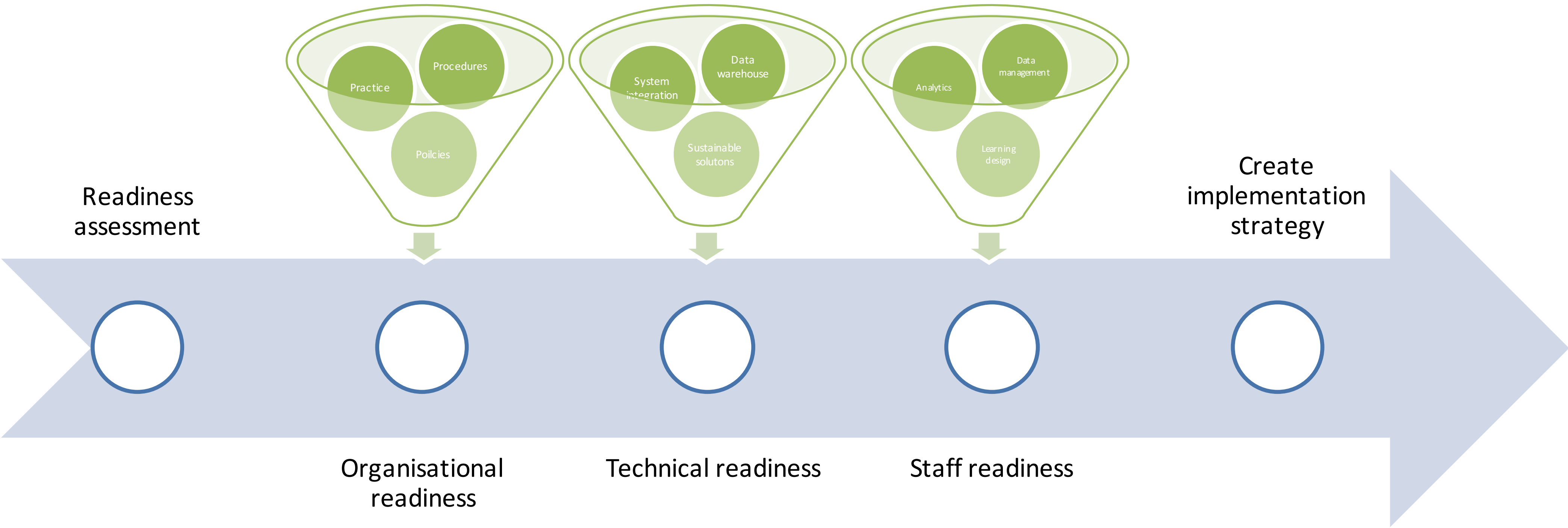


- 2-fach Pseudonymisierung
- MD5-Hash



Schön, D., & Ifenthaler, D. (2018). Prompting in pseudonymised learning analytics - implementing learner centric prompts in legacy systems with high privacy requirements. Paper presented at the International Conference on Computer Supported Education, Funchal, Madeira, Portugal, 15-03-2018.

01	02	03	04
Status Quo Learning Analytics	Unterstützung von Lehr-Lern-Prozessen	Umgang mit Learning Analytics Daten	**Ausblick**



Roll, M., & Ifenthaler, D. (2017). *Leading change towards implementation of learning analytics*. Paper presented at the AECT International Convention, Jacksonville, FL, USA, 2017-11-06.

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

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.

1. Data Collection	1.1 Know where to find the right data/data sources
	1.2 Know how to obtain/access data
	1.3 Understand data quality and limitations – accuracy, completeness
2. Data Management	2.1 Identify the technologies to preserve data
	2.2 Know and apply data manipulation methods
	2.3 Know and apply data curation and data re-use methods
	2.4 Understand Data Description(Metadata)
3. Data Analysis	3.1 Know and apply the basic data analysis methods
	3.2 Understand and apply the basic data analysis actions
	3.3 Understand and apply the basic data presentation methods
4. Data Comprehension & Interpretation	4.1 Understand data
	4.2 Understand statistics
	4.3 Know how to interpret data
	4.4 Generate potential connections to instruction
	4.5 Make decisions based on data
5. Data Application	5.1 Use data to inform instruction
	5.2 Know how to share and cite data
	5.3 Evaluate the data-driven intervention
6. Data Ethics	6.1 Explain the use of informed consent
	6.2 Know how to protect individuals' data privacy, confidentiality, integrity and security
	6.3 Understand authorship, ownership, data access (governance), re-negotiation and data-sharing

Learning Analytics sowie deren verwendete Daten und Algorithmen müssen unverzerrt und fehlerfrei in jeglichen Anwendungsszenarien sein

01

Unverzerrt.

02

Transparent.

< 73 >

Learning Analytics müssen Transparent hinsichtlich der Sammlung, Verwendung und Weiterverarbeitung von Daten sowie der Zugriffsberechtigungen sein

Learning Analytics bedürfen einer breiten Akzeptanz aller Stakeholder hinsichtlich deren Potentiale für Lernen und Lehren an der Hochschule

03

Akzeptanz.

04

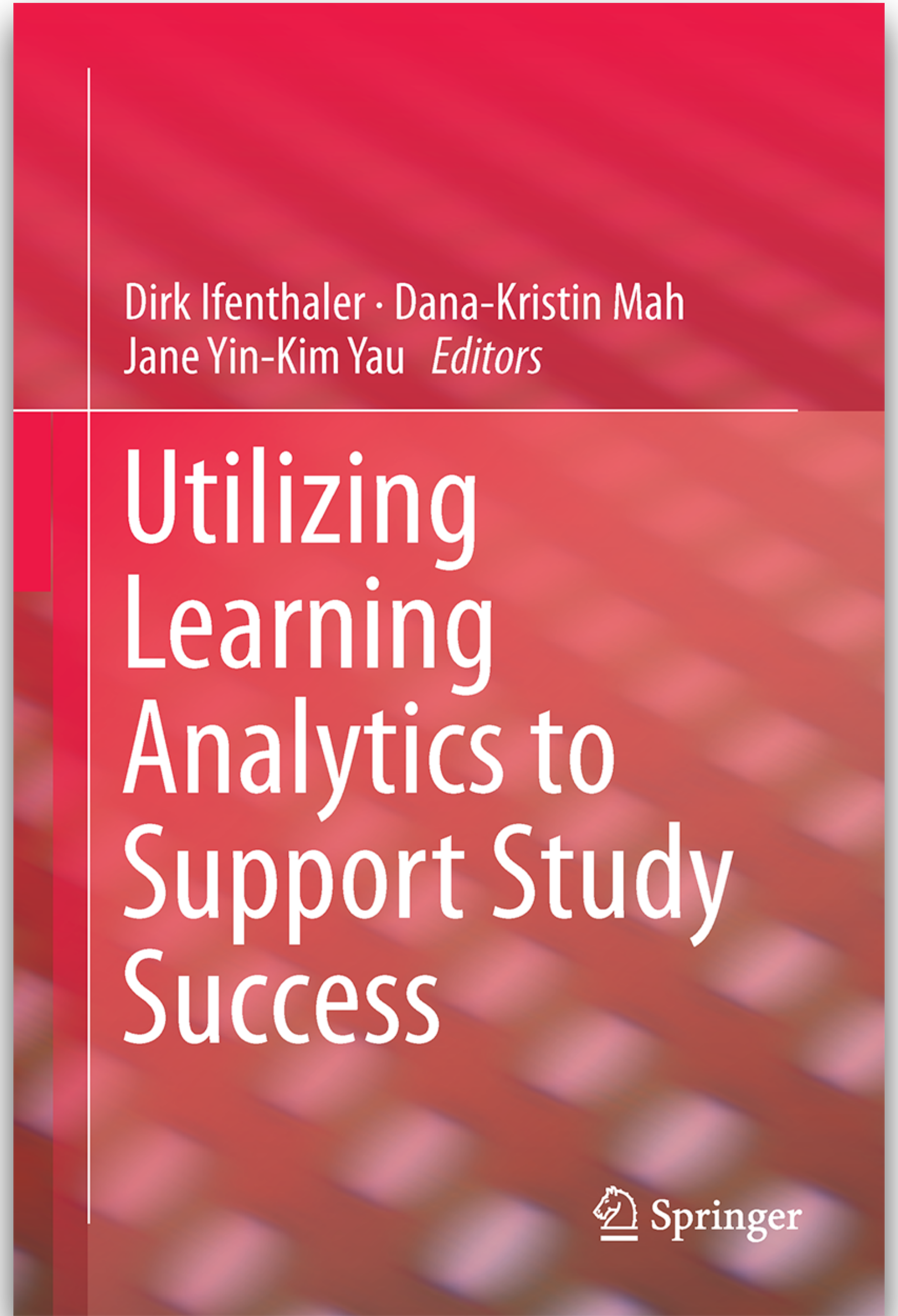
Evidenz.

< 75 >

Learning Analytics bedürfen einer präzisen theoretischen Fundierung und umfassender empirischer Forschung (experimentell, Längsschnitt)

People cannot learn from technology, rather, technology is a vehicle to support the processes of learning

Clark, R. E. (1994). Media will never influence learning. *Educational Technology Research and Development, 42*(2), 21-29.



- Theoretical perspectives linking learning analytics and study success.
- Technological innovations for supporting student learning.
- Issues and challenges for implementing learning analytics at higher education institutions.
- Case studies showcasing successfully implemented learning analytics strategies at higher education institutions.

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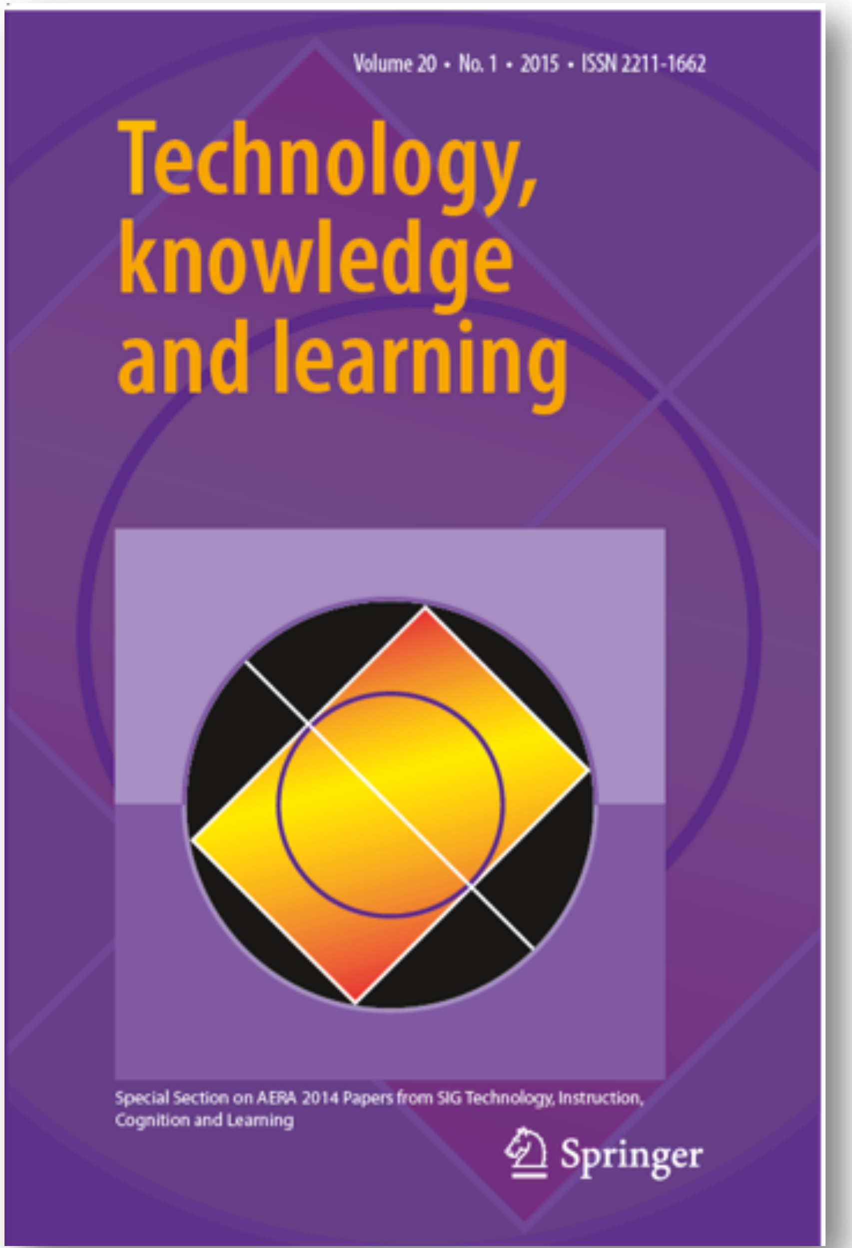

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Learning Analytics

Potentiale und Herausforderungen in der digital unterstützten Lehre

Dirk Ifenthaler

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UNESCO Deputy Chair of Data Science in Higher Education Learning and Teaching

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