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Learning Analytics als Treiber für Change Prozesse an Hochschulen

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@ifenthaler

IN OMNIBUS VERITAS · UNIVERSITÄT MANNHEIM

Curtin University

UNIVERSITAS LATVIENSIS · 19 19 · SCIENTIAE ET PATRIAE

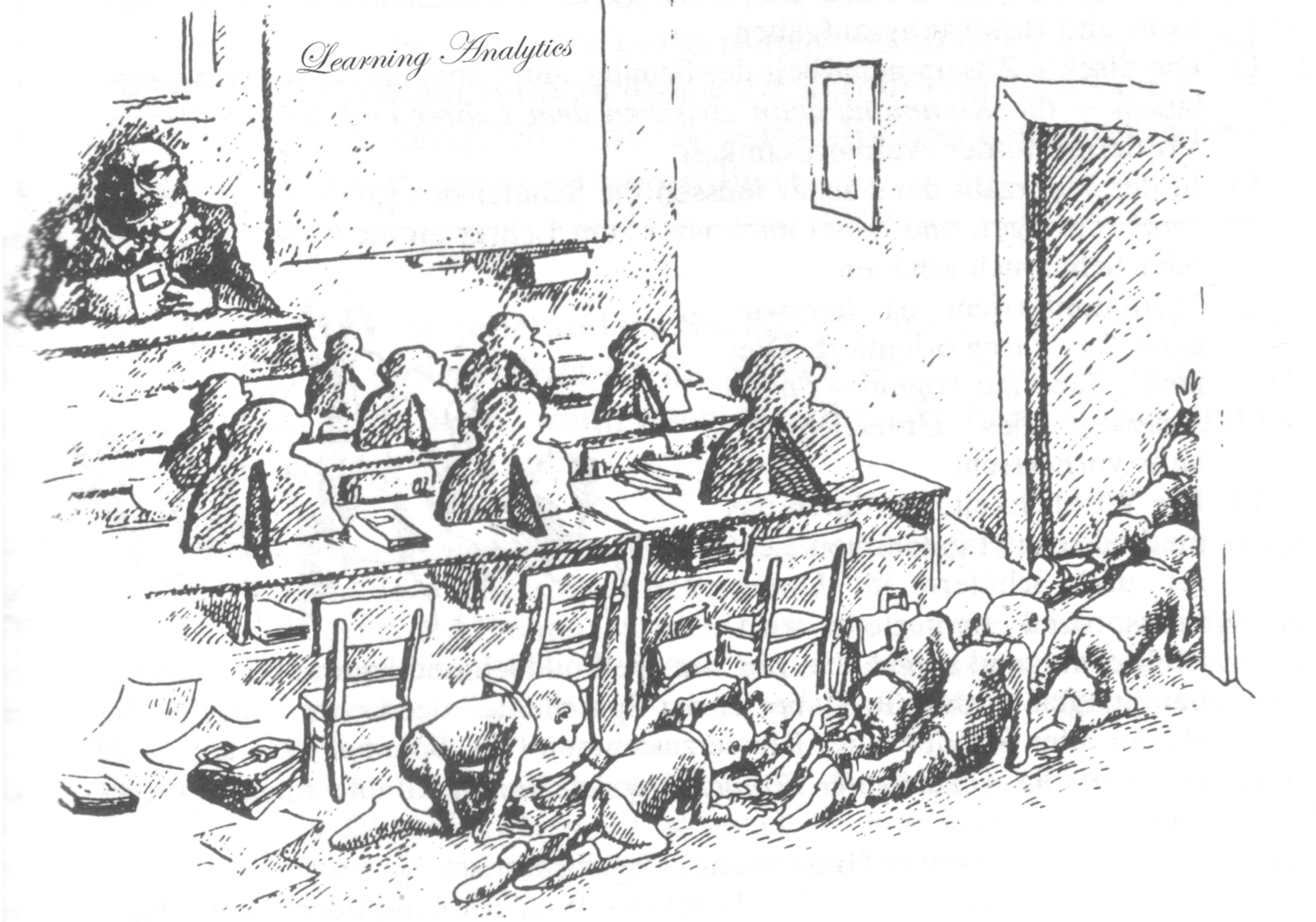
UNIVERSITY OF MANNHEIM

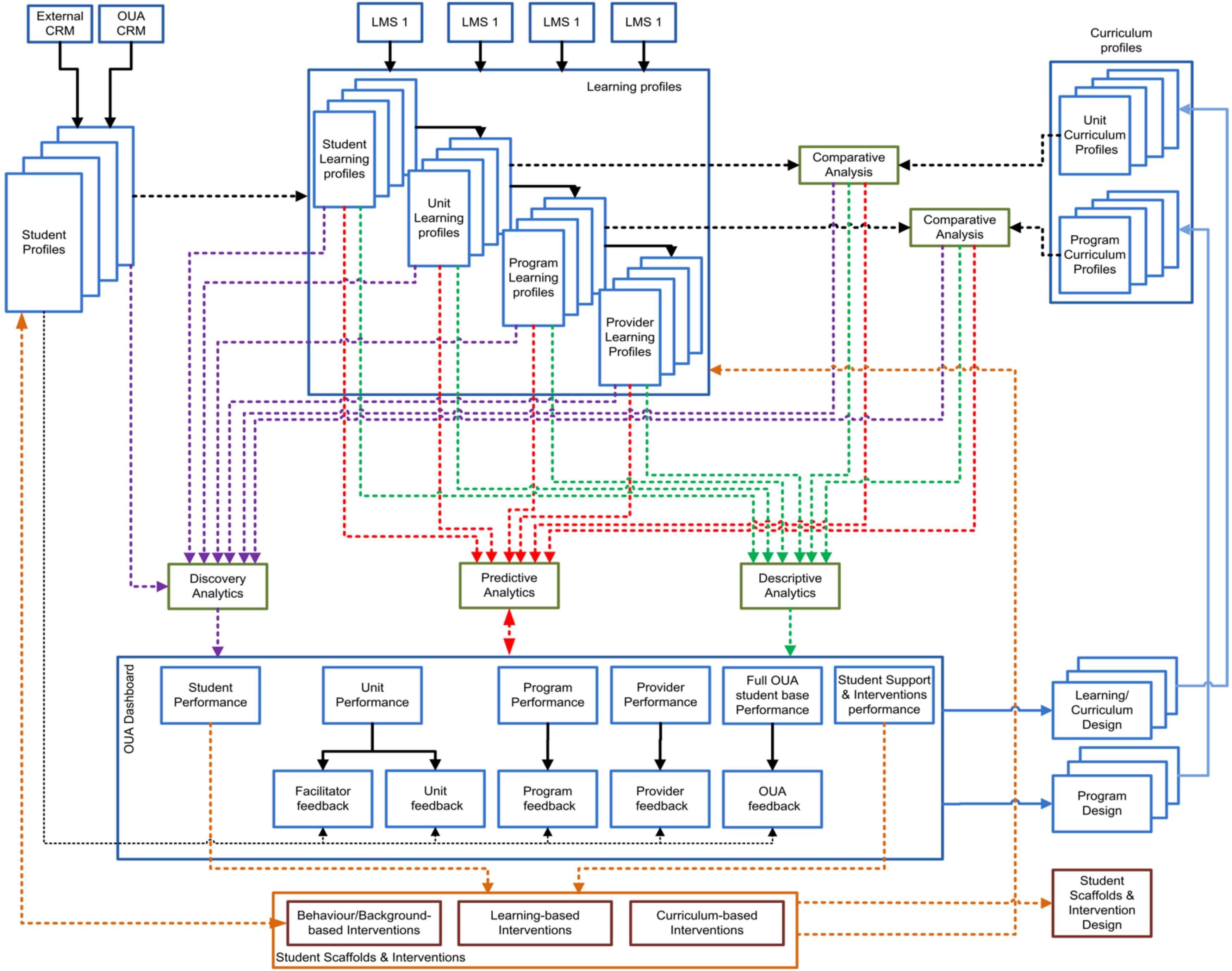
Curtin University

LATVIJAS UNIVERSITATE

ANNO 1919

UNIVERSITY OF LATVIA


Learning Analytics



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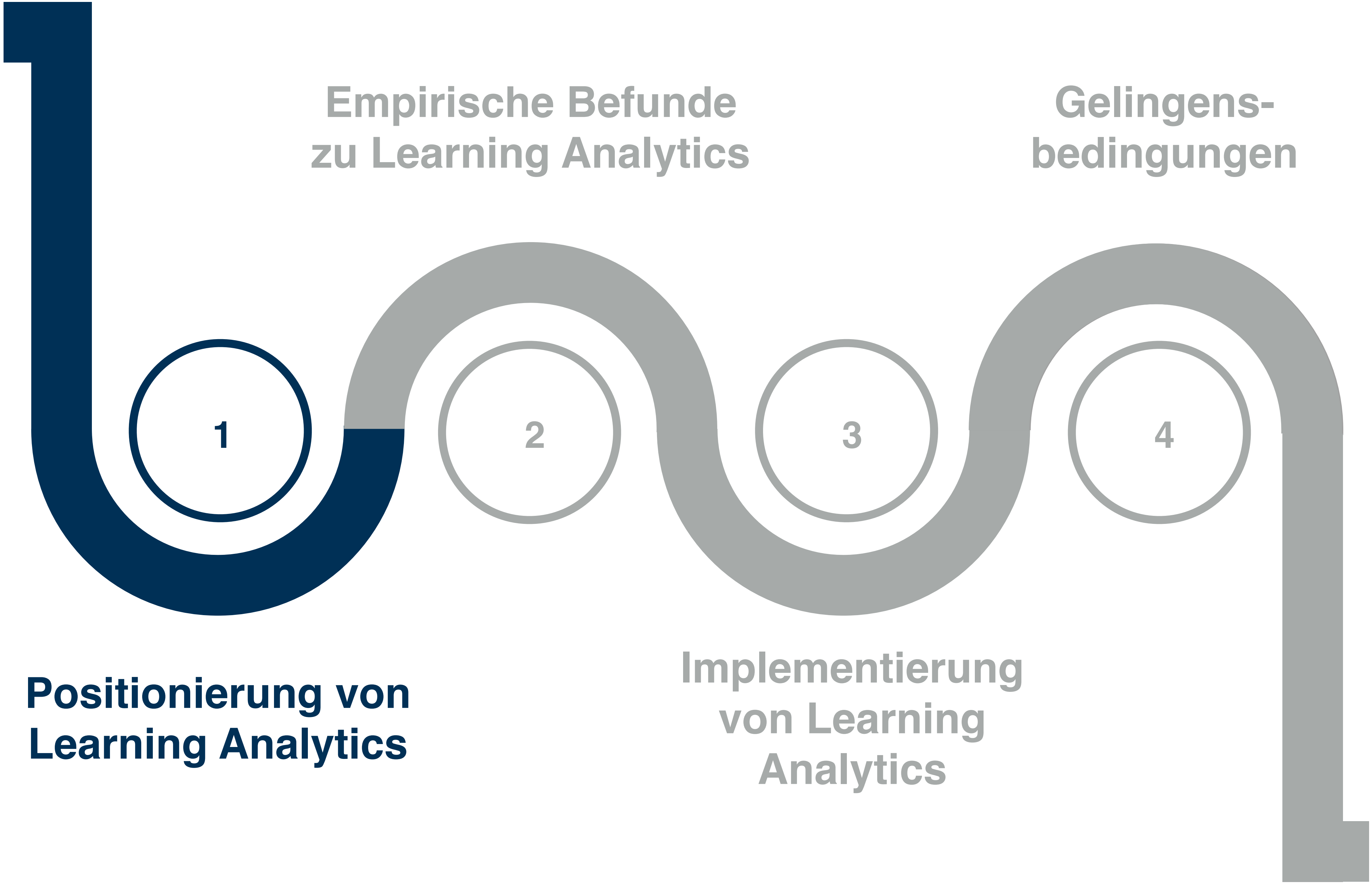
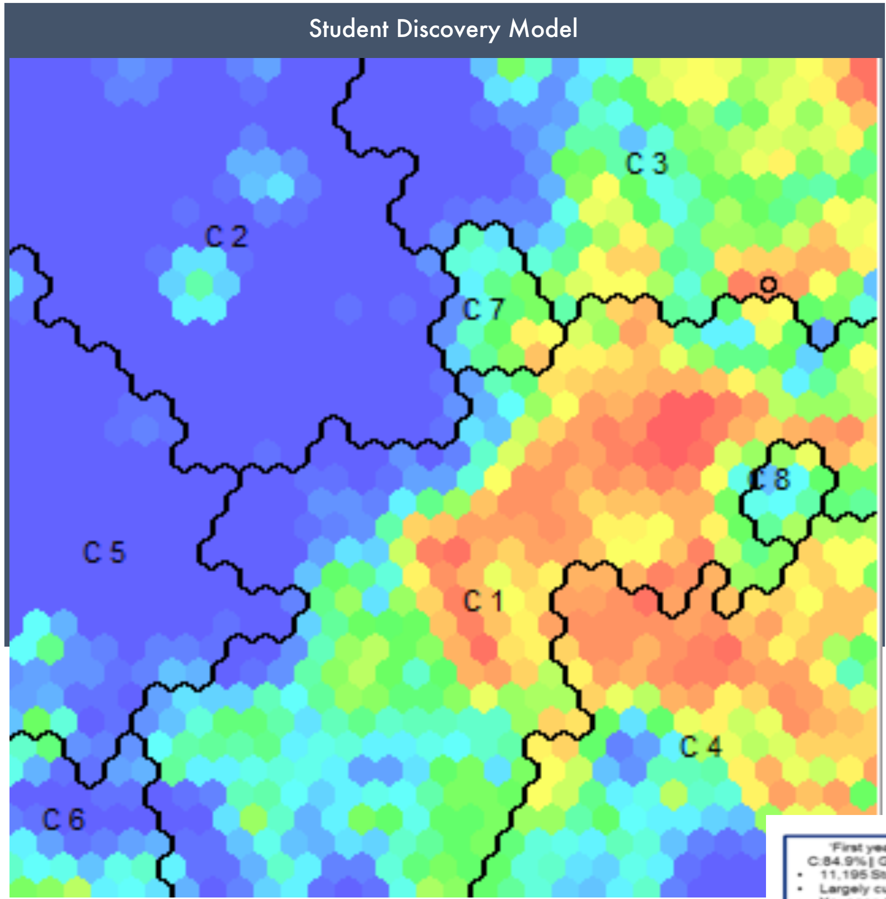
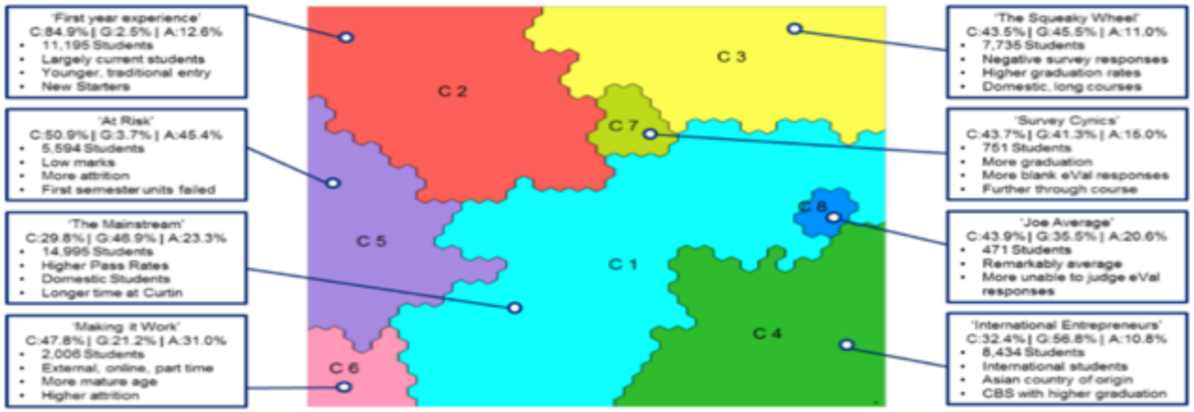

Empirische Befunde zu Learning Analytics
Gelingens-bedingungen
1
2
3
4
Positionierung von Learning Analytics
Implementierung von Learning Analytics

Learning Analytics entstanden aus den zunehmenden Möglichkeiten, Daten aus dem Bildungsbereich zu sammeln und zu analysieren.

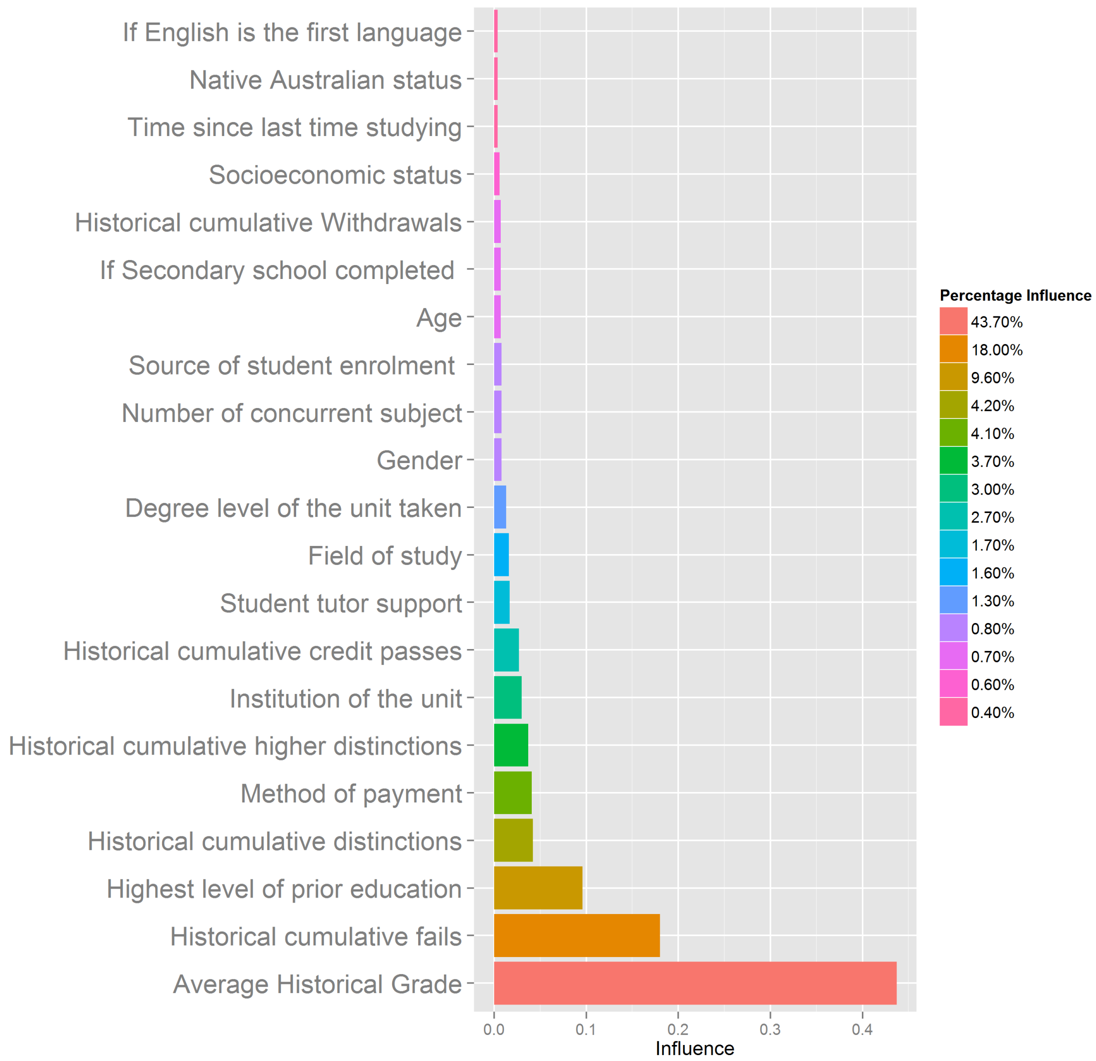
Gašević, D., Jovanović, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: Links with self-reported measures and academic performance. *Journal of Learning Analytics*, *4*(2), 113–128. https://doi.org/jla.2017.42.10



Mittels self-organising Maps können Muster in großen Datenmengen identifiziert werden.



Gibson, D. C., & Ifenthaler, D. (2020). Adoption of learning analytics. In D. Ifenthaler & D. C. Gibson (Eds.), *Adoption of data analytics in higher education learning and teaching* (pp. 3–20). Springer. https://doi.org/10.1007/978-3-030-47392-1_1



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

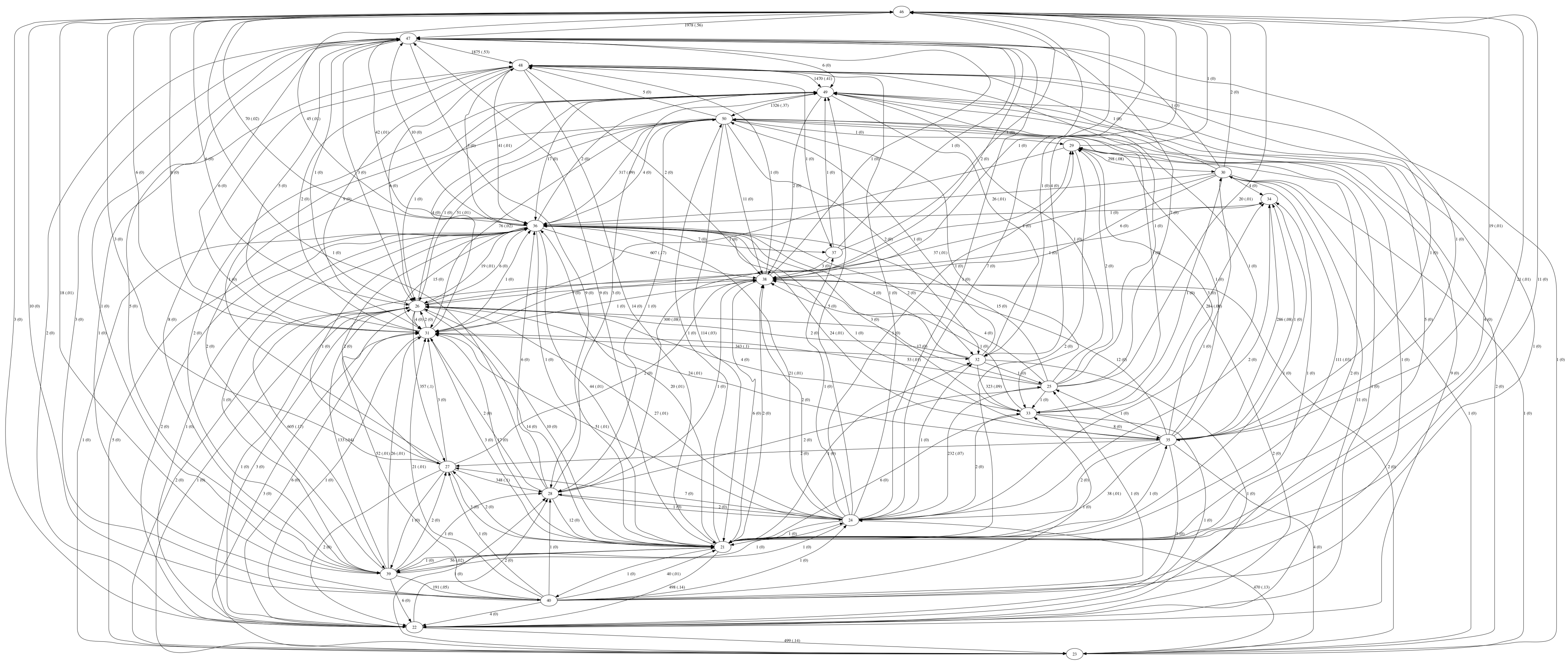
Higher Education Institution	R^2	Adjusted R^2	R^2-SVR	Predictive accuracy (SVM)
UniC	.464	.463***	.489	81.69 %
UniG	.453	.453***	.460	79.65 %
UniS	.431	.431***	.460	79.64 %
UniA	.372	.372***	.381	76.57 %
UniM	.438	.437***	.443	80.71 %
UniR	.364	.364***	.353	76.31 %
UniO	.434	.433***	.460	80.28 %
UniU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

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

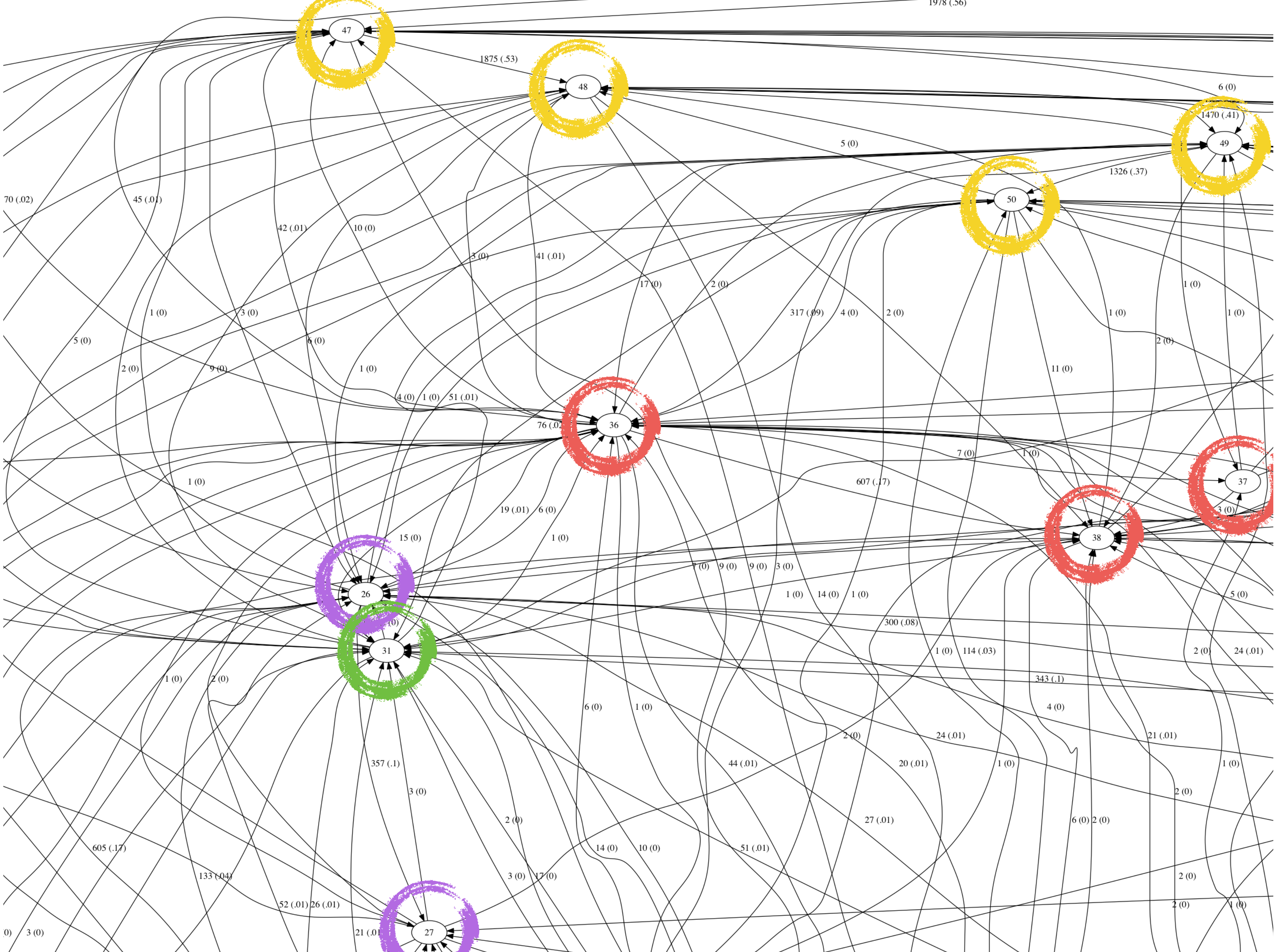
Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning*, *19*(1–2), 221–240. https://doi.org/10.1007/s10758-014-9226-4

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). Brill. https://doi.org/10.1163/9789004399273_010

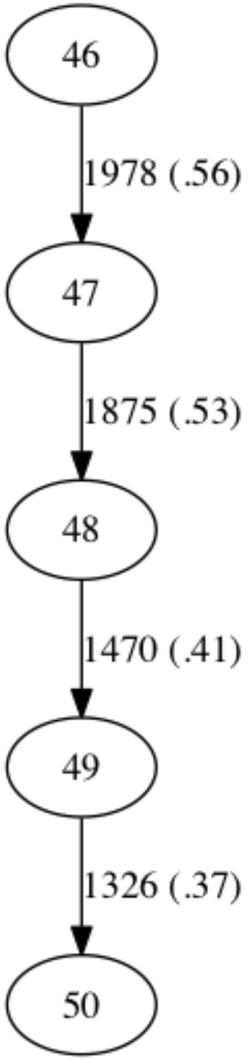


Ifenthaler, D., Gibson, D. C., & Dobozy, E. (2018). Informing learning design through analytics: Applying network graph analysis. *Australasian Journal of Educational Technology*, *34*(2), 117–132. https://doi.org/10.14742/ajet.3767

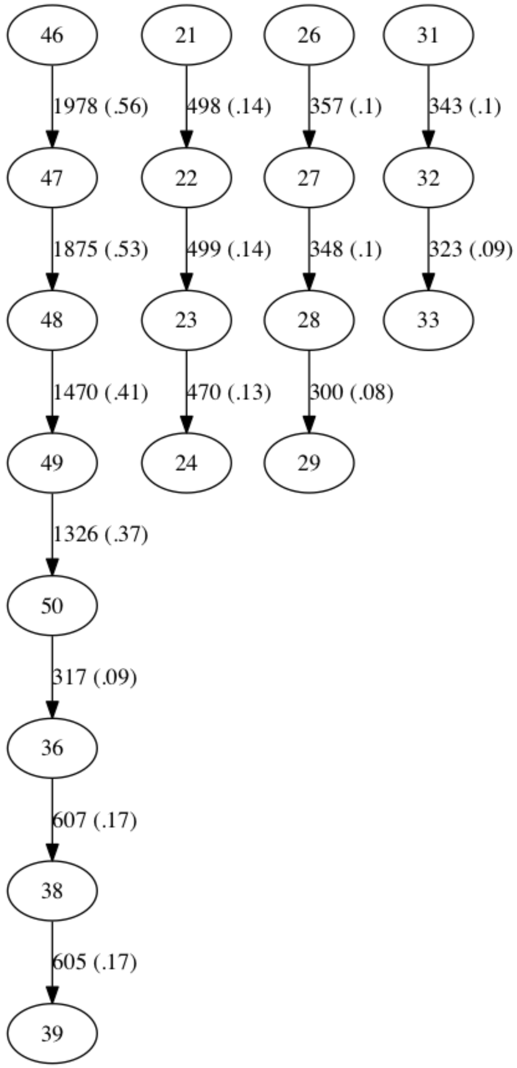


1978 (.56)
47
1875 (.53)
48
6 (0)
1470 (.41)
49
5 (0)
1326 (.37)
50
70 (.02)
45 (.01)
42 (.01)
10 (0)
3 (0)
41 (.01)
17 (0)
2 (0)
1 (0)
317 (.09)
4 (0)
2 (0)
1 (0)
1 (0)
1 (0)
3 (0)
5 (0)
6 (0)
2 (0)
2 (0)
9 (0)
1 (0)
11 (0)
4 (0)
1 (0)
51 (.01)
36
7 (0)
1 (0)
1 (0)
607 (.17)
37
3 (0)
19 (.01)
6 (0)
15 (0)
1 (0)
38
7 (0)
9 (0)
9 (0)
3 (0)
26
1 (0)
14 (0)
1 (0)
5 (0)
300 (.08)
31
1 (0)
114 (.03)
2 (0)
24 (.01)
1 (0)
2 (0)
343 (.1)
6 (0)
1 (0)
4 (0)
2 (0)
24 (.01)
21 (.01)
357 (.1)
44 (.01)
20 (.01)
1 (0)
1 (0)
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

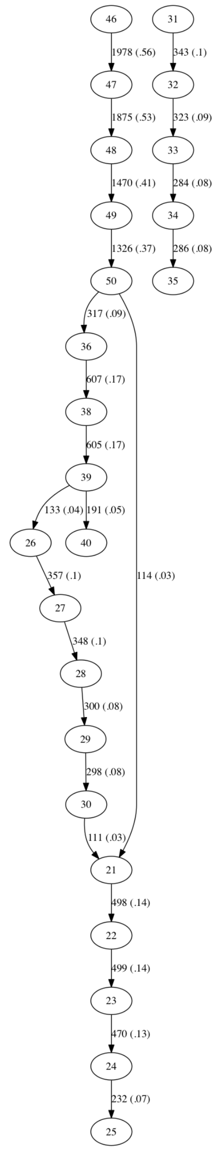
More than 1.000 students



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. https://doi.org/10.14742/ajet.3767

Educational Data Mining bereitet aus der Menge verfügbaren Daten relevante Informationen für den Bildungsbereich auf.

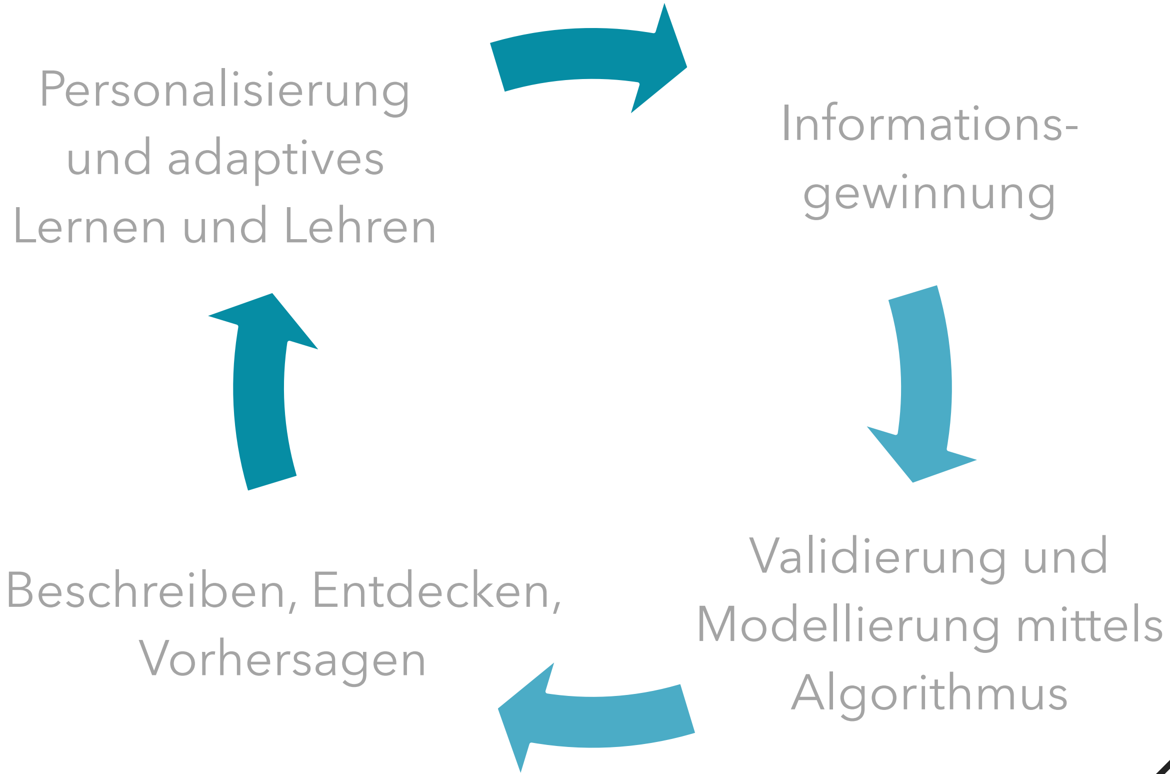
Peña-Ayala, A. (Ed.). (2014). *Educational data mining*. Springer. https://doi.org/10.1007/978-3-319-02738-8.

Learning Analytics verwenden statische Daten von Lernenden und dynamische, in Lernumgebungen gesammelte, Daten über Aktivitäten (und den Kontext) der Lernenden, um diese in nahezu Echtzeit zu analysieren und zu visualisieren, mit dem Ziel der Modellierung, Unterstützung und Optimierung von *Lern-Lehrprozessen*, *Lernumgebungen* und *pädagogischen Entscheidungen*.

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 448–451). Sage. https://doi.org/10.4135/9781483346397.n187

LA

Learning Analytics



Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 448–451). Sage. https://doi.org/10.4135/9781483346397.n187

Academic

Assessment

Games

Education

LEARNING ANALYTICS

Measurement

Retention

School

Teacher

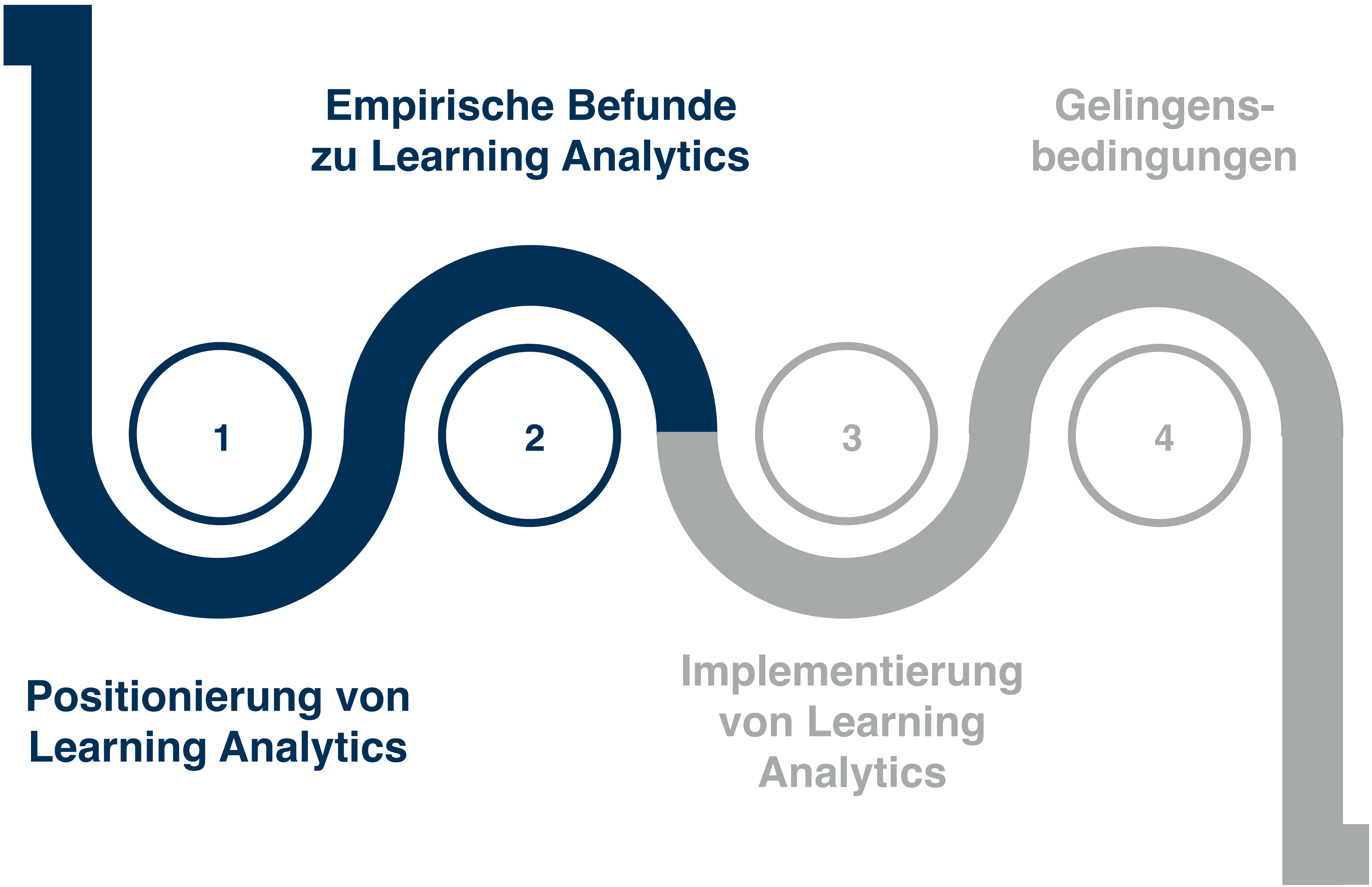
Ifenthaler, D. (2020). Change management for learning analytics. In N. Pinkwart & S. Liu (Eds.), *Artificial intelligence supported educational technologies* (pp. 261–272). Springer. https://doi.org/10.1007/978-3-030-41099-5_15

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. 448–451). Sage. https://doi.org/10.4135/9781483346397.n187

	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. 448–451). Sage. https://doi.org/10.4135/9781483346397.n187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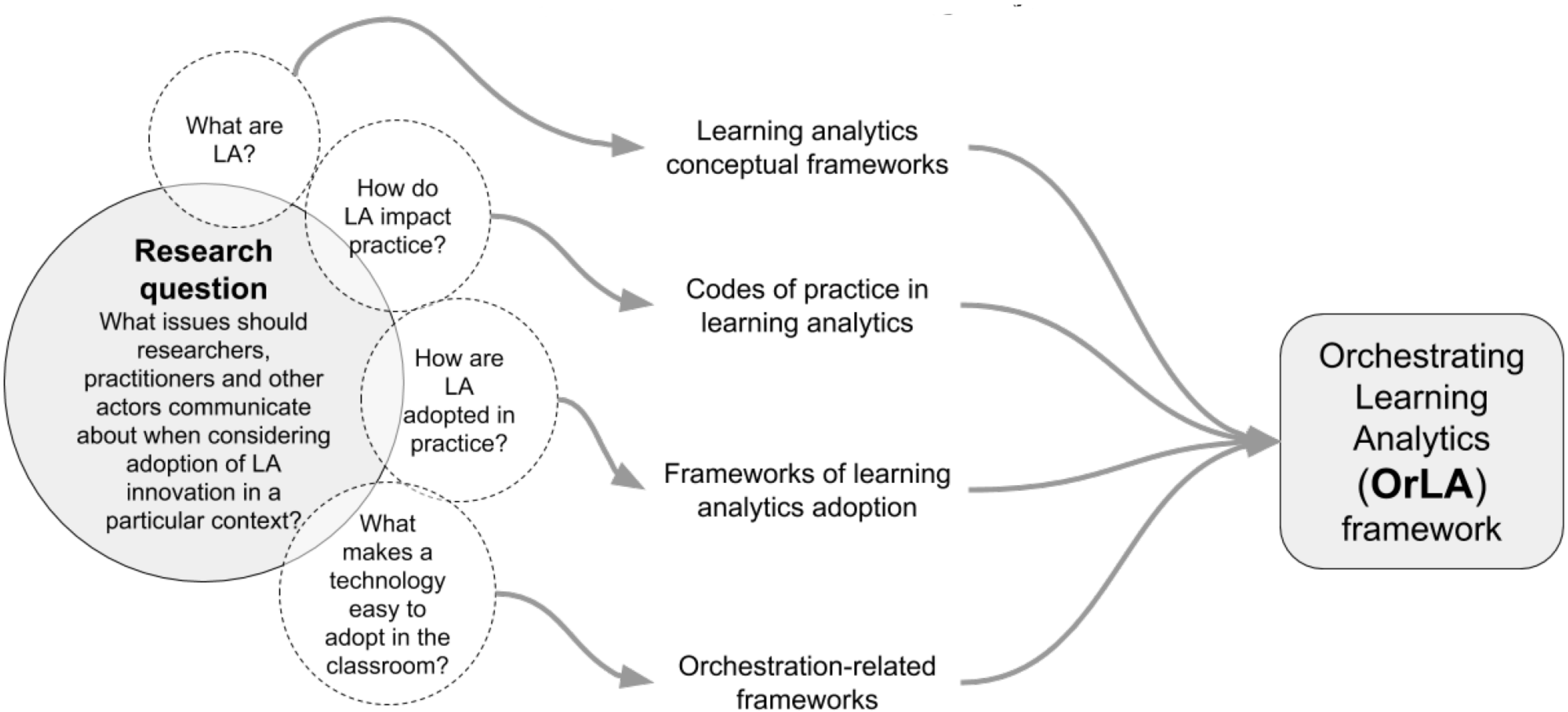
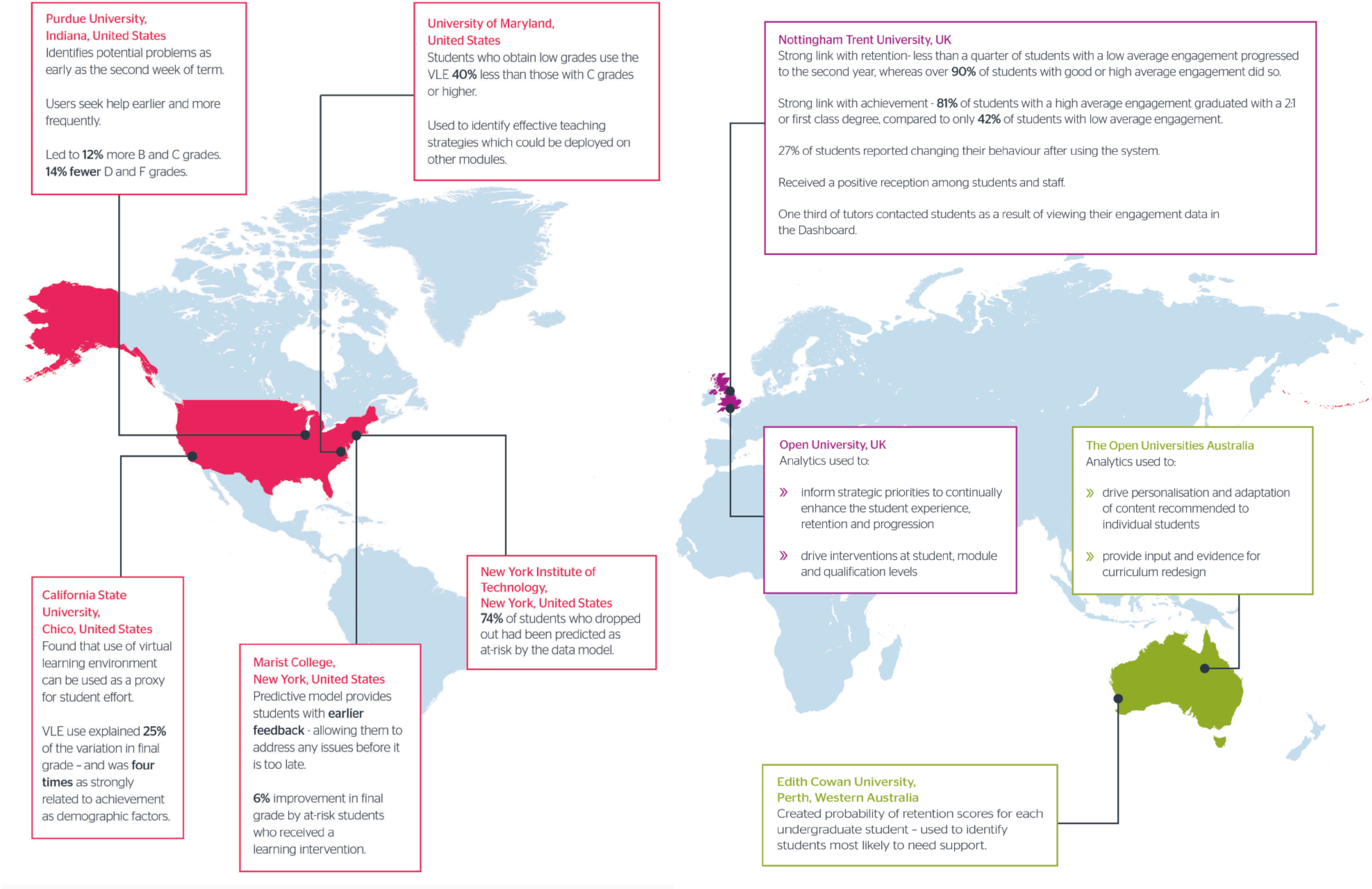


Prieto, L. P., Rodríguez-Triana, M. J., Martínez-Maldonado, R., Dimitriadis, Y., & Gašević, D. (2019). Orchestrating learning analytics (OrLA): Supporting inter-stakeholder communication about adoption of learning analytics at the classroom level. *Australasian Journal of Educational Technology*, *35*(4),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



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

2014

Mittels umfangreicher Learning Analytics Daten können Modelle von Lernenden generiert werden.

N=40

Papamitsiou, Z., & Economides, A. (2014). Learning analytics and educational data mining in practice: a systematic literature review of empirical evidence. *Educational Technology & Society, 17*(4), 49–64.

2016

Papamitsiou, Z., & Economides, A. (2016). Learning analytics for smart learning environments: a meta-analysis of empirical research results from 2009 to 2015. In J. M. Spector, B. Lockee, & M. Childress (Eds.), *Learning, design, and technology* (pp. 1–23). Cham: Springer.

N=66

Learning Analytics beeinflussen signifikant den Lernprozess.

2018

Interventionen basierend auf Learning Analytics können den Lernerfolg signifikant verbessern.

N=11

Larrabee Sønderlund, A., Hughes, E., & Smith, J. (2018). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology, 50*(5), 2594–2618. doi:10.1111/bjet.12720

2019

Kilis, S., & Gulbahar, Y. (2019). A snapshot of research on learning analytics: a systematic review. In M. S. Khine (Ed.), *Emerging trends in learning analytics* (pp. 45–64). Leiden, NL: Brill.

N=39

Lern-umgebungen sind nicht ausreichend für Learning Analytics ausgestattet.

2019

Learning Analytics können umfassende Potentiale für Lernen entfalten.

N=150

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education, 16*(39), 1–27. doi:10.1186/s41239-019-0171-0

2020

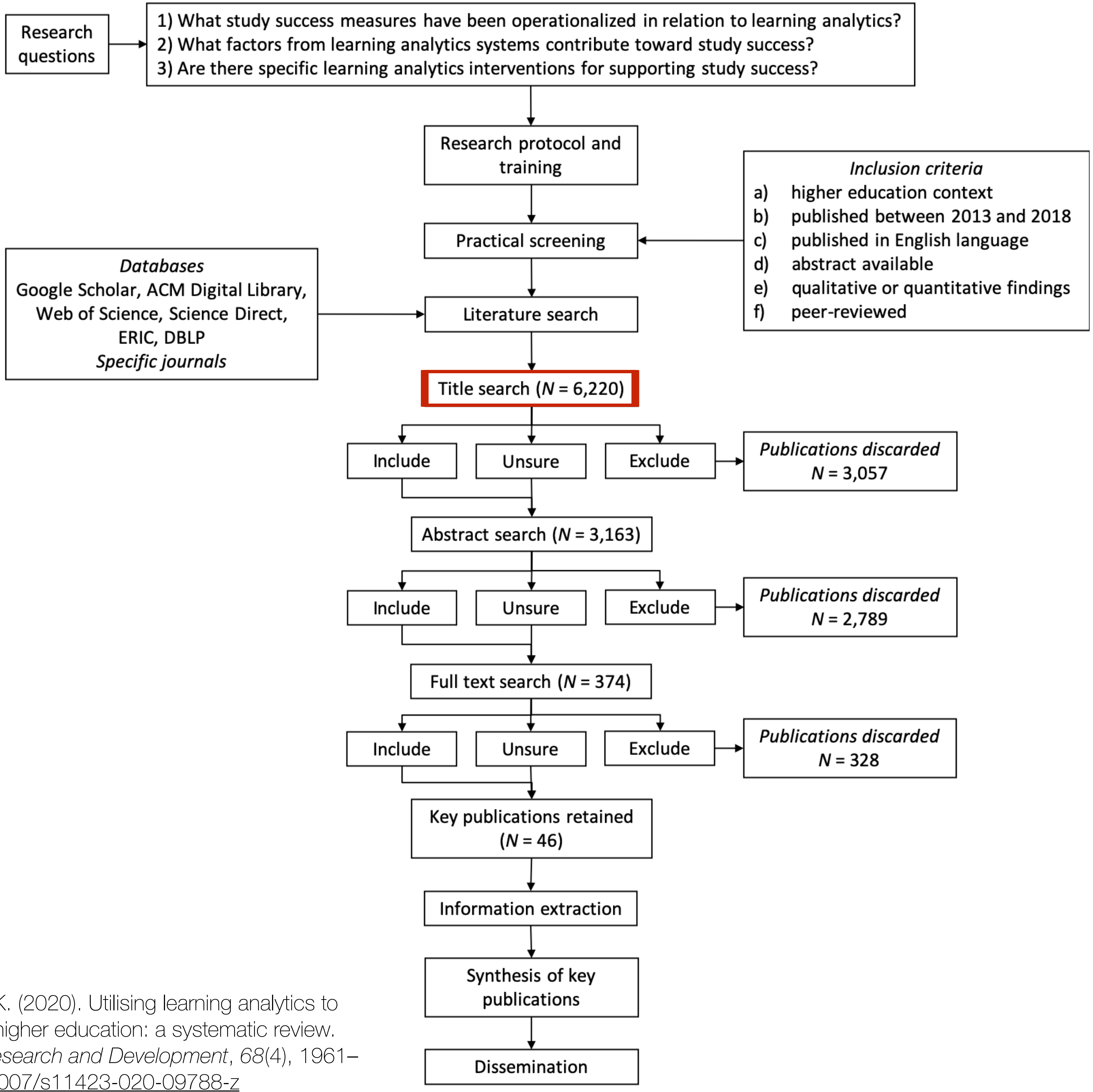
Matcha, W., Uzir, N. A., Gašević, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: a self-regulated learning perspective. *IEEE Transaction of Learning Technologies, 13*(2), 226–245. doi:10.1109/TLT.2019.2916802

N=29

Die Entwicklung von Learning Analytics Dashboards ist nur wenig pädagogisch begründet.

KI Anwendungsfeld	Beispiel-anwendungen	Anzahl der Studien
Profiling	Zulassungsentscheidungen und Kursplanung; Studienabbruch, Studierendenmodelle und Studienleistungen	58
Intelligente Tutorensysteme	Auswahl und Präsentation von Kursinhalten; automatisches Feedback; Unterstützung von Kollaboration; Tools für Lehrende	29
Automatische Prüfungssysteme	Automatische Benotung; Feedback; Evaluation von Lernfortschritt und Beteiligung; Lehrevaluation	36
Adaptive Systeme	Auswahl und Präsentation von Kursinhalten; Empfehlung personalisierter Inhalte; Support für für Lehrende; Monitoring der Lernenden; Repräsentation von Inhalten und Curricula	27

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(39), 1–27. https://doi.org/10.1186/s41239-019-0171-0

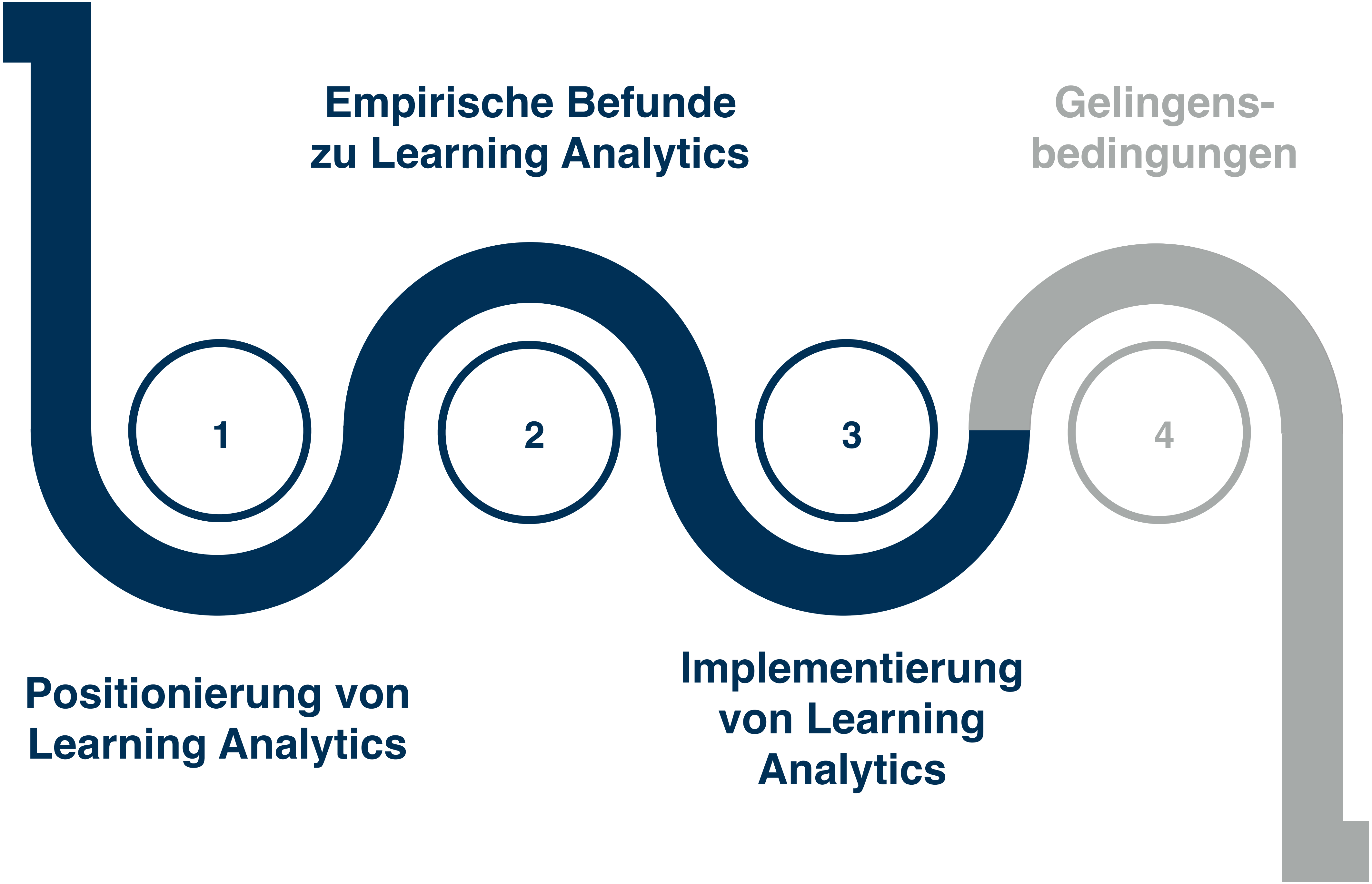


Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: a systematic review. *Educational Technology Research and Development*, *68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

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. (2020). Utilising learning analytics to support study success in higher education: a systematic review. *Educational Technology Research and Development*, *68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z


Empirische Befunde
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Analytics

Um Learning Analytics in Bildungsorganisationen zu Implementieren bedarf es umfassender Rahmenkonzeptionen.

#1

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

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

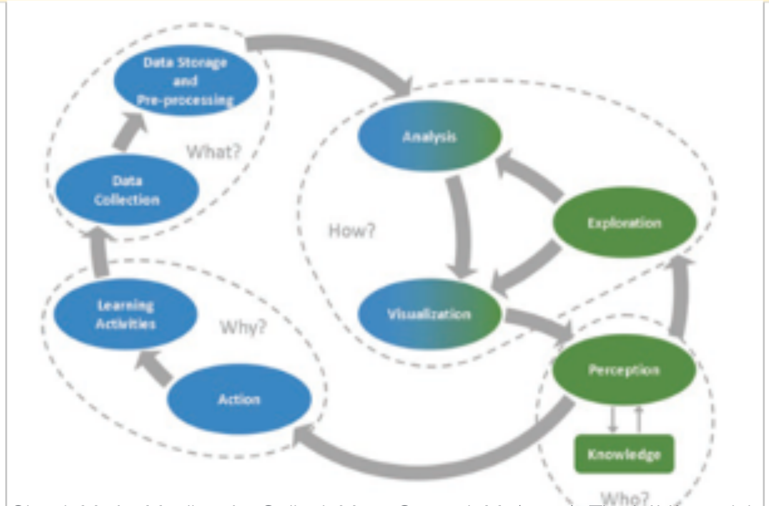
Implementation guidelines

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.

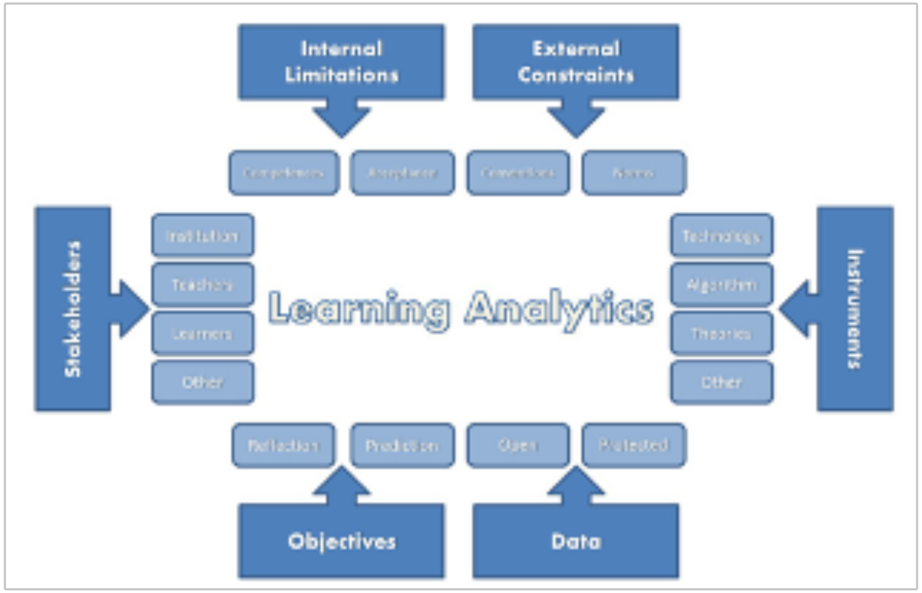
It is also very important that learning analytics stakeholders **understand fully** what learning analytics adaptive teaching entails and how personalised learning works.

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. https://doi.org/10.3991/ijai.v1i1.10978

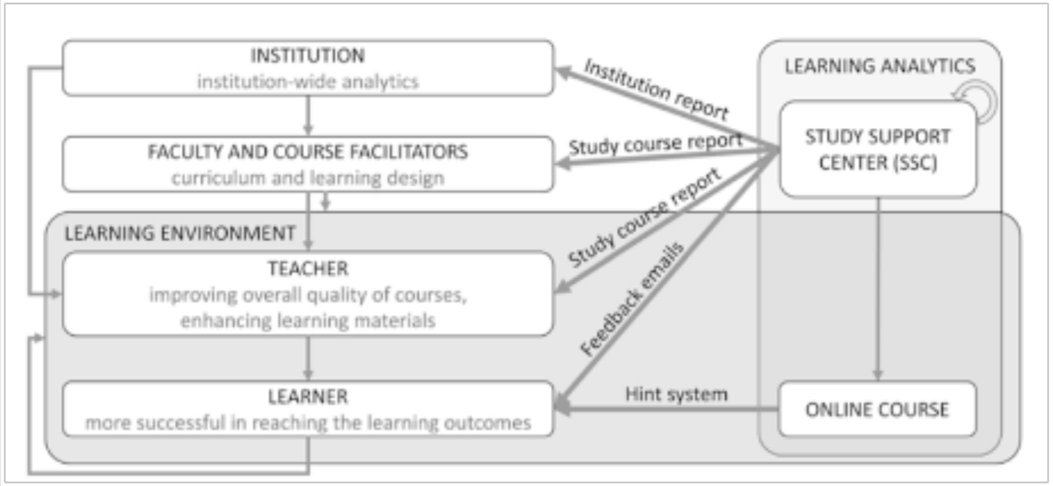


Chatti, M. A., Muslim, A., Guliani, M., & Guesmi, M. (2020). The LAVA model: Learning analytics meets visual analytics. In D. Ifenthaler & D. C. Gibson (Eds.), Adoption of data analytics in higher education learning and teaching (pp. 70–93). Cham: Springer.



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

Leitner, P., Ebner, M., & Ebner, M. (2019). Learning analytics challenges to overcome in higher education institutions. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 91–104). Springer.



Egetenmeier, A., & Hommel, M. (2020). Adoption of learning analytics. In D. Ifenthaler & D. C. Gibson (Eds.), *Adoption of data analytics in higher education learning and teaching* (pp. 113–134). Springer.

Herausforderung für die Implementierung von Learning Analytics sind die Interaktion und Fragmentation von Informationen sowie deren konzeptuellen Eigenarten.

#2

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. https://doi.org/10.1016/j.iheduc.2015.10.002

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. https://doi.org/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. https://doi.org/10.1007/s10758-014-9226-4

Learning Analytics verwenden reaktive und non-reaktive Datengewinnung für eine zuverlässige und gültige Unterstützung von Lern- und Lehrprozessen.

#3

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics*, *3*(2), 220–238. https://doi.org/10.18608/jla.2016.32.11

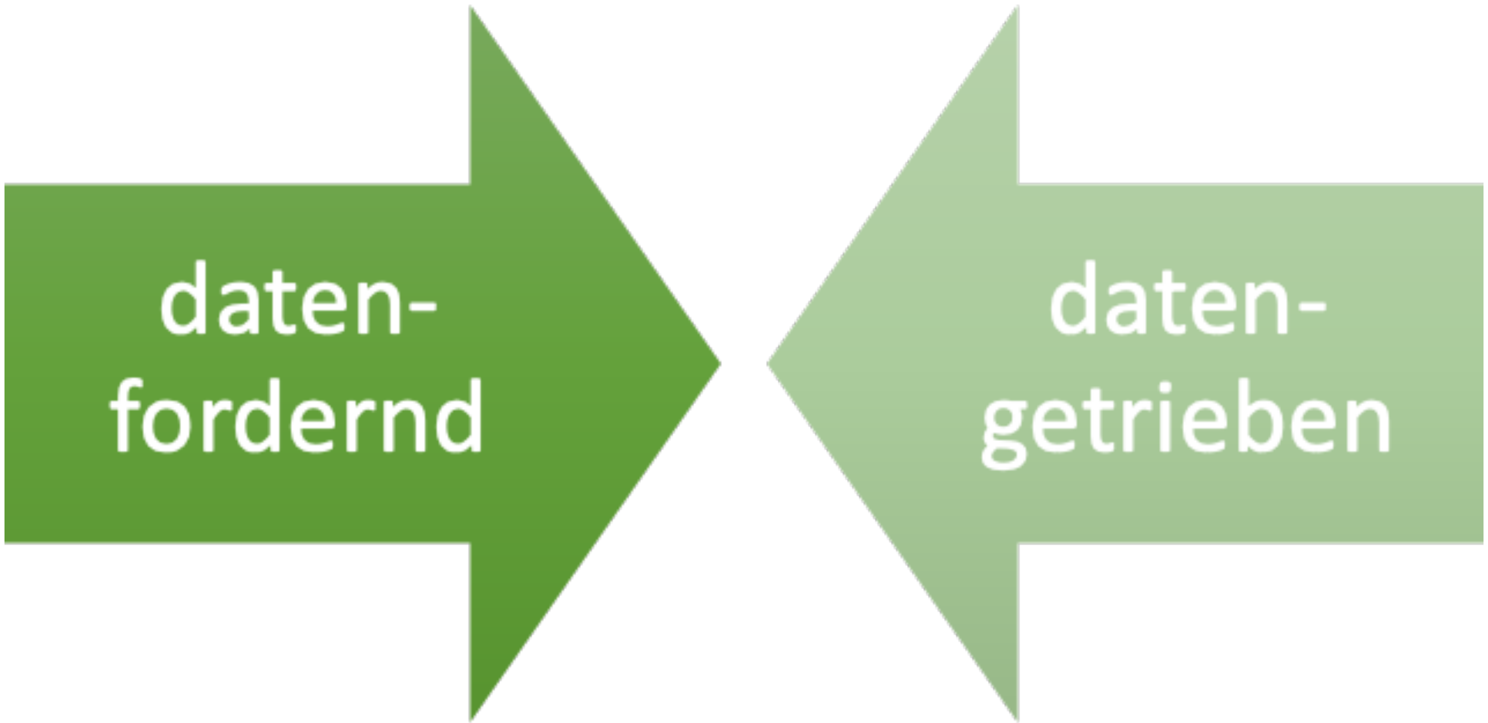
Understanding of learning analytics

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. https://doi.org/10.3991/ijai.v1i1.10978

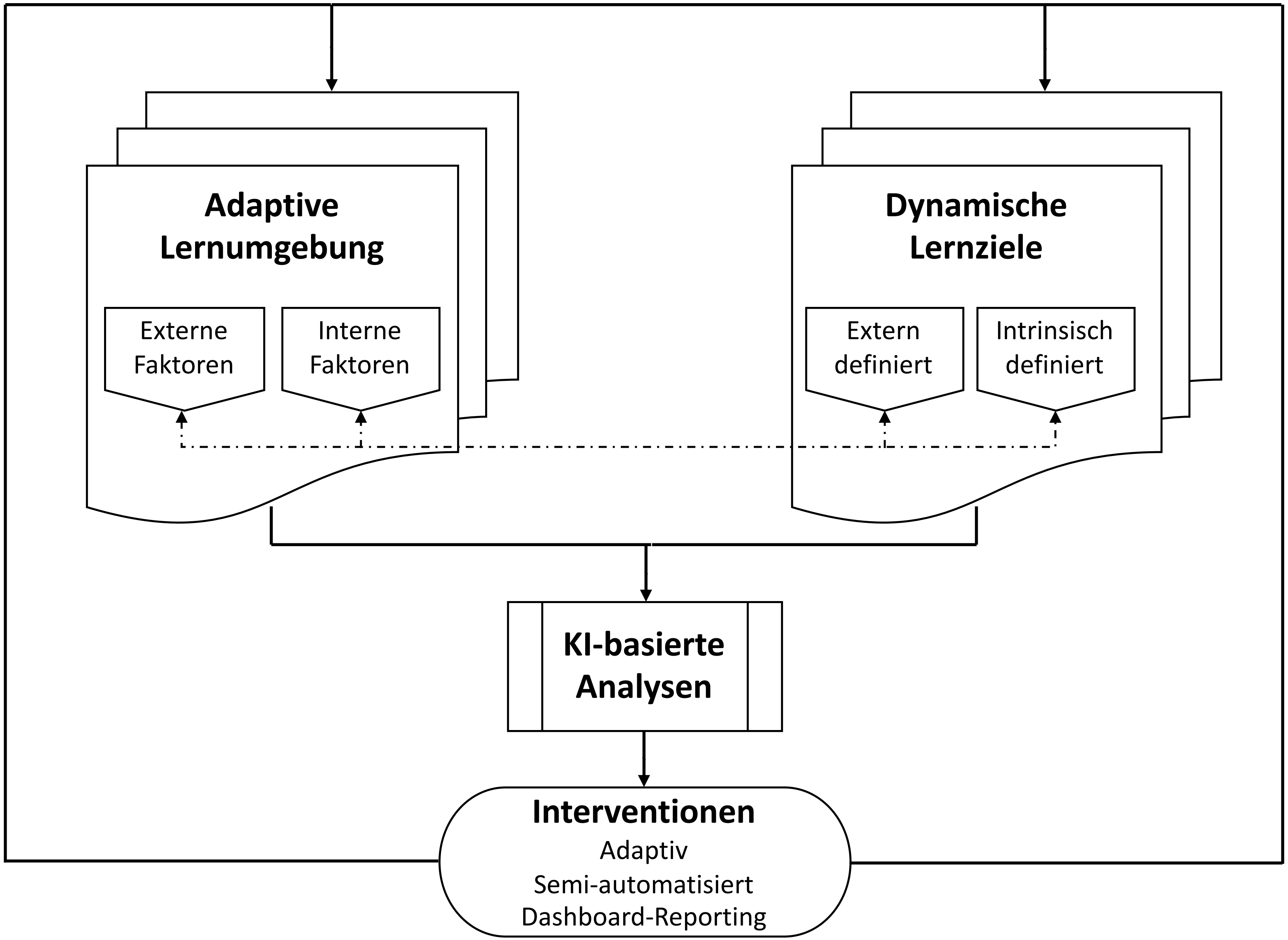


Ifenthaler, D. (2021). Learning analytics for school and system management. In OECD (Ed.), OECD digital education outlook 2021: pushing the frontiers with artificial intelligence, blockchain and robots (pp. 161–172). OECD Publishing.

Table 2. Summary of learning analytics indicators mapped to three data profiles

	Student profile	Learning profile	Curriculum profile
Students answers/ grades	N/A	Content access (video/ audio trace data) pen trace data (self-)assessment (score, grade, completion) data	N/A
Students social learning behaviour/ engagement	Prior academic performance prior competence/skills demographic background social behaviour trait self-report survey current workload study pattern	Course access (login) content access discussion/forum (length, quality) trace data engagement trace data (self-)assessment (score, grade, completion) data	N/A
At-risk/ low-performers	Prior academic performance prior competence/skills demographic background socioeconomic background academic goals technology preparedness Completed/ withdrawn courses motivation/interest prior learning behaviour prior academic institutions enrolment history/ mode/ load	Course access (login) content access assignment submission engagement trace data discussion/forum (length, quality) trace data (Self-)assessment (score, grade, completion) data final grade reflection/ feedback access social network usage	Course characteristics course survey
Student performance	Prior academic performance demographic background socioeconomic background enrolment history/ mode/ load counselling activities psychological test outcomes	(Self-)assessment (score, grade, completion) data final grade course access content access discussion/forum (length, quality) trace data engagement trace data	N/A
Course completion	Prior academic performance demographic background completed/ withdrawn courses enrolment history/ mode/ load	Course access (login) content access discussion/forum (length, quality) trace data engagement trace data (self-)assessment (score, grade, completion) data	N/A

Yau, J., & Ifenthaler, D. (2020). Reflections on different learning analytics indicators for supporting study success. *International Journal of Learning Analytics and Artificial Intelligence for Education*, *2*(2), 4–23. https://doi.org/10.3991/ijai.v2i2.15639



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Bundesinstitut für Berufsbildung

Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.

Literaturrecherche Datenbanken Jahrgänge 2007-2021:
28.782 Publikationen

Jahrgänge 2019-2021:
9.913 Publikationen

Automatische Suche nach irrelevanten Begriffen:
1.919 Publikationen ausgeschlossen

7.994 Titel angeschaut

6.435 Publikationen ausgeschlossen

1.559 Abstracts angeschaut

1.118 Publikationen ausgeschlossen

441 Volltexte angeschaut

189 Publikationen ausgeschlossen

252 relevante Publikationen

\+ **22** zufällige, relevante Publikationen aus 2007-2018

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Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.

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KAMAELEON

274 Publikationen

- **318** Indikatoren des internen und externen Lernumfelds
- **27** Kategorien

Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.

INTERNES LERNUMFELD

Demographische Angaben	Bisherige Leistungen, Vorwissen & Vorerfahrungen	Werte & Lebensauffassung	Überzeugungen & Einstellungen zum (digitalen) Lernen	Persönliche Präferenzen & Vorgehensweisen beim Lernen
Kompetenzen, Fähigkeiten & Fertigkeiten	Persönlichkeit	Selbstwahrnehmungen in Bezug auf Lernen	Bedürfnisse & Bedürfnisbefriedigung	Motivation
Emotionen	Mentale/ kognitive Zustände	Physiologische Maße	Verpflichtungen außerhalb des Kurses	Soziale Beziehungen, Einfluss & Unterstützung
Wahrnehmung des Kurses & kursspezifische Einstellungen	Merkmale der Lehrperson	Merkmale des Arbeitsplatzes/ Jobs	Merkmale des Studiums	

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Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.

INTERNES LERNUMFELD

Demographische Angaben

- Geschlecht
- Alter/Geburtsjahr
- Rasse
- Zugehörigkeit zu einer ethnischen Minderheit
- Kultur
- Muttersprache
- Aufenthaltsstatus/internationaler Status
- Familienstand
- Kinder
- Sozioökonomischer Status
- Bildungsabschluss der Eltern
- Athlet

INTERNES LERNUMFELD

Bisherige Leistungen, Vorwissen & Vorerfahrungen

- Höchster erreichter Bildungsabschluss
- Art der Hochschulzugangsberechtigung
- Note der Hochschulzugangsberechtigung
- Rangplatz bei der Zulassung zum Kurs
- Rangplatz in verschiedenen Fächern/bisherige Leistungen im Vergleich zu anderen Lernenden
- Durchschnittsnote/GPA
- Note in relevanten vorausgehenden Prüfungen
- Vorwissen bzgl. der Kursinhalte
- Bisher besuchte Kurse mit thematischem Bezug
- Bisherige Erfahrungen mit dem Kursformat
- Bisherige „Turning points" bzgl. des Faches/Kursinhaltes
- Anzahl bisher erlangter Credits
- Delay Index
- Wahrgenommener Delay Index
- Wiederholung des Kurses
- Dauer der Mitgliedschaft in der Lerncommunity
- Angemessenheit bisher erworbener Lerntechniken

Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.

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EXTERNES LERNUMFELD

Merkmale der Lehrperson	Merkmale des Arbeitsplatzes/ Jobs	Merkmale des Studiums
Merkmale des Kurses	Unterrichts-methode	Merkmale des Lernmaterials
Merkmale der Lerngruppe	Feedback im Kurs	Merkmale der Bildungs-institution
Physische & zeitliche Lernumgebung	Multi Tasking	

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Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.

EXTERNES LERNUMFELD

Merkmale des Kurses

- Bildungsniveau
- Schwierigkeitsniveau
- Größe
- Thema/Kursinhalt
- Kurslänge
- Online- vs. Offline-Kurs
- Prozentsatz an besuchten Online-Kursen
- Art des zu erwerbenden Wissens
- Hausaufgaben
- Benotete Kursbeiträge
- Pretest
- Pflichtkur
- Fortschrit rs

EXTERNES LERNUMFELD

Physische und zeitliche Lernumgebung

- Physische Qualitäten des Kursraums (qualitative Untersuchung)
- Anordnung der Stühle im Kursraum (qualitative Untersuchung)
- Räumlicher Kontext
- Tageszeit
- Hintergrundmusik (qualitative Untersuchung)
- Präsenz anderer Personen
- Distanz zum Kursort
- Art der Wohnform
- Erleichternde Bedingungen

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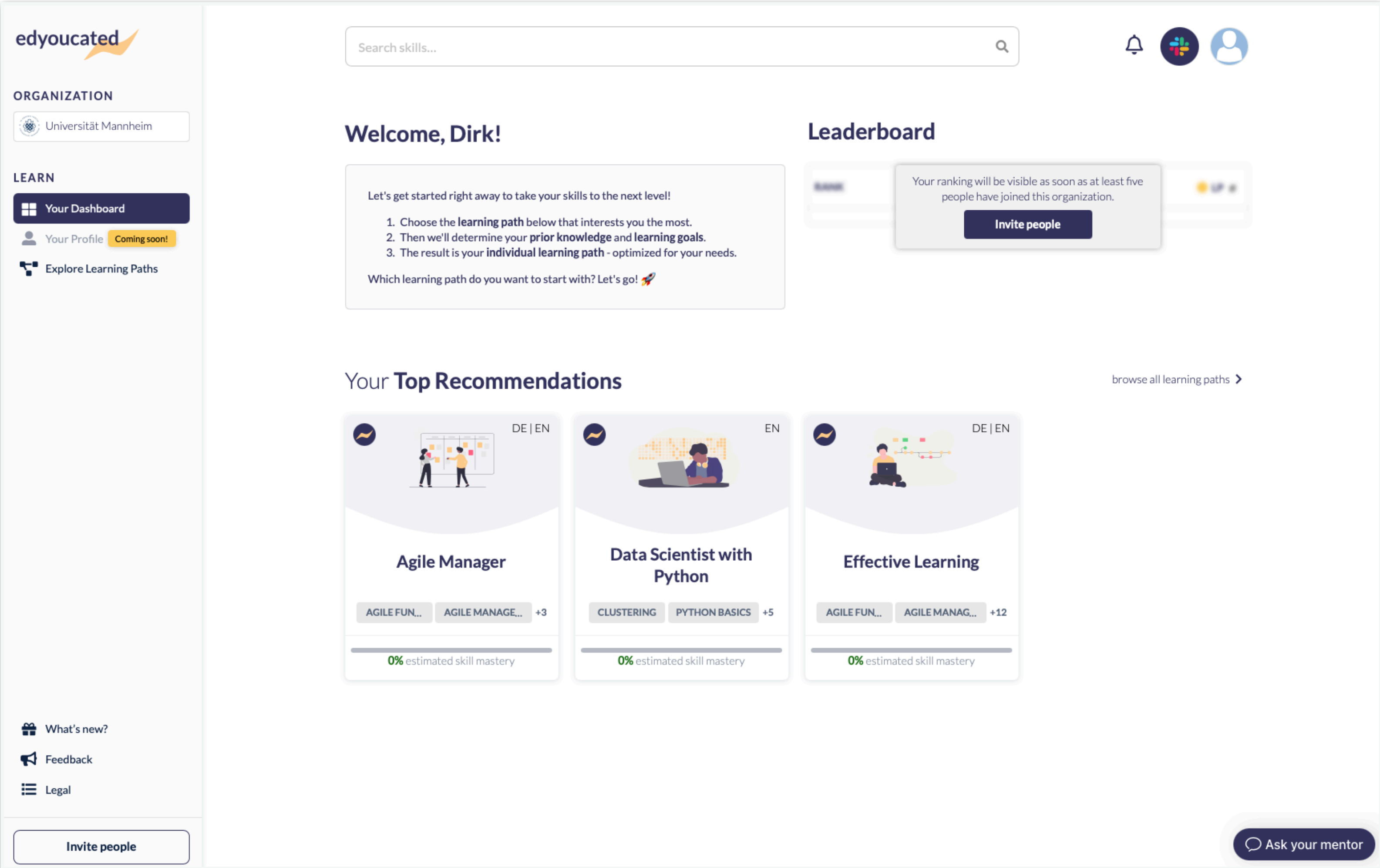
Hemmler, Y., & Ifenthaler, D. (forthcoming). Kontextbasierte und adaptive Maßnahmen für effektive Lernunterstützung in der Weiterbildung. In S. Schumann, S. Seeber, & S. Abele (Eds.), *Digitalisierung und digitale Medien in der Berufsbildung: Konzepte und empirische Befunde*. wbv.



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Bundesinstitut für Berufsbildung

https://edyoucated.org

Es existiert (bislang) keine organisationsweite Implementierung von Learning Analytics Systemen.

#4

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

Readiness to adopt learning analytics

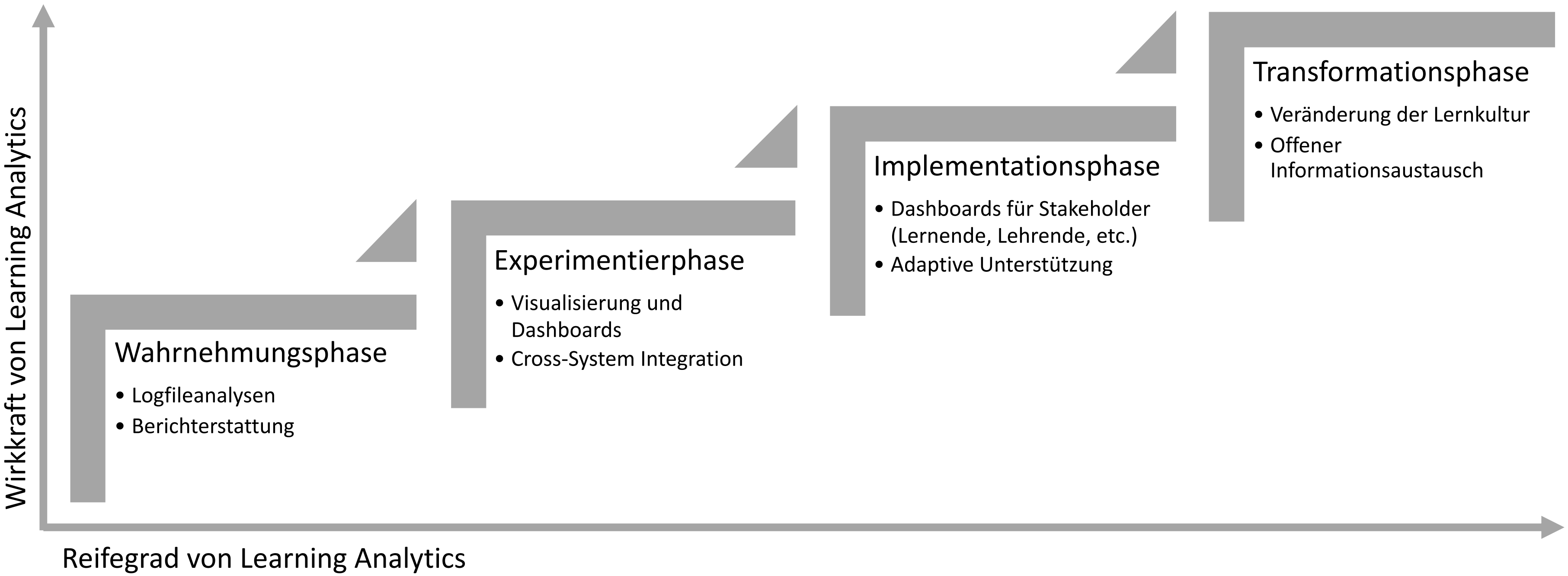
There are currently staff and technological **resources required** by the institution before they can go ahead and adopt learning analytics.

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

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. https://doi.org/10.3991/ijai.v1i1.10978



Ifenthaler, D. (2020). Change management for learning analytics. In N. Pinkwart & S. Liu (Eds.), *Artificial intelligence supported educational technologies* (pp. 261–272). Springer. https://doi.org/10.1007/978-3-030-41099-5_15

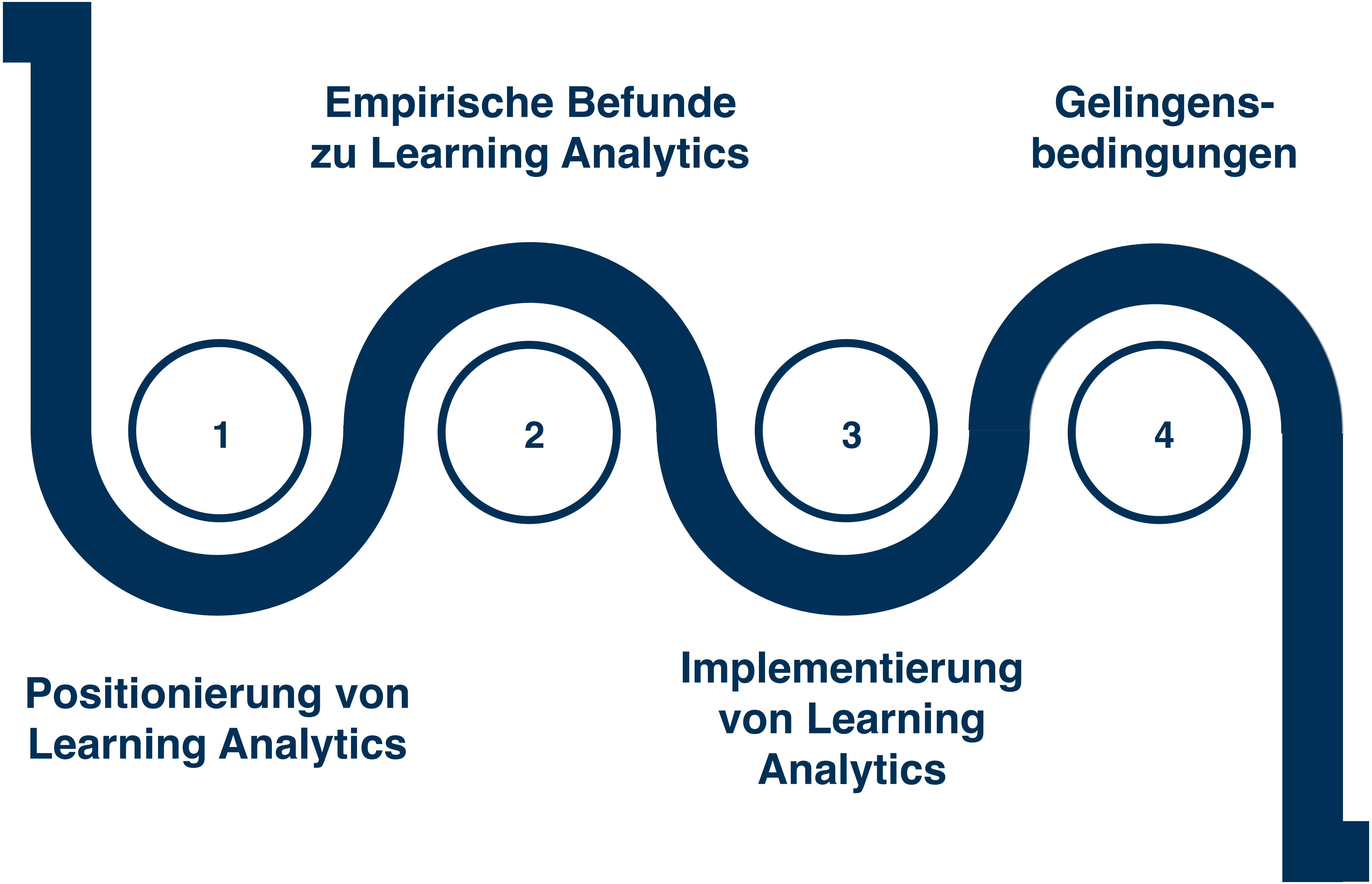
Die Implementierung von Learning Analytics Systemen erfordert eine Weiterentwicklung von universitären Systemen, Prozessen und Personal

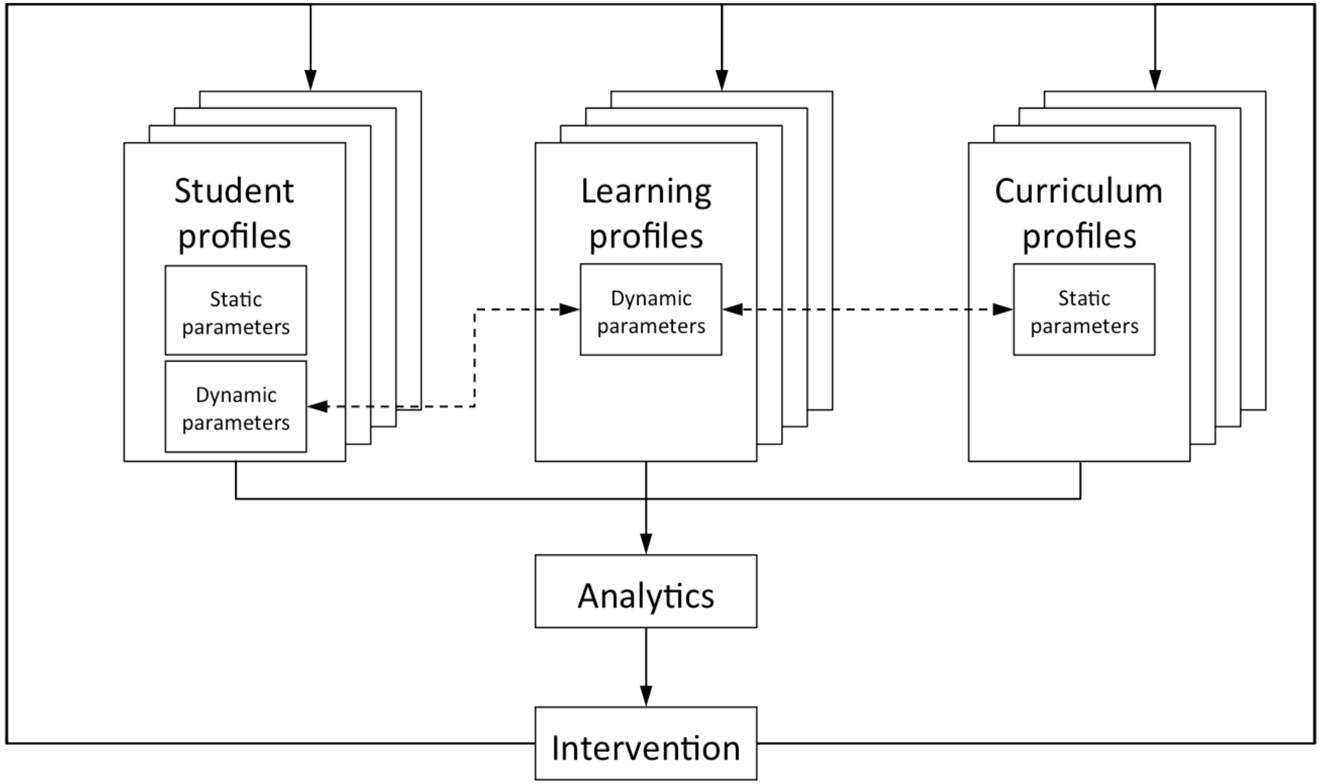
Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends*, *61*(4), 366–371. https://doi.org/10.1007/s11528-016-0154-0

TABLE 10.1 Decision matrix. The last column shows the final prioritization as product of the four aspects: students' willingness to use a feature, perceived learning support, technological effort of implementation and the organizational effort

Feature	Students' willingness to use a feature	Students' perceived learning support	Technological effort of implementation	Organizational effort	Prioritization
reminder for deadlines	3	2	3	3	54
self-assessments	3	3	2	2	36
timeline showing current status and goal	2	3	2	2	24
feedback on assignments	3	2	1	3	18
newsfeed with relevant news matching the learning content	2	1	2	3	12
time spent online	1	2	3	2	12
learning recommendations	3	3	1	1	9
rating scales for provided learning material	1	1	3	3	9
revision of former learning content	3	3	1	1	9
time needed to complete a task or read a text	1	1	3	2	6
comparison with fellow students	1	1	2	2	4
suggestion of learning partners	1	2	1	1	2
term scheduler, recommending relevant courses	2	1	1	1	2

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). Brill. https://doi.org/10.1163/9789004399273_010


Empirische Befunde
zu Learning Analytics
Gelingens-
bedingungen
1
2
3
4
Positionierung von
Learning Analytics
Implementierung
von Learning
Analytics

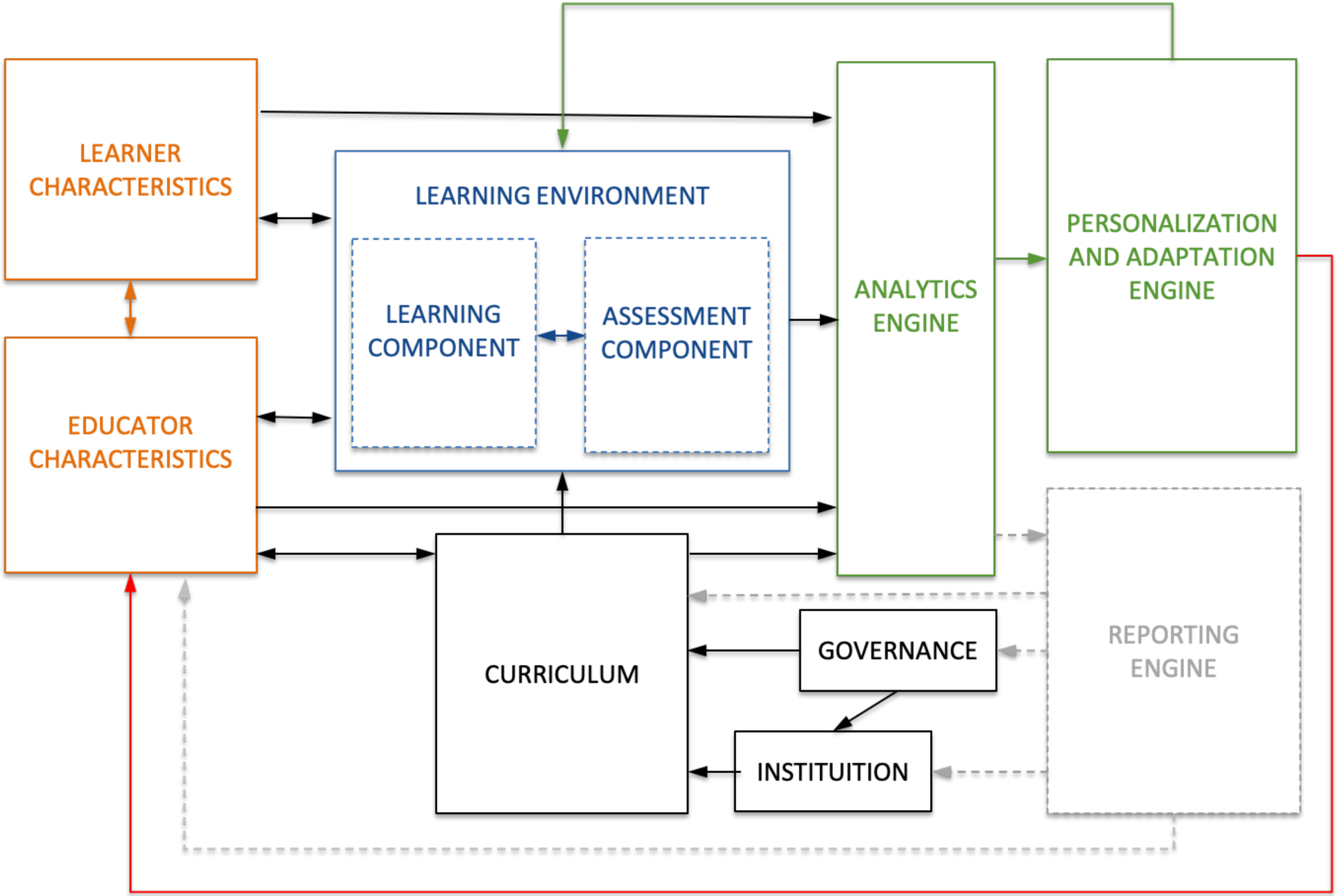


LeAP

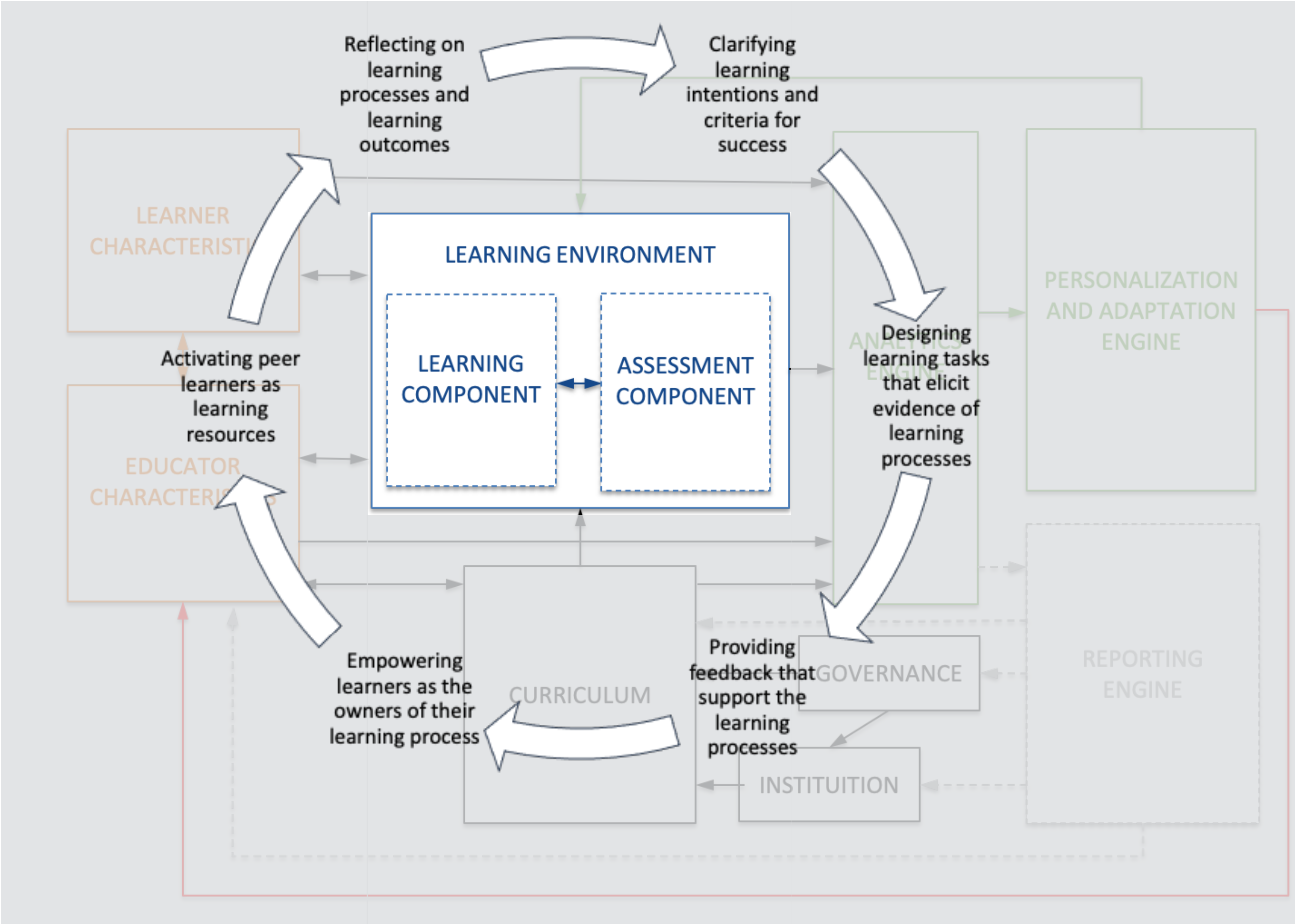
Klasen, D., & Ifenthaler, D. (2019). Implementing learning analytics into existing higher education legacy systems. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 61–72). Springer. https://doi.org/10.1007/978-3-319-64792-0_4

01

Daten- und Lern-Architektur.



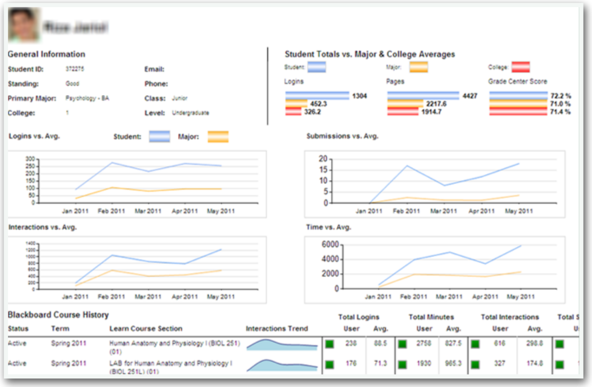
Ifenthaler, D., & Greiff, S. (2021). Leveraging learning analytics for assessment and feedback. In J. Liebowitz (Ed.), *Online learning analytics* (pp. 1–18). Auerbach Publications. https://doi.org/10.1201/9781003194620

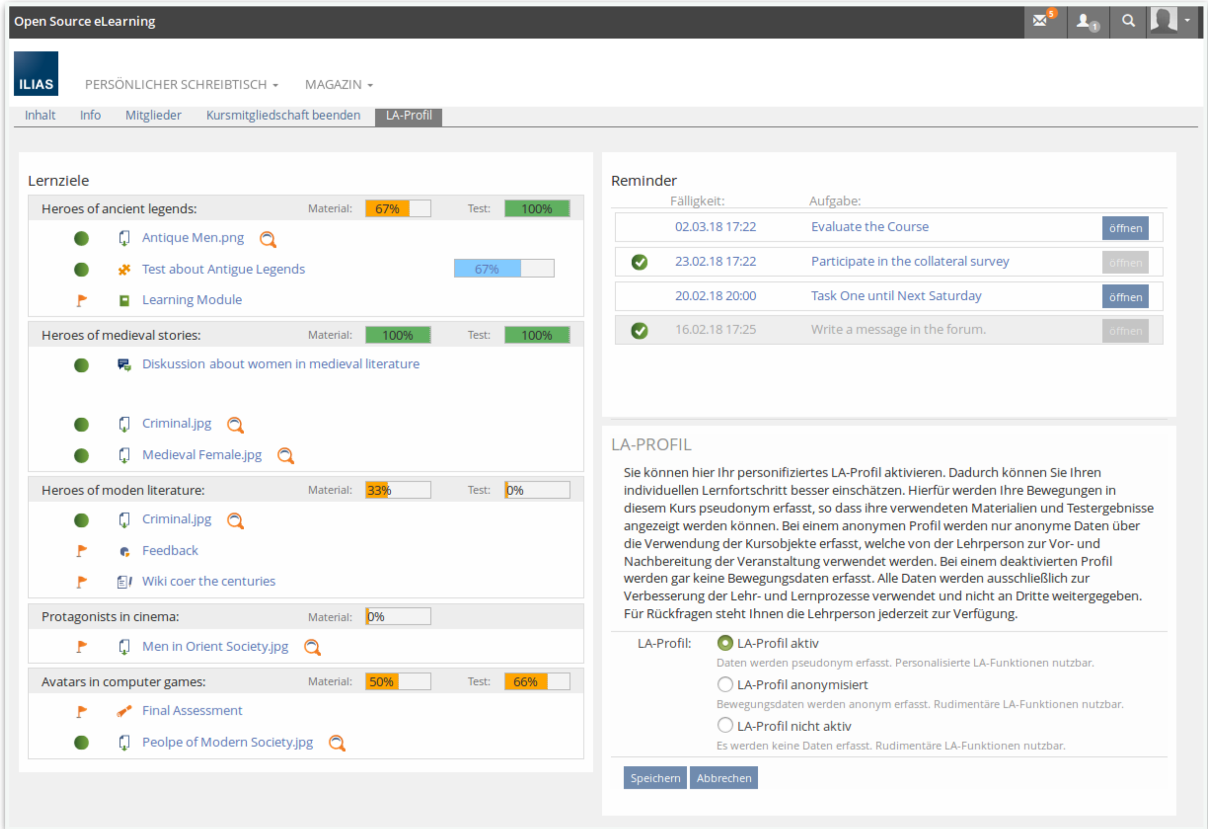


Ifenthaler, D., & Greiff, S. (2021). Leveraging learning analytics for assessment and feedback. In J. Liebowitz (Ed.), *Online learning analytics* (pp. 1–18). Auerbach Publications. https://doi.org/10.1201/9781003194620

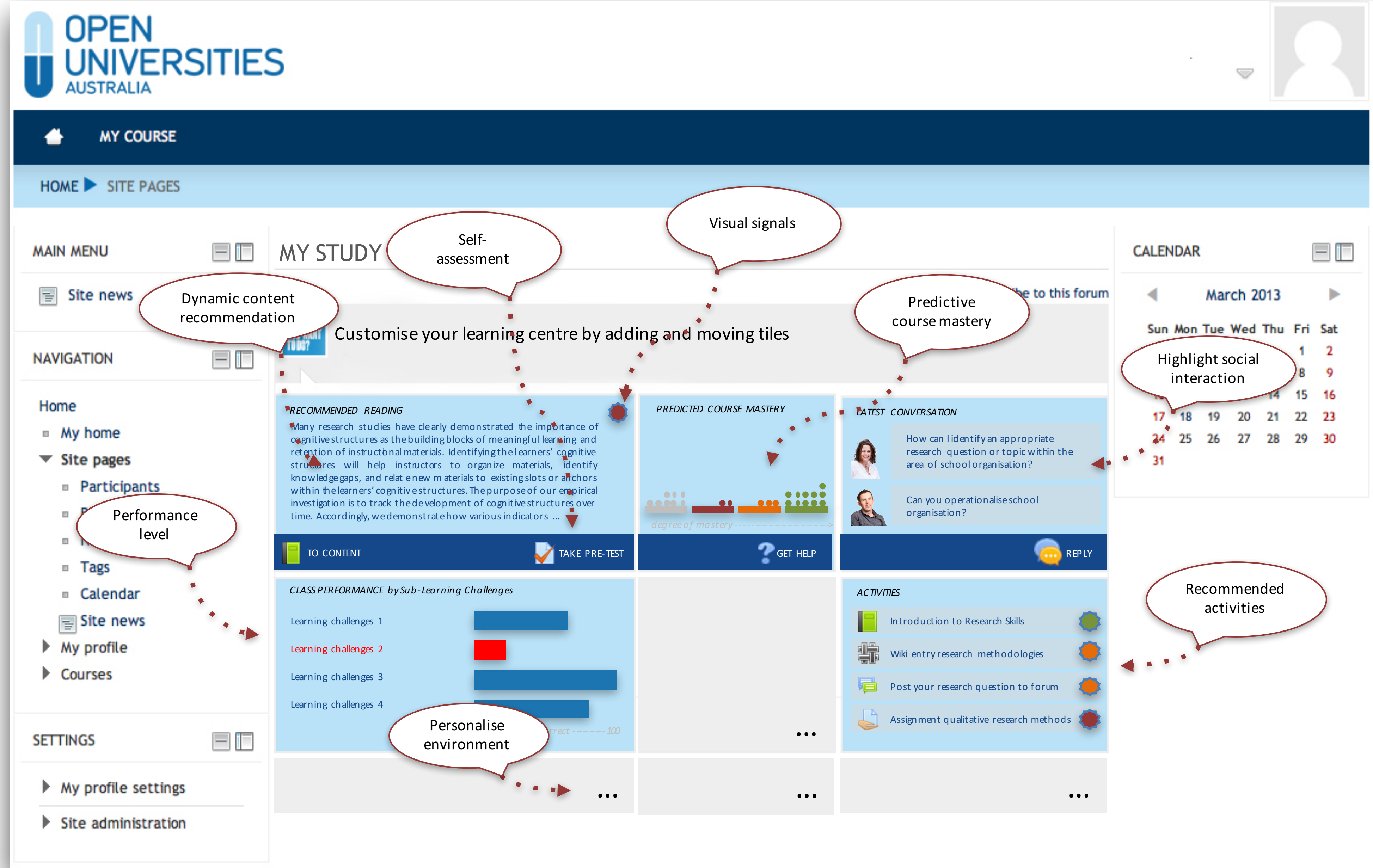
02

Dashboard/ Visualisierung.

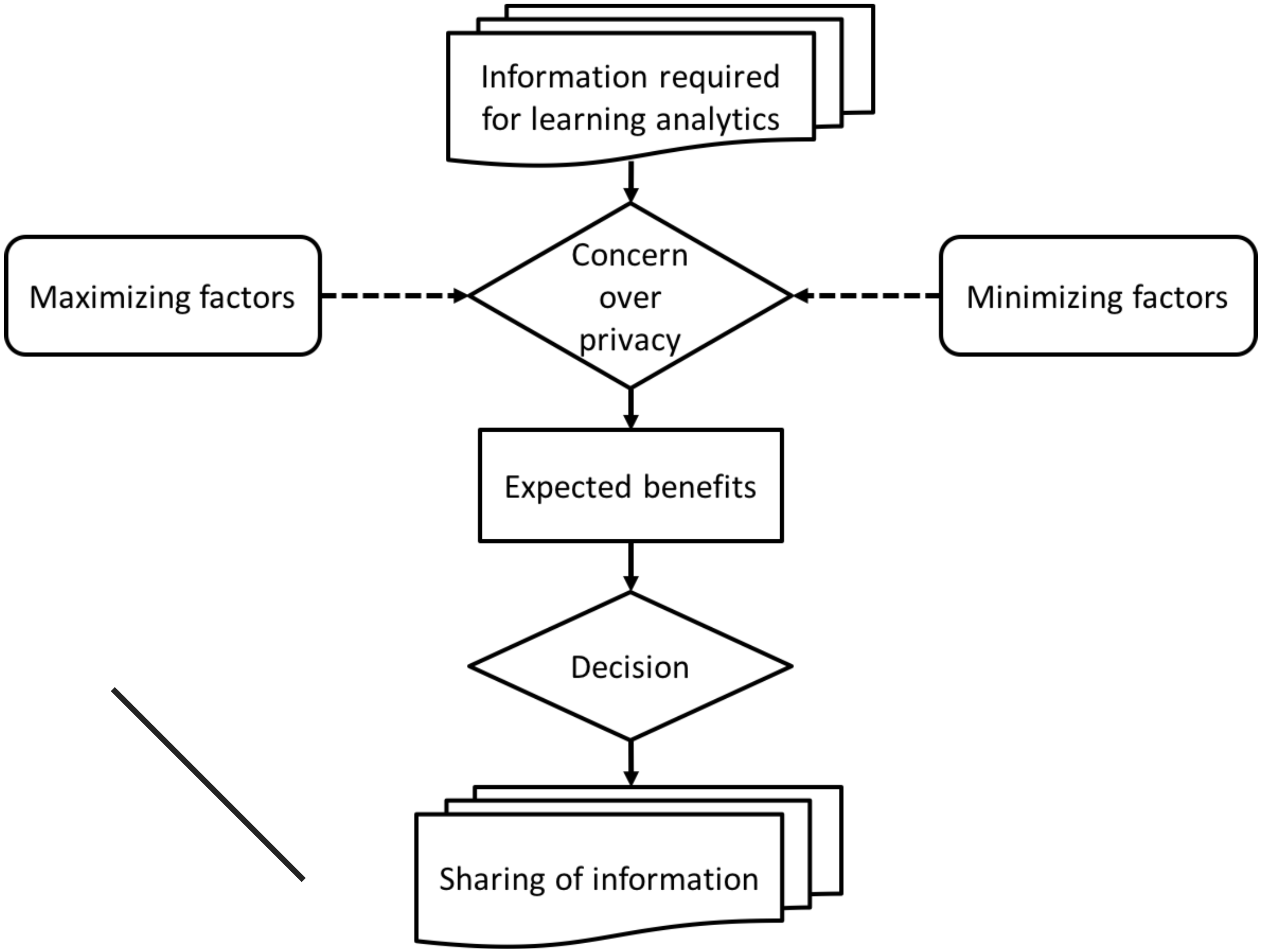




Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior*, *78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030



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. https://doi.org/10.1007/s10758-014-9226-4



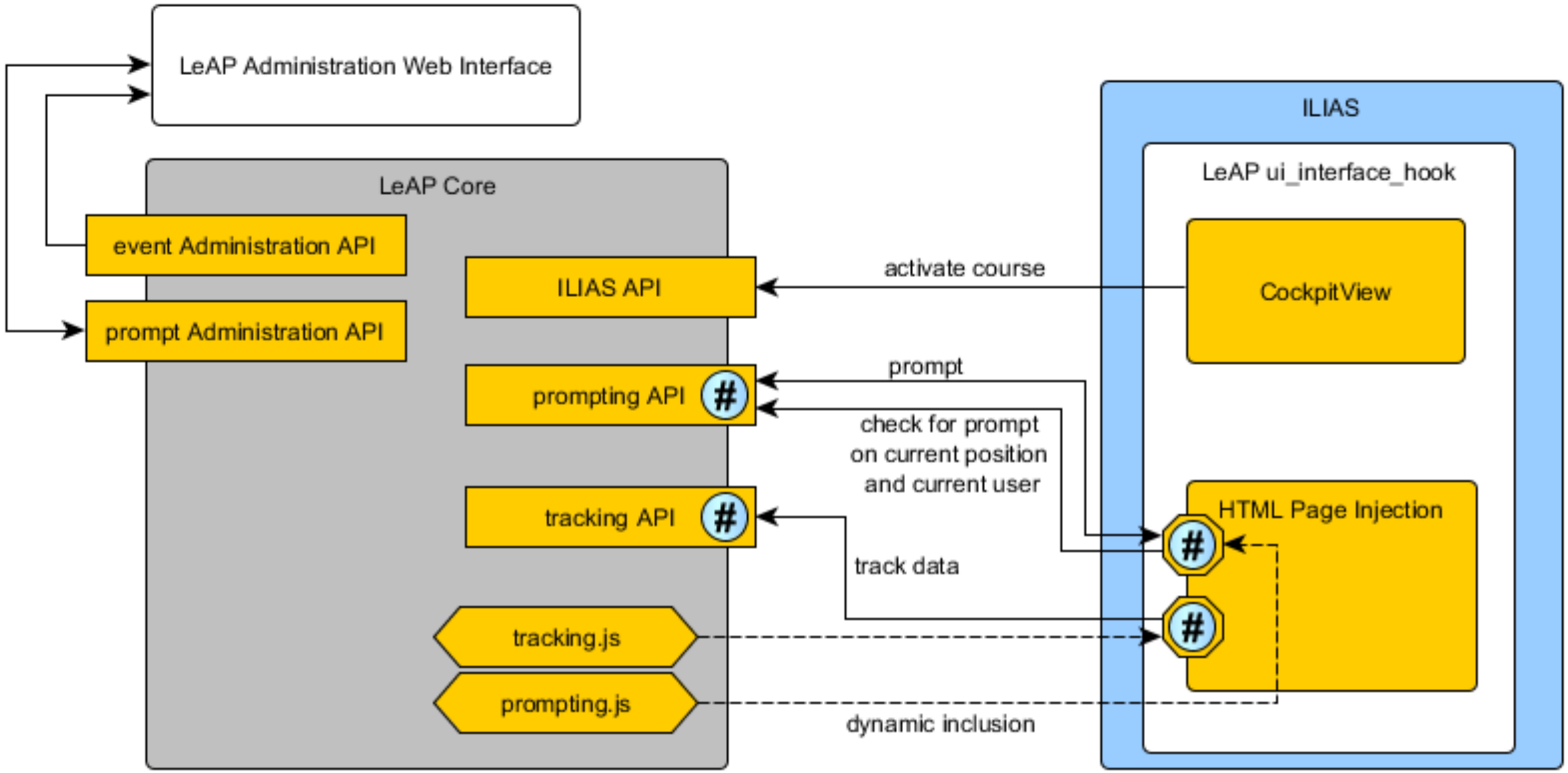
03

Datenschutz
Ethische Anforderungen.

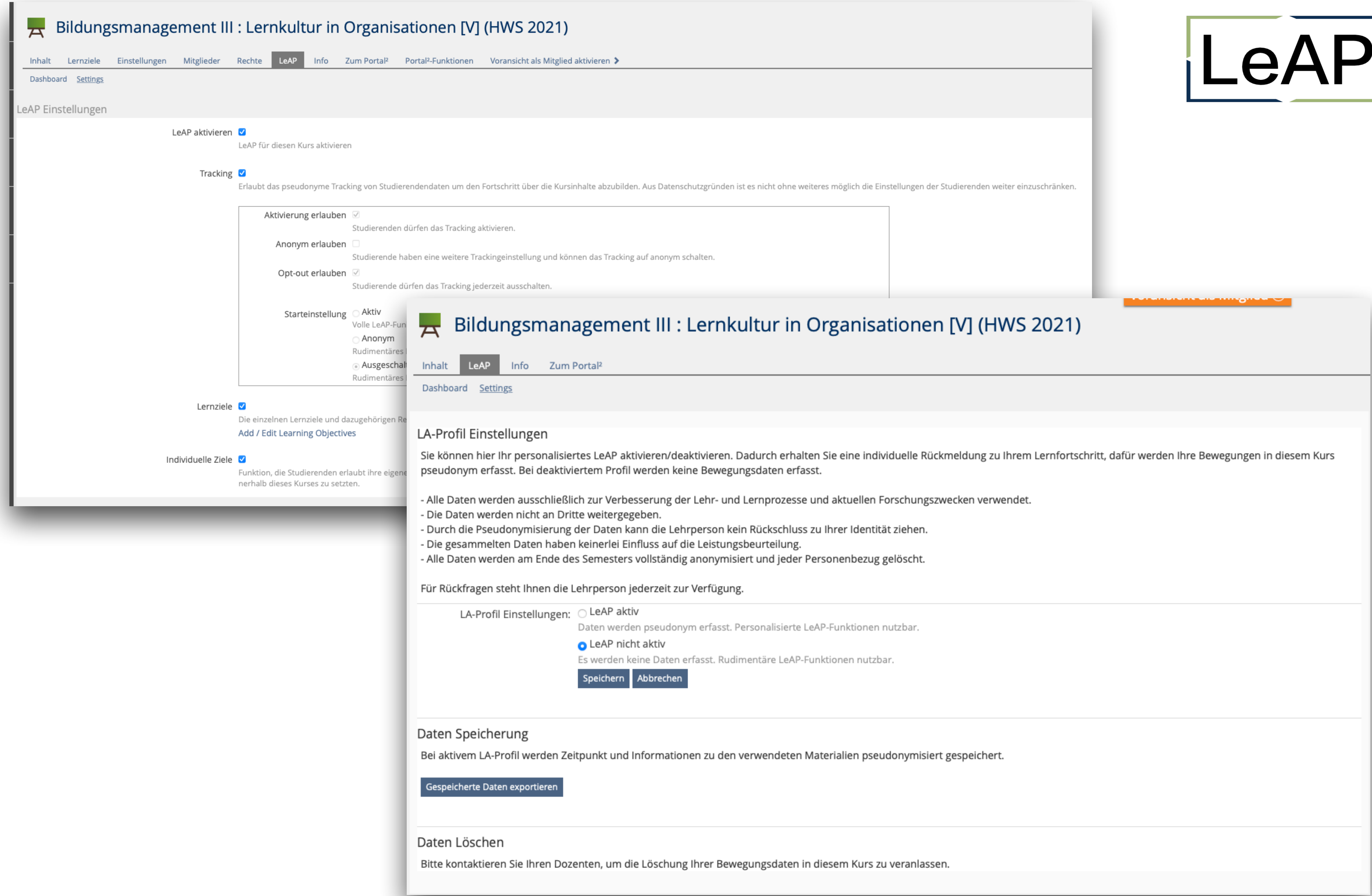
Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development*, *64*(5), 923–938. https://doi.org/10.1007/s11423-016-9477-y

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

Ifenthaler, D. (2022). Ethische Perspektiven auf künstliche Intelligenz im Kontext der Hochschule. In T. Schmohl & A. Watanabe (Eds.), *Künstliche Intelligenz in der Hochschulbildung. hancen und Grenzen des KI-gestützten Lernens und Lehrens*. transcript-Verlag.



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). Springer. https://doi.org/10.1007/978-3-319-64792-0_4

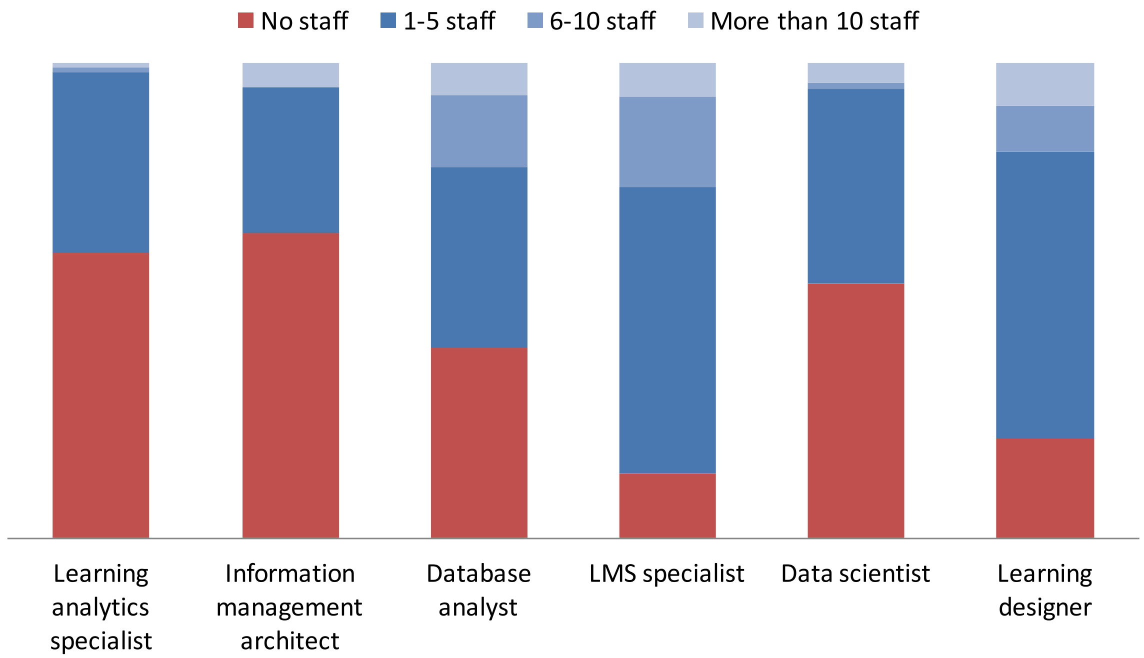


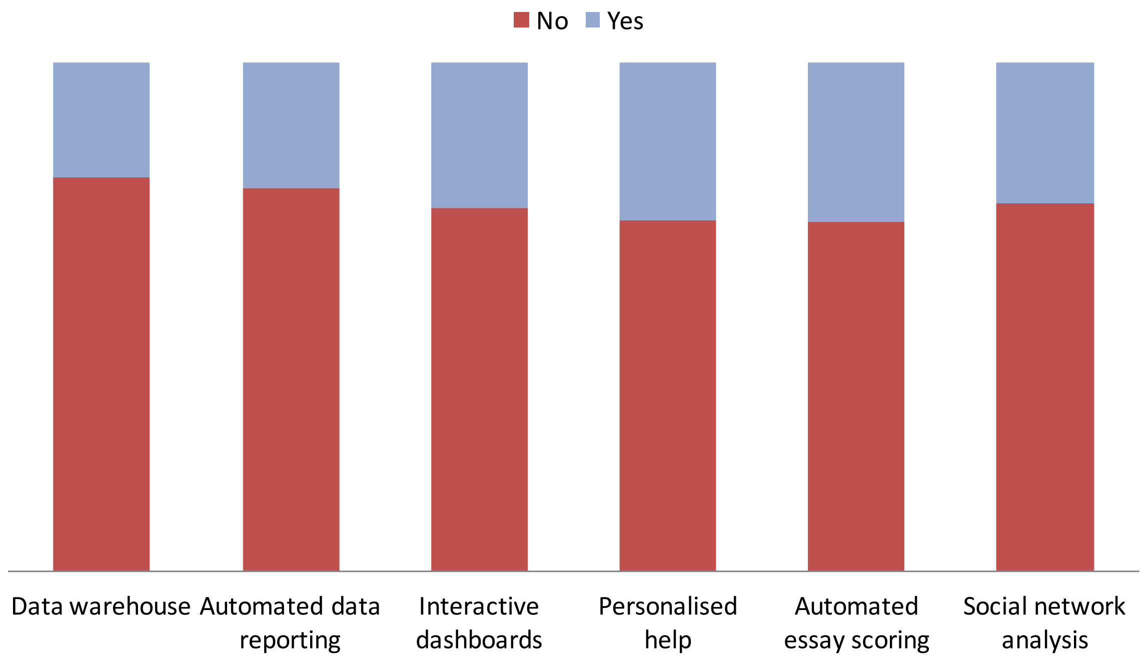
LeAP

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). Springer. https://doi.org/10.1007/978-3-319-64792-0_4

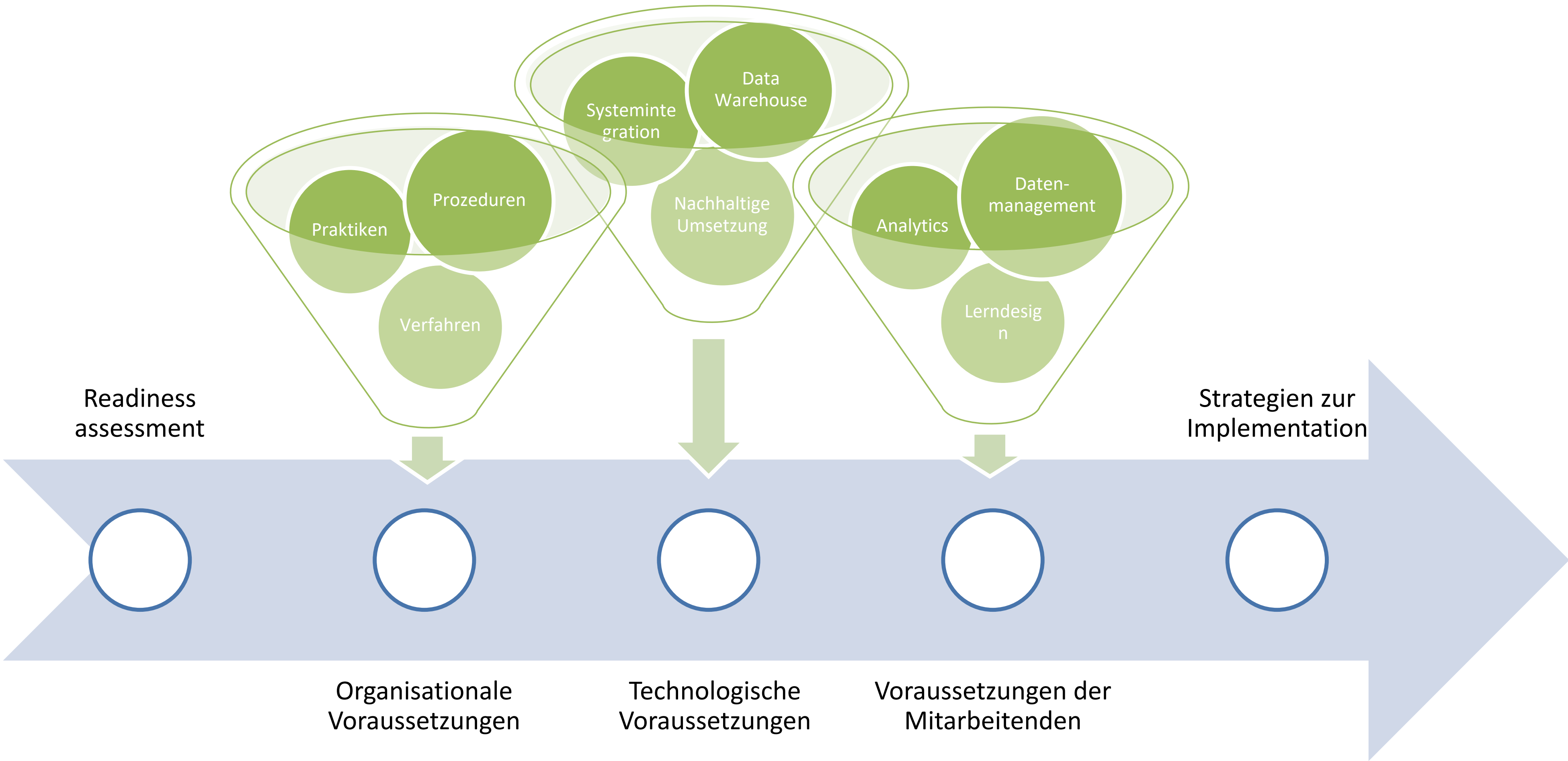
04

Organisations-
entwicklung.



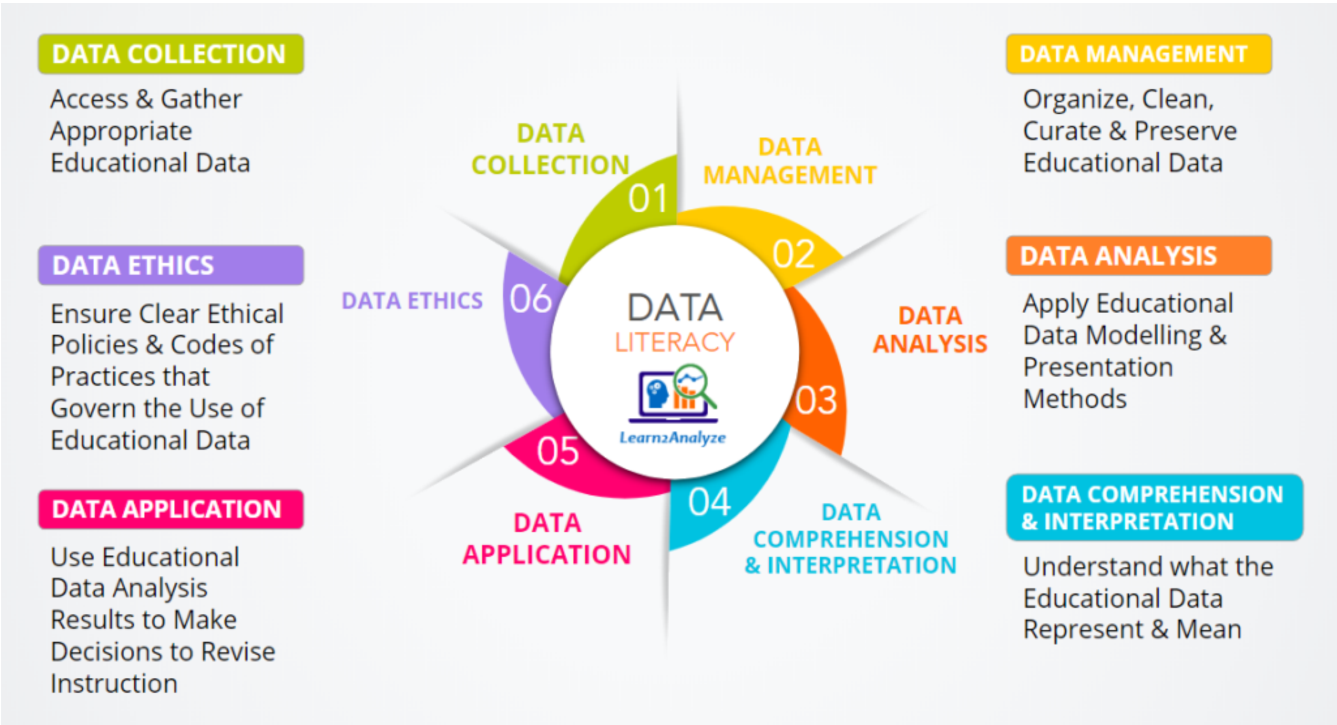


Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends*, *61*(4), 366–371. https://doi.org/10.1007/s11528-016-0154-0



Ifenthaler, D. (2020). Change management for learning analytics. In N. Pinkwart & S. Liu (Eds.), *Artificial intelligence supported educational technologies* (pp. 261–272). Springer. https://doi.org/10.1007/978-3-030-41099-5_15

Bildungsdatenkompetenz (Educational Data Literacy) ist ethisch verantwortliches sammeln, managen, analysieren, verstehen, interpretieren und anwenden von Daten aus dem Kontext des Lernen und Lehrens.



Learn2Analyze

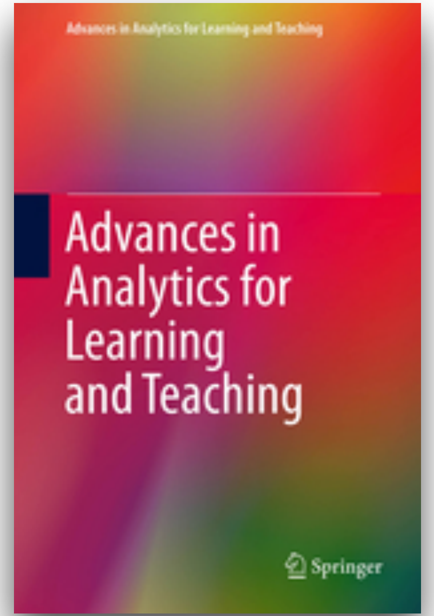
Papamitsiou, Z., Filippakis, M., Poulou, M., Sampson, D. G., Ifenthaler, D., & Giannakos, M. (2021). Towards an educational data literacy framework: enhancing the profiles of instructional designers and e-tutors of online and blended courses with new competences. *Smart Learning Environments*, *8*, 18. https://doi.org/10.1186/s40561-021-00163-w

05

Bildungsdaten-kompetenz.

Bildung ist zu komplex, um sie auf bloße Datenanalysen und Algorithmen zu reduzieren.

Selwyn, N. (2016). Is technology good for education? Polity Press.


Advances in Analytics for Learning and Teaching
Advances in Analytics for Learning and Teaching
Springer


Understanding Models for Learning and Instruction
Learning and Instruction in the Digital Age
Computer-Based Diagnostics and Systematic Analysis of Knowledge
Multiple Perspectives on Problem Solving and Learning in the Digital Age
Towards Learning and Instruction in Web 3.0
Digital Knowledge Maps in Education
Ubiquitous and Mobile Learning in the Digital Age
Assessment in Game-Based Learning
Curriculum Models for the 21st Century
Digital systems for open access to formal and informal learning
Emerging Technologies for STEAM Education
E-Learning Systems, Environments and Approaches
Serious Games Analytics
Foundation of Digital Badges and Micro-Credentials
Competencies in Teaching, Learning and Educational Leadership in the Digital Age
Utilizing Learning Analytics to Support Study Success
Learning Technologies for Transforming Large-Scale Teaching, Learning, and Assessment
Game-Based Assessment Revisited
Digital Workplace Learning
Digital Technologies: Sustainable Innovations for Improving Teaching and Learning
Cognition and Exploratory Learning in the Digital Age
Technology, knowledge and learning

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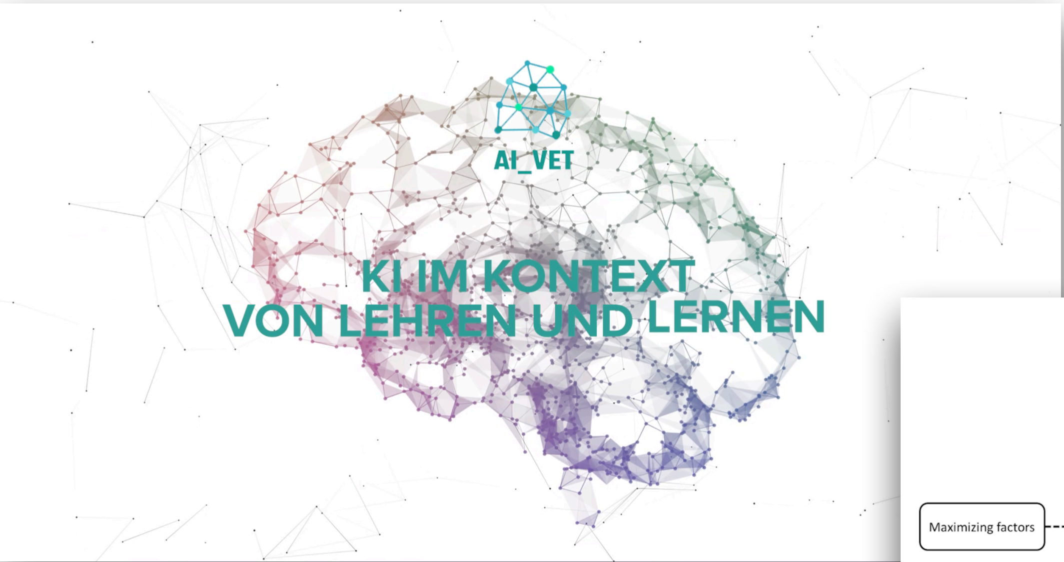
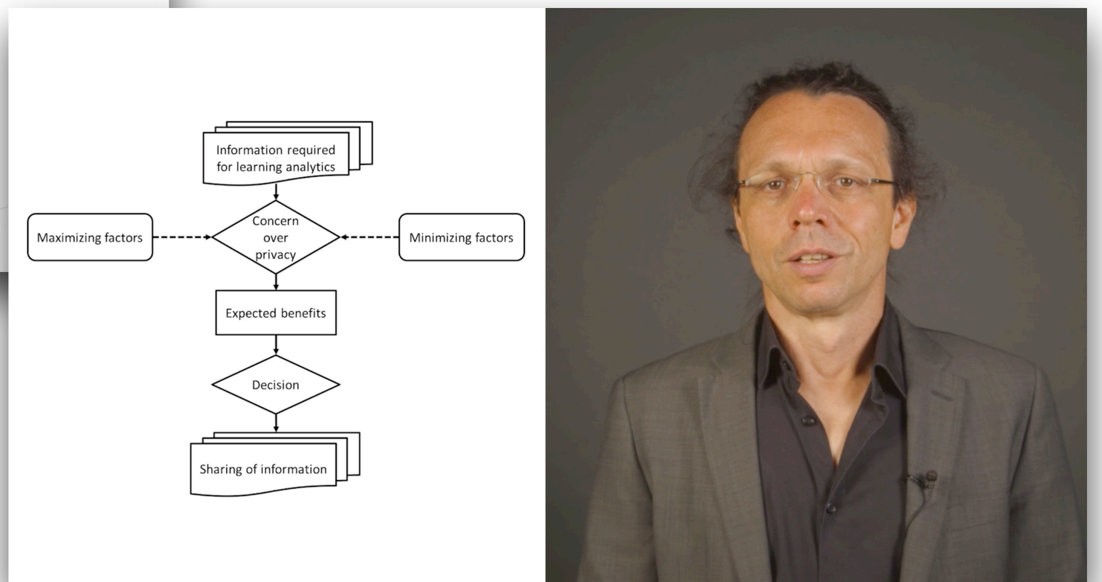
BILDUNGSDATENKOMPETENZ

Frühjahr 2022





GEFÖRDERT VOM Bundesministerium für Bildung und Forschung

bibb Bundesinstitut für Berufsbildung

STELA

LeAP

Learn2Analyze

Erasmus+

UNESCO

https://uploads-ssl.webflow.com/5c129f8354b32854d3b7279d/5cadd8dd07b6cb5f93e85eca_AI%20and%20education.jpg

Learning Analytics als Treiber für Change Prozesse an Hochschulen

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