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Curtin University

Two Sides of the Same Coin? Revisiting Data Indicators for Learning Analytics

Date
19 December 2022 (Monday)

Time
5:00 pm–6:00 pm (HK Time)

Click for registration

Abstract

Learning analytics, a socio-technical data mining and analytic practice in educational contexts, show promise in supporting learning processes and enhancing study success in higher education, through collecting and analysing data from learners, learning processes, and learning environments to provide meaningful feedback and scaffolds when needed. However, learning analytics have seen a dominance in data-driven analytics approaches, not necessarily focussing on learning or psychological theory. Accordingly, data indicators for learning analytics identify a majority of data-driven approaches. This presentation will review learning analytics indicators from several systematic reviews grounded in learning and psychological theory. Further, the challenges of implementing indicators into productive higher education ecosystems will be highlighted.

Bio

Dirk Ifenthaler is Professor and Chair of Learning Design and Technology at the University of Mannheim, Germany, and UNESCO Deputy Chair on Data Science in Higher Education Learning and Teaching at Curtin University, Australia. Dirk's research focuses on the

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Image credit: https://lifars.com/wp-content/uploads/2019/12/Hacking-with-Artificial-Intelligence.jpg

Two Sides of the Same Coin?

Revisiting Data Indicators for Learning Analytics

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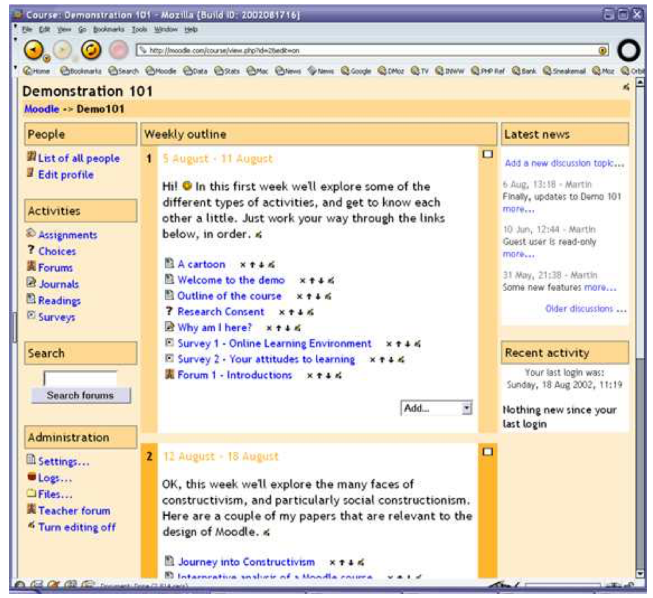
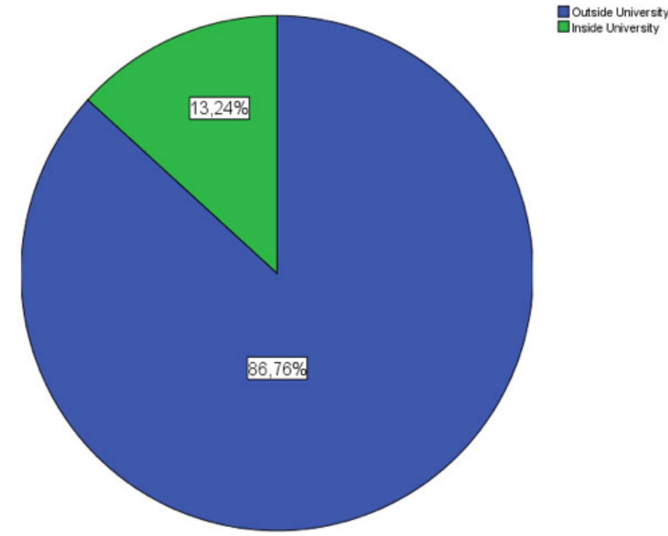
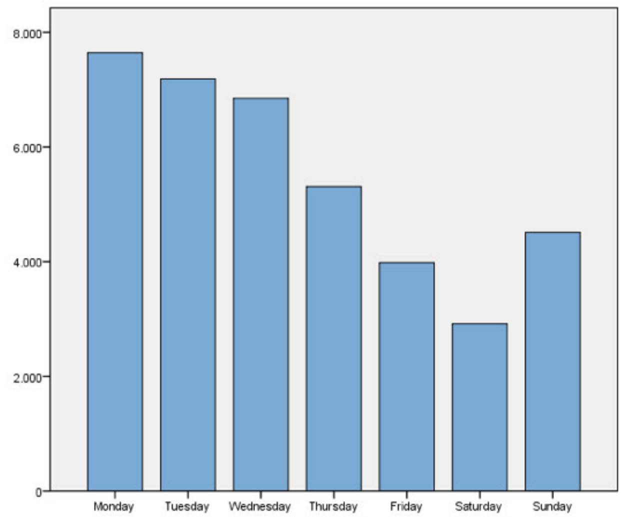
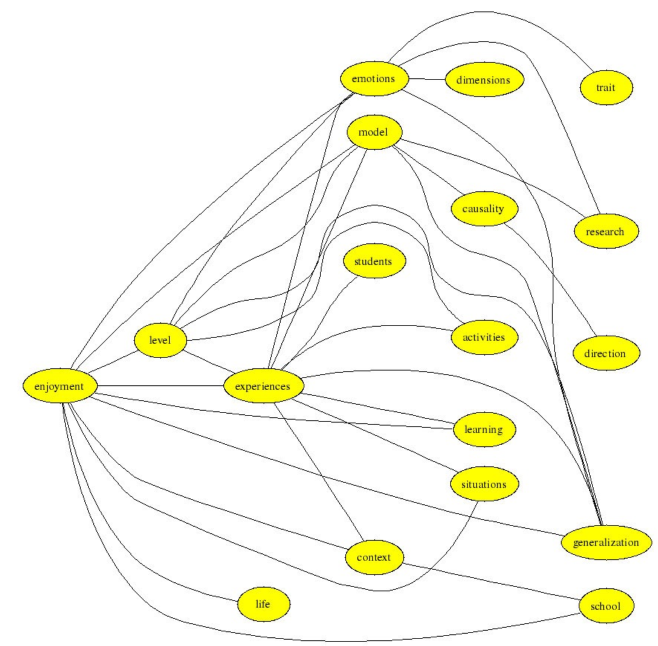
IN OMNIBUS VERITAS · UNIVERSITÄT MANNHEIM

Curtin University



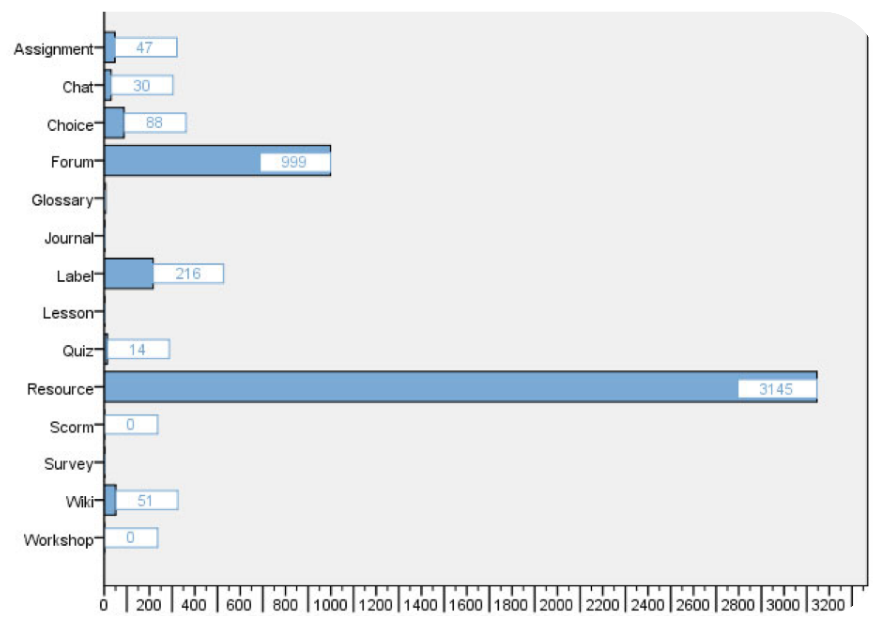


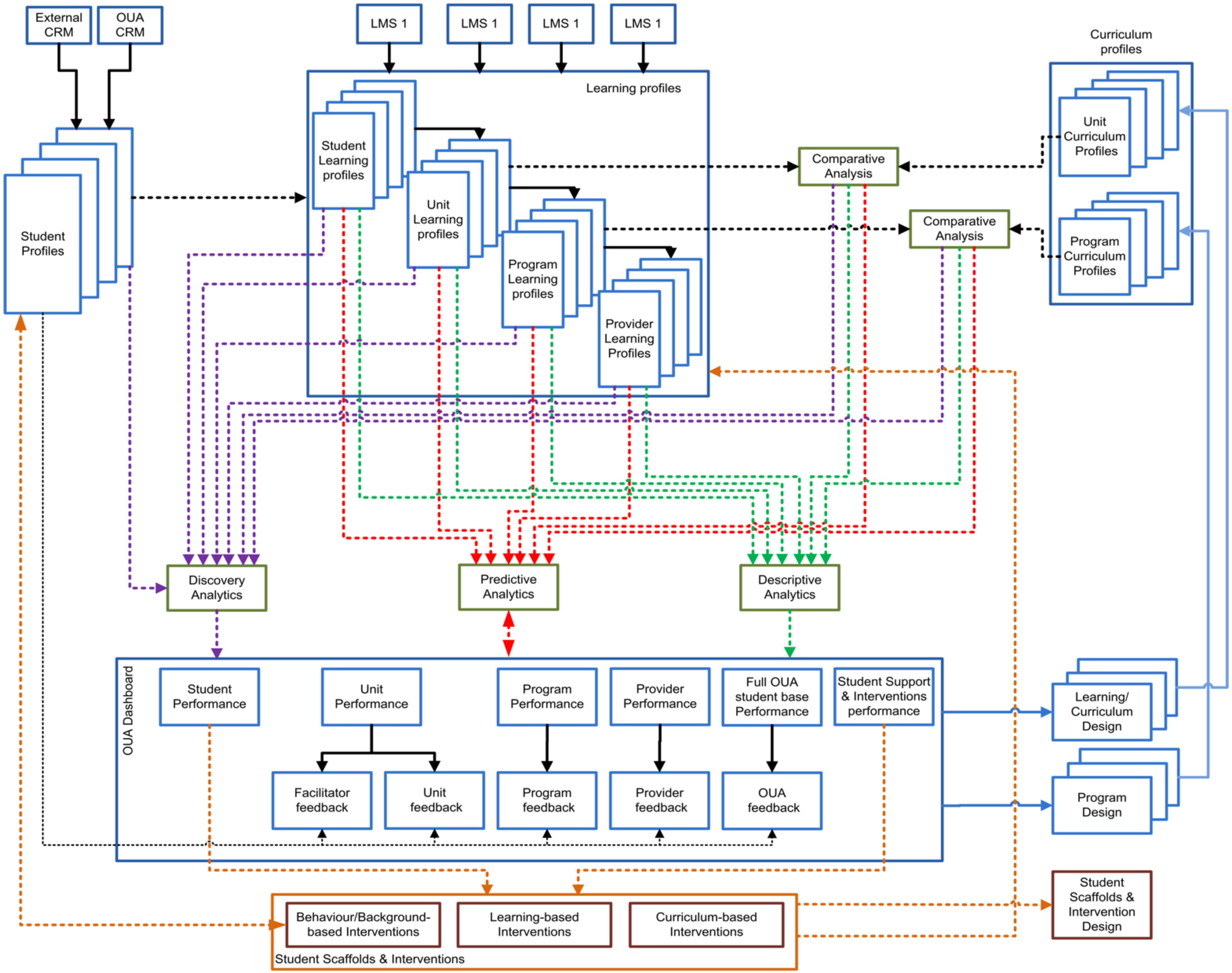




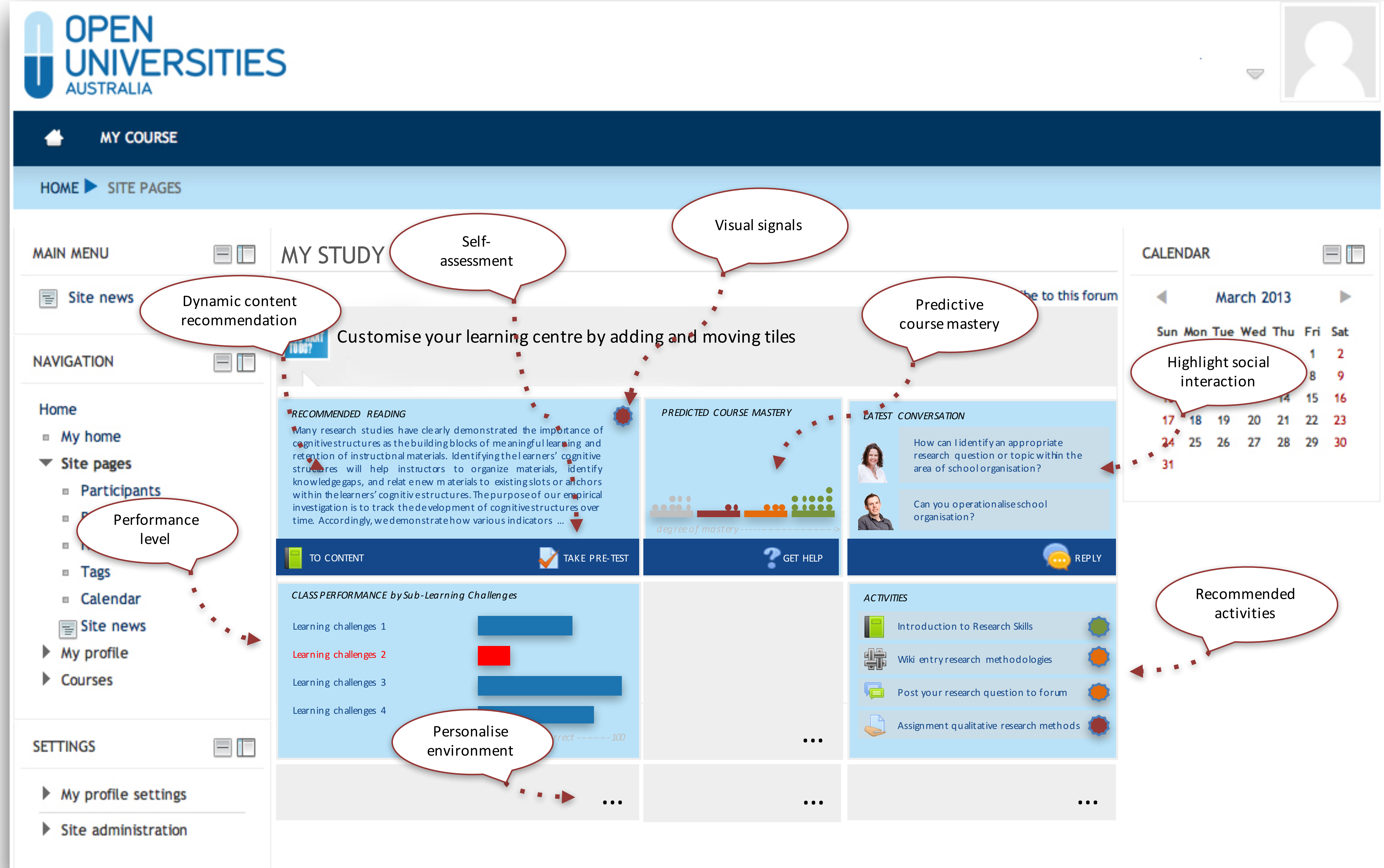
Learning analytics in 2002?

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

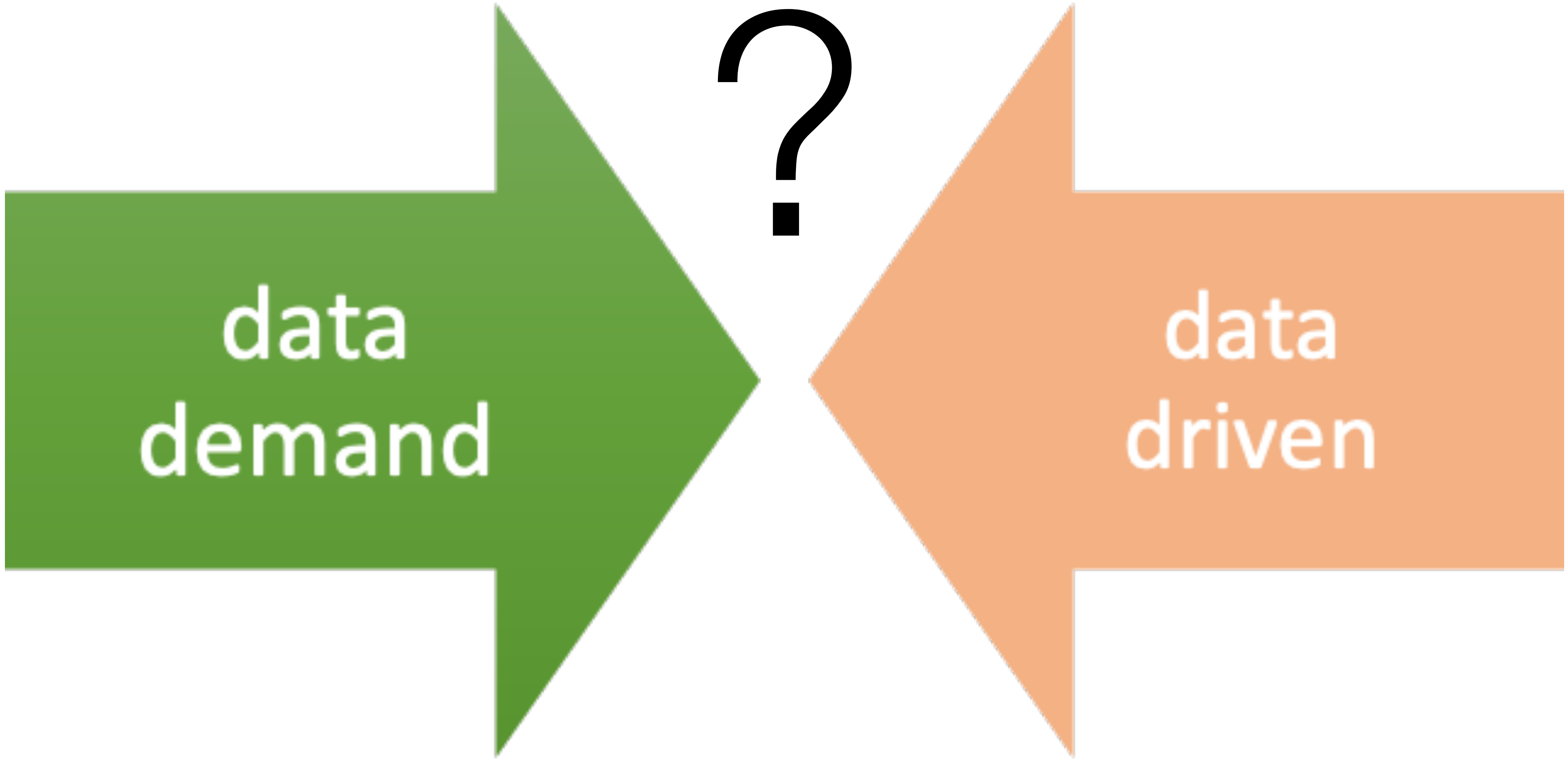




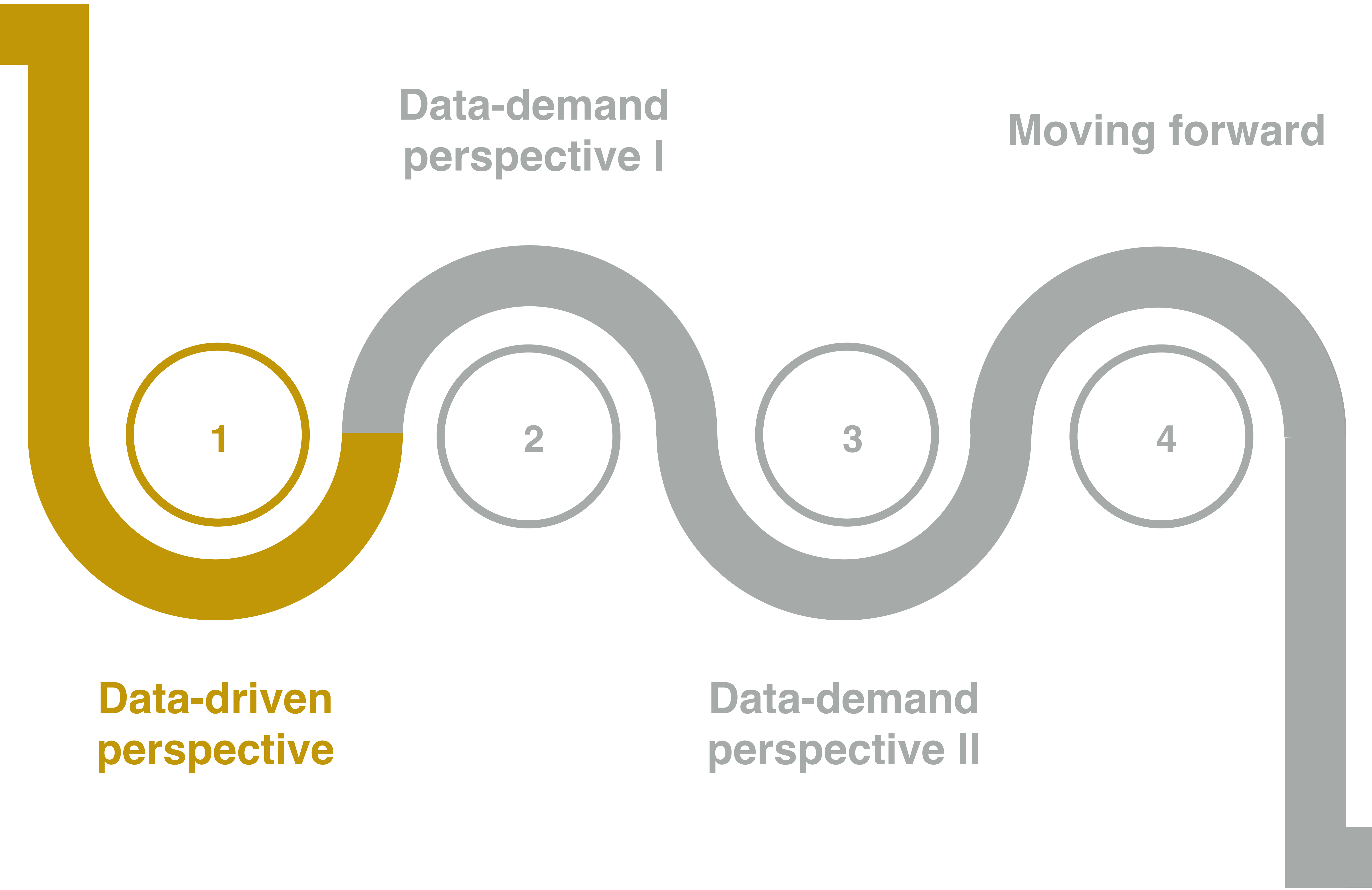
Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning*, *19*(1–2), 221–240. https://doi.org/10.1007/s10758-014-9226-4



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. (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.


Data-demand perspective I
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Data-driven perspective
Data-demand perspective II

N = 1,030,778 enrolments

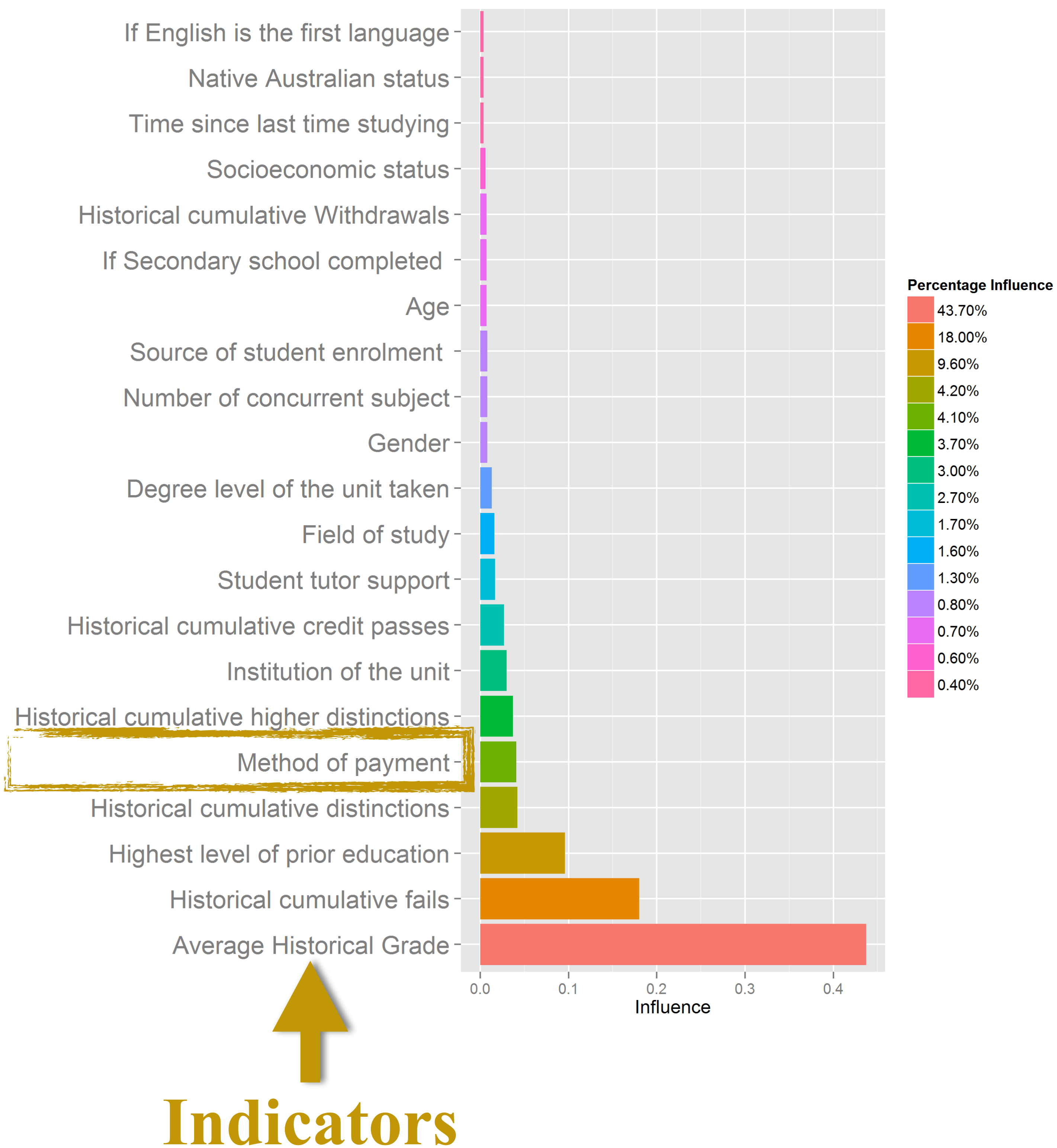


Table 1 Model descriptions for student profile

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

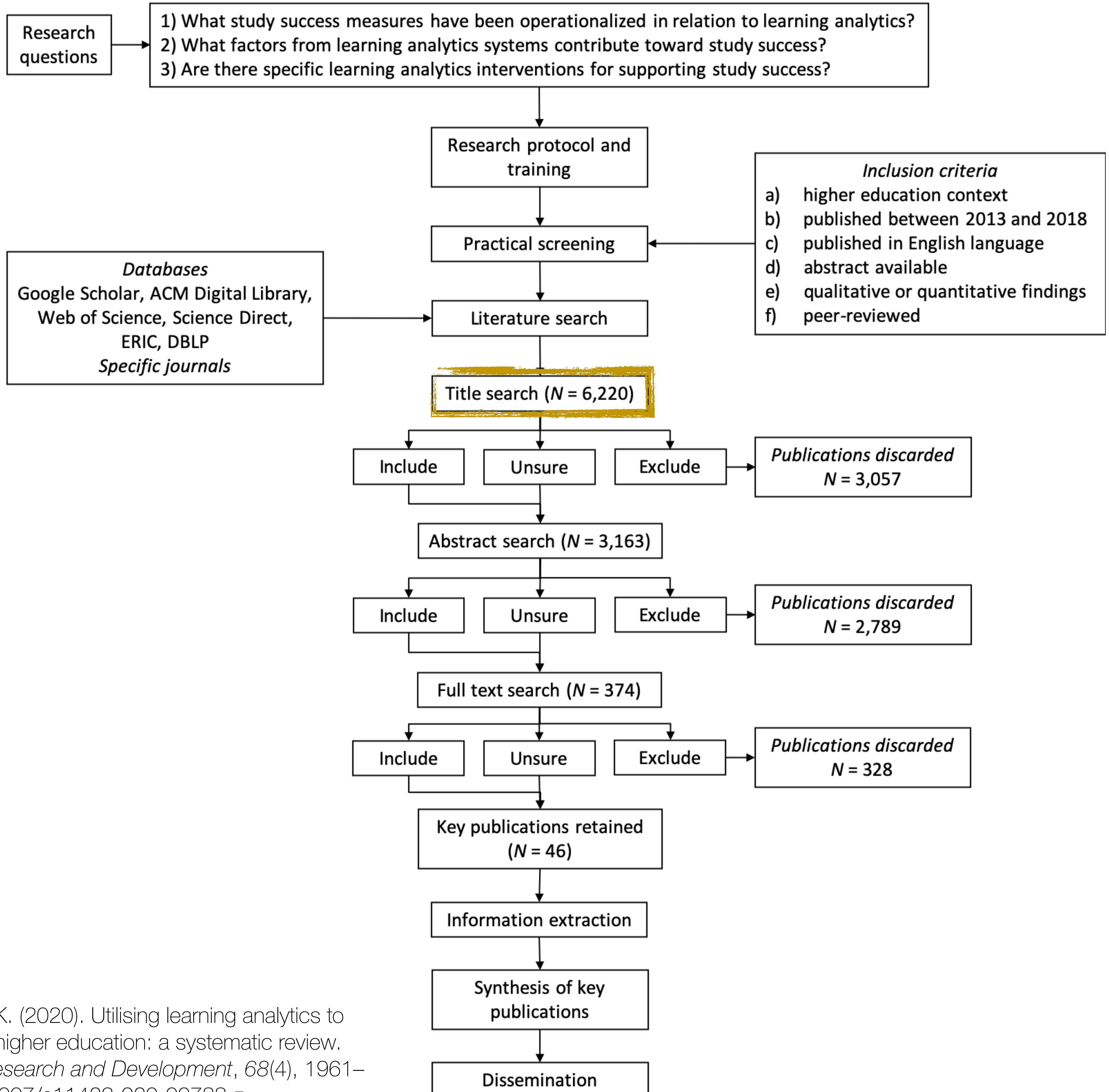
*** $p < .001$; *SVR* support vector regression, *SVM* support vector machines

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



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

Author	Country	Sample (*N*)	Demographic background	Key purpose of the study	Indicators	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

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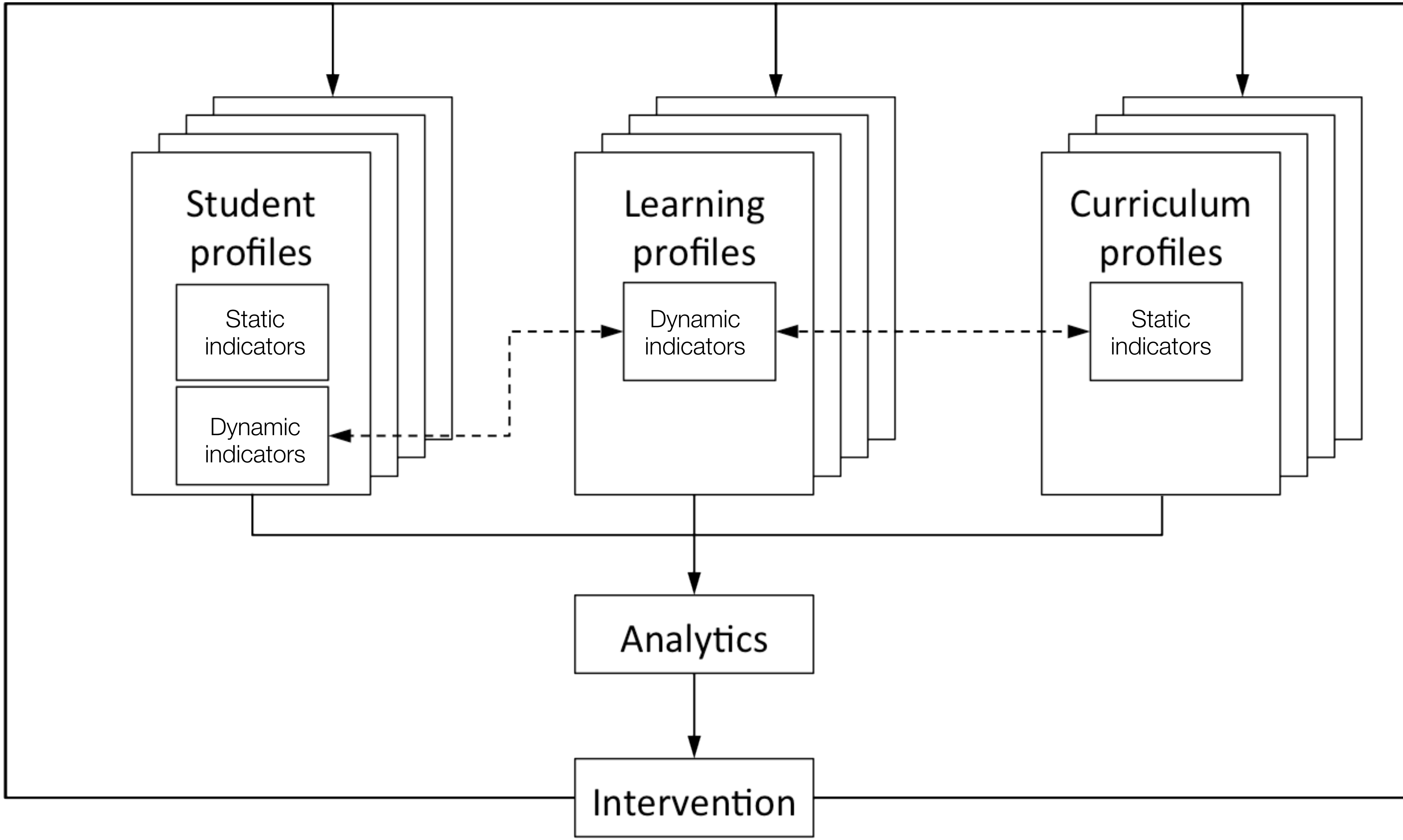

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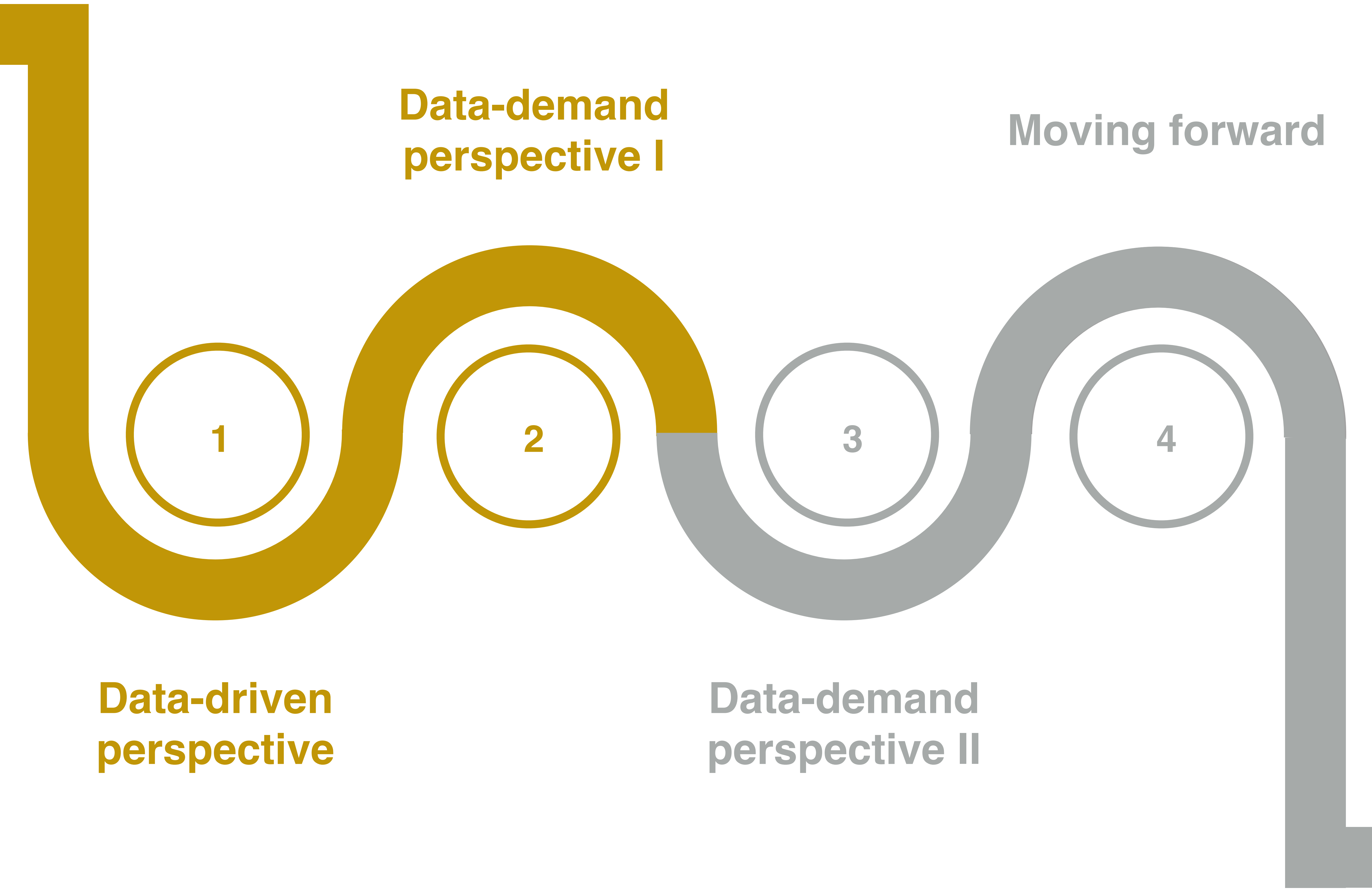
Table 2. Summary of learning analytics indicators mapped to three data profiles

	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

Reflections on indicators for learning analytics identify a majority of **data-driven approaches**.

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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Data-driven perspective
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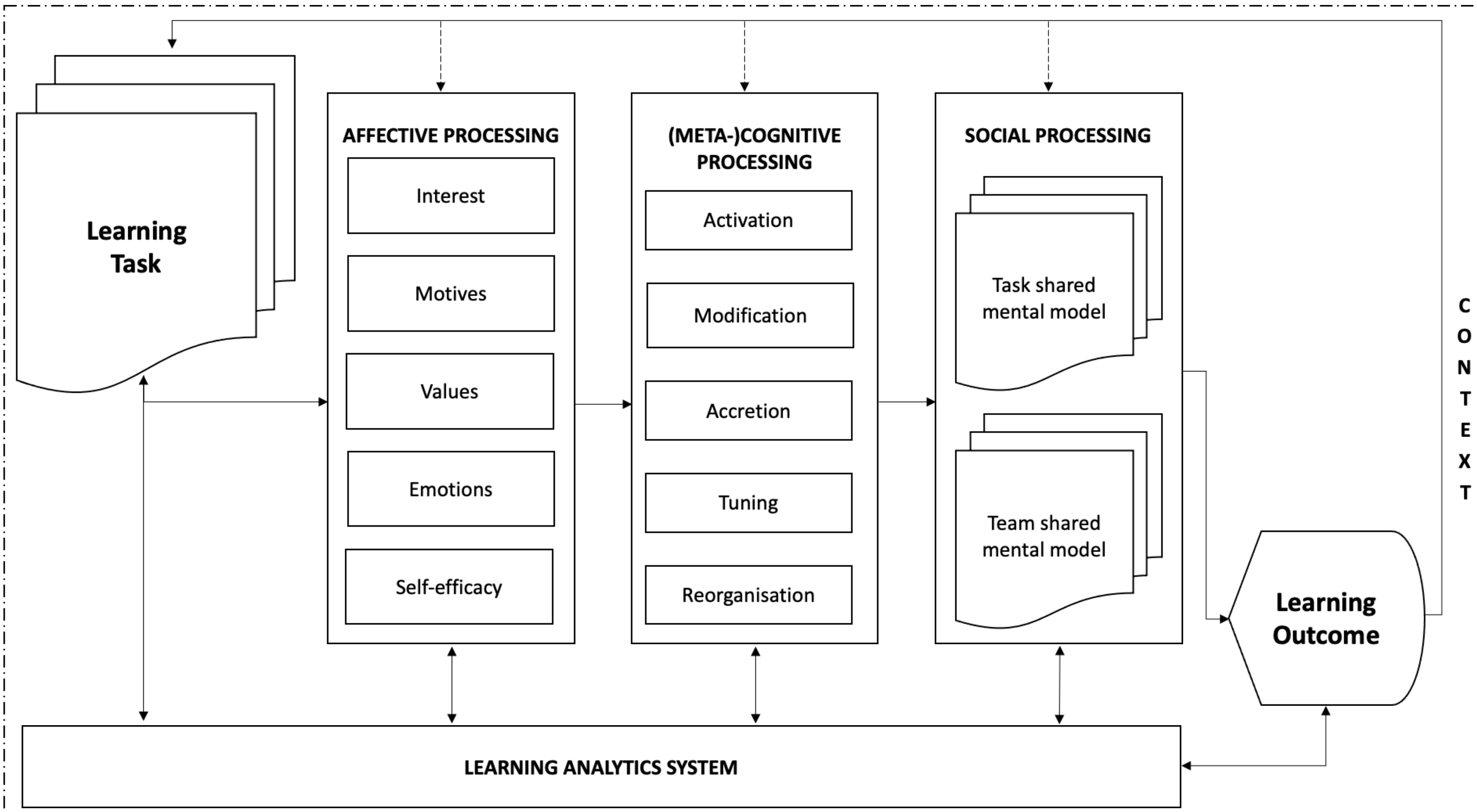
Learning Task
AFFECTIVE PROCESSING
Interest
Motives
Values
Emotions
Self-efficacy
(META-)COGNITIVE PROCESSING
Activation
Modification
Accretion
Tuning
Reorganisation
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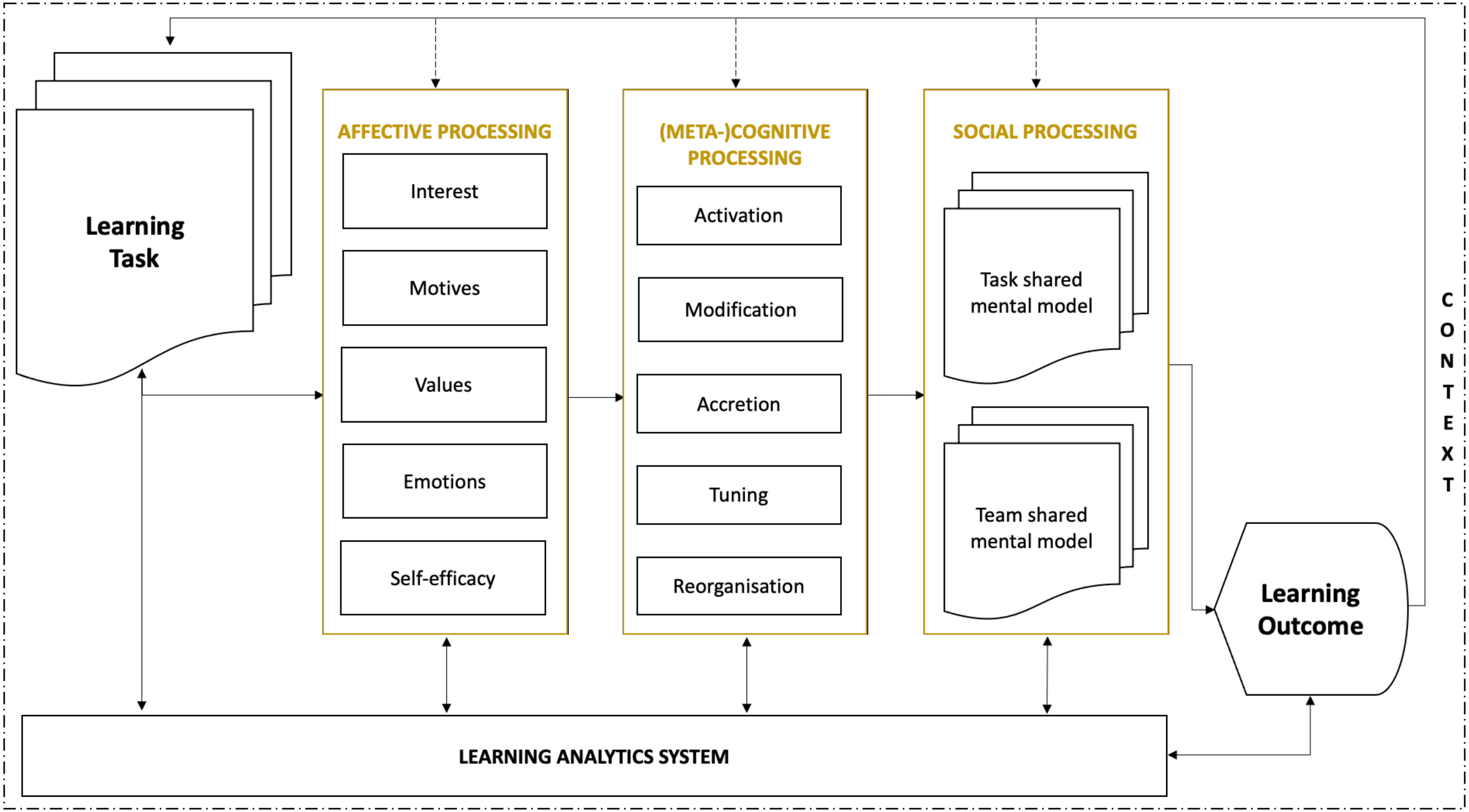
Task shared mental model
Team shared mental model
Learning Outcome
CONTEXT
LEARNING ANALYTICS SYSTEM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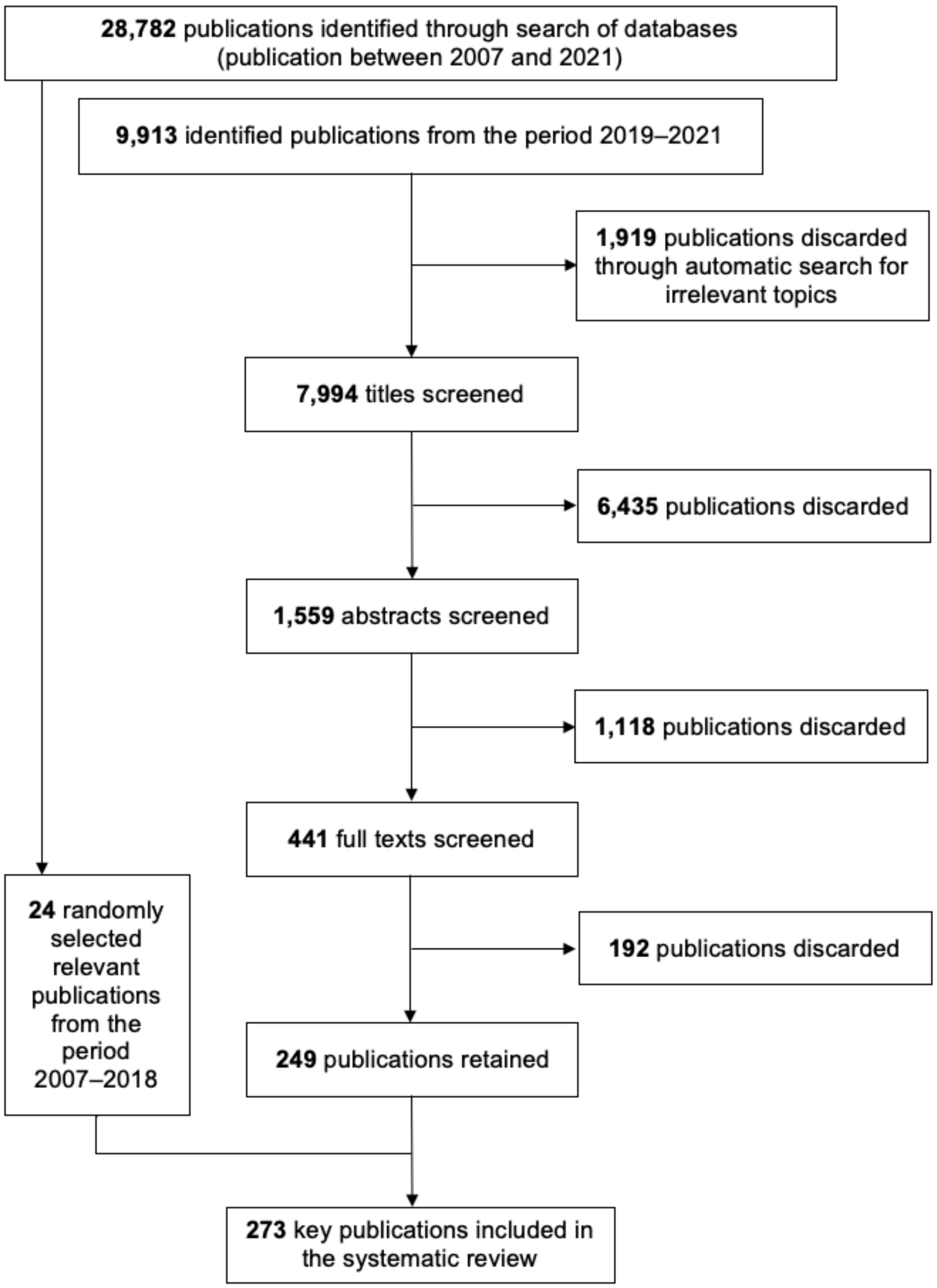

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26 dimensions including **228** indicators

Hemmler, Y., & Ifenthaler, D. (2022). Four perspectives on personalized and adaptive learning environments for workplace learning. In D. Ifenthaler & S. Seufert (Eds.), *Artificial intelligence education in the context of work* (pp. 27–39). Springer. https://doi.org/10.1007/978-3-031-14489-9_2

Context	Dimension	Indicators
Internal	Demographics	Gender, age, race, belonging to an underrepresented minority, culture, origin/nationality [a], mother tongue, international status, marital status, children, socioeconomic status, parents' education, athlete
Internal	Past performance, prior knowledge, and prior experiences	Highest educational degree, type of high school diploma, high school diploma grade, selection rank allowing access to the course, rank in different subjects, Grade Point Average, prior knowledge regarding the course content, thematically similar courses attended so far, previous turning point themes regarding the course content, prior credits, delay index, perceived delay index, repeating the course, previous experience with the course format, web experience [a], duration of learning community membership, abroad experience [a], adequacy of previous acquired study techniques
Internal	Values and life attitudes	Materialism, intrinsic life values, optimism, religious commitment [b], conformity [a], long-term/short-term orientation, tradition, security [a], power [a], achievement, hedonism
Internal	Beliefs and attitudes towards (digital) education	Beliefs about mistakes, sense of responsibility for learning, attitudes towards digitalization and digital education, innovativeness, beliefs about assessments, importance of employment chances
Internal	Personal learning preferences and approaches	Deep/surface approach, learning style, learning strategies, cognitive style, cognitive strategies, individual tendency for procrastination, individual tendency for self-handicapping, preference for face to-face courses, habits
Internal	Skills and competencies	Self-regulated learning skills, self-management skills, motivation regulation skills, study ability, intelligence, working memory capacity, metacognitive skills, emotional intelligence, leadership abilities, self-profiling and career control,
Internal	Personality	True Colors Personality, Big Five, need for cognition, grit, resilience, perfectionism, risk affinity, trait self control [a], trait mindfulness, trait anxiety

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Hemmler, Y., & Ifenthaler, D. (2022). Four perspectives on personalized and adaptive learning environments for workplace learning. In D. Ifenthaler & S. Seufert (Eds.), *Artificial intelligence education in the context of work* (pp. 27–39). Springer. https://doi.org/10.1007/978-3-031-14489-9_2

Context	Dimension	Indicators
Internal	Needs and need satisfaction	Need satisfaction, need dissatisfaction, autonomy, relatedness, competence
Internal	Self-perceptions regarding learning	Self-efficacy, belief in self-improvement, attributions regarding learning, self-reflection, real self regarding the course content, ideal self regarding the course content, course specific self-concept, creative self-concept
Internal	Motivation	General motivation for the course, reasons for participation, source of motivation, type of motivation (e.g., intrinsic, extrinsic, collective, individual), goal orientation, voluntariness of participation, course preference, intention to complete the course
Internal	Emotions	Valence [a], positive emotions, negative emotions, positive activating emotions [a], positive deactivating emotions [a], negative activating emotions, negative deactivating emotions, excitement, joy, surprise, curiosity, pride, satisfaction, hope, security, anxiety, fear of missing out, fear of loosing face, annoyance, frustration, confusion [a], overburdening [b], discomfort, shame, hopelessness, insecurity, boredom, stress, burnout, depressive symptoms, positive activating emotions in the learner's environment, positive deactivating emotions in the learner's environment, negative activating emotions in the learner's environment, negative deactivating emotions in the learner's environment
Internal	Mental/ cognitive states	Cognitive load, ego depletion, attention, (cognitive) involvement, engagement, disengagement [a], trust, cognitive presence, effort, energy level [a], mood, fatigue, exhaustion, tension
Internal	Physiological measures	Eye tracking data, electroencephalography (EEG), face video, heart rate, electrodermal activity, blood pressure, body temperature
Internal	Obligations and commitments outside the course	Leisure activities [b], family commitments [b], care of dependent, professional commitments, commitments in other courses, number of courses enrolled in, professional commitments

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Context	Dimension	Indicators
		knowledge type, homework, course length, grading, online/offline, percentage of online courses, pretest, compulsory course, time in course/course progress
External	Teaching method	Teacher-guided methods, student-activating methods, jigsaw, flipped classroom, blended learning, problem-based learning, service learning [a], project-based learning, MOOC, collaborative learning, m-learning, self-regulated learning interventions, group metacognitive scaffolding, learning community intervention, peer tutoring
External	Characteristics of the learning material and the learning system	Media type, rewarded errors [a], synchronicity, augmented reality, spatial contiguity, human agent, human agent-delivered behavior modeling, gamification, amount of motion in learning videos, seductive details, valence of seductive details, disfluency, deduction/induction, nonlinear learning, elaborative interrogation, student response system, personalization, social media learning, type of discussion settings, number of discussion topics, type of learning management system, exam format, presence of eye movement modeling examples, system-paced/learner-paced, smartwatch prompts, type of smartwatch prompts, social comparison nudges, compare object for social comparison nudges
External	Characteristics of the learning group	Timing of group formation, number of active learners in the group, homogeneity, cohesion [a], group size, average grade, average prior knowledge, gap between an individual's prior knowledge and the group's average prior knowledge, number of group members who normally sit nearby in the course [a]
External	Characteristics of the educational institution	Reputation, sponsorship, institution type, size, country
External	Feedback	Receipt of feedback, type of feedback, complexity, valence, source of feedback, communication channel, frequency of emoticons in feedback, valence of emoticons

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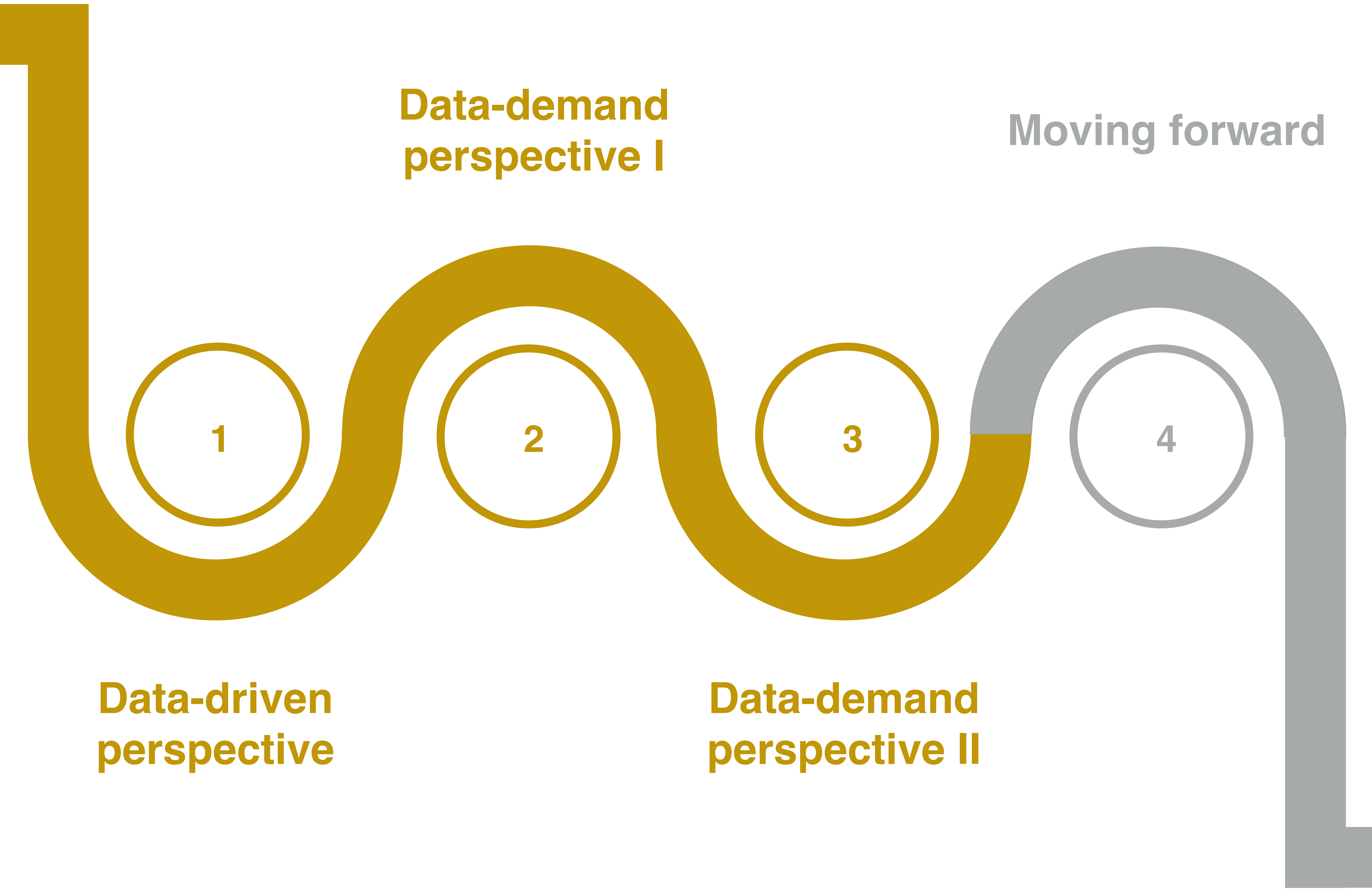
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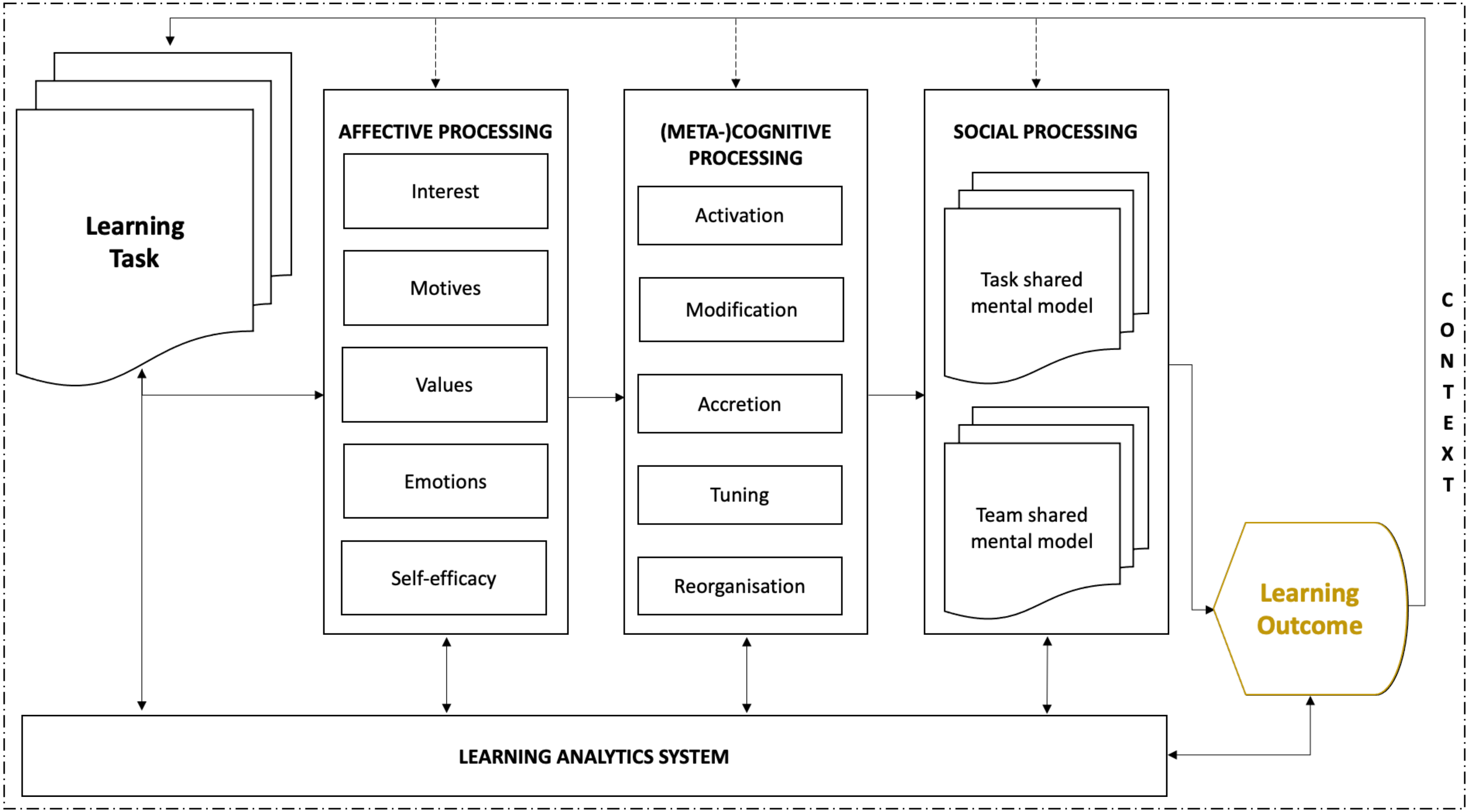
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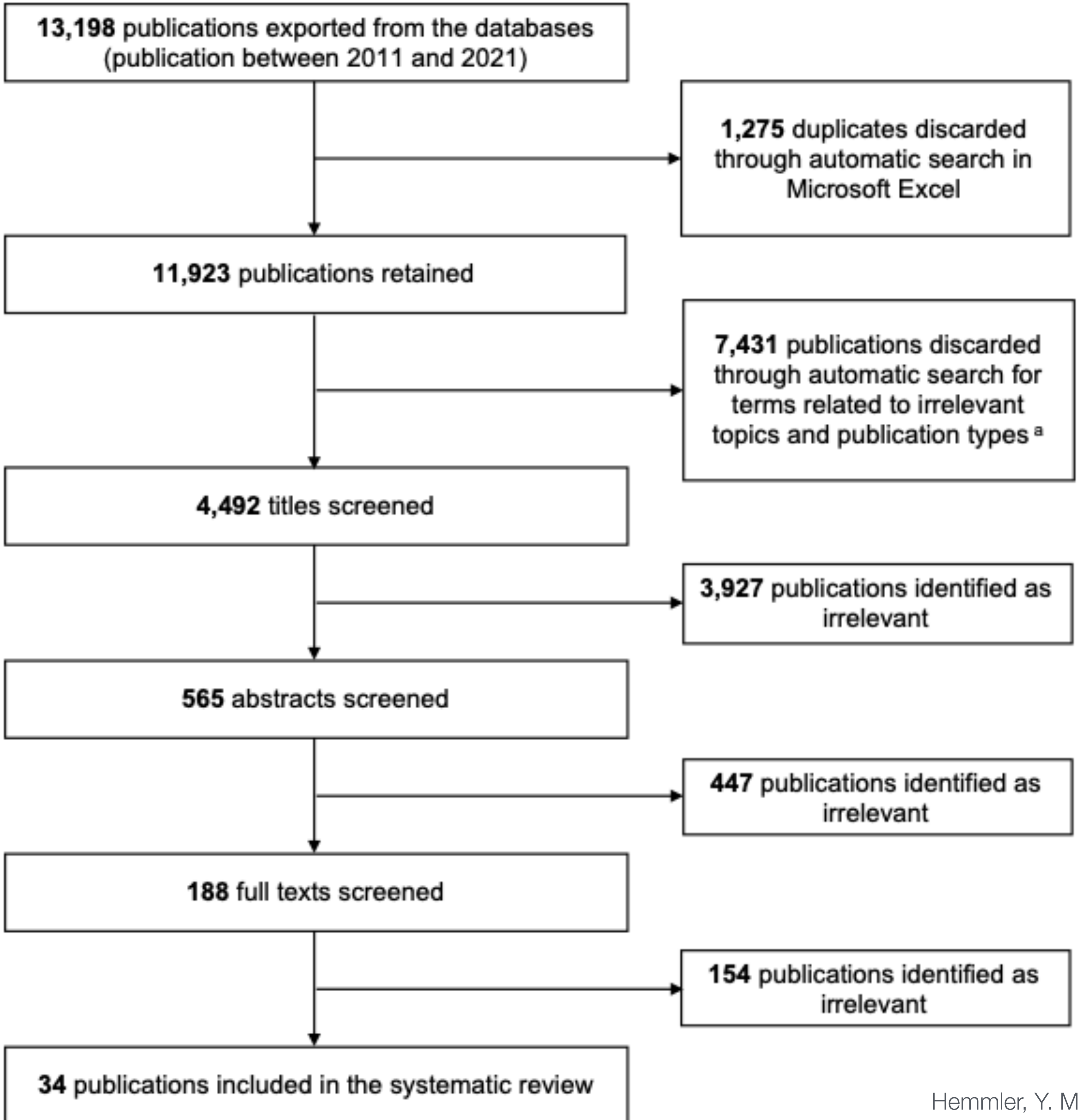

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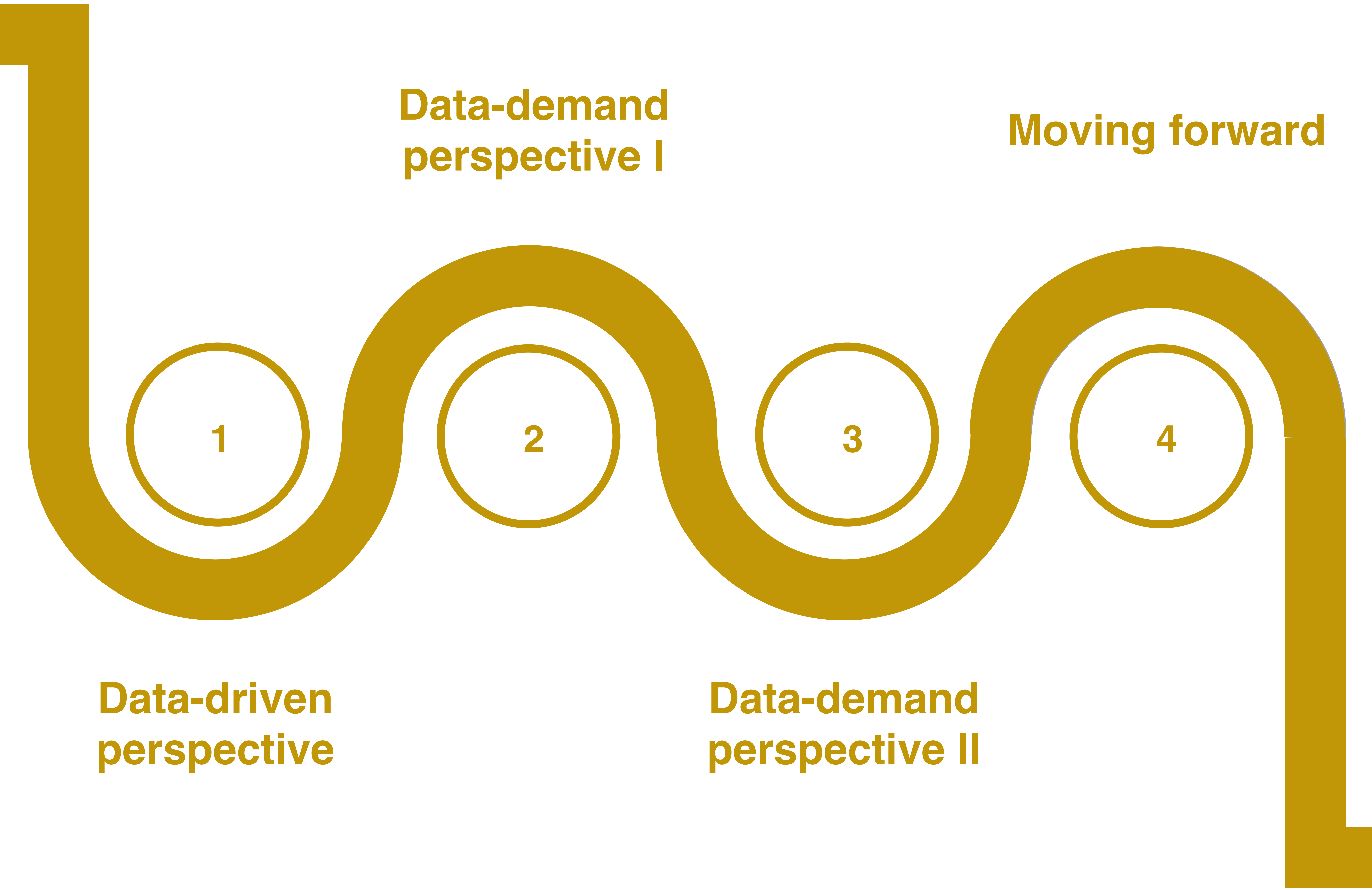
5 dimensions including **43** indicators

Hemmler, Y. M., Rasch, J., & Ifenthaler, D. (2022). A categorization of workplace learning goals for multi-stakeholder recommender systems: A systematic review. *TechTrends*. https://doi.org/10.1007/s11528-022-00777-y intrinsic (high self-regulation) ⟷ external (low self-regulation)

Intrinsic learning goals	Personal development goals	Career development goals	Task-specific goals	Basic requirements goals
• Satisfy one's desire for studying [23, 30] • Learning out of interest [23] • Satisfy curiosity [8, 12] • Expand knowledge [23, 26] • Mastery goal orientation [6, 8, 14, 15, 16, 18, 21, 22, 25, 29, 31]	• Social networking [2, 3, 9, 13] • Become a team player and share knowledge [2, 30] • Be a role model for subordinate personnel [33] • Socialization within the organization [20] • Personal professional development [2, 4, 5, 9, 13, 30] • Performance goal orientation [14, 16, 22, 25, 29, 31] • Personal validation [13] • Increase self-esteem [26] • Reach credibility and recognition [9, 13] • Be prepared for unfamiliar situations [23] • Develop new skills for the job [1, 2, 3, 7, 11, 13, 20, 23, 24, 26, 31], e.g.: – Learn additional technical nursing skills – Improve writing skills – Improve coaching skill – Improve PowerPoint skills	• Enhance career opportunities [4, 9, 28] • Try a different career [26] • Stand out from others [23] • Get a job [26] • Develop or start an own business [26] • Get into another training of study [26] • Get a job promotion [13, 20, 26] • Salary increase [13] • Obtain a certificate [7, 23, 27]	• Solve work-task related problems [19, 20] • Adapt to changing job requirements [28] • Adapt to technological innovations [20] • Policy and school development [2] • Drive innovation in older people care [9] • Achieve a more positive societal regard for older people and older people care [9] • Develop and coordinate a behavioral telehealth program [10] • Improve current behavioral telehealth services [10] • Provide behavioral telehealth information and education to others [10] • Improve science instruction in elementary schools [17] • Write a piece for publication [1]	• Meet mandatory requirements [4, 5, 26, 28] • Meet the specifications set by supervisors [19] • Onboarding [34] • Eliminate underperformance [34] • Be up to date / get important information [17] • Develop skills specified by the organization [28] • Get continuing education credit [24]

Hemmler, Y. M., Rasch, J., & Ifenthaler, D. (2022). A categorization of workplace learning goals for multi-stakeholder recommender systems: A systematic review. *TechTrends*. https://doi.org/10.1007/s11528-022-00777-y


Data-demand perspective I
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Data-demand perspective II

Learning analytics indicators need to address specific **persisting dilemmas in the measurement of change**.

Ifenthaler, D. (2010). Zur Notwendigkeit einer systematischen Erfassung von Bildungsverläufen. Methodologische Anforderungen einer Veränderungsmessung. *Lehrerbildung auf dem Prüfstand*, *3*(Sonderheft), 86-105.

Over-correction-under-correction dilemma.

Unreliability-invalidity dilemma.

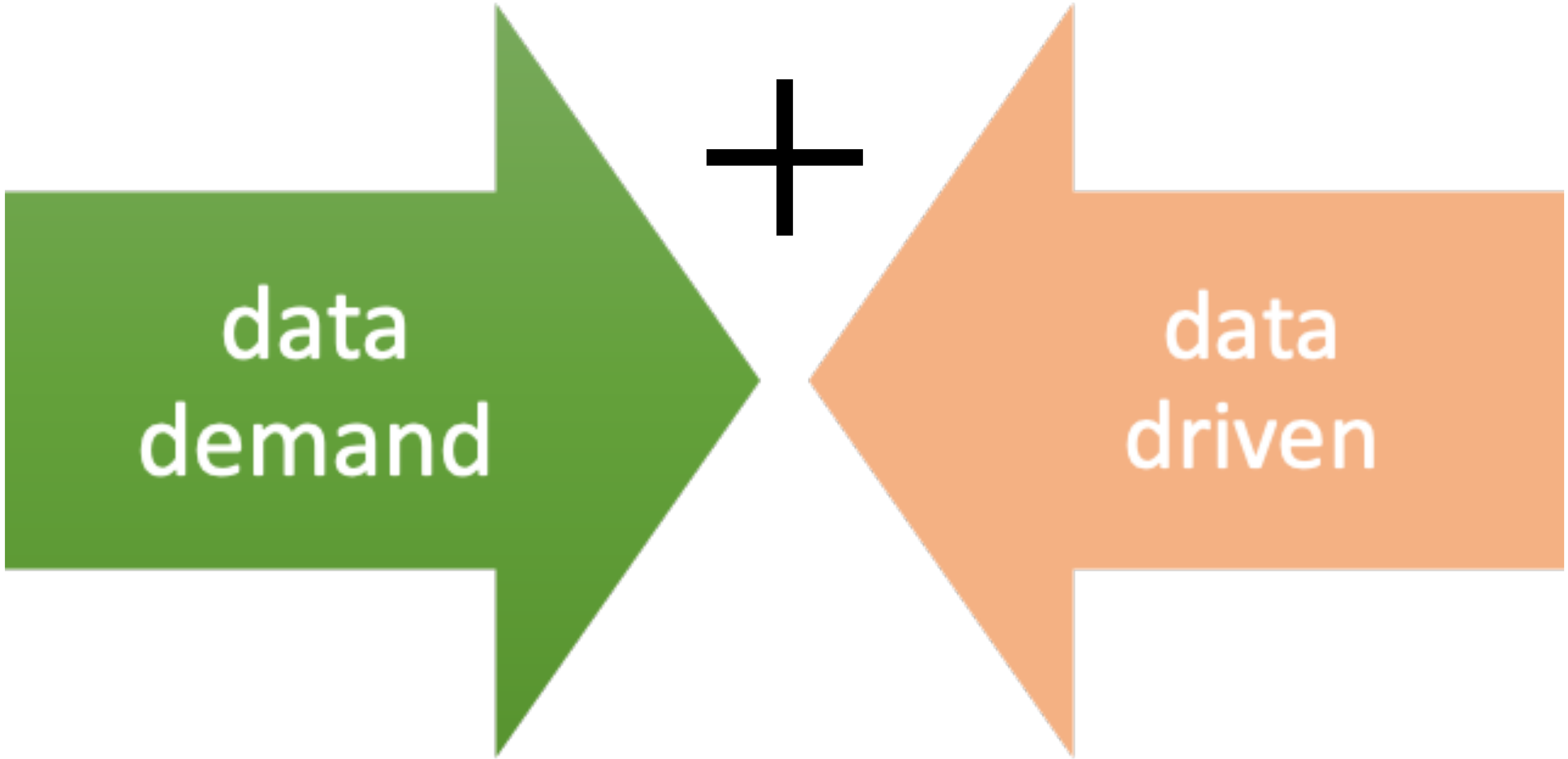
Physicalism-subjectivism dilemma.

Ifenthaler, D. (2010). Zur Notwendigkeit einer systematischen Erfassung von Bildungsverläufen. Methodologische Anforderungen einer Veränderungsmessung. *Lehrerbildung auf dem Prüfstand*, *3*(Sonderheft), 86-105.

Is there enough intra-individual learner **variability** on the indicator to justify the need for analytics?

Learning designers need to be enabled to **translate pedagogical constructs into data modalities**, and vice versa.

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



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.

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

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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

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Two Sides of the Same Coin?

Revisiting Data Indicators for Learning Analytics

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