



Centre for the Science of
Learning & Technology

Learning Analytics: What's It For ?

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ICDE Leadership Summit 2017



OVERVIEW

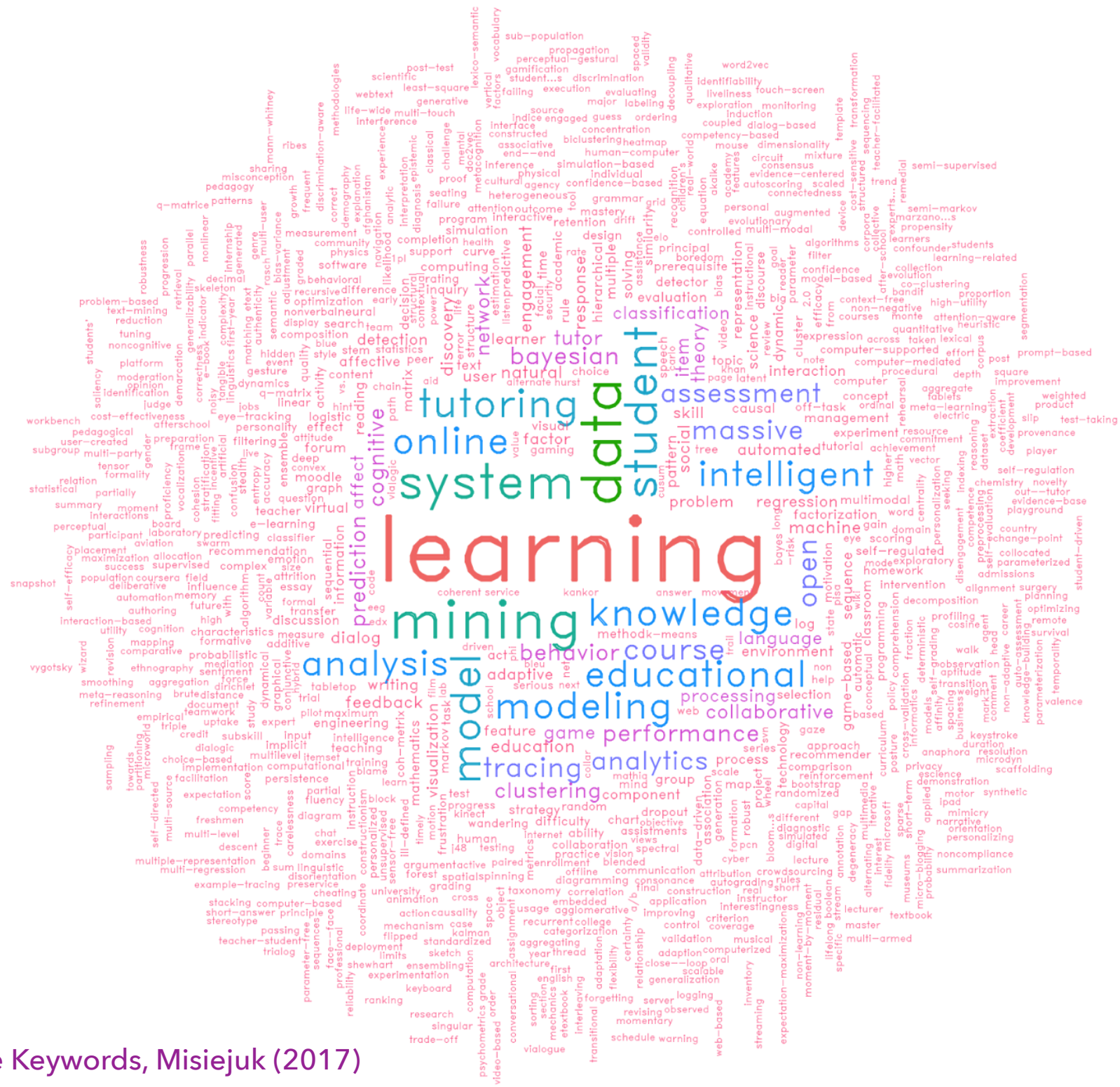
- ▶ SLATE
- ▶ Learning Analytics
- ▶ Quick History
- ▶ Learning Analytics Research
- ▶ Key Questions

CENTRE FOR THE SCIENCE OF LEARNING & TECHNOLOGY

SLATE.UIB.NO @SLATERESEARCH

- ▶ Established in 2016 by the Norwegian Ministry of Education & University of Bergen
- ▶ A national competence and international research centre
- ▶ SLATE carries out research that will clarify and explore concepts such as learning analytics, big and small data in education, assessment for learning, and learning & technology, in all facets of human learning
- ▶ Multidisciplinary
- ▶ Conduct integrated research that will advance the frontiers of the sciences of learning, as well as inform education practice and policy

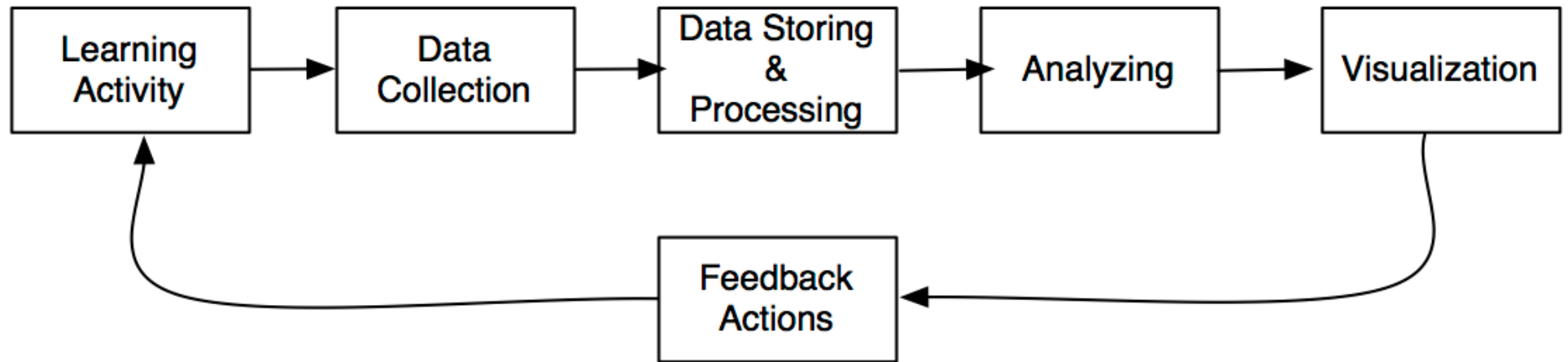
LEARNING ANALYTICS



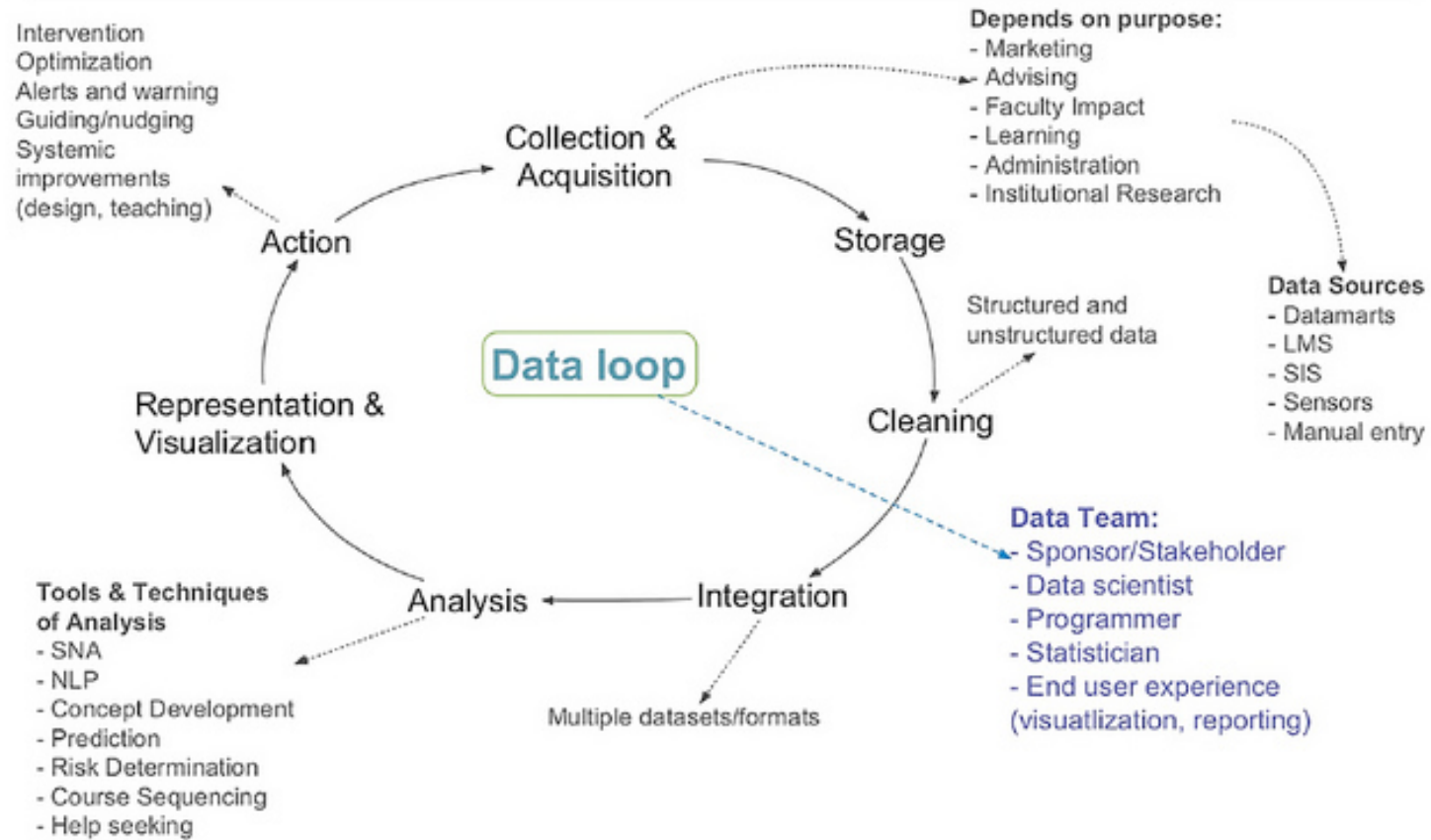
LAK Single Keywords, Misiejuk (2017)

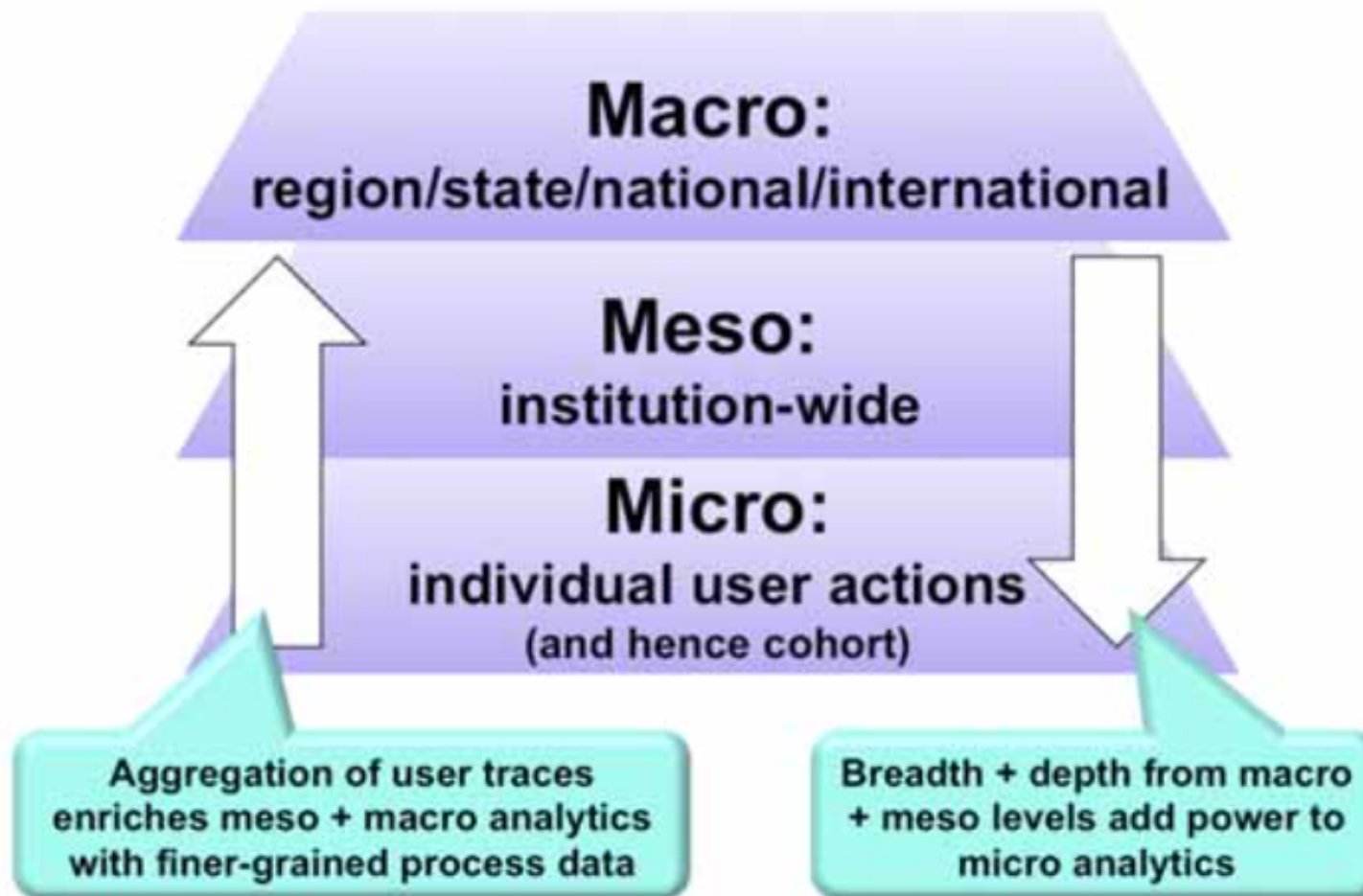
“LEARNING ANALYTICS IS THE MEASUREMENT, COLLECTION, ANALYSIS AND REPORTING OF DATA ABOUT LEARNERS AND THEIR CONTEXTS, FOR PURPOSES OF UNDERSTANDING AND OPTIMIZING LEARNING AND THE ENVIRONMENTS IN WHICH IT OCCURS”

1st International Conference on Learning Analytics & Knowledge

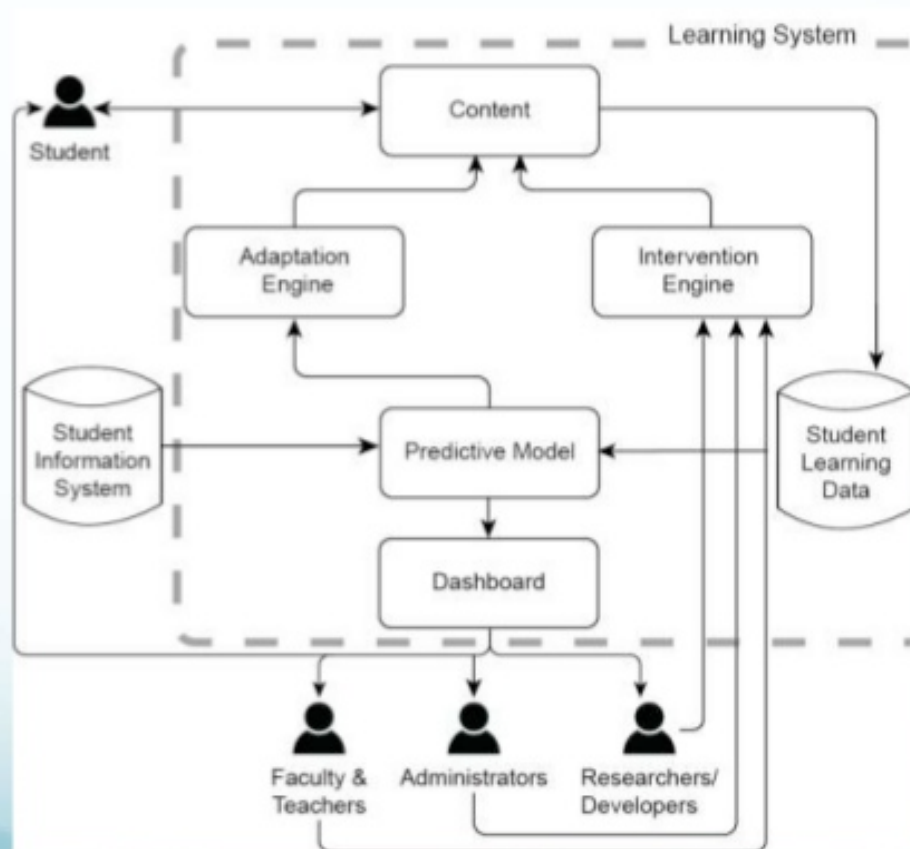


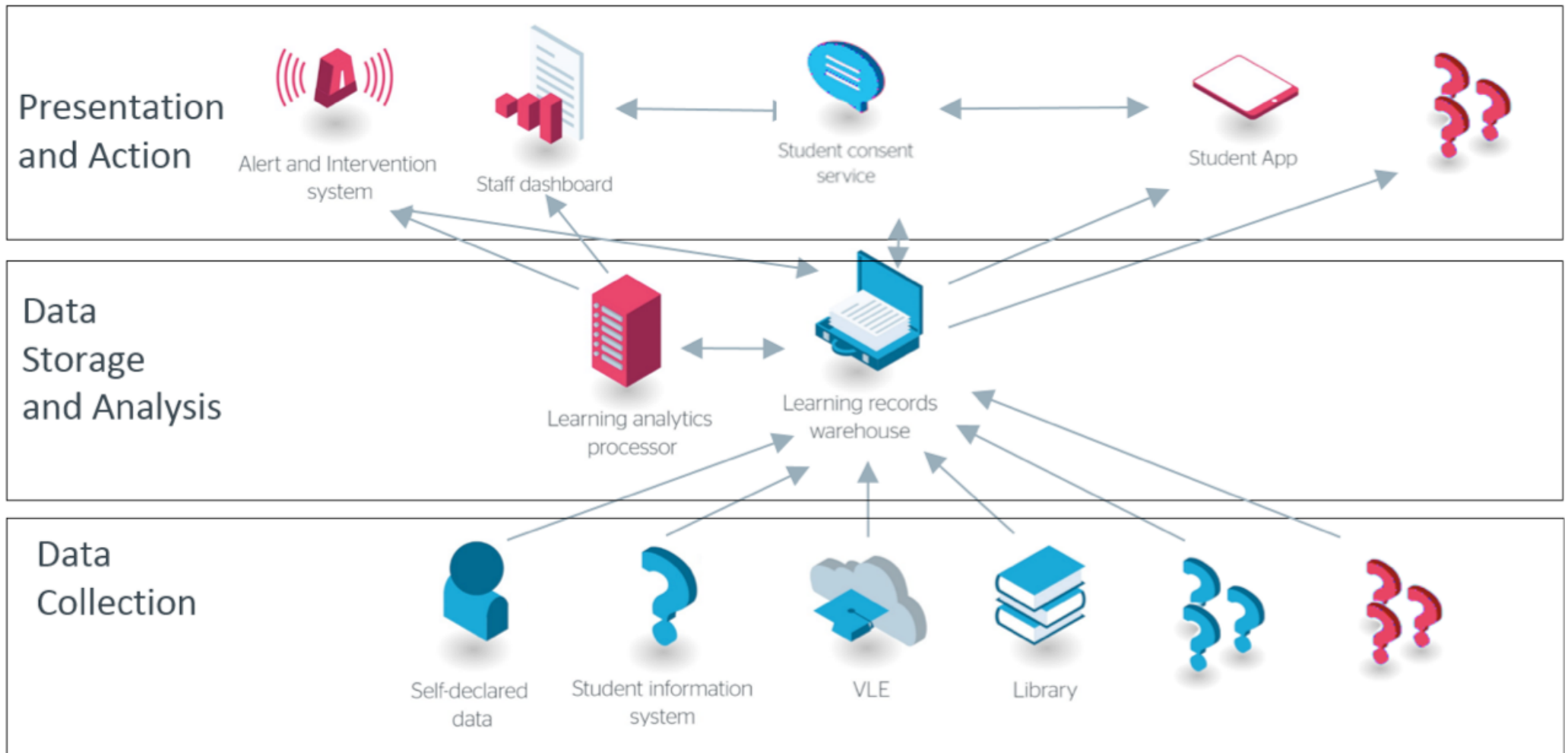
Analytics Model





EDM/LA Enables Adaptive Learning Systems

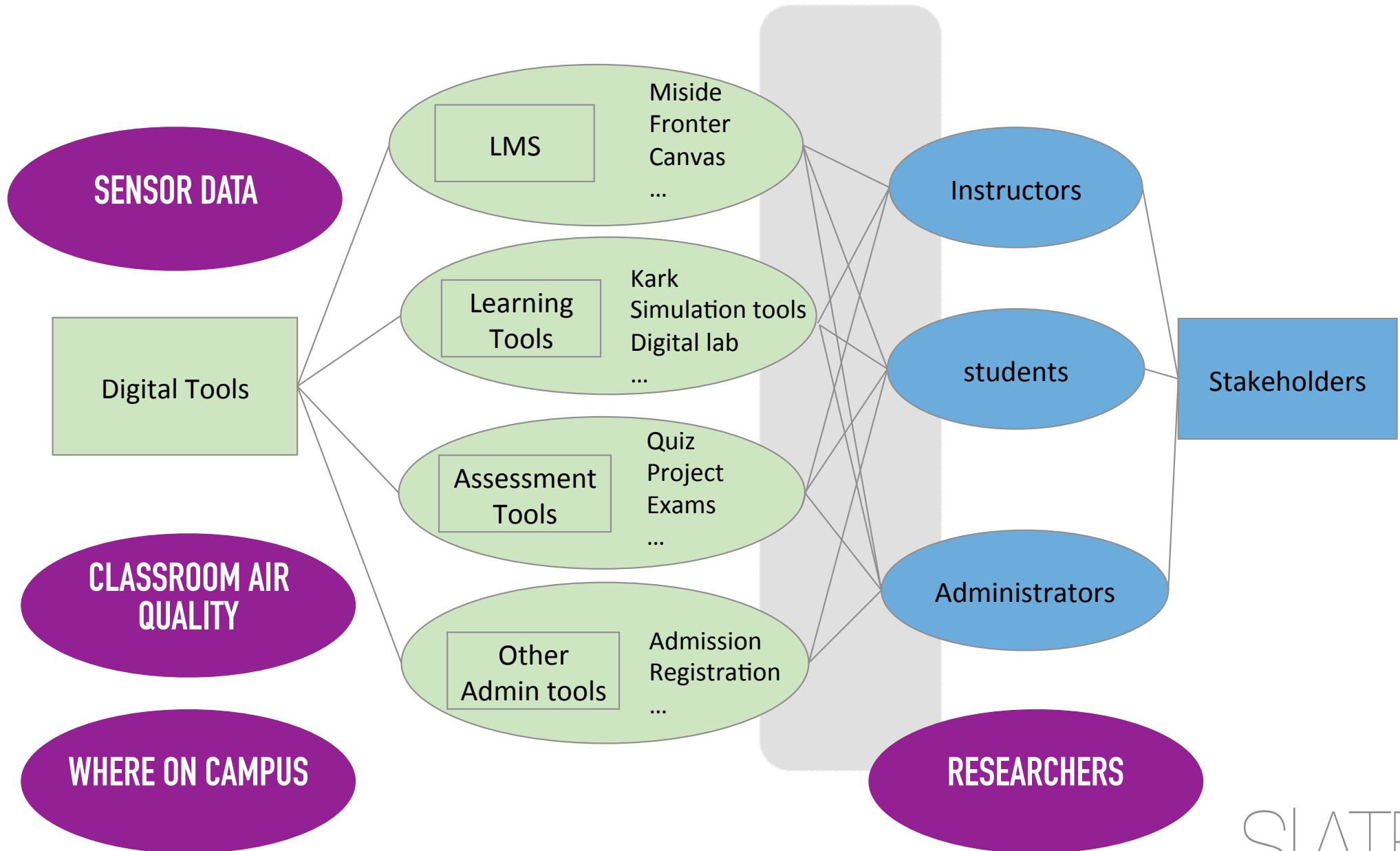




Jisc Learning Analytics Architecture

<https://analytics.jiscinvolve.org/wp/2016/06/28/a-technical-look-into-learning-analytics-data-and-visualisations/>

WHAT DATA?



DEVELOPING A SEARCH STRING

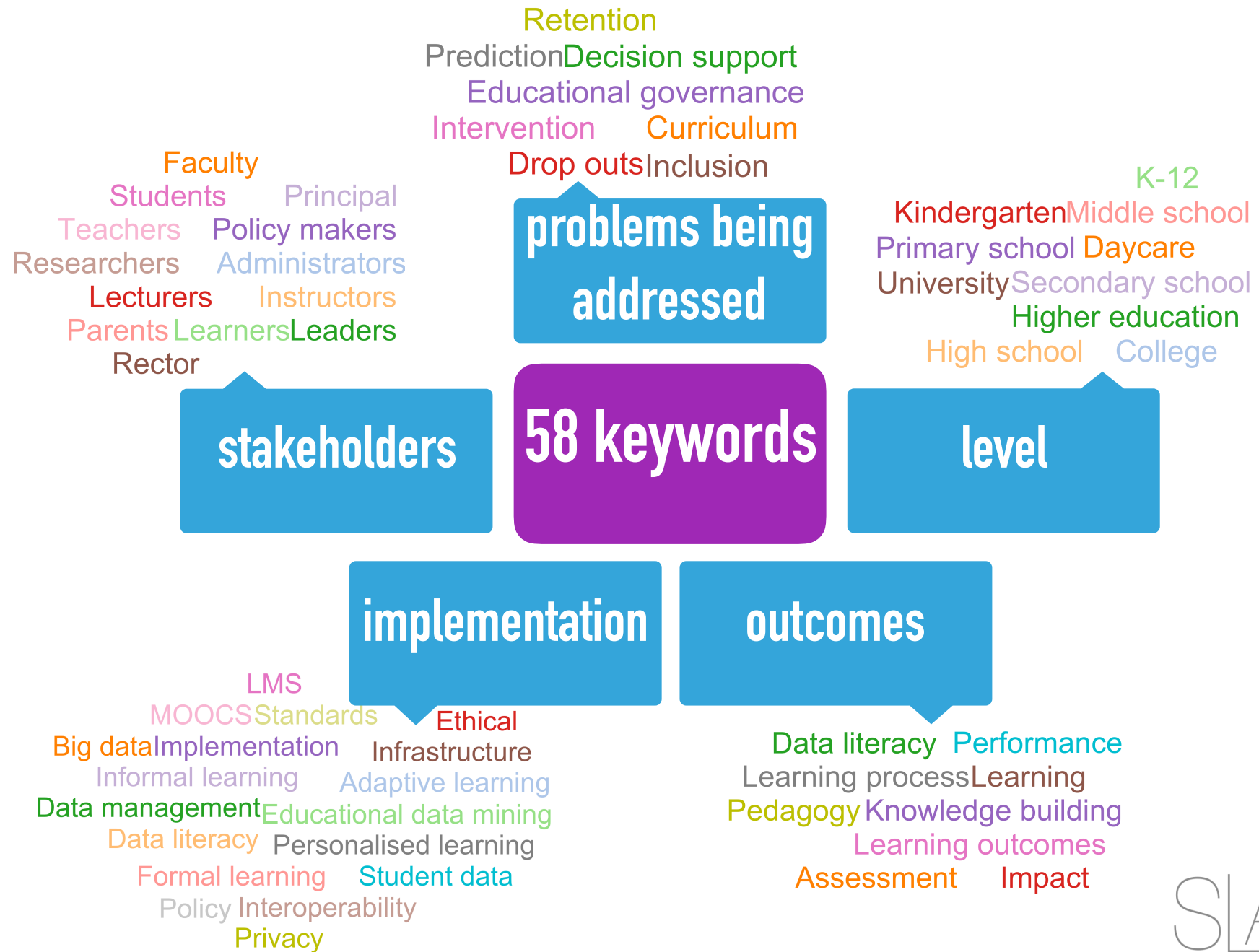
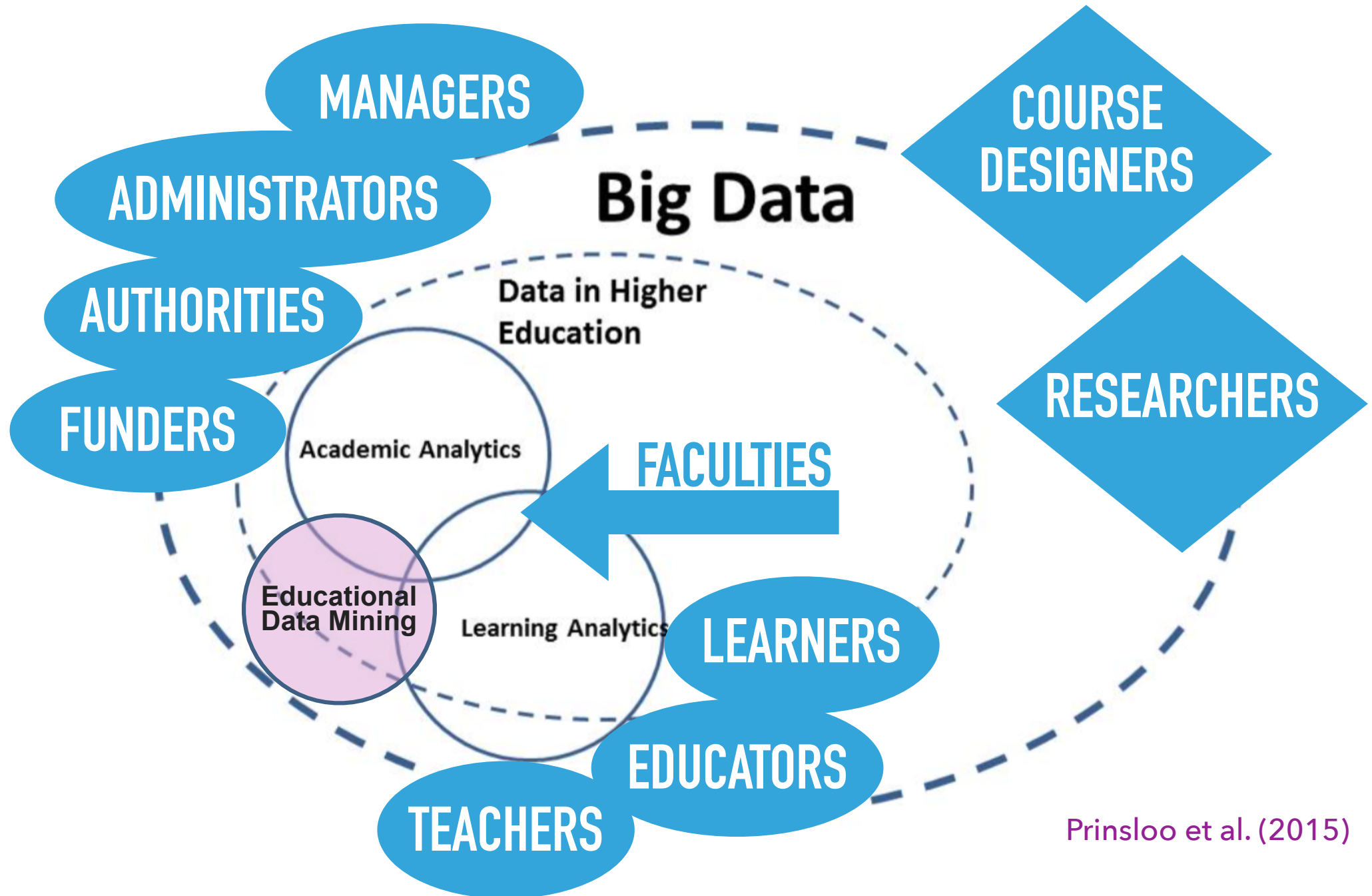


Diagram 1: Mapping Learning and Academic Analytics in the Context of Big Data



Prinsloo et al. (2015)

QUICK HISTORY

<https://solaresearch.org/>

SOLAR

SOCIETY for LEARNING
ANALYTICS RESEARCH

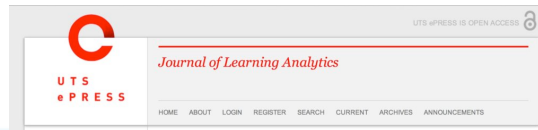
FOUNDATION OF THE SOCIETY FOR LEARNING ANALYTICS RESEARCH

FIRST INTERNATIONAL CONFERENCE ON LEARNING ANALYTICS AND KNOWLEDGE **2011**



FIRST LAK DATASET & CHALLENGE

FIRST LEARNING ANALYTICS SUMMER INSTITUTE **2013**



FIRST ISSUE OF JOURNAL OF LEARNING ANALYTICS

2014 START OF LEARNING ANALYTICS COMMUNITY EXCHANGE PROJECT



2017



Misiejuk (2017)





The 8th International

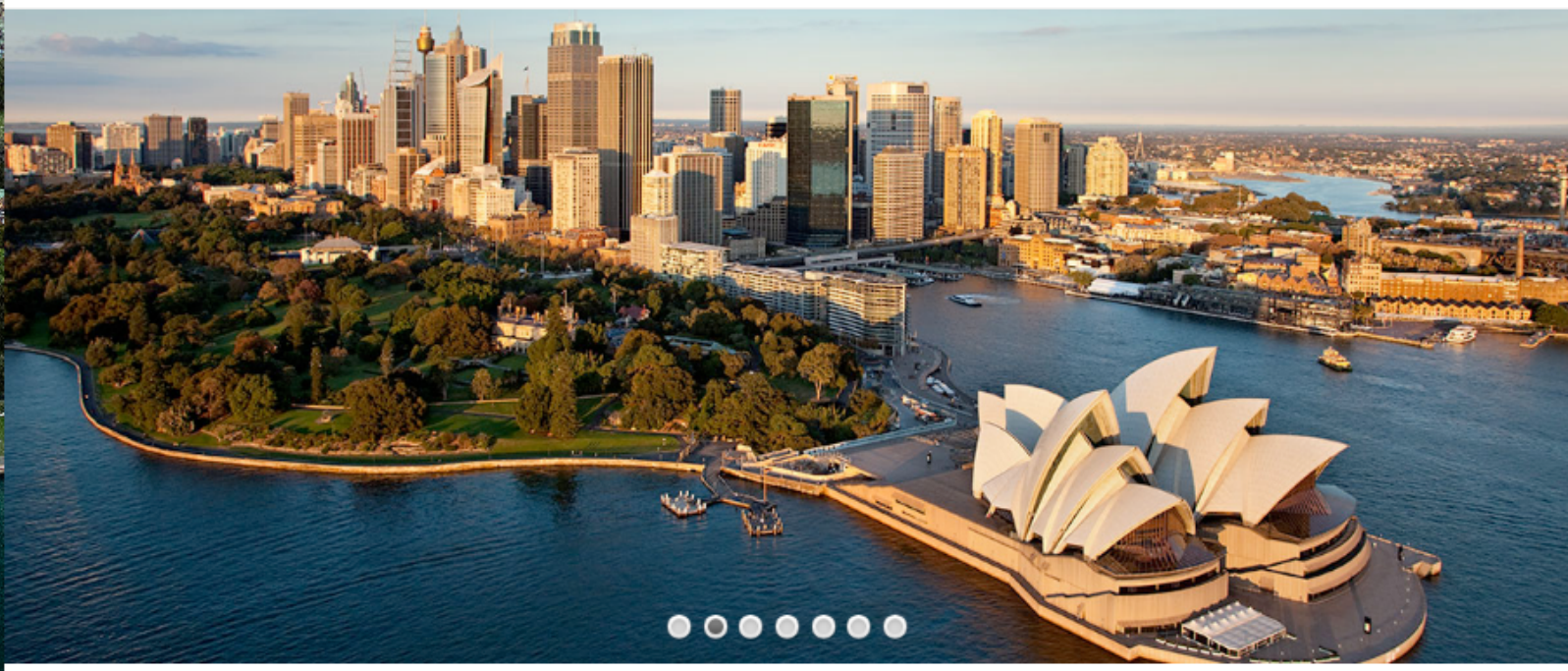
Learning Analytics & Knowledge Conference

SMC Conference & Function Centre, Sydney, NSW, Australia

March 5-9, 2018



[HOME](#) [ABOUT](#)



Welcome to LAK'18 - Sydney, Australia

LEARNING ANALYTICS RESEARCH

LEARNING ANALYSIS AS A RESEARCH FIELD

3 distinct, but overlapping fields

- ▶ Educational data mining (EDM)
- ▶ Learning analytics and knowledge (LAK)
- ▶ Big Data

EDUCATIONAL DATA MINING (EDM)

- ▶ intelligent data mining
- ▶ roots in Artificial Intelligence in Education & Intelligent Tutoring Systems research, as far back as the 1970s
- ▶ applies computational approaches such as data mining, machine learning classification, clustering, Bayesian modelling, relationship mining, discovery with models, statistics, and visualisation to information generated in educational settings to better understand students and the settings in which they learn

LEARNING ANALYTICS AND KNOWLEDGE (LAK)

- ▶ Emerging research field and design discipline
- ▶ LA is a set of data generation and analysis techniques and tools that may be utilised to gain a deep understanding of profound questions for research, policy and practice, generated by 21st Century learning and skills development
- ▶ LAK facilitates a clear theoretical understanding of what is learning, how we assess it, how we foster it, and how we operationalise it in productive educational practices, teaching and learning environments

BIG DATA IN EDUCATION

- ▶ Generally refers to large amounts of data produced by a high number of diverse sources – but also means complex data
- ▶ Data generated by people in action (e.g., computer logs, an essay) or generated by technology (e.g., sensor readings, photos, videos, GPS signals, etc.)
- ▶ The analysis of “big” data sets generated in educational context could identify and validate patterns cross institutions, regions and countries, but also can benefit the school, the classroom teacher, and individual learners

LEARNER-CENTRIC
VS
LEARNING-CENTRIC
ANALYTICS

LEARNER-CENTRIC VS LEARNING-CENTRIC ANALYTICS

(Stein 2012)

Learner-centric analytics measures student behaviour in technological environments

- ▶ Learner engagement measured through the number of times a student visits learning materials, logs on an LMS, how long they view a flipped classroom video
- ▶ Give input on design of learning environments, learning material, etc.

 Learner engagement \neq Learning

LEARNER-CENTRIC VS LEARNING-CENTRIC ANALYTICS

(Stein 2012)

Learning-centric analytics has to do with conceptual growth and requires examining student artefacts to detect conceptual acquisition

- ▶ focus is on "learning", "learning outcomes"
- ▶ have to examine artefacts that students develop to identify if learning has taken place.
- ▶ one's understanding of learning, impacts the analytics design

KINDS OF ANALYTICS

CONTENT ANALYTICS

"(...) visibility into the amount of content that is being created, the nature of that content and how it is used" [13]

TEXT ANALYTICS

"(...) the application of text mining techniques to solve business problems" [14]

VISUAL ANALYTICS

"(...) the science of analytical reasoning supported by interactive visual interfaces" [15]

TEACHING ANALYTICS

"(...) focuses on the design, development, evaluation, and education of visual analytics methods and tools for teachers in primary, secondary, and tertiary educational settings." [16]

MULTIMODAL LEARNING ANALYTICS [17]

MICROGENETIC LEARNING ANALYTICS

"(...) microgenetic techniques derived from the field of human development with computational methods derived from the emerging field of learning analytics" [18]

LEARNING-RESOURCE ANALYTICS [19]

DISPOSITION ANALYTICS

"(...) aims to capture meaningful data regarding student's dispositions to their own learning" [20]

DISCOURSE ANALYTICS

"(...) builds on extensive work in the discursive properties of higher quality discourse for learning related to learners" [20]

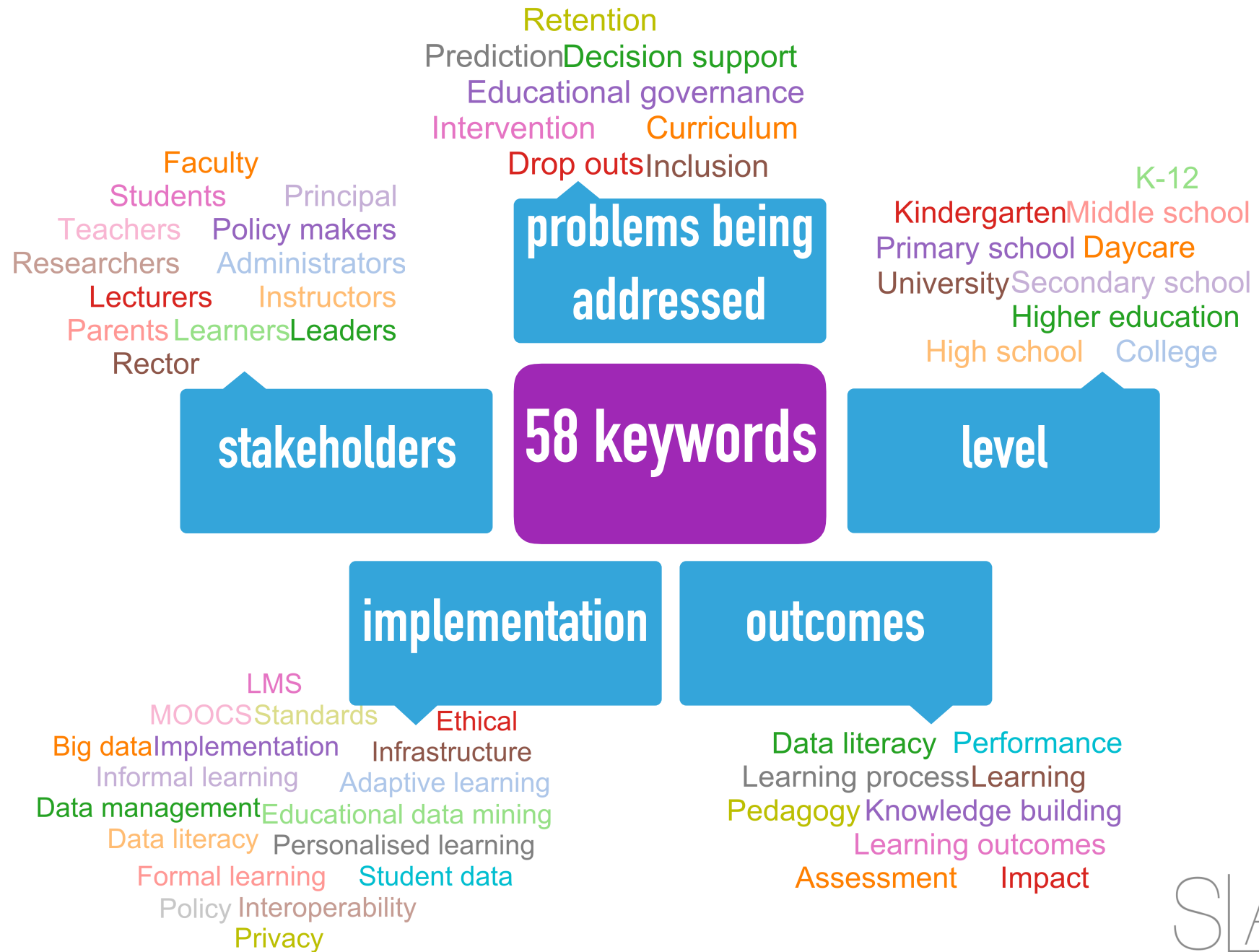
CONTEXT ANALYTICS

"(...) the cumulative history that is derived from data observations about entities (people, places, and things)" [21]

SOCIAL LEARNING ANALYTICS

"(...) aims to capture meaningful data regarding the role of social interaction in learning, including discourse and the structure of social networks" [20]

DEVELOPING A SEARCH STRING



EXAMPLE: CORRELATION BETWEEN USER ACTIONS & FINAL GRADE

Construction of the Analytic Data Set (ADS)

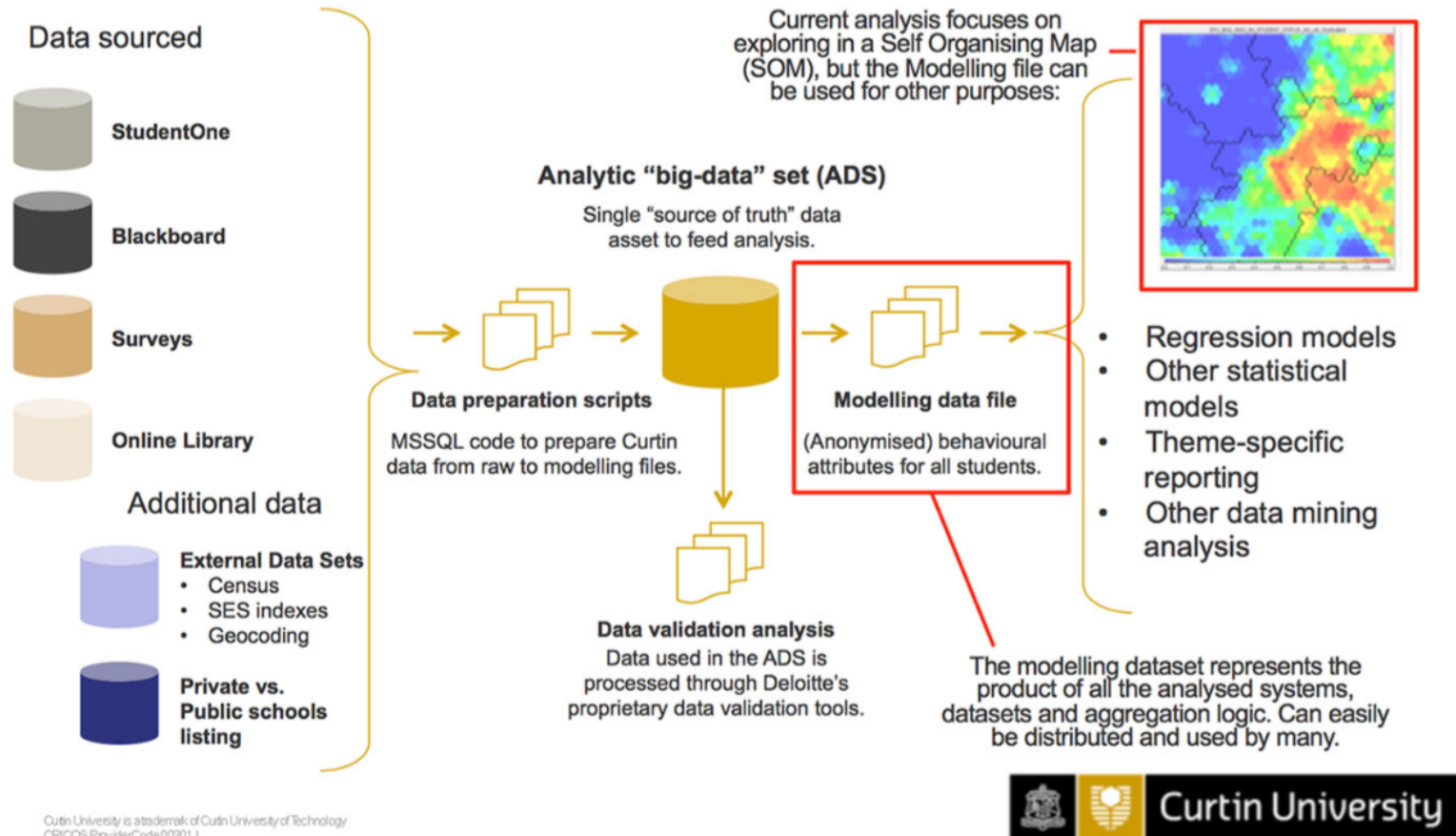


Fig. 4 Data sources, analytic data set (ADS) and self-organizing map

EXAMPLE: MEASURING STUDENT PERFORMANCE

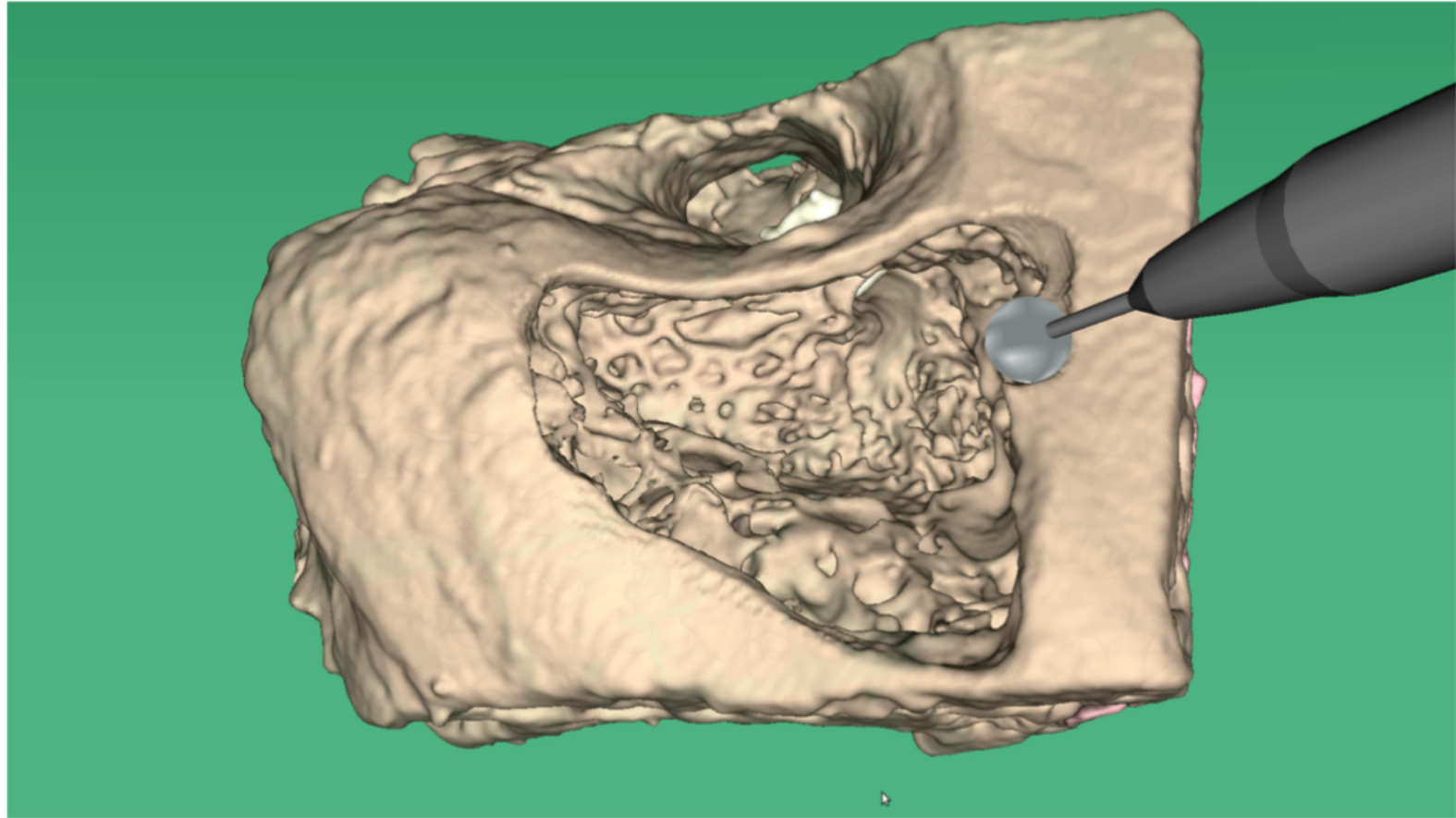


Figure 2: The simulation environment showing the drill and a partially dissected temporal bone

EXAMPLE: DROPOUT PREDICTOR, INTERVENTION

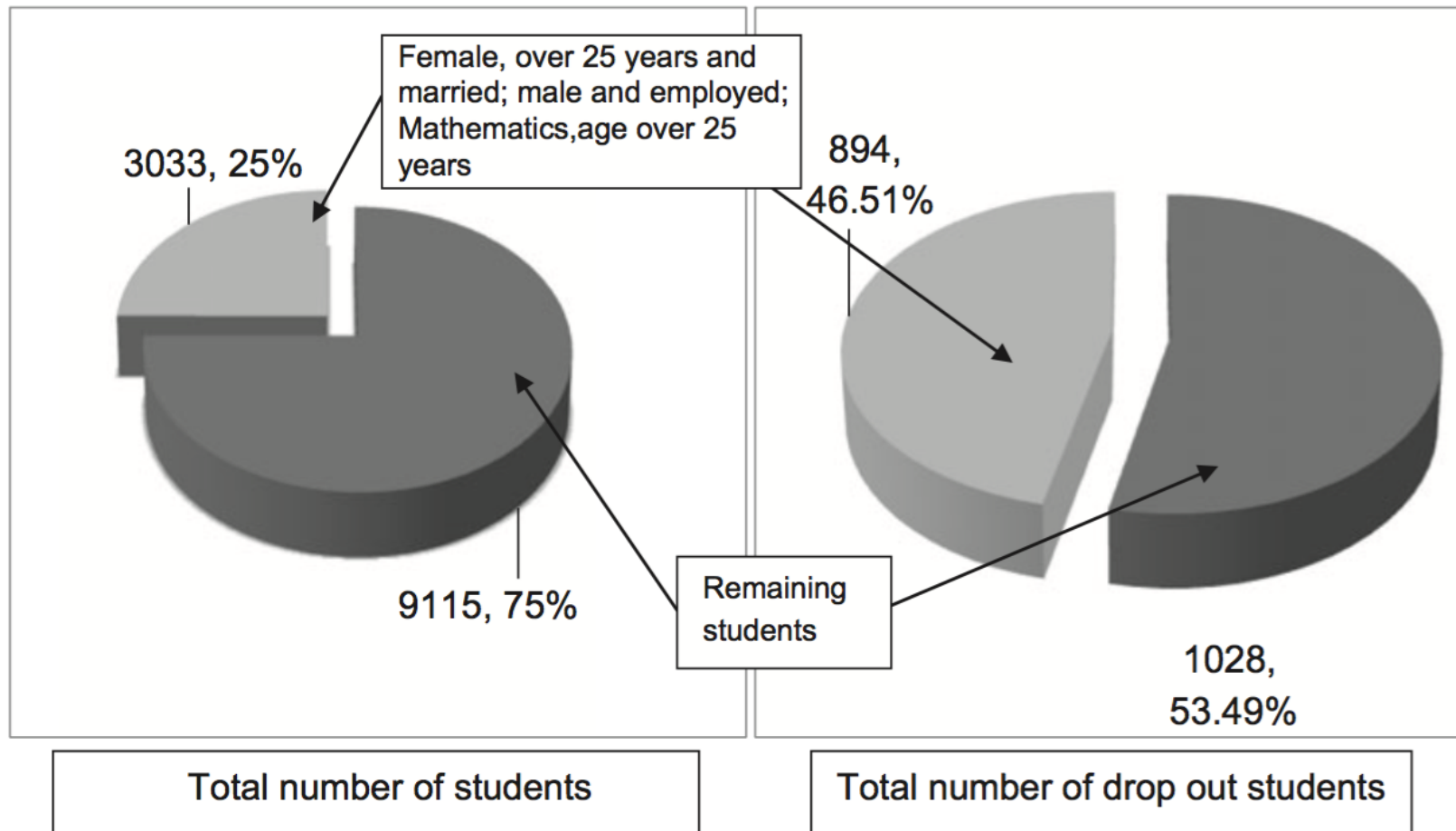


Figure 1. Graphical representation of synthesis of observations.

EXAMPLE: DATA VISUALISATION, ACTIVITY ENGAGEMENT

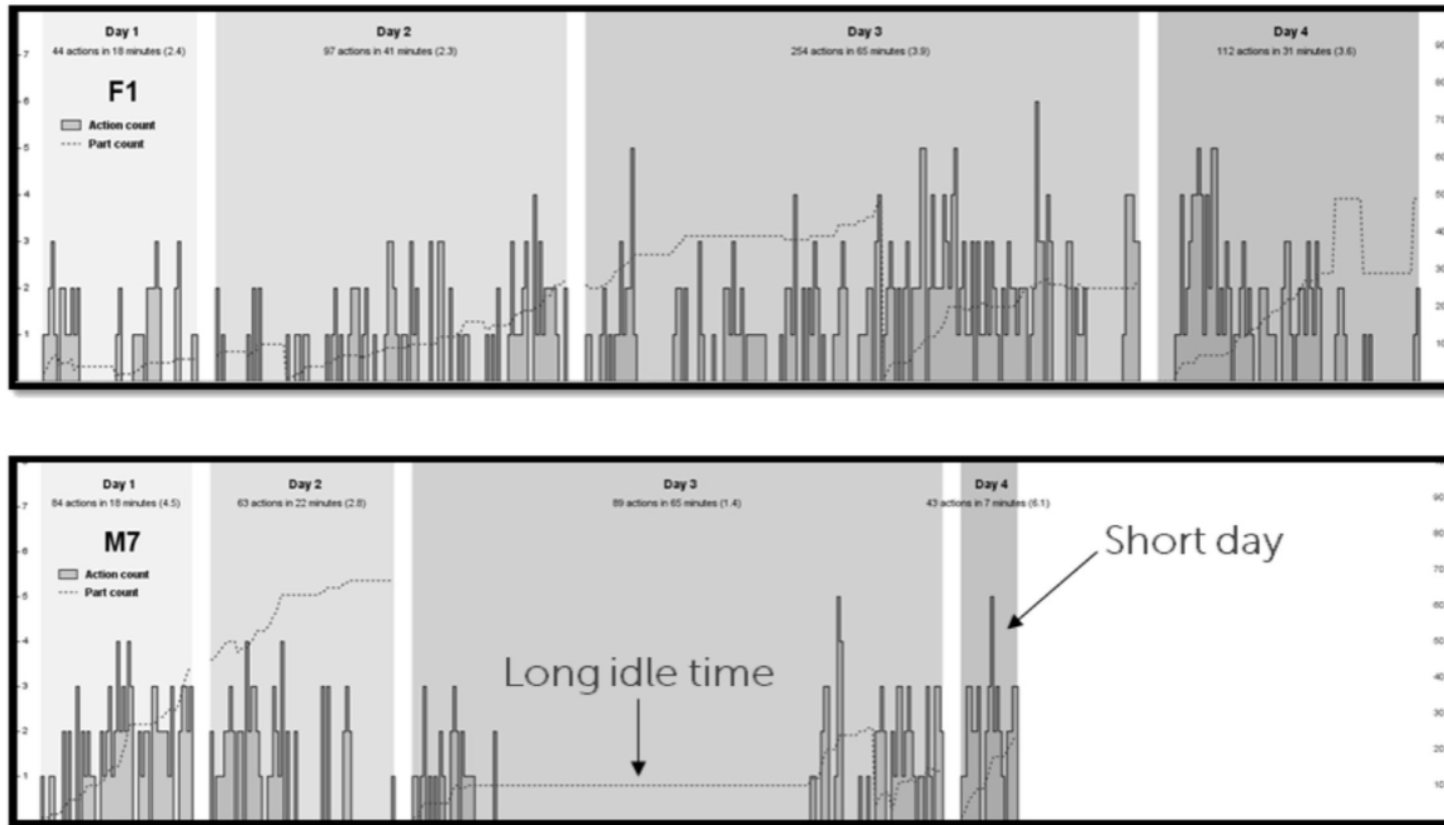


Fig. 6. Time series analysis: A comparison of an engaged student (F1) with a disengaged student (M7). The results conform to our classroom observations.

EXAMPLE: MODELS OF EMOTION

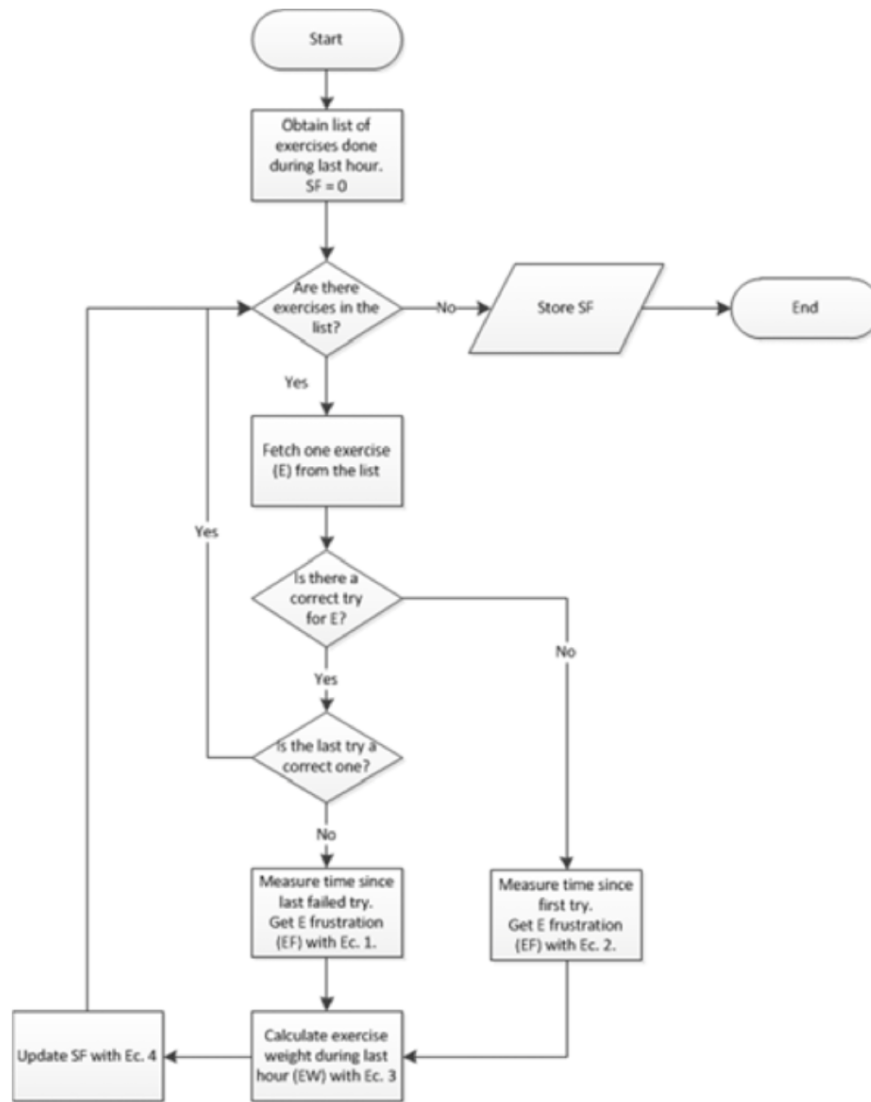


Figure 2: Flow chart of process used to detect frustration

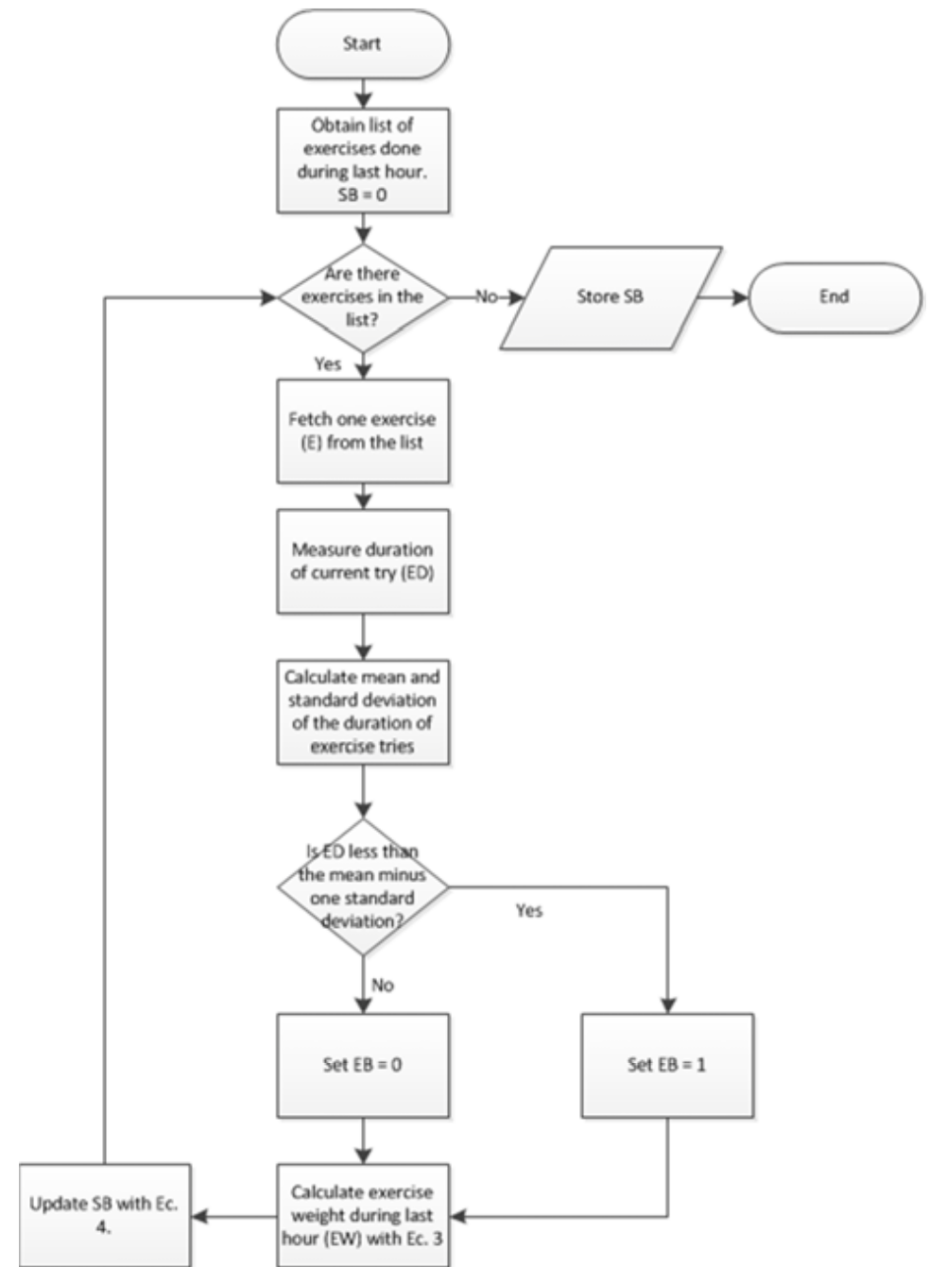


Figure 4: Flow of rules for the detection of boredom

EXAMPLE: DASHBOARDS FOR INSTRUCTORS

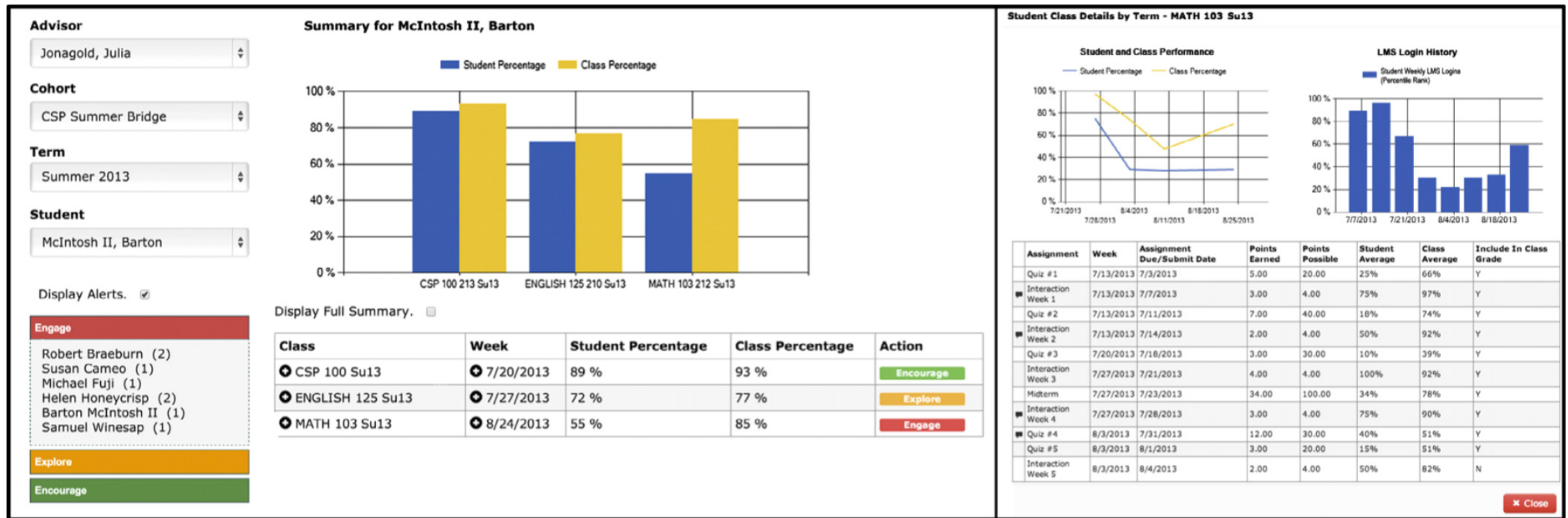


Fig. 1. Example dashboard displays from Student Explorer early warning system. Summary (left) dashboard presents most recent formative data across courses. Course detail (right) dashboard presents all assignment details, a historical performance graph, and LMS login history about a specific course in which the selected student is enrolled.

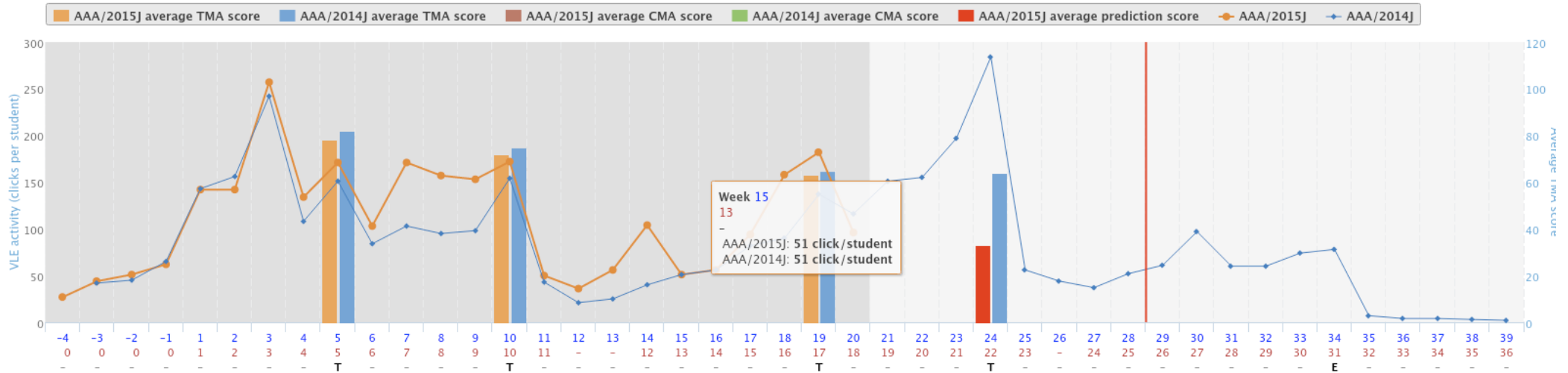
EXAMPLE: OU ANALYSE DASHBOARD FOR INSTRUCTORS

<https://analyse.kmi.open.ac.uk>

AAA 2015J - Week 20

Time machine (choose week):

20

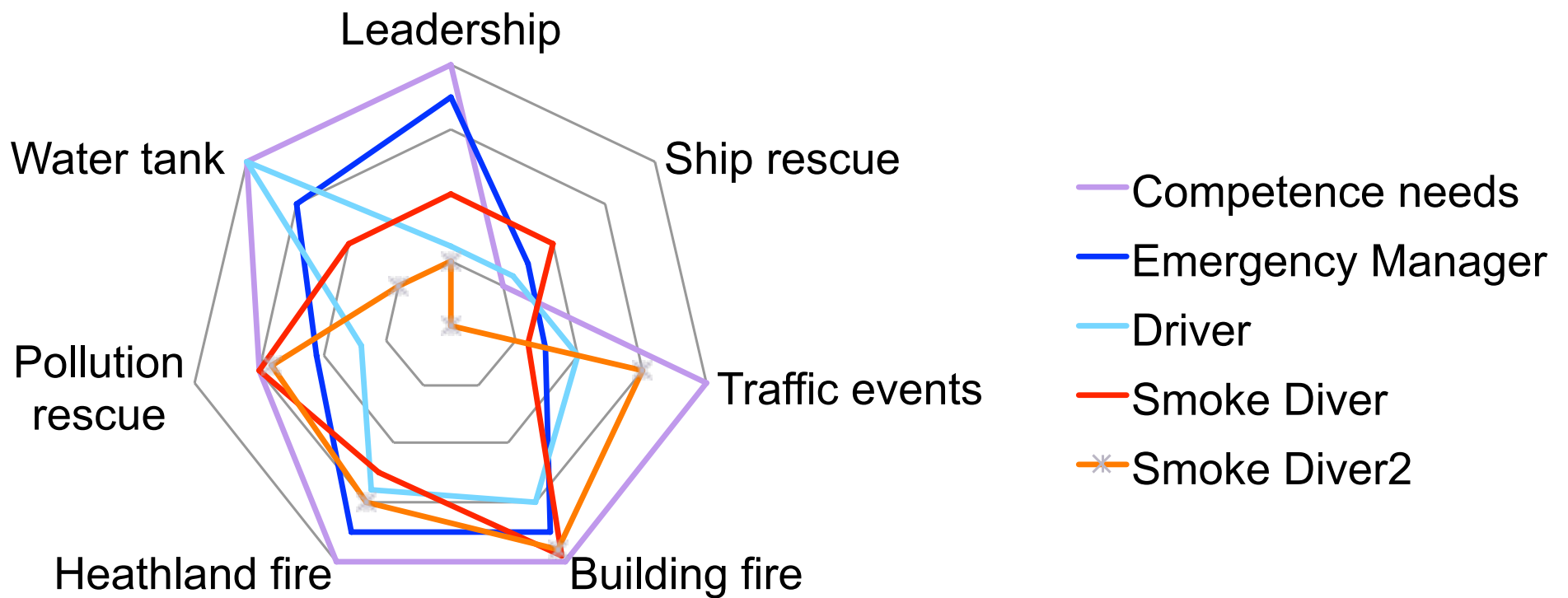


Registered students 910 19 WRT Previous week	VLE active students 635 121 WRT Previous week	Students predicted not to submit 307 116 WRT Previous week	Last TMA result (average) 63 2.4 WRT Previous presentation	TMA submissions 0 586 WRT Previous week
--	---	--	--	---

25 Export Select columns

Student PI	Name	TMA	Risk of non-submission	Next TMA prediction	Next TMA grade prediction	Risk of Failure	Final result prediction	Final result
A0000194	Flores Joseph	71 NS NS		Not submit	Not Submit		Fail	Fail: no resit
A0000251	Taylor Raymond	76 84 72		Submit	Fail		At risk	Pass
A0000305	Thomas George	93 93 90		Not submit	Not Submit		At risk	Pass
A0000511	Allen Patrick	97 97 95		Submit	Fail		Pass	Distinction
A0000653	Jones Robert	95 94 85		Submit	Fail		Pass	Pass
A0000658	James Catherine	93 94 97		Submit	Fail		Pass	Distinction
A0000742	Turner Timothy	91 75 74		Submit	Fail		At risk	Pass

EXAMPLE: VISUALISATIONS



Wasson & Hansen

EXAMPLE: ETHICS & PRIVACY

Jisc Global practice for learning analytics
A literature review of the ethical and legal issues

Code of practice for learning analytics

A literature review of the ethical and legal issues

Niall Scaler

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The **DELICATE** Checklist
to implement trusted
Learning Analytics



- D** **DETERMINATION** – Why you want to apply Learning Analytics?
 - ▶ What is the added value (Organisational and data subjects)
 - ▶ What are the rights of the data subjects (e.g., EU Directive 95/46/EC)
- E** **EXPLAIN** – Be open about your intentions and objectives
 - ▶ What data will be collected for which purpose?
 - ▶ How long will this data be stored?
 - ▶ Who has access to the data?
- L** **LEGITIMATE** – Why you are allowed to have the data?
 - ▶ Which data sources you have already (aren't they enough)
 - ▶ Why are you allowed to collect additional data?
- I** **INVOLVE** – Involve all stakeholders and the data subjects
 - ▶ Be open about privacy concerns (of data subjects)
 - ▶ Provide access to the personal data collected (about the data subjects)
- C** **CONSENT** – Make a contract with the data subjects
 - ▶ Ask for a consent from the data subjects before the data collection
 - ▶ Define clear and understandable consent questions (Yes / No options)
 - ▶ Offer the possibility to opt-out of the data collection without consequences
- A** **ANONYMISE** – Make the individual not retrievable
 - ▶ Anonymise the data as far as possible
 - ▶ Aggregate data to generate abstract metadata models (Those do not fall under EU Directive 95/46/EC)
- T** **TECHNICAL** – Procedures to guarantee privacy
 - ▶ Monitor regularly who has access to the data
 - ▶ If the analytics change, update the privacy regulations (new consent needed)
 - ▶ Make sure the data storage fulfills international security standards
- E** **EXTERNAL** – If you work with external providers
 - ▶ Make sure they also fulfil the national and organisational rules
 - ▶ Sign a contract that clearly states responsibilities for data security
 - ▶ Data should only be used for the intended services and no other purposes

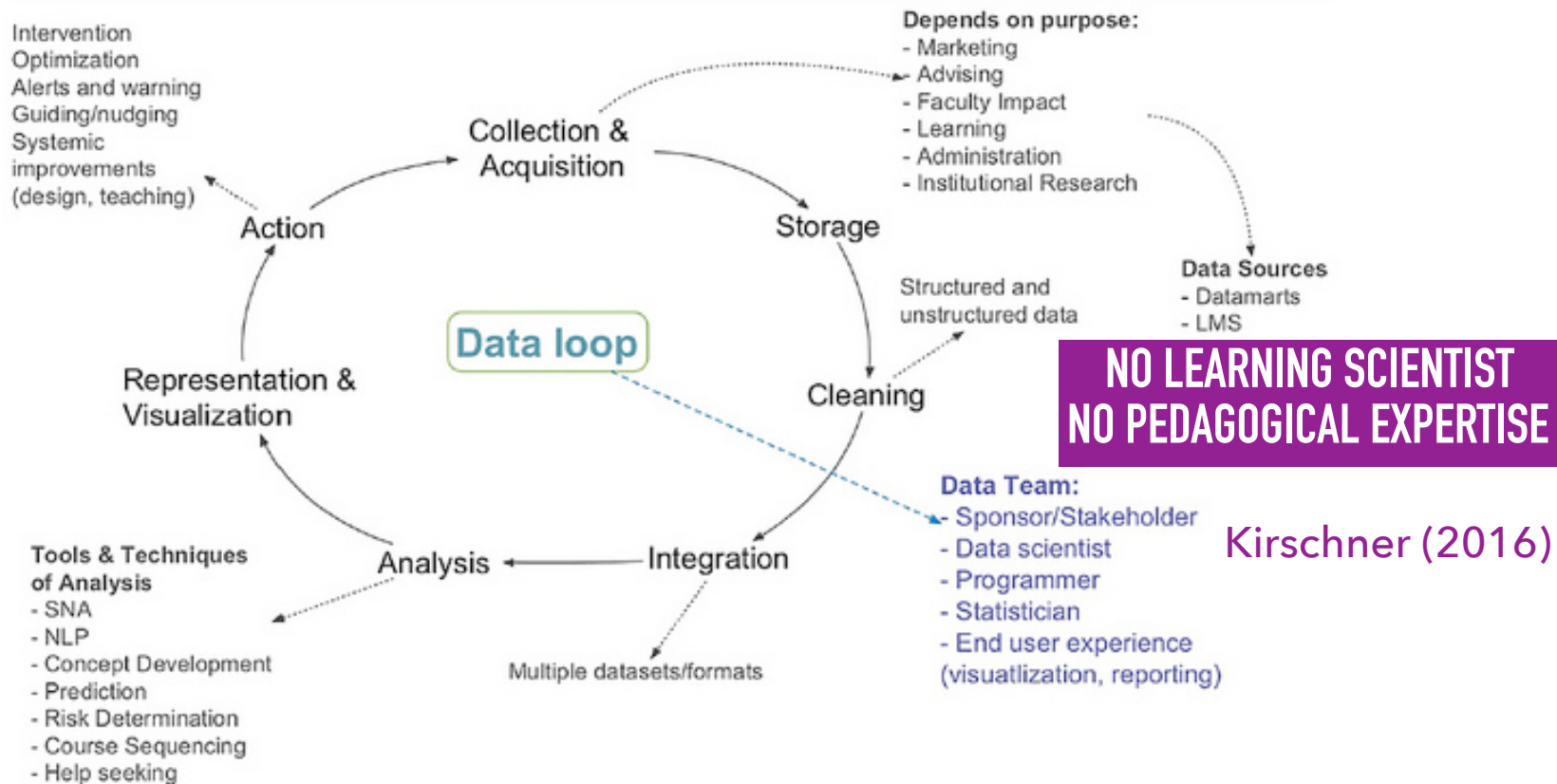
Drachsler, H. & Greller, W. (2016). Privacy and Analytics – it's a DELICATE issue. A Checklist to establish trusted Learning Analytics. 6th Learning Analytics and Knowledge Conference 2016, April 25-29, 2016, Edinburgh, UK.



SOME IMPRESSIONS

- ▶ wide range of research topics
- ▶ few **impact studies** (“very little credible research has demonstrated any large-scale benefits to learners or institutions” Ferguson)
- ▶ the definition of “learning analytics” is still under discussion
- ▶ often lack of theoretical, historical or pedagogical perspective “**data rich -- theory poor**”
- ▶ predominance of studies in higher education, informal learning, and distance education settings; few studies concerned about “schools”
- ▶ **privacy & ethics** issues rarely addressed

Analytics Model



Siemens (2013)



JRC SCIENCE FOR POLICY REPORT

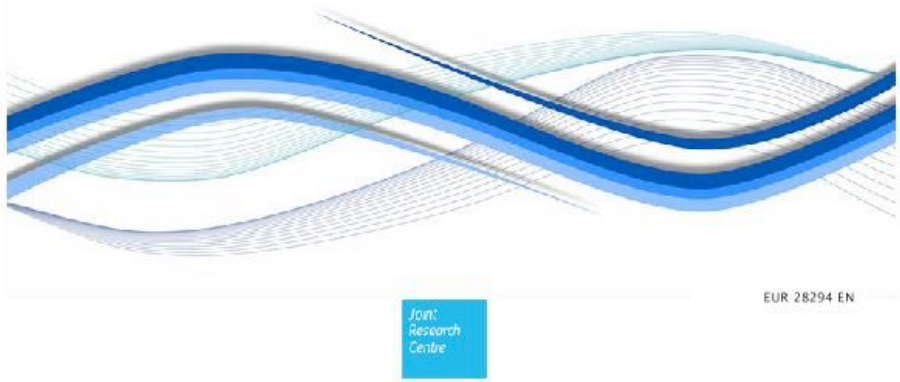
Research Evidence on the Use of Learning Analytics

*Implications for Education
Policy*

Editors:
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Jonatan Castaño Muñoz

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2016



Joint
Research
Centre

EUR 28294 EN

MAIN FINDINGS

- ▶ wide gap between the potentials identified in research & implementation
- ▶ tools focussed on visualising engagement and activity for early alerts & targets intervention
- ▶ evidence of formal validation is lacking
 - ▶ lack of evidence of more effective learning
 - ▶ evidence of successful implementation is scarce
- ▶ need for careful build-up of research and experimentation



KEY QUESTIONS



KEY QUESTIONS



Do we see real improvements in learning outcomes for learners?

We may be able to see patterns in learners' data, but can we take action based on those patterns that improves their learning?

We may be able to personalise learning based on learners' data, but does that make any difference to how much they learn?

Do learning analytics optimise the learning process?

Does that lead to more efficient processes, allow resources to be better targeted, and save money and time?

Do learning analytics lead to improvements in retention, completion and progression?

If a system is deployed across an organisation, do the teachers and learners actually use it?

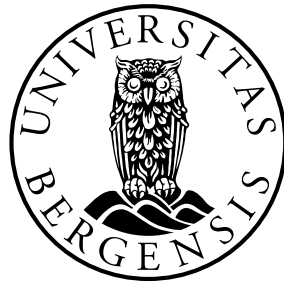
Can the many ethical issues around privacy, transparency, surveillance, data ownership and control, and data protection be addressed effectively, or will they prove to be barriers?

LEARNING ANALYTICS
IS IN ITS INFANCY !

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