SLATE

Centre for the Science of Learning & Technology

Learning Analytics: What's It For ?

Director, Professor Barbara Wasson

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Assessment in Higher Education 2017

UNIVERSITAS BERGENSIS

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 research and competence 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

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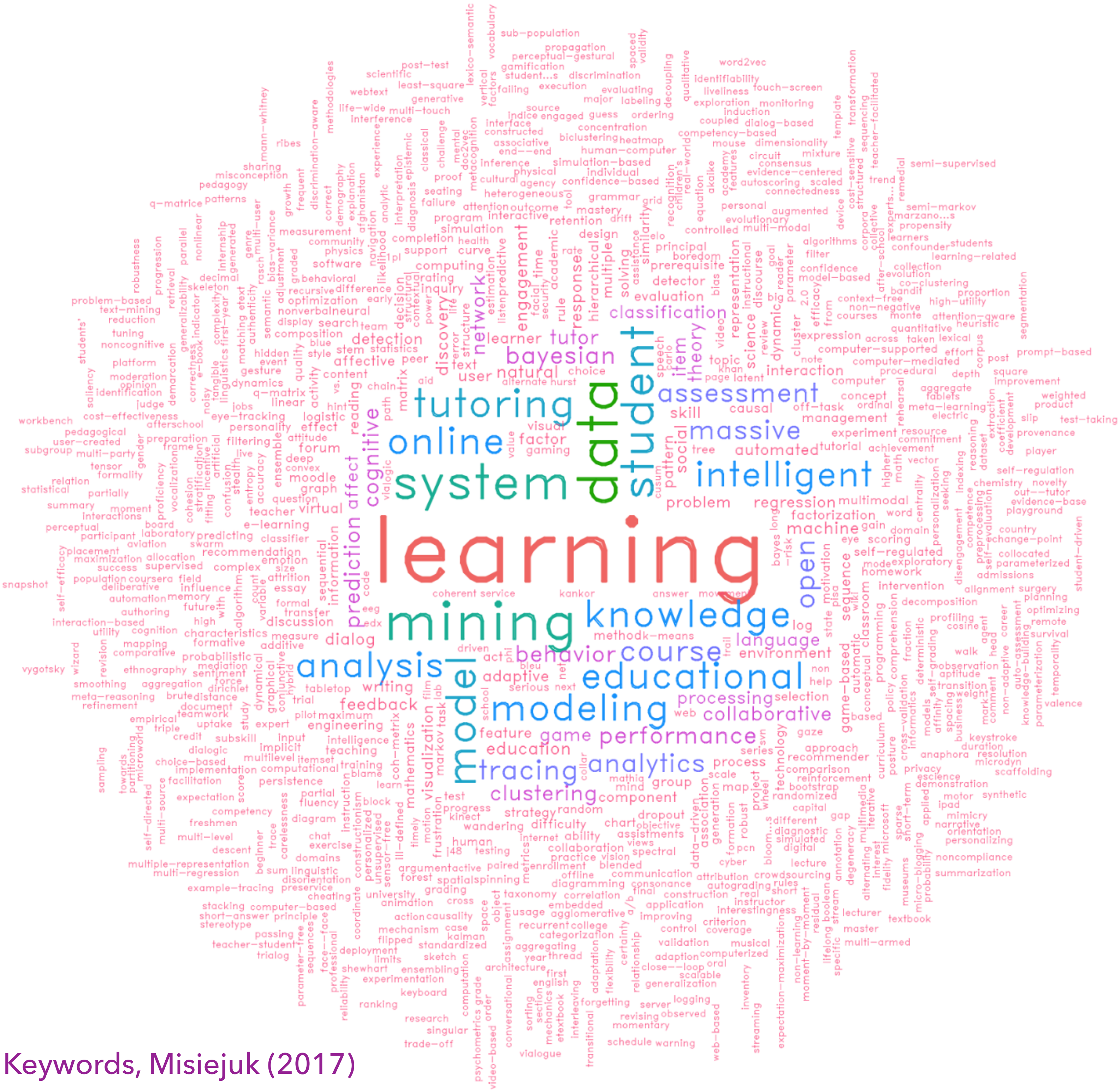
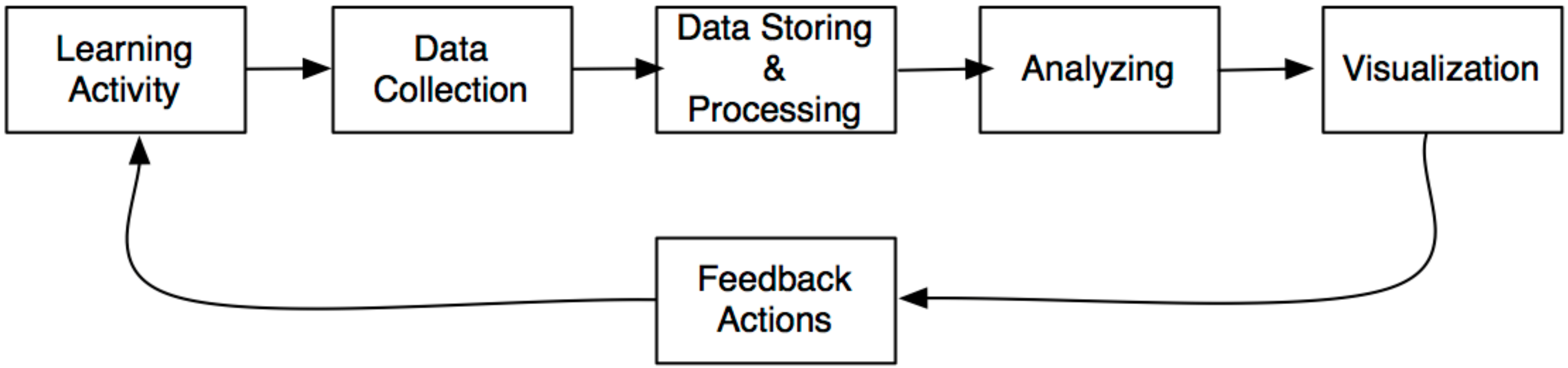
LEARNING ANALYTICS



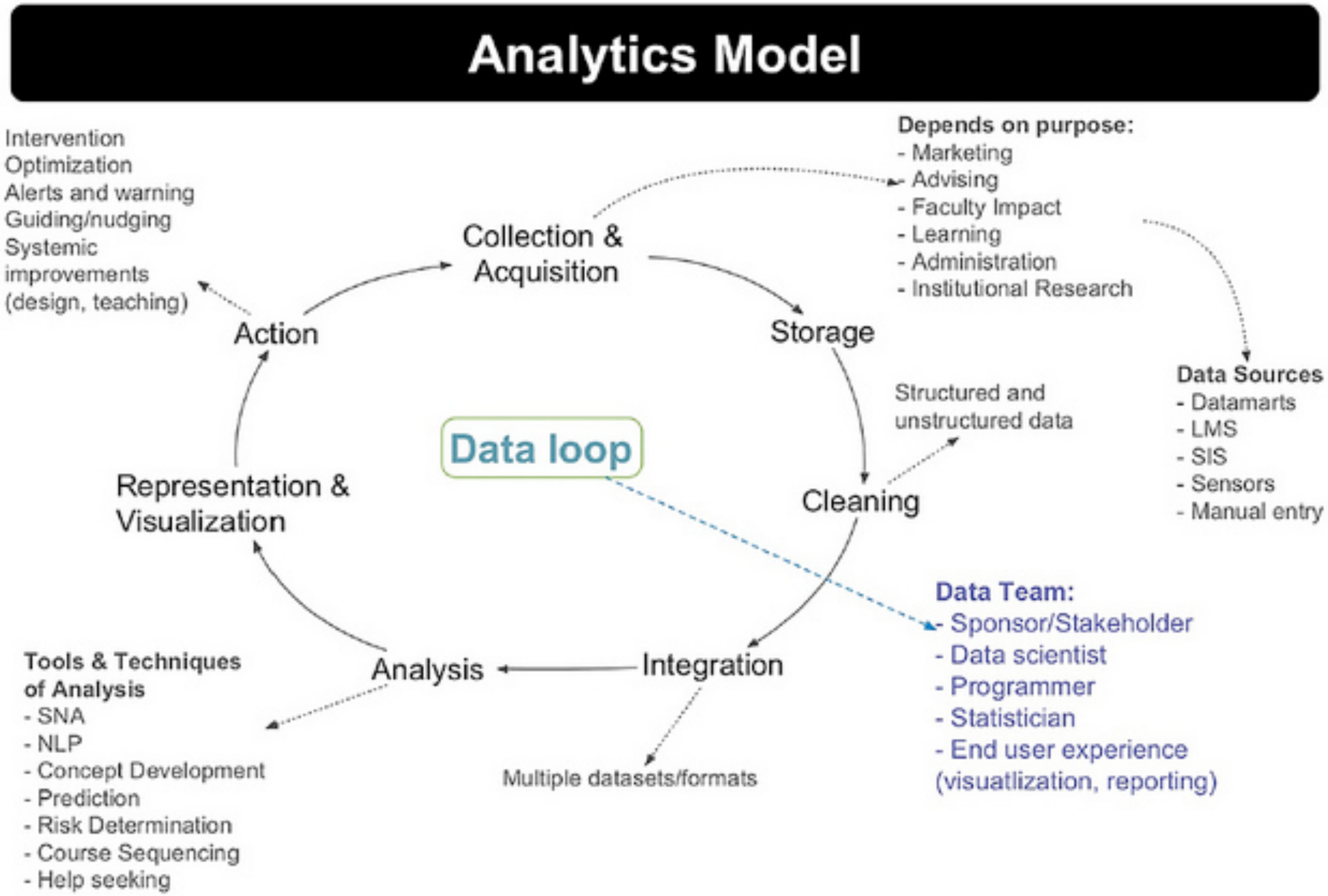
LAK Single Keywords, Misiejuk (2017)

“**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"

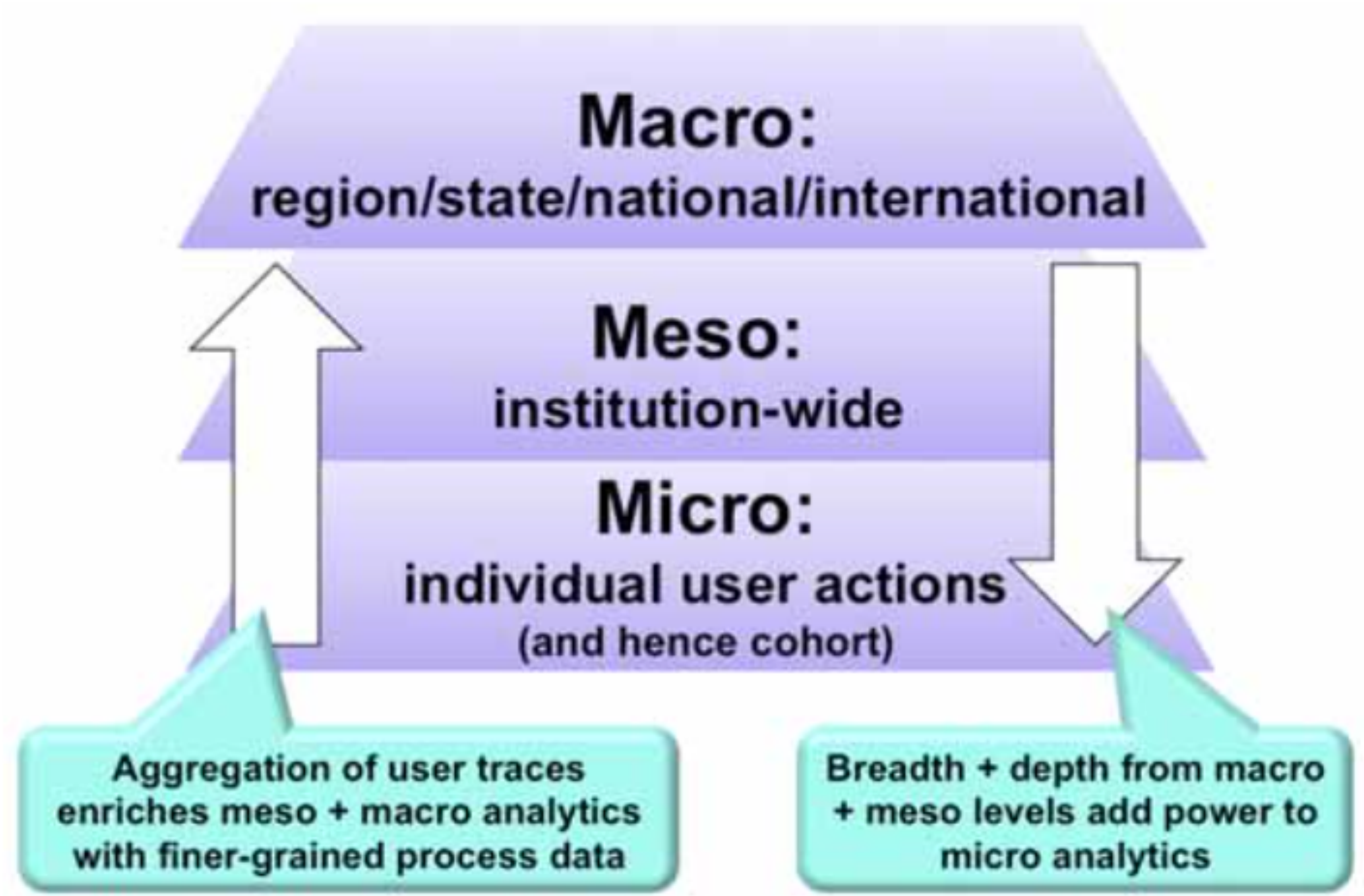
1st International Conference on Learning Analytics & Knowledge



ISO/IEC JTC1/SC36 LA
Hoel, T., Chen, W., & Cho, Y-S (2016)

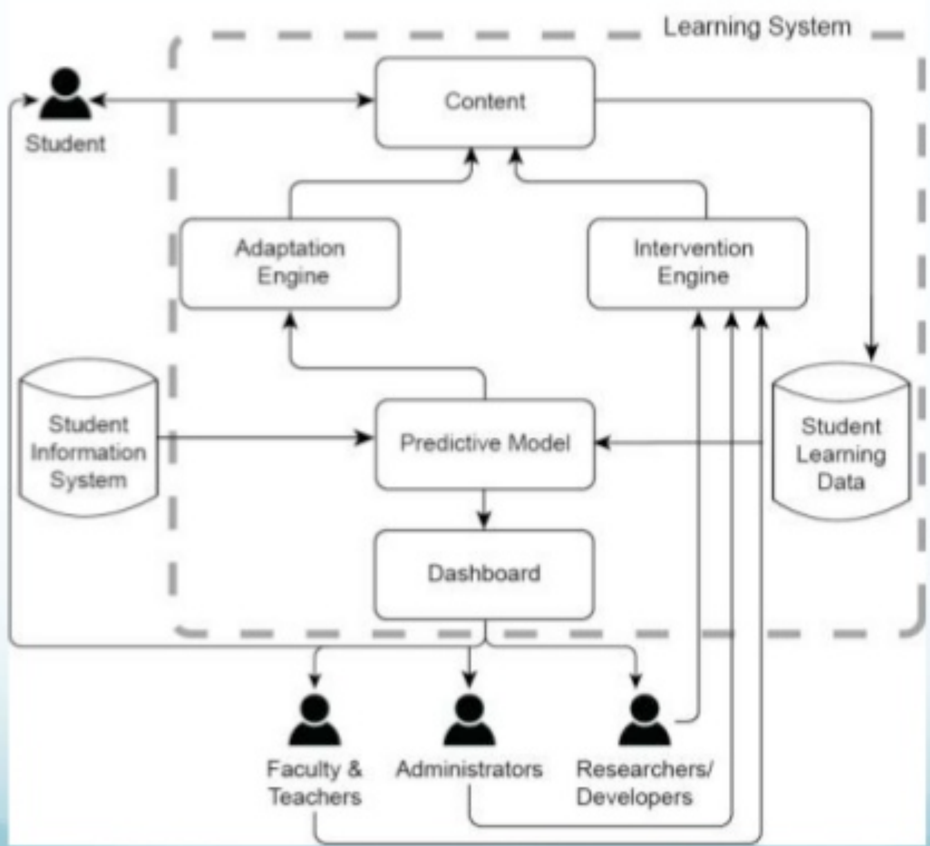


Siemens (2013)

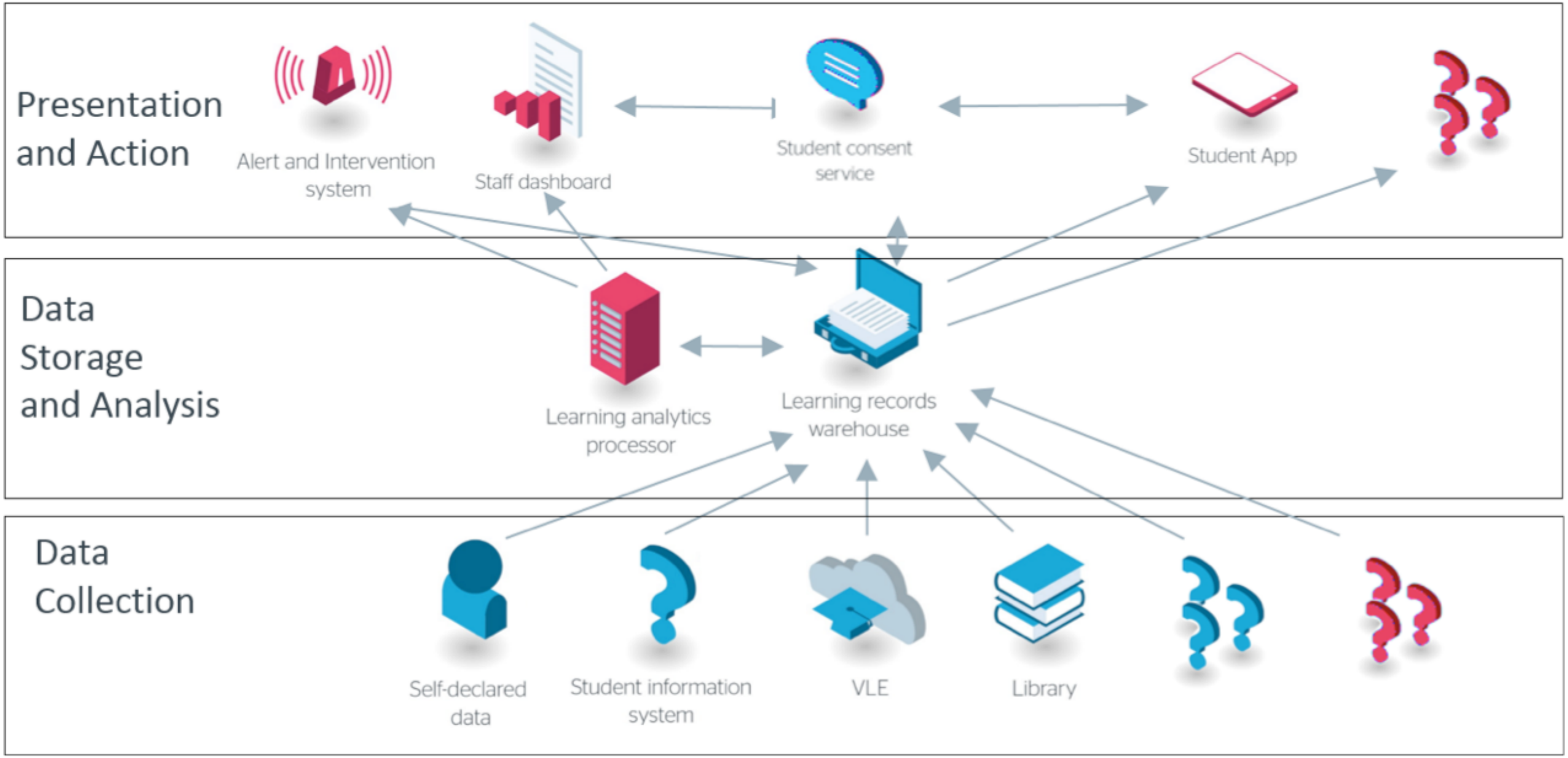


Buckingham Shum, S. (2012)
UNESCO Policy Brief, November 2012

EDM/LA Enables Adaptive Learning Systems



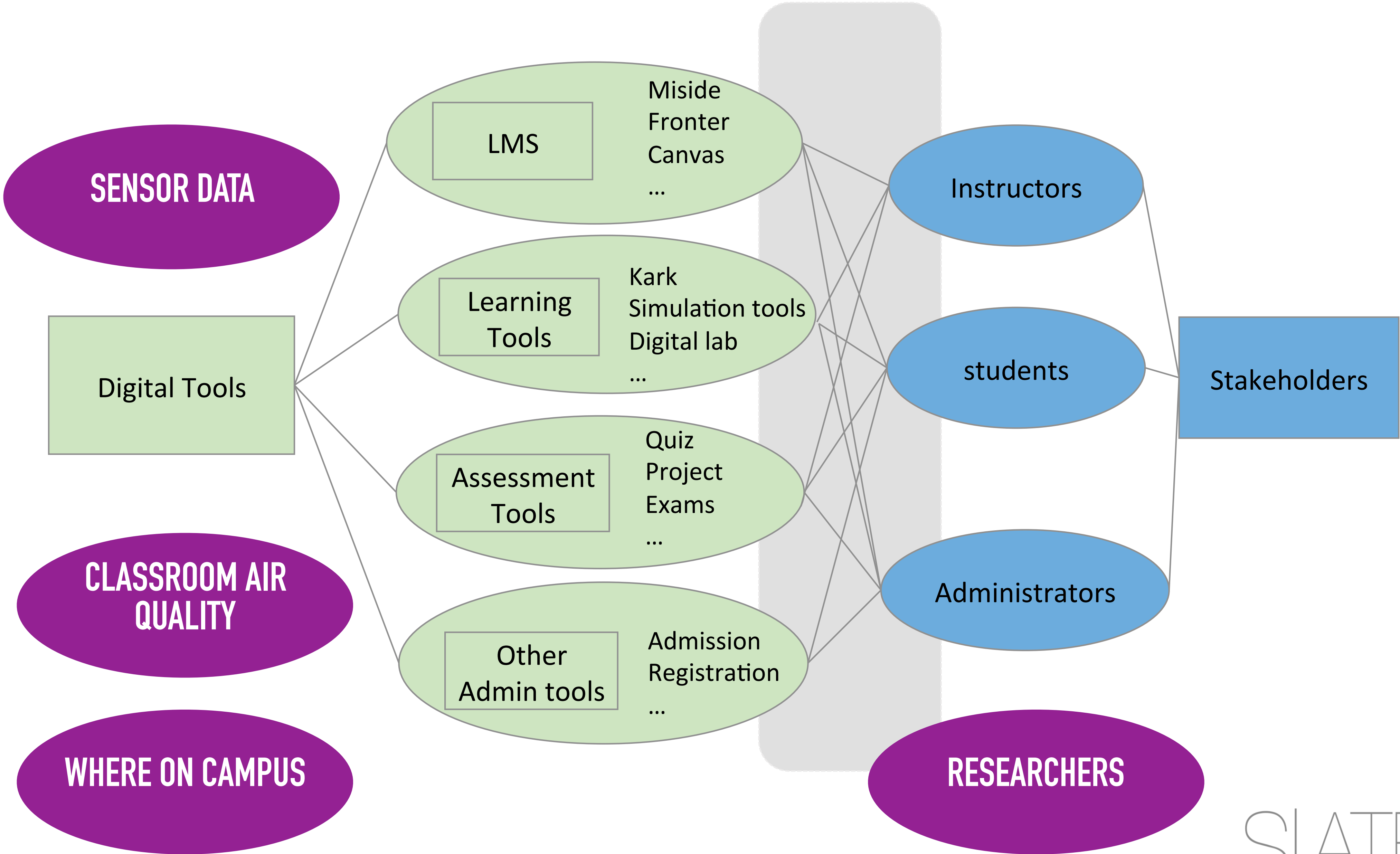
Bienkowski (2012)



Jisc Learning Analytics Architecture

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

WHAT DATA?



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*in cooperation with Kunnskapssenter for utdanning

DEVELOPING A SEARCH STRING

58 keywords

problems being addressed

Retention
Prediction Decision support
Educational governance
Intervention Curriculum
Drop outs Inclusion

stakeholders

Faculty
Students Principal
Teachers Policy makers
Researchers Administrators
Lecturers Instructors
Parents Learners Leaders
Rector

level

K-12
Kindergarten Middle school
Primary school Daycare
University Secondary school
Higher education
High school College

implementation

LMS
MOOCS Standards
Ethical
Big data Implementation
Infrastructure
Informal learning
Adaptive learning
Data management Educational data mining
Data literacy
Personalised learning
Formal learning
Student data
Policy Interoperability
Privacy

outcomes

Data literacy Performance
Learning process Learning
Pedagogy Knowledge building
Learning outcomes
Assessment Impact

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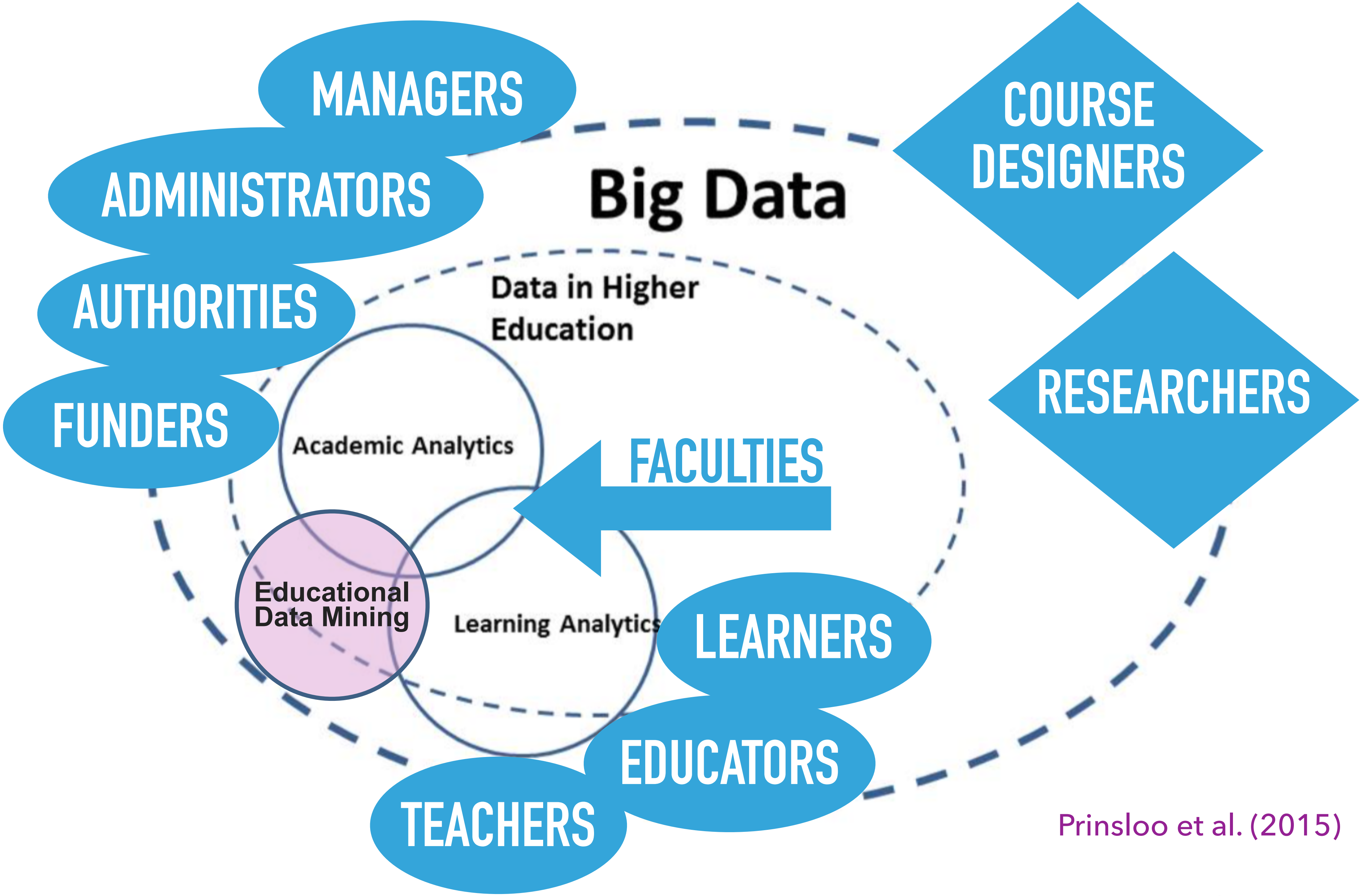
Diagram 1: Mapping Learning and Academic Analytics in the Context of Big Data



Prinsloo et al. (2015)

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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

LAK '11

2012

FIRST FLARE EVENT

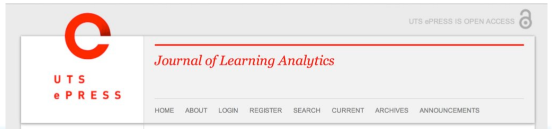
USA (PURDUE), UK (OU), AUSTRALIA (UTS)

FIRST LAK DATASET & CHALLENGE

FIRST LEARNING ANALYTICS SUMMER INSTITUTE

2013

Learning Analytics Summer Institute (LASI)
Stanford University, July 1-5 2013



FIRST ISSUE OF JOURNAL OF LEARNING ANALYTICS

2014

START OF LEARNING ANALYTICS COMMUNITY EXCHANGE PROJECT

LACE

2017

Misiejuk (2017)

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http://www.slate.uib.no/lasi-nordic2017

The 8th International
Learning Analytics & Knowledge Conference
SMC Conference & Function Centre, Sydney, NSW, Australia
March 5–9, 2018
LAK 18
hosted by
THE UNIVERSITY OF SYDNEY
SOLAR
SOCIETY for LEARNING ANALYTICS RESEARCH
HOME
ABOUT
Welcome to LAK'18 – Sydney, Australia

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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

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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

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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 ≠ Learning

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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

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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]

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level

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Kindergarten Middle school
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University Secondary school
Higher education
High school College

implementation

LMS
MOOCS Standards
Ethical
Big data Implementation
Infrastructure
Informal learning
Adaptive learning
Data management Educational data mining
Data literacy Personalised learning
Formal learning Student data
Policy Interoperability
Privacy

outcomes

Data literacy Performance
Learning process Learning
Pedagogy Knowledge building
Learning outcomes
Assessment Impact

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EXAMPLE: CORRELATION BETWEEN USER ACTIONS & FINAL GRADE

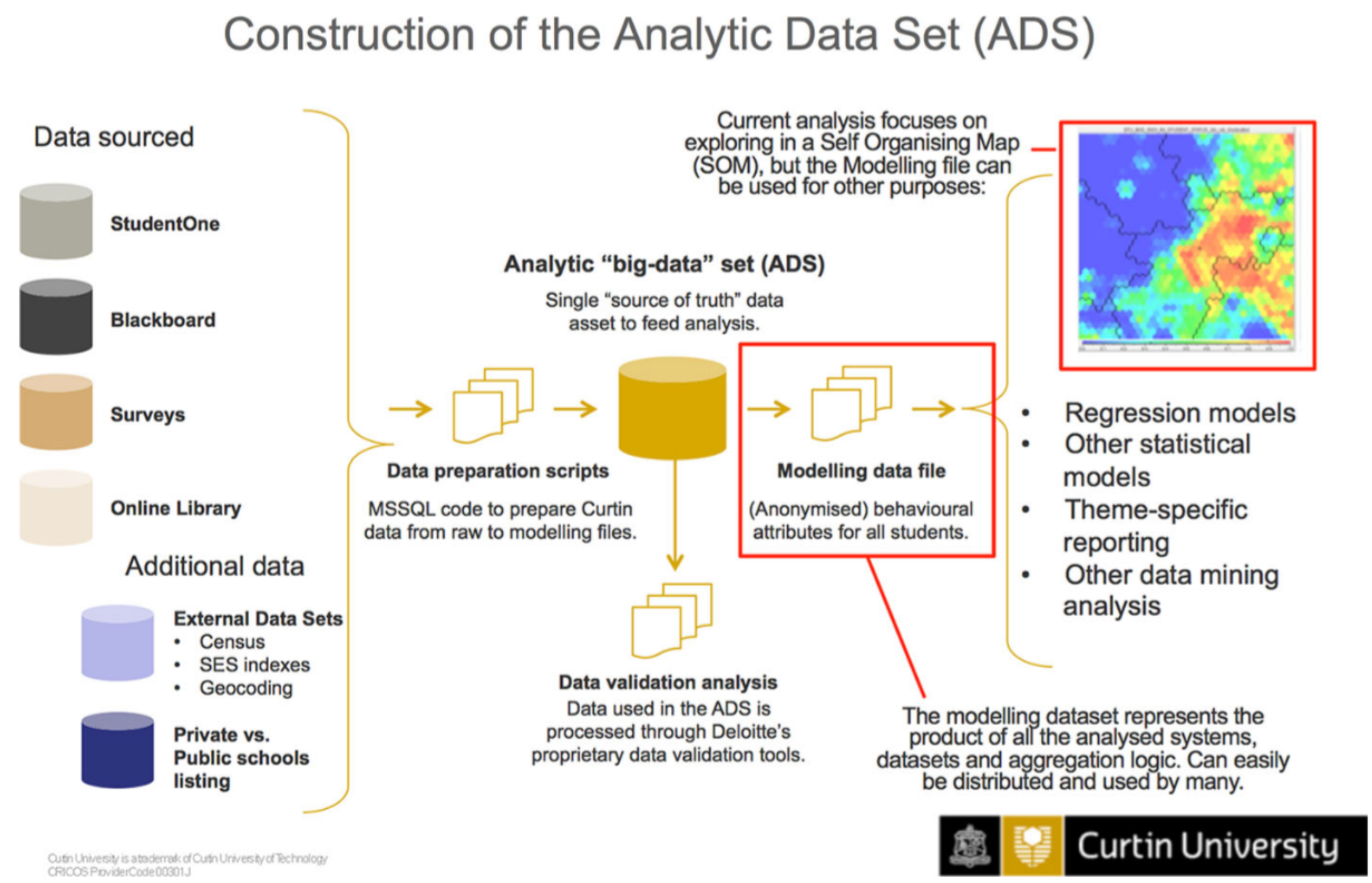

Fig. 4 Data sources, analytic data set (ADS) and self-organizing map

Gibson et al. (2016)

EXAMPLE: MEASURING STUDENT PERFORMANCE

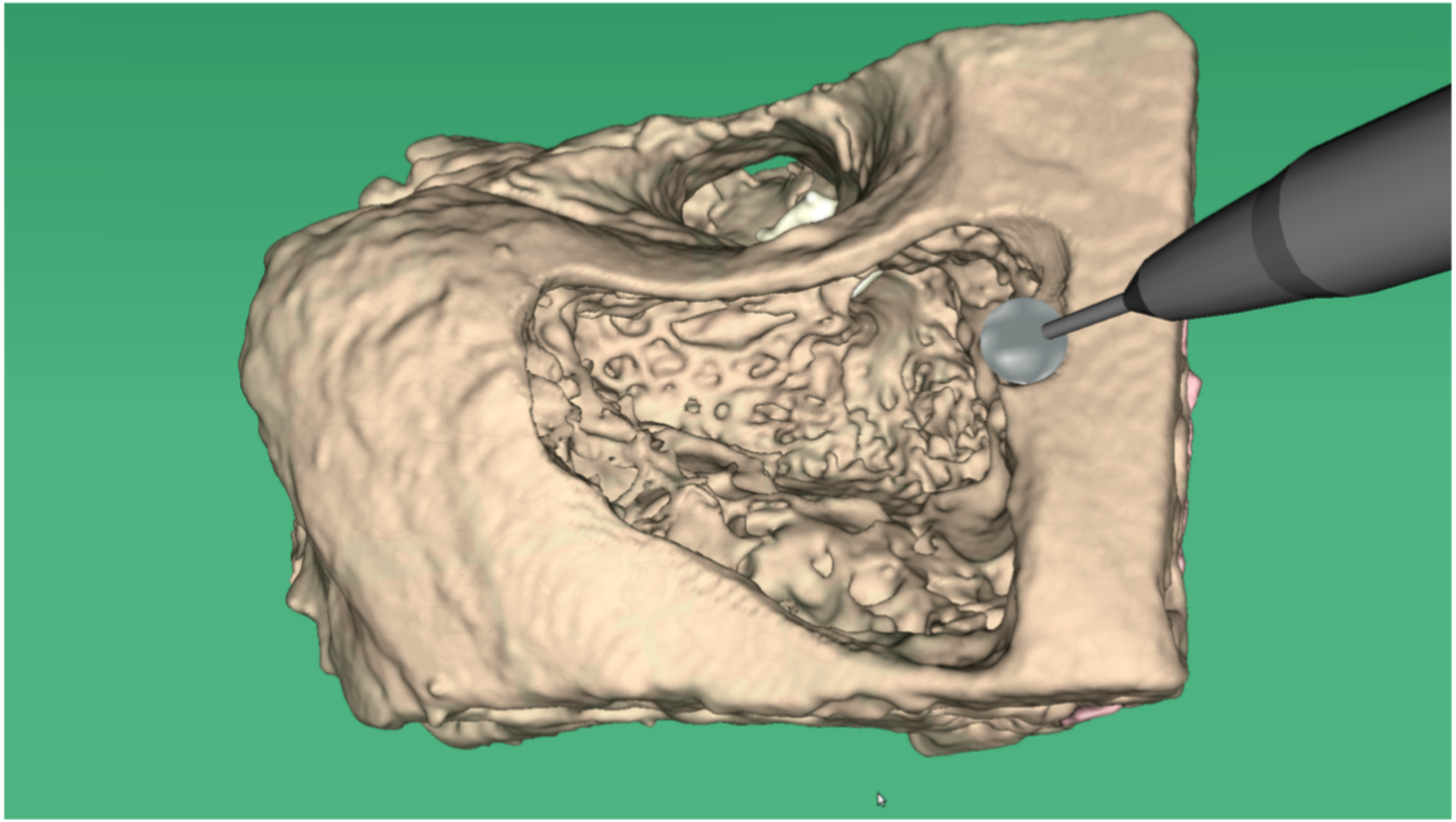

Figure 2: The simulation environment showing the drill and a partially dissected temporal bone

Kennedy et al. (2013)

EXAMPLE: DROPOUT PREDICTOR, INTERVENTION

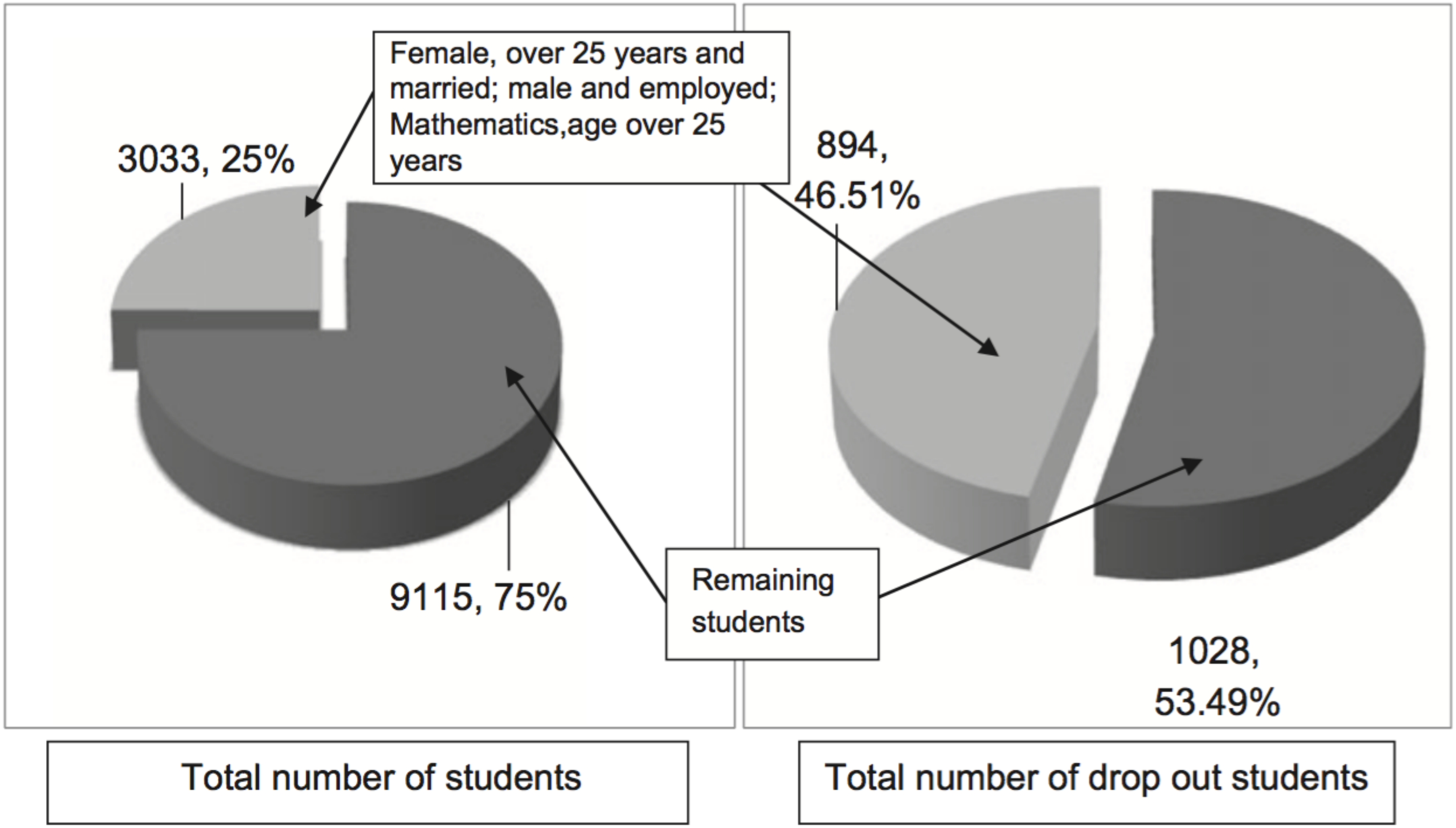

Figure 1. Graphical representation of synthesis of observations.

Yasmin (2013)

EXAMPLE: DATA VISUALISATION, ACTIVITY ENGAGEMENT

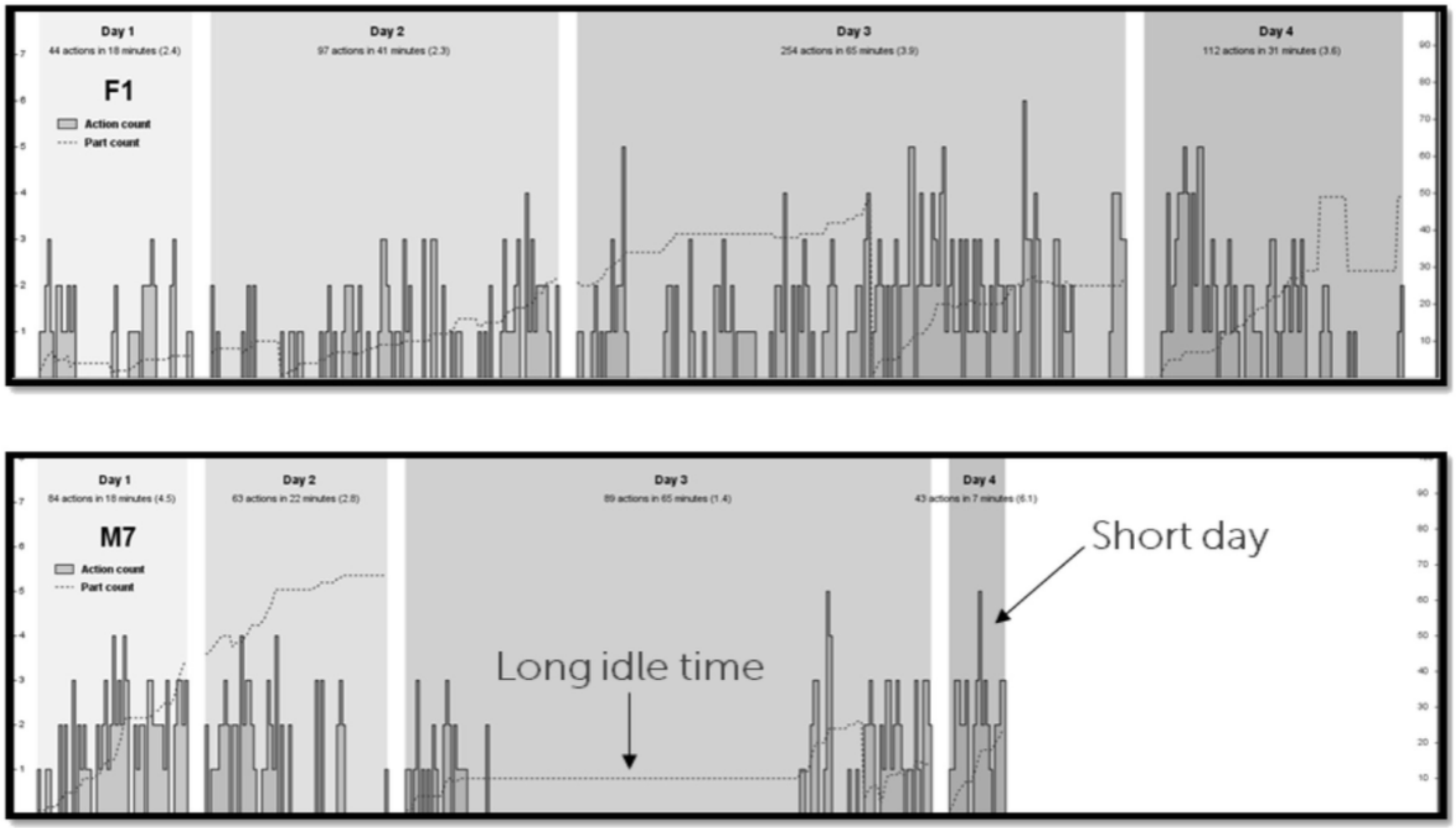

Fig. 6. Time series analysis: A comparison of an engaged student (F1) with a disengaged student (M7). The results conform to our classroom observations.

Xie et al., 2014

EXAMPLE: MODELS OF EMOTION

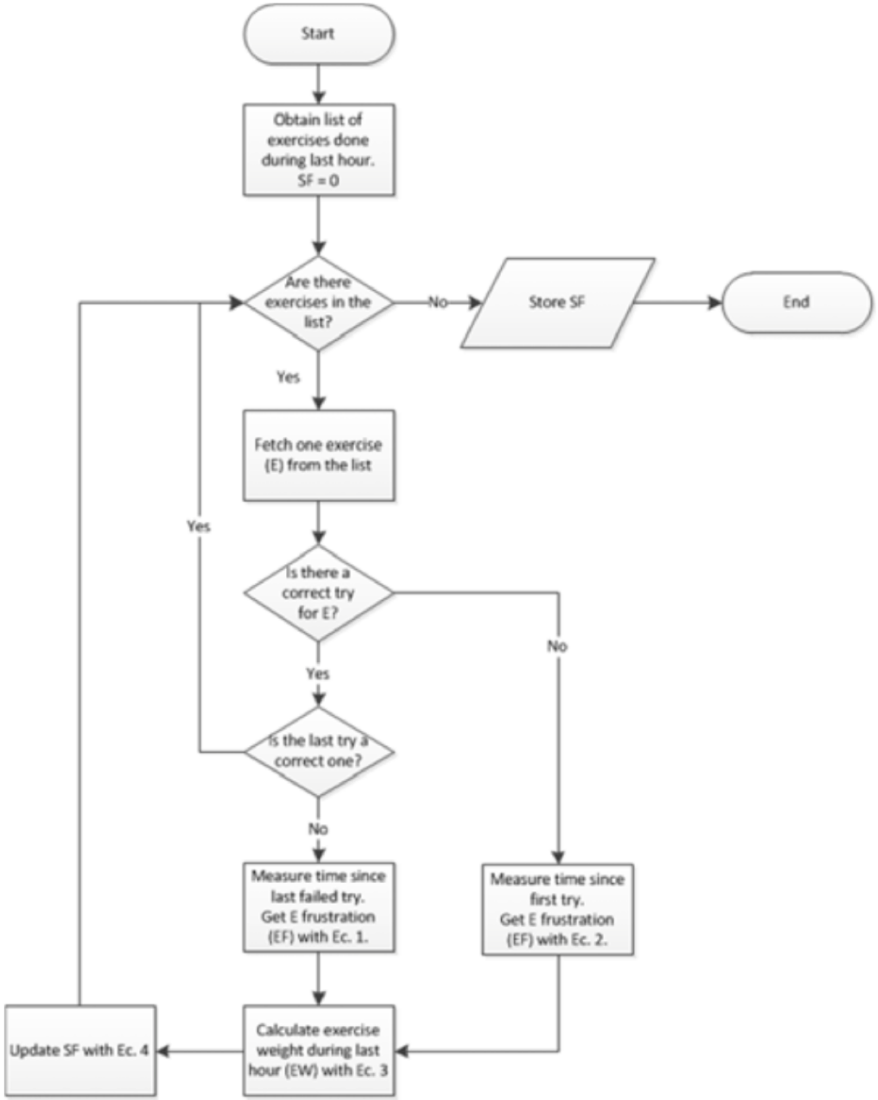

Figure 2: Flow chart of process used to detect frustration

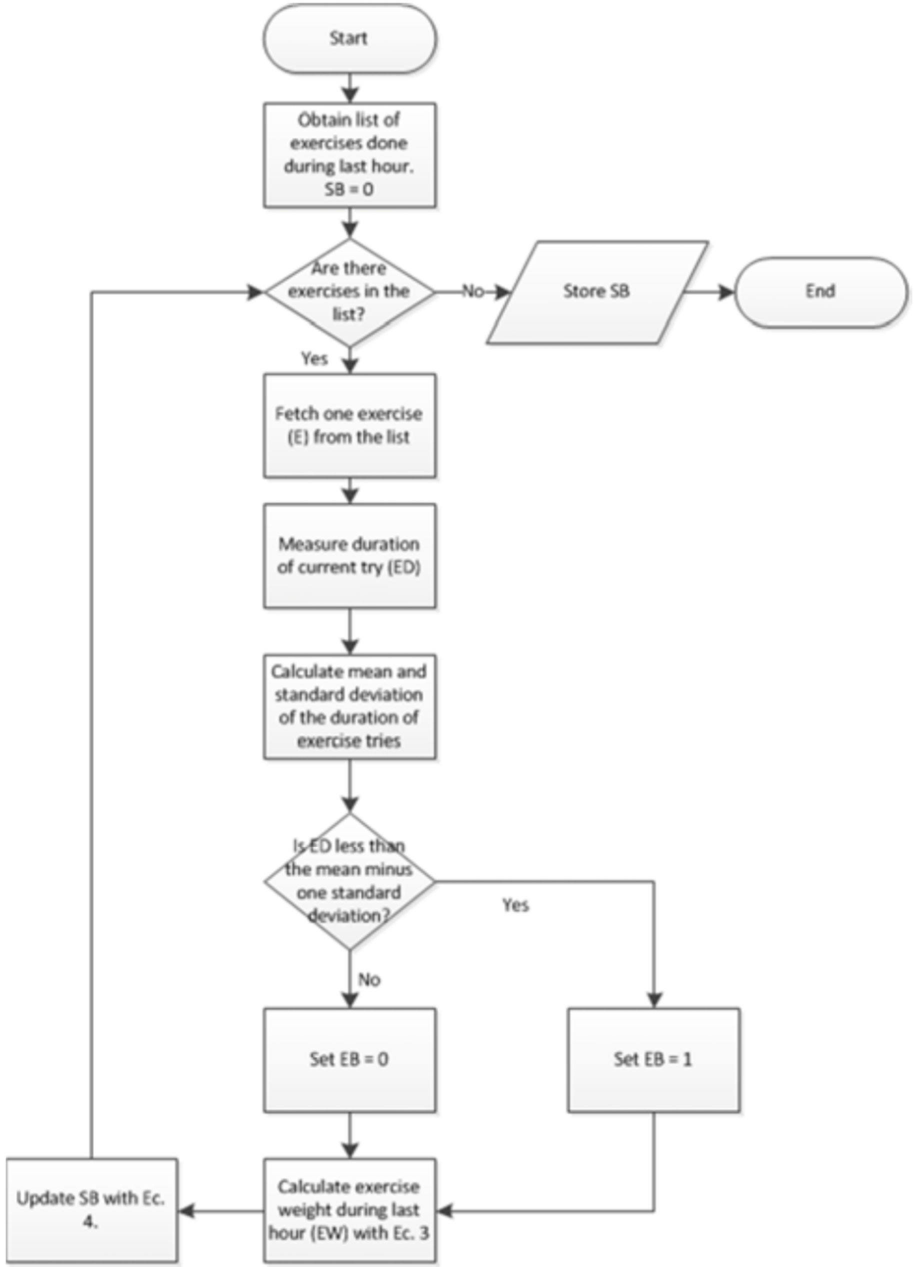

Figure 4: Flow of rules for the detection of boredom

Leony et al. (2015)

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EXAMPLE: TOPICS & PARTICIPATION

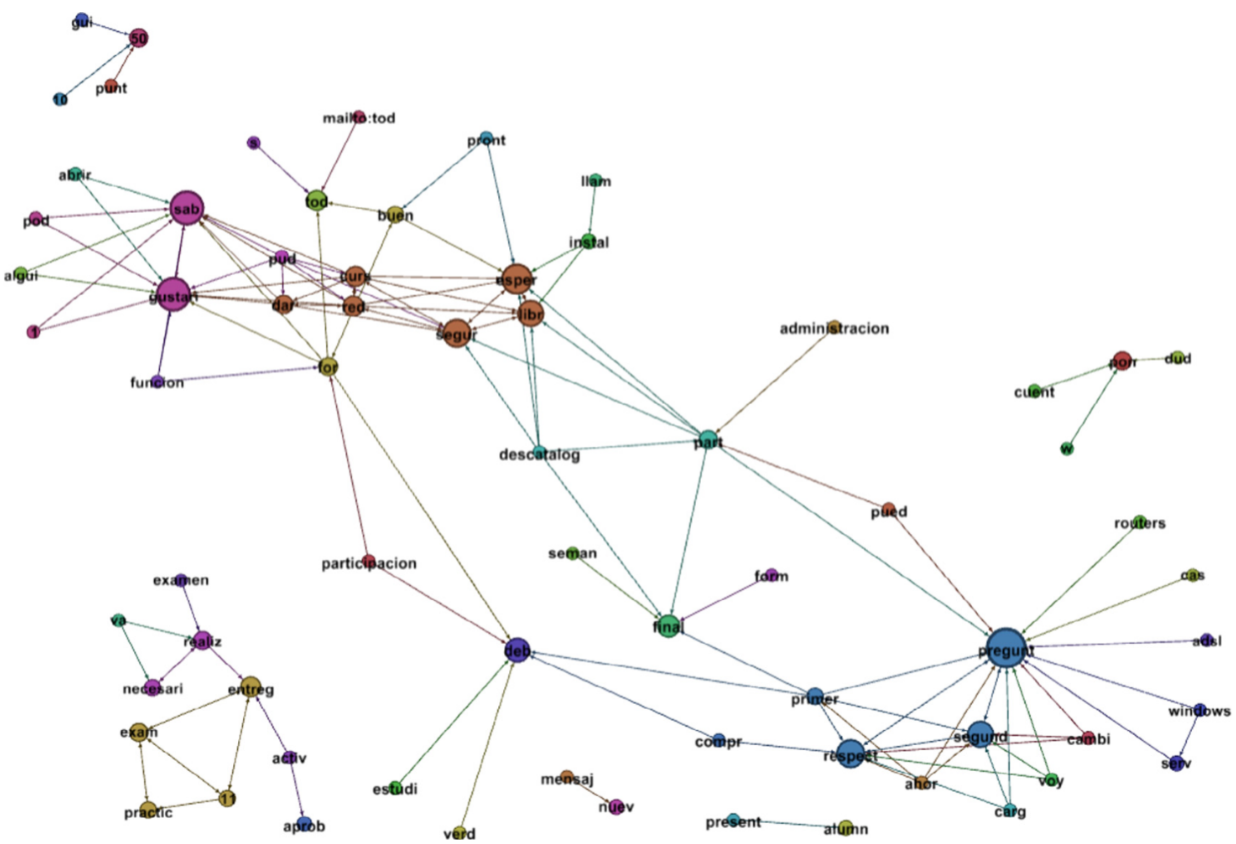

Fig. 5. Topic network deployed from the *Student* forum (course 2011–2012).

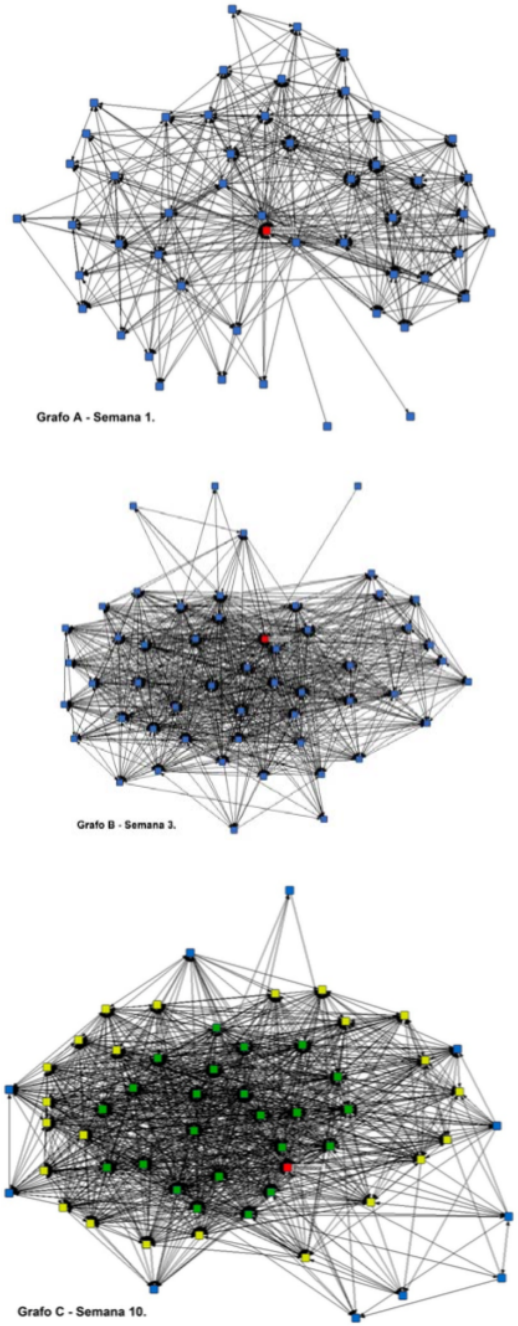

Figure 1: Evolution of the social network in the subject of «Educational Technology» in (A) the first week, (B) the third week, and (C) the tenth week of the course.

Tobarra et al. (2014); Gewerc-Barujel et al. (2014)

EXAMPLE: DASHBOARDS FOR INSTRUCTORS

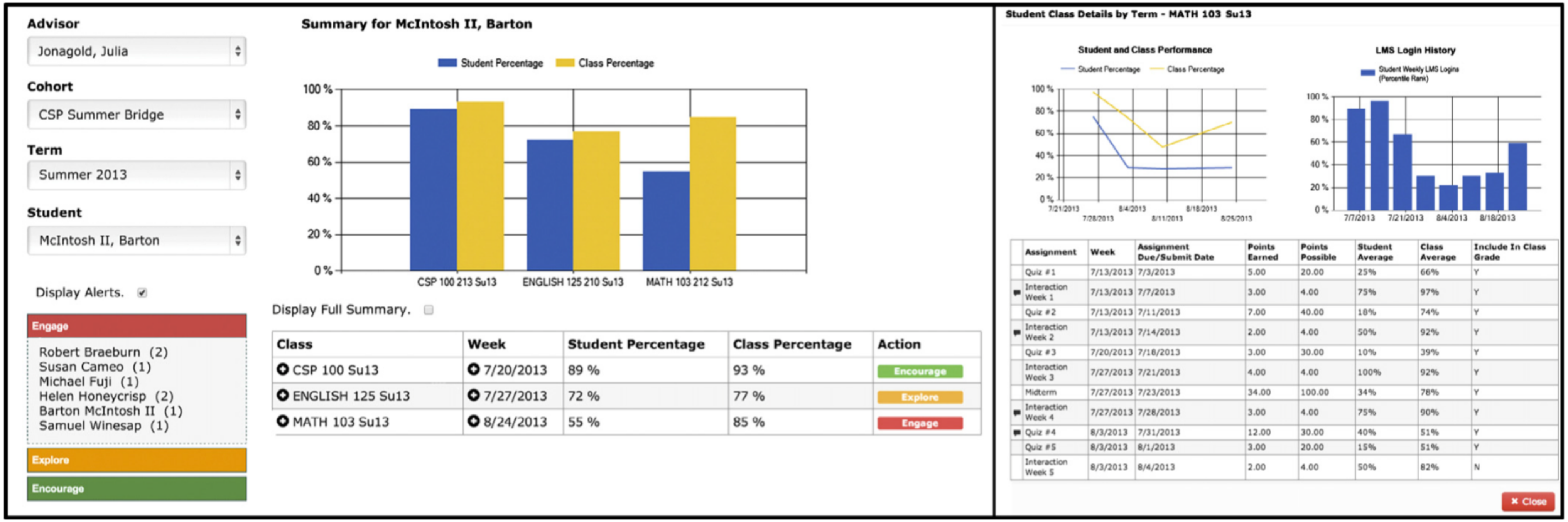

Fig. 1. Example dashboard displays from Student Explorer early warning system. Summary (left) dashboard presents most recent formative data across courses. Course detail (right) dashboard presents all assignment details, a historical performance graph, and LMS login history about a specific course in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

Lonn et al. (2015)

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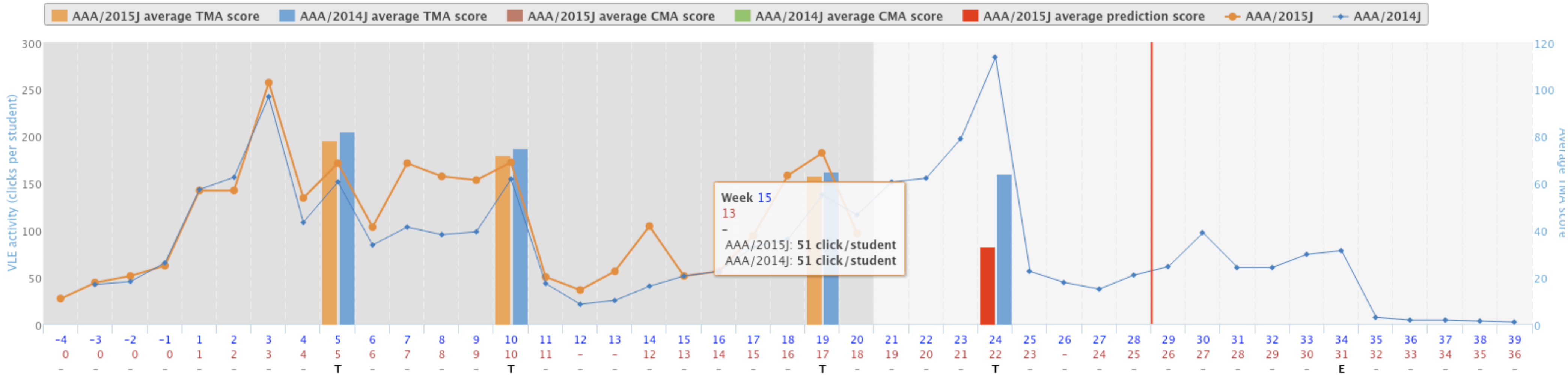
EXAMPLE: OU ANALYSE DASHBOARD FOR INSTRUCTORS

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

AAA 2015J - Week 20

Time machine (choose week): 20

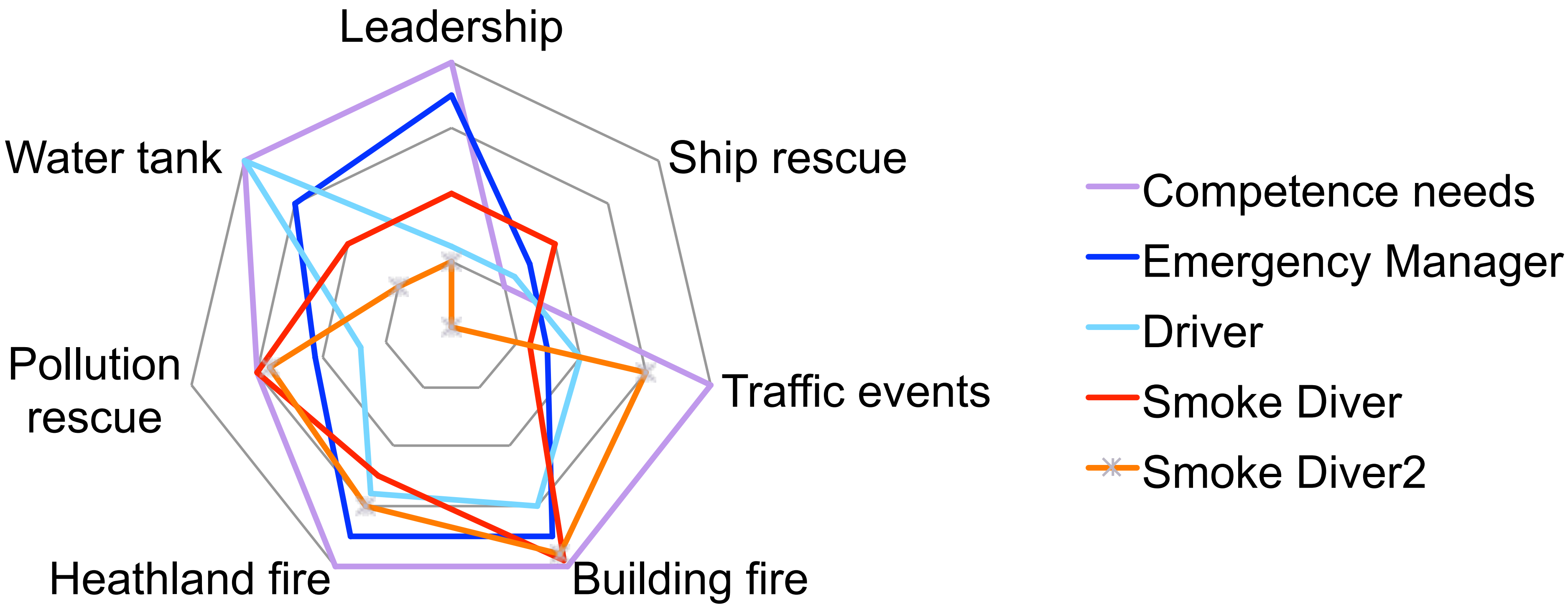


Registered students	VLE active students	Students predicted not to submit	Last TMA result (average)	TMA submissions
910	635	307	63	0
↓9 *WRT* Previous week	↓121 *WRT* Previous week	↑116 *WRT* Previous week	↓2.4 *WRT* Previous presentation	↓586 *WRT* Previous week

25 ▾ Export Select columns ▾

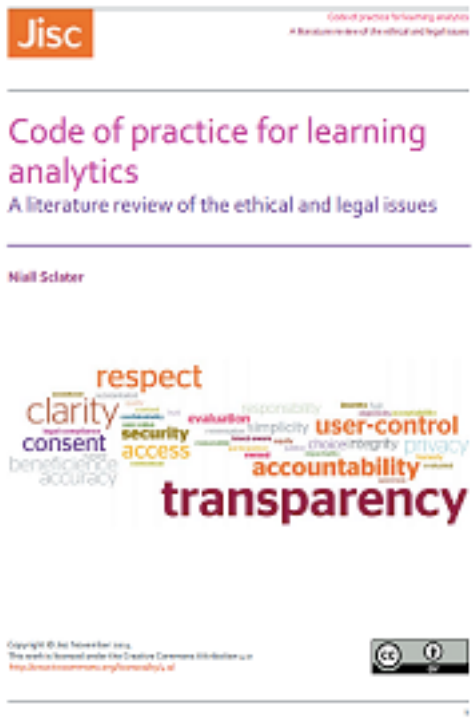
Student PI	Name	TMA	Risk of non-submission	Next TMA prediction	Next TMA grade prediction	Risk of Failure	Final result prediction	Final result
A0000194	Flores Joseph	71 NS NS		Not submit	Not Submit		Fail	Fail: no resit
A0000251	Taylor Raymond	76 84 72		Submit	Fail		At risk	Pass
A0000305	Thomas George	98 98 90		Not submit	Not Submit		At risk	Pass
A0000511	Allen Patrick	97 97 95		Submit	Fail		Pass	Distinction
A0000653	Jones Robert	95 94 89		Submit	Fail		Pass	Pass
A0000658	James Catherine	98 94 97		Submit	Fail		Pass	Distinction
A0000742	Turner Timothy	91 76 74		Submit	Fail		At risk	Pass

EXAMPLE: VISUALISATIONS



Wasson & Hansen

EXAMPLE: ETHICS & PRIVACY



The DELICATE Checklist
to implement trusted
Learning Analytics

LACE

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.

LACE Project is supported by the European Commission Seventh Framework Programme under grant 619424.

Learning Analysis Research Objectives

- Student/student behaviour modelling
- Prediction of performance
- Increase (self-) reflection & (self-) awareness
- Prediction of dropout & retention
- Improve assessment & feedback services
- Recommendation of resources

Papamitsiou & Economides (2014)
40 papers 2008-2013

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SOME IMPRESSIONS

- wide range of research topics
- few impact studies ("very little credible research has demonstrated any large-scale benefits to learners or institutions" (see also Ferguson et al. 2016))
- 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

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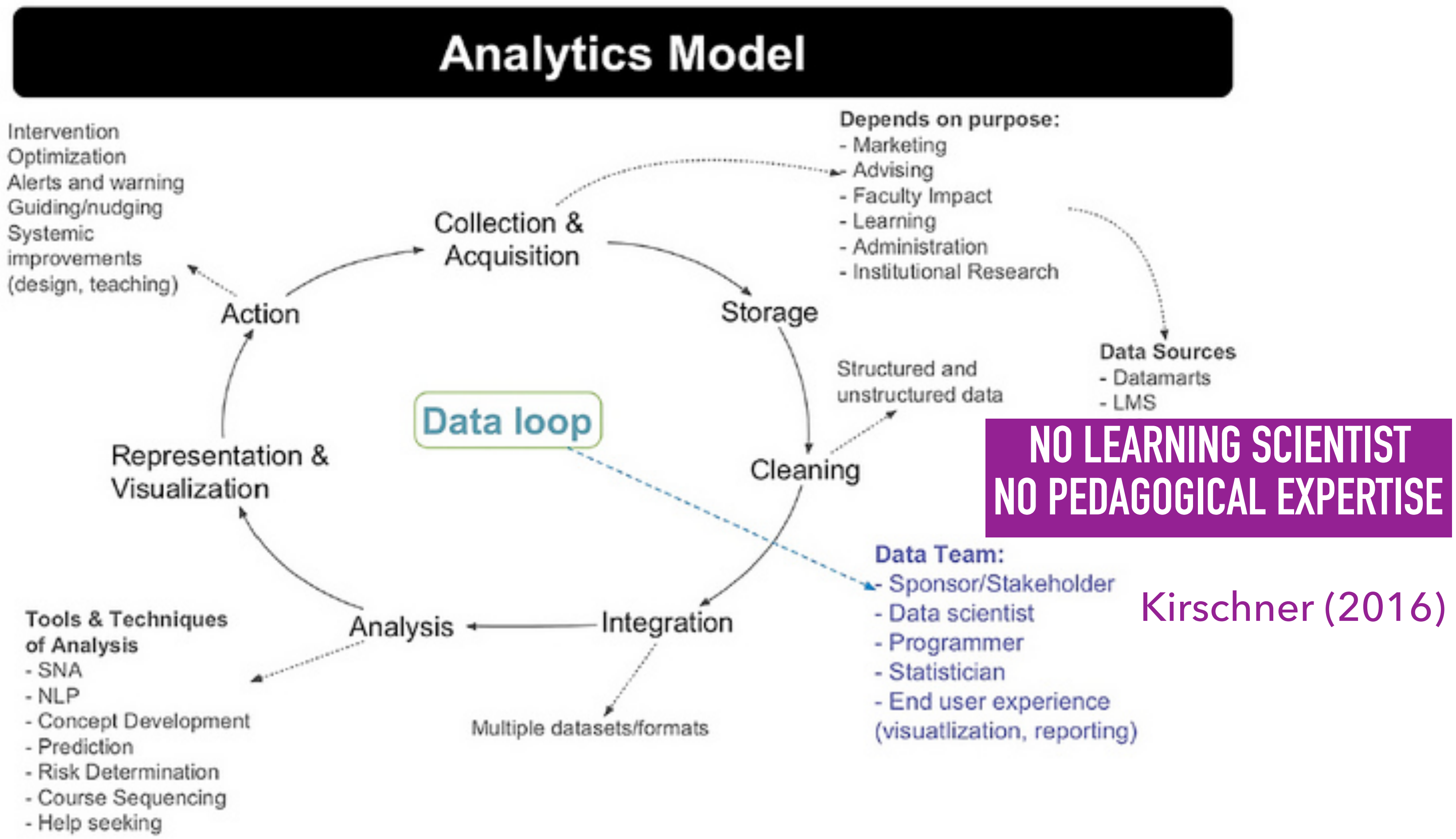

Siemens (2013)


European Commission

JRC SCIENCE FOR POLICY REPORT

Research Evidence on the Use of Learning Analytics

Implications for Education Policy

Editors:
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Authors and contributors:
Rebecca Ferguson, Andrew Brasher,
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2016

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Joint Research Centre

MAIN FINDINGS


European Commission

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- 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

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KEY QUESTIONS

KEY QUESTIONS

LACE

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?

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LEARNING ANALYTICS

IS IN ITS INFANCY !

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