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Learning Analytics:

Realising the Potential for Personalised Progress

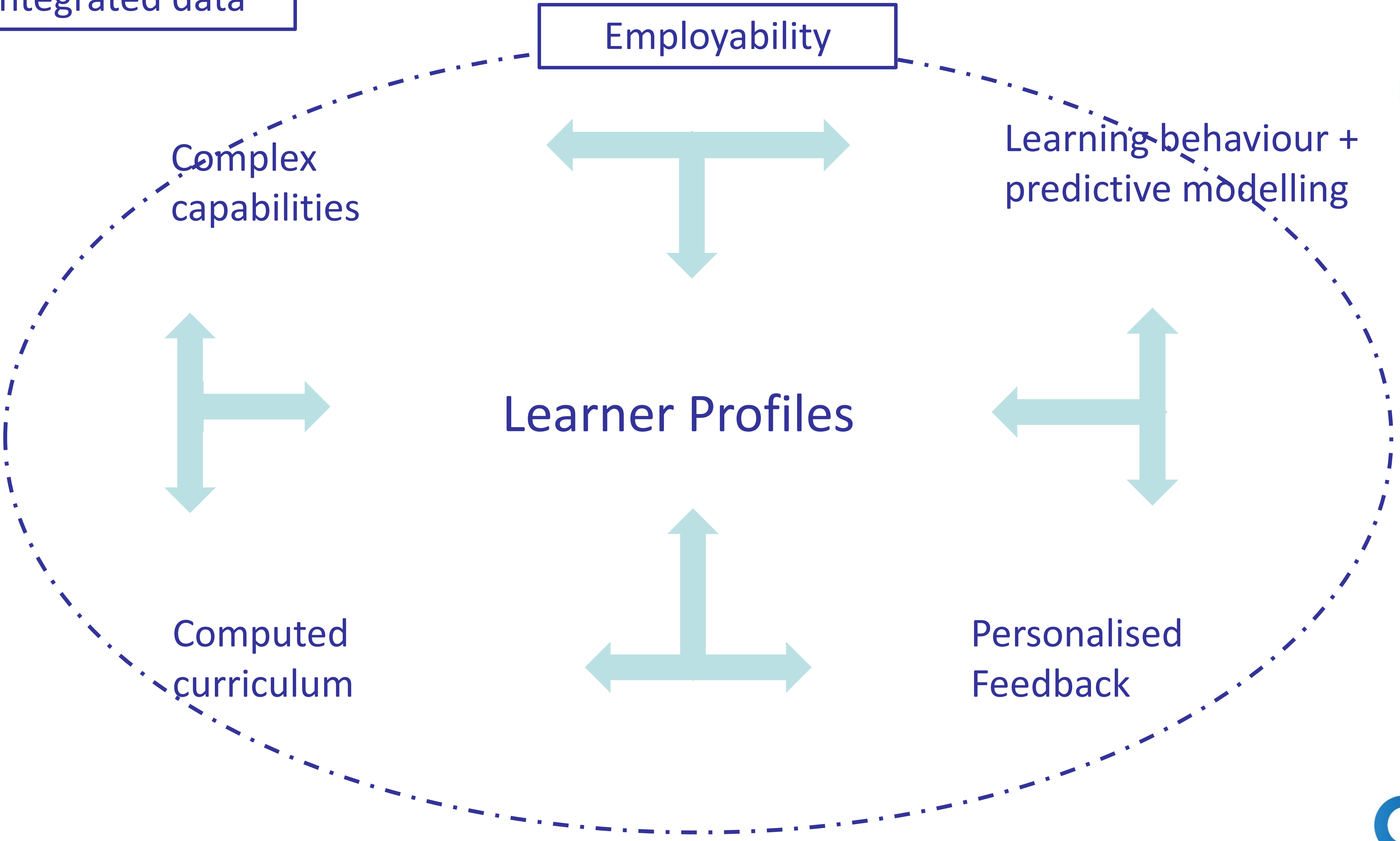
University of South Australia

Australia's University of Enterprise

Key Points:

- From conceptualization to prediction to innovation
- Need a purposeful move to translation and impact
- A need for alternate methodologies from micro to macro
- Data integration and improving validity of measures
- Focus on leadership and advocacy
- Intentional bridge building across disciplines

Integrated data



Overview:

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- LA Maturity
- Current trends
- Emergent LA work
- Next Generation LA

C3L

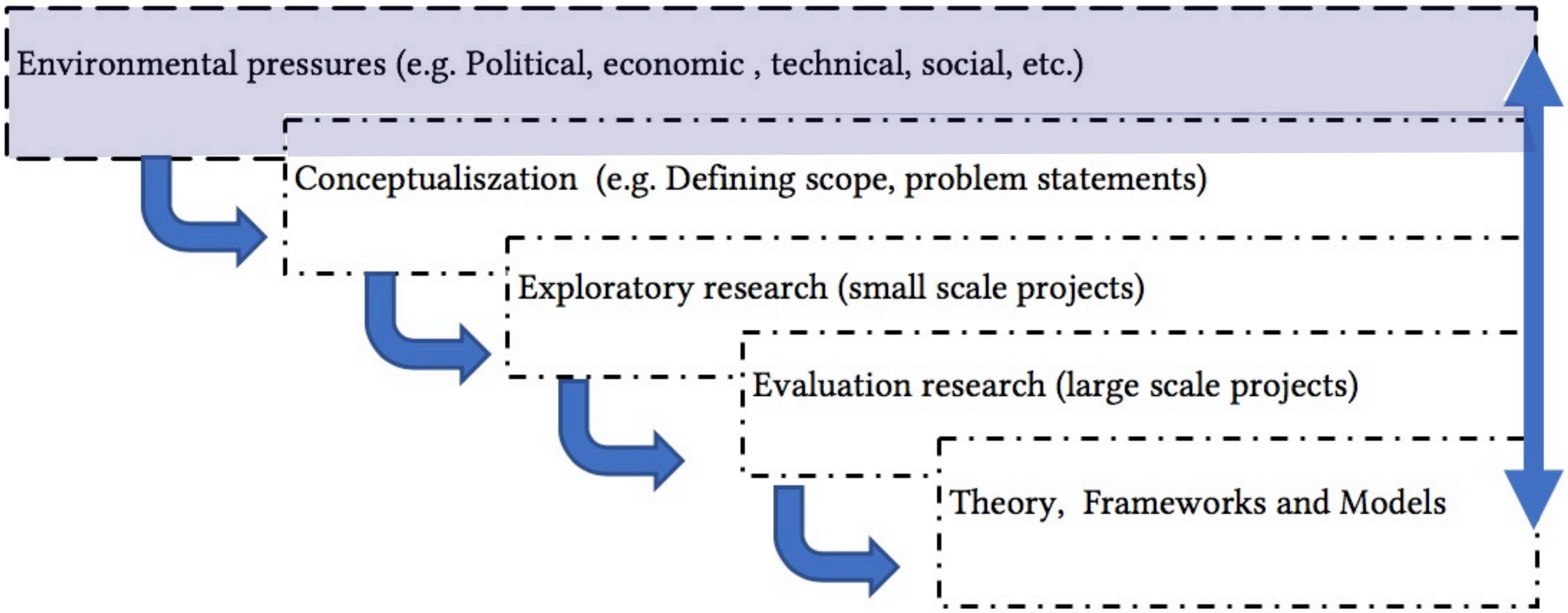
Learning Analytics:

…is the *collection*, *collation*, *analysis* and *reporting* of data about learners and their contexts, for the purposes of **understanding** and **optimizing** learning

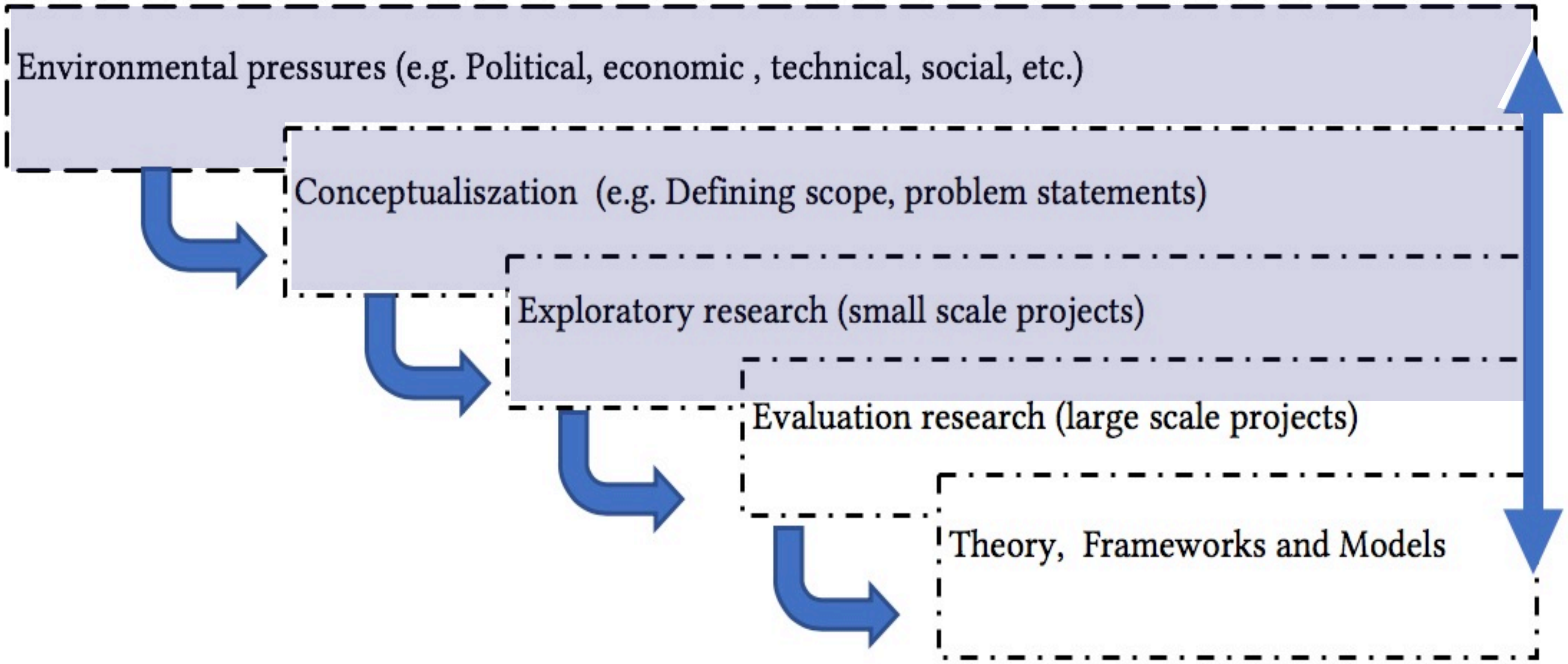
LA Maturity:

- Over the past decade LA has rapidly moved from definition to prediction to analytical models and developments

LA Maturity:


Environmental pressures (e.g. Political, economic , technical, social, etc.)
Conceptualiszation (e.g. Defining scope, problem statements)
Exploratory research (small scale projects)
Evaluation research (large scale projects)
Theory, Frameworks and Models

LA Maturity: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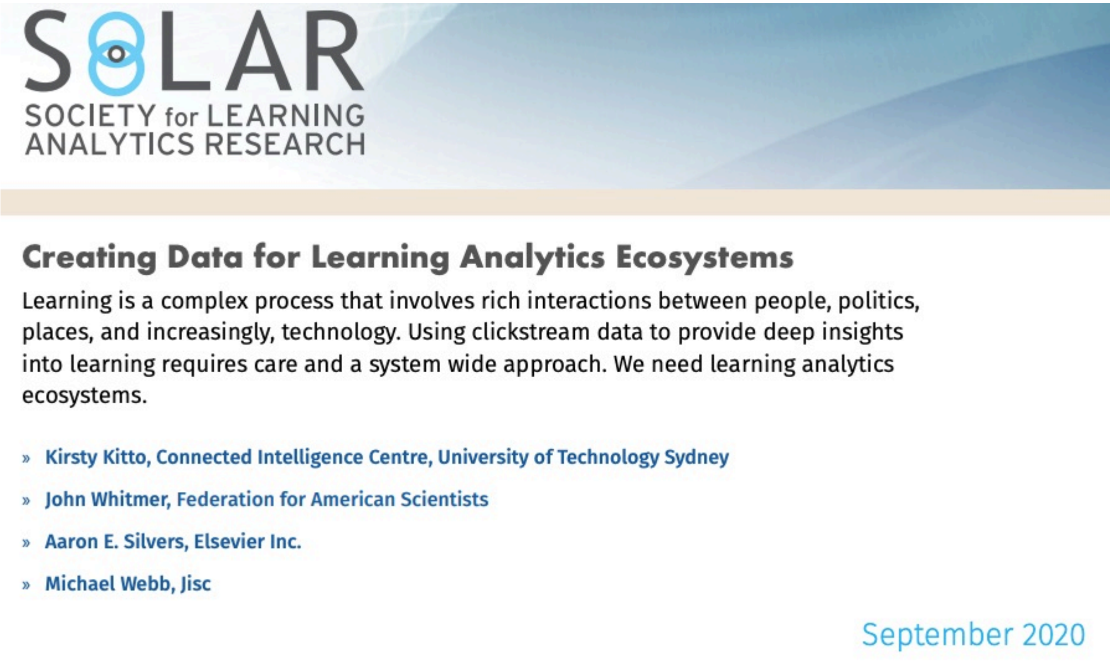
Conceptualiszation (e.g. Defining scope, problem statements)
Exploratory research (small scale projects)
Evaluation research (large scale projects)
Theory, Frameworks and Models

LA Maturity:

- Feedback, dashboards, multi-modal data and how these improve Self-Regulated Learning (SRL).
- A recognition of the need for alternate and integrated data


SOLAR
SOCIETY for LEARNING ANALYTICS RESEARCH

Creating Data for Learning Analytics Ecosystems

Learning is a complex process that involves rich interactions between people, politics, places, and increasingly, technology. Using clickstream data to provide deep insights into learning requires care and a system wide approach. We need learning analytics ecosystems.

» Kirsty Kitto, Connected Intelligence Centre, University of Technology Sydney
» John Whitmer, Federation for American Scientists
» Aaron E. Silvers, Elsevier Inc.
» Michael Webb, Jisc

September 2020

https://www.solaresearch.org/wp-content/uploads/2020/09/SoLAR_Position-Paper_2020_09.pdf

Current Trends:

Learning analytics generates increased feedback opportunities

But what are we doing with that feedback?

- Predictive models/Recommender systems
- LA dashboards

Current Trends:

University of South Australia

Courses (current)

(+) show previous courses

Study Period 5 - 2015

Course	Current Grade	Last Site Login	Risk Level	Late Assessment Submissions	Number of Site Logins	Forum Contributions	Lecture Recording Views
ACCT Accounting Internal, City West	C – Course Average: P1	5 days ago (12 Sep 2015) Course Average: 2 days ago	Low Course Average: Low	0 – Course Average: 0	29 ▼ Course Average: 36	3 ▼ Course Average: 12	10 ▼ Course Average: 4
MARK Market Internal, City West	P2 ▼ Course Average: C	1 days ago (15 Sep 2015) Course Average: 1 days ago	Medium Course Average: Medium	1 ▼ Course Average: 0	10 ▲ Course Average: 11	0 ▼ Course Average: 12	4 ▲ Course Average: 4
COMP Business External, City West	C ▲ Course Average: C	1 days ago (15 Sep 2015) Course Average: 2 days ago	Low Course Average: Low	0 – Course Average: 0	10 ▼ Course Average: 36	0 – Course Average: 0	10 ▼ Course Average: 4
INFS Business Internal, City West	HD – Course Average: P2	0 days ago (16 Sep 2015) Course Average: 4 days ago	Lowest Course Average: Lowest	0 – Course Average: 0	46 ▲ Course Average: 11	20 ▼ Course Average: 5	10 ▲ Course Average: 8

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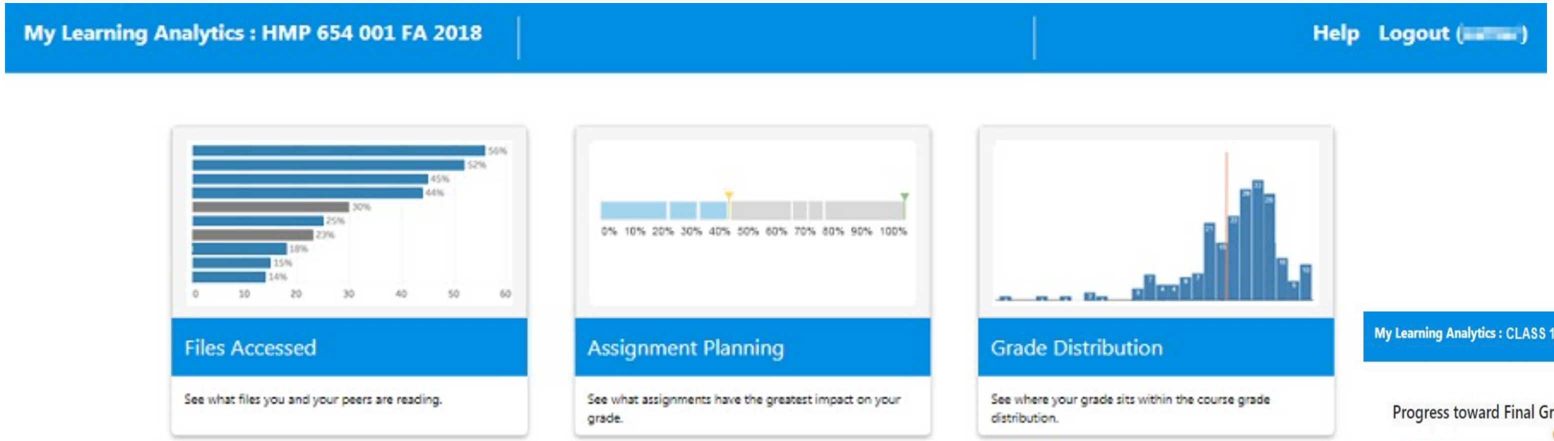
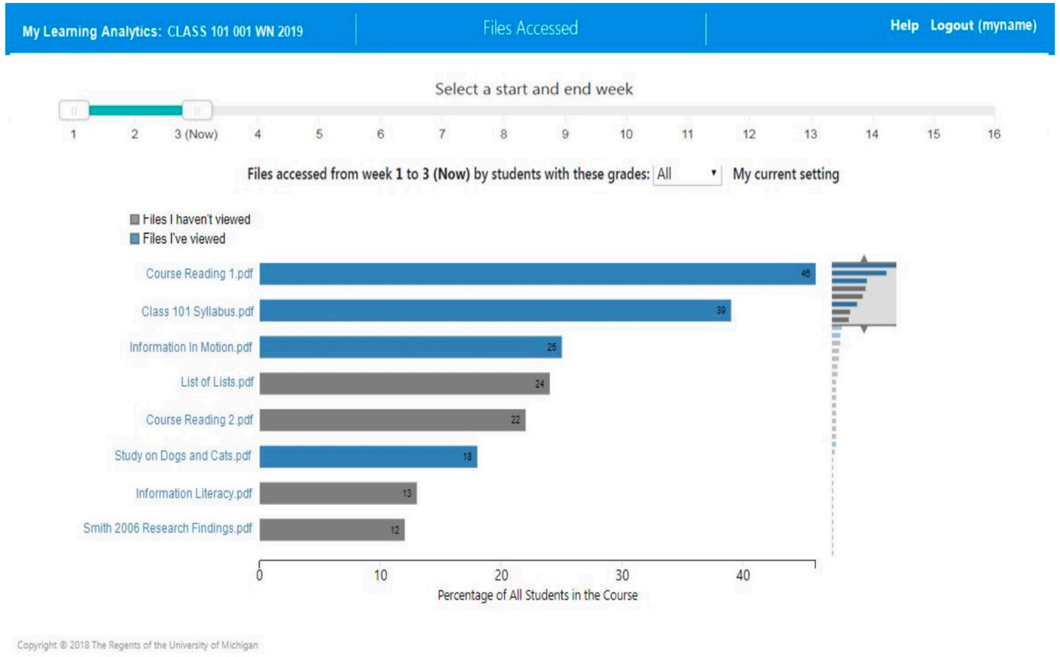
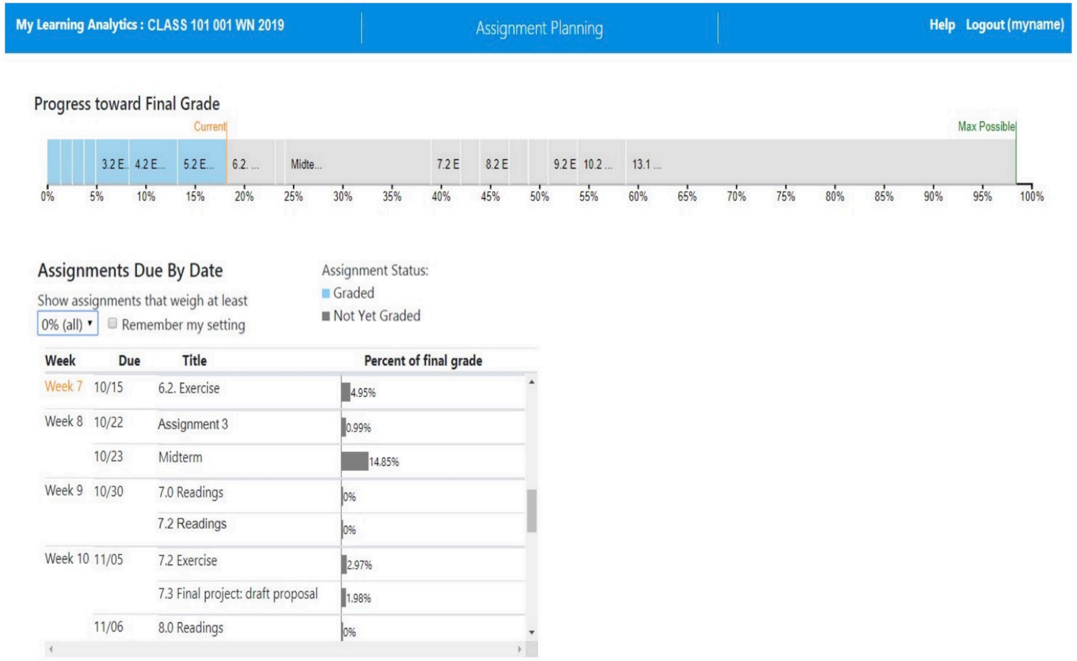
Current Trends:







Kia, F. S., et al (2020). How patterns of students dashboard use are related to their achievement and self-regulatory engagement. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 340-349).

Current Trends:

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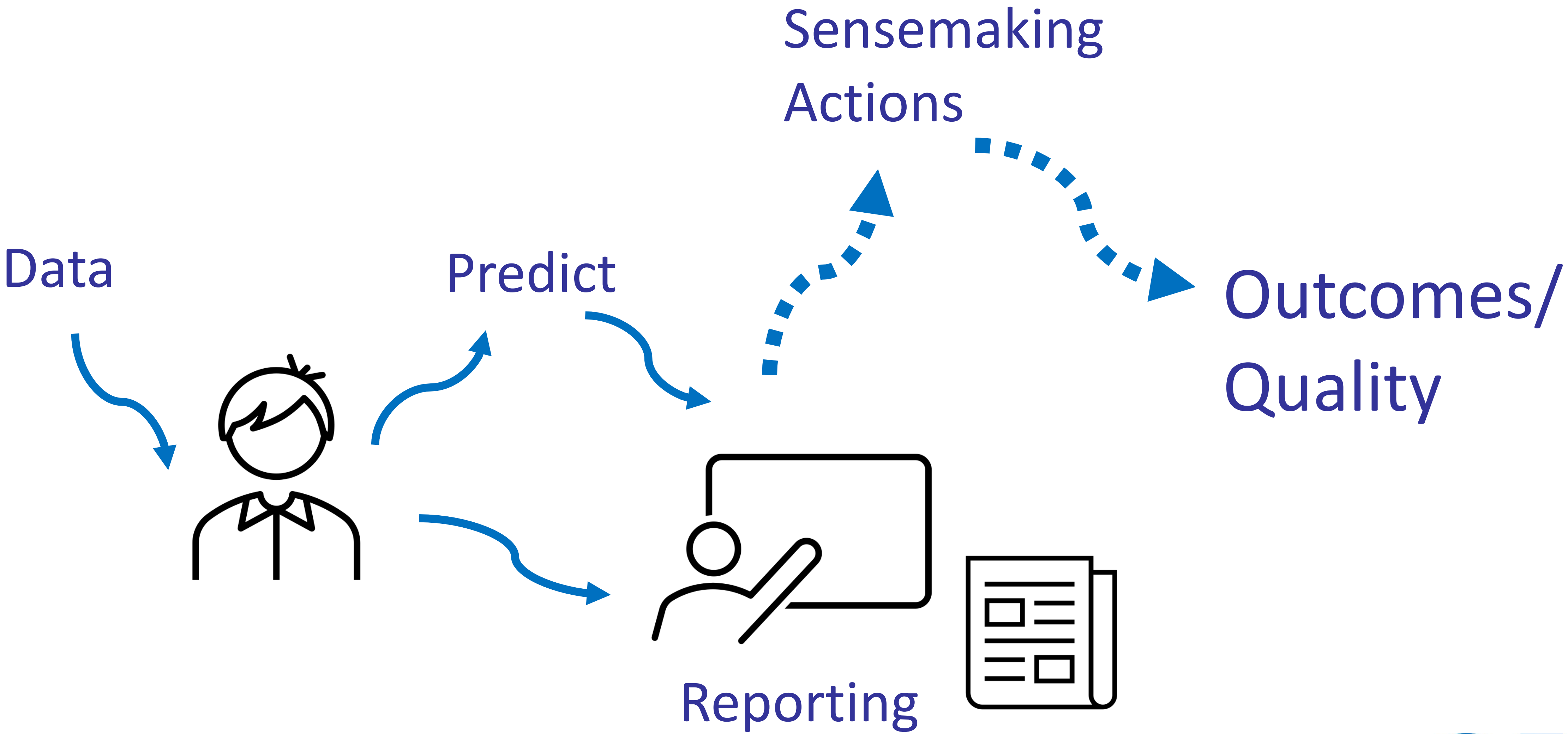
- LA – Dashboards failing to support Student Self Regulated Learning (SRL)

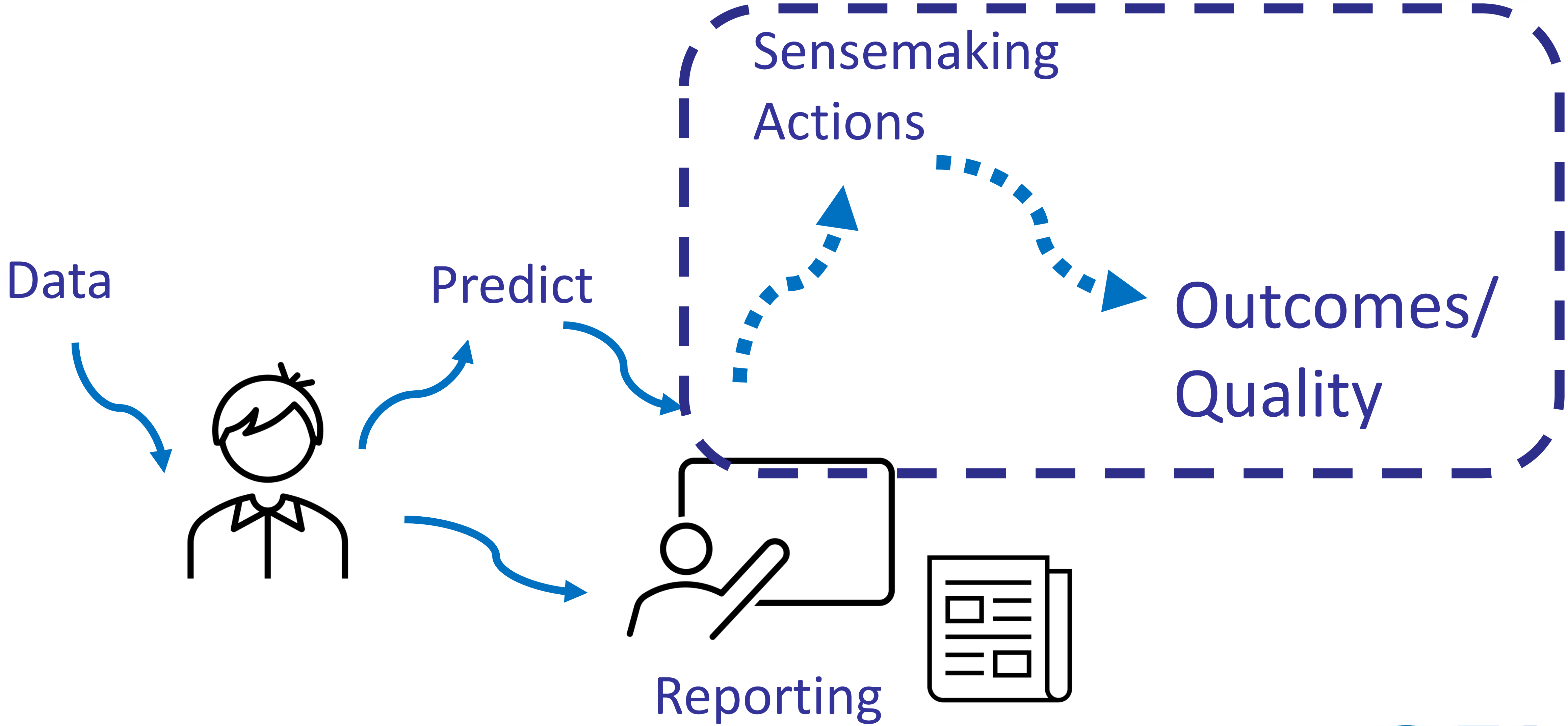
- LA – Dashboards are (at present) diagnostic **not** developmental

W. Matcha, N. A. Uzir, D. Gašević and A. Pardo, "A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective," in *IEEE Transactions on Learning Technologies*, vol. 13, no. 2, pp. 226-245, 1 April-June 2020, doi: 10.1109/TLT.2019.2916802

Current Trends:



Current Trends:



Learning Analytics :

Pursuit of personalised and adaptive learning

Predictive models

LA Dashboard of engagement activity

Assessment and feedback

Learner Profiles:

A learner profile comprehensively represents a learner's understanding, competencies, skills, and attributes.

Personalised progress:

Complex capabilities

Learning behaviour + predictive modelling

Learner Profiles

Computed curriculum

Personalised Feedback

Integrated data

Employability

Complex capabilities

Learning behaviour + predictive modelling

Learner Profiles

Computed curriculum

Personalised Feedback

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C3L

Individual Student Overview

Full Name
Student name

Student Id

ED Id

Gender

DOB

House

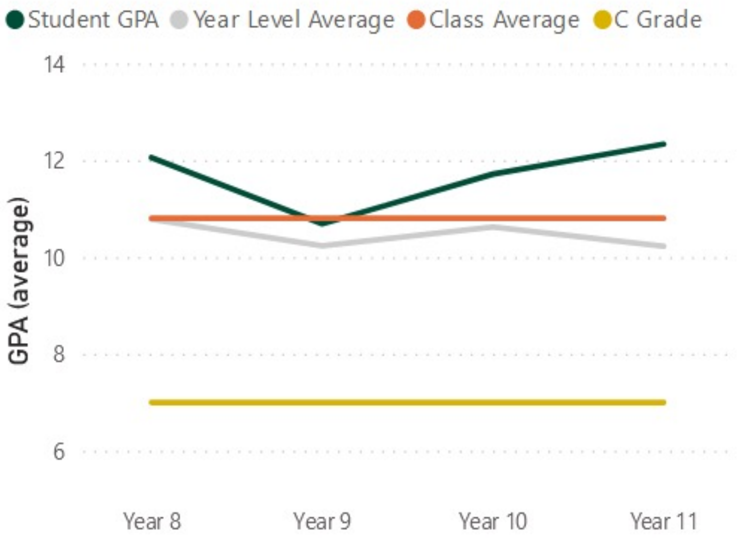
Roll Class

Current Result	Remembering	Understanding	Applying	Analysing	Evaluating	Creating	Creating+
GPA				11.59			
NAPLAN		7.67					
PAT MATHS		128.30					
PAT READING		132.00					

Attendance

1071/1256 (85%)
Late: 1 (approved 0%)
NP: 185 (approved 99.46%)

Student GPA



Student Grades

Subject Name	Grade
8 ARTS - DIGITAL MEDIA	A-
8 ARTS - MUSIC	B+
8 DESIGN & TECHNOLOGIES	A-
8 DESIGN & TECHNOLOGIES C	A
8 ENGLISH	A-
8 HISTORY	B+
8 MATHEMATICS	B-
8 PHYSICAL EDUCATION C	B+
8 SCIENCE	B+

Year & Semester

- Year 8 Semester 1
- Year 8 Semester 2
- Year 9 Semester 1
- Year 9 Semester 2
- Year 10 Semester 1
- Year 10 Semester 2
- Year 11 Semester 1

Individual Student Overview

Student Name

Student name

Student Id

SACE Id

Gender

DOB

House

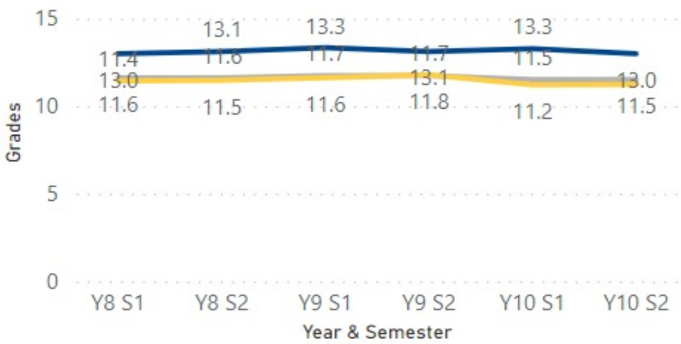
Roll Class

Grades

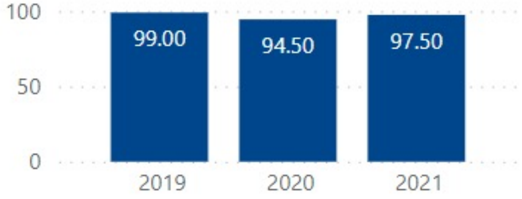
Year 10 Semester 2

Subject Name	Grade	Application	Behaviour
American History	A	E	E
Art	A-	E	E
Business, Finance & the Law	A-	E	E
Business, Finance, and the Law	A	E	E
Commerce	A	E	E
Design and Technologies	A	E	E
Design and Technologies	B+	E	E

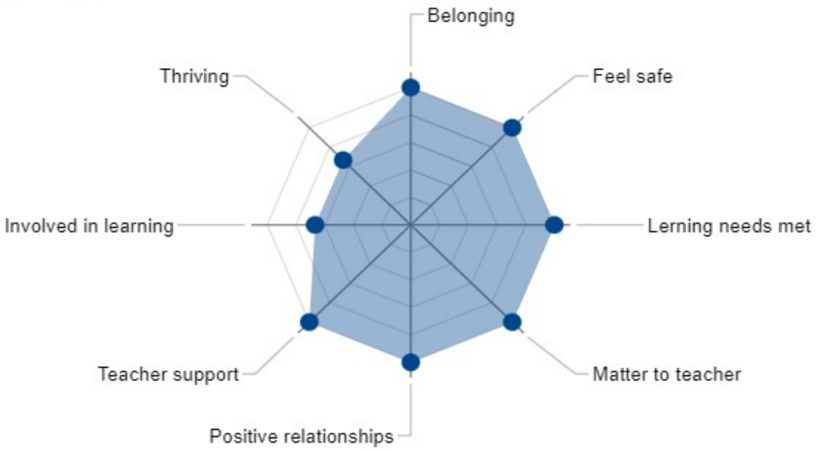
GPA Over Time



Attendance Percent by Year



Pulse Check



Co-curricular and Leadership

Year	Term	Details
2020	Winter	Academic Endeavour - S1
2020	Winter	Academic Excellence - S1
2021	Winter	Activities Day
2021	Winter	Community Awareness Day (CAD)
2021	Winter	De La Salle Day
2021	Winter	Driver Education
2020	Winter	Netball
2021	Winter	Netball

SEQTA

English	13
Science	13
Maths	12

PAT Score

Maths	271.40
Reading	271.90

Creative thinking:

- A core capability – highly valued
- Numerous perspectives and understandings
- Difficult to assess

Creative thinking:

Psychology of Aesthetics, Creativity, and the Arts

ISSN: 1931-3896

https://doi.org/10.1037/aca0000510

Automated Scoring of Figural Creativity Using a Convolutional Neural Network

David H. Cropley and Rebecca L. Marrone
The Centre for Change and Complexity in Learning, University of South Australia

One of the abiding challenges in creativity research is assessment. Objectively scored tests of creativity such as the Torrance Tests of Creativity and the test of Creative Thinking–Drawing Production (TCT-DP; Urban & Jellen, 1996) offer high levels of reliability and validity but are slow and expensive to administer and score. As a result, many creativity researchers default to simpler and faster self-report measures of creativity and related constructs (e.g., creative self-efficacy, openness). Recent research, however, has begun to explore the use of computational approaches to address these limitations. Examples include the Divergent Association Task (Olson et al., 2021) that uses computational methods to rapidly assess the semantic distance of words, as a proxy for divergent thinking. To date, however, no research appears to have emerged that uses methods drawn from the field of artificial intelligence to assess existing objective, figural (i.e., drawing) tests of creativity. This article describes the application of machine learning, in the form of a convolutional neural network, to the assessment of a figural creativity test—the TCT-DP. The approach shows excellent accuracy and speed, eliminating traditional barriers to the use of these objective, figural creativity tests and opening new avenues for automated creativity assessment.

Creative thinking:

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- Whole of School model
- Students presented with creativity task – aligned with discipline
- Assessed using AI model – scalable and reliable
- Demonstrate individual progress in creative thinking skills

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Complex problem solving:

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- AI integration (Human – AI interactions)
- Multi-modal data
- Complex capabilities
- Feedback on teamwork/ problem solving

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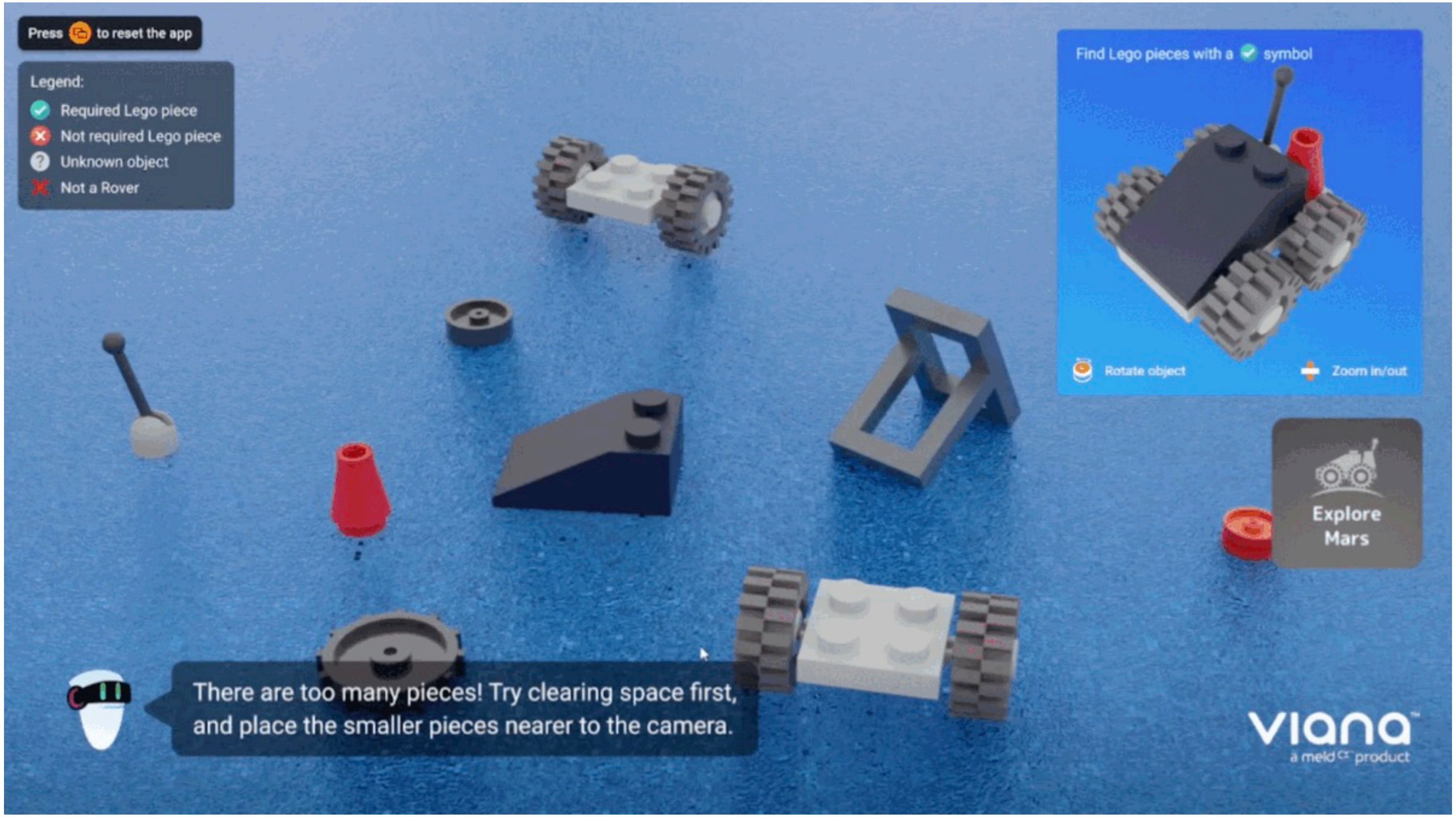
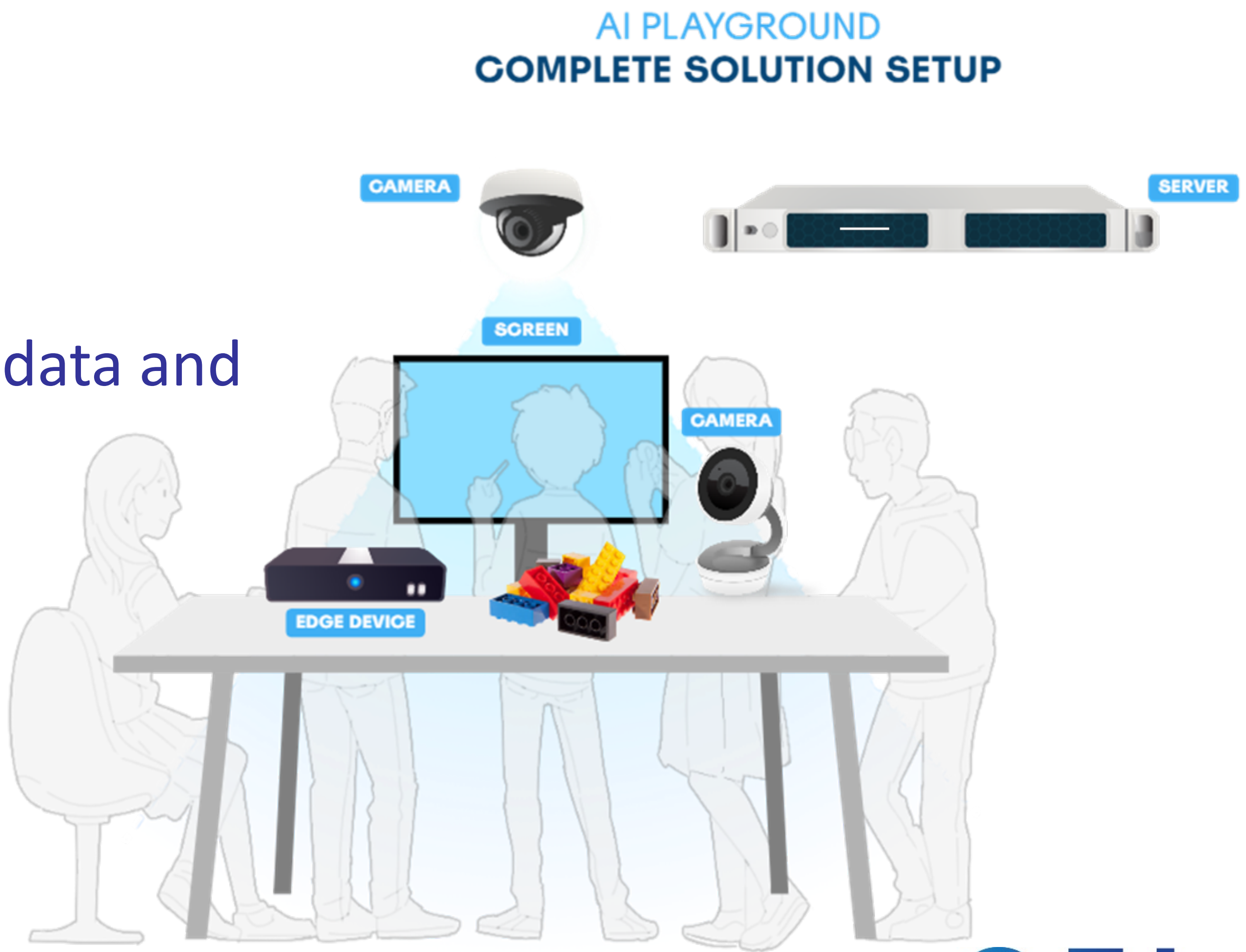
AI playground:



AI playground:

- Data collection
  - video + audio
  - Data traces

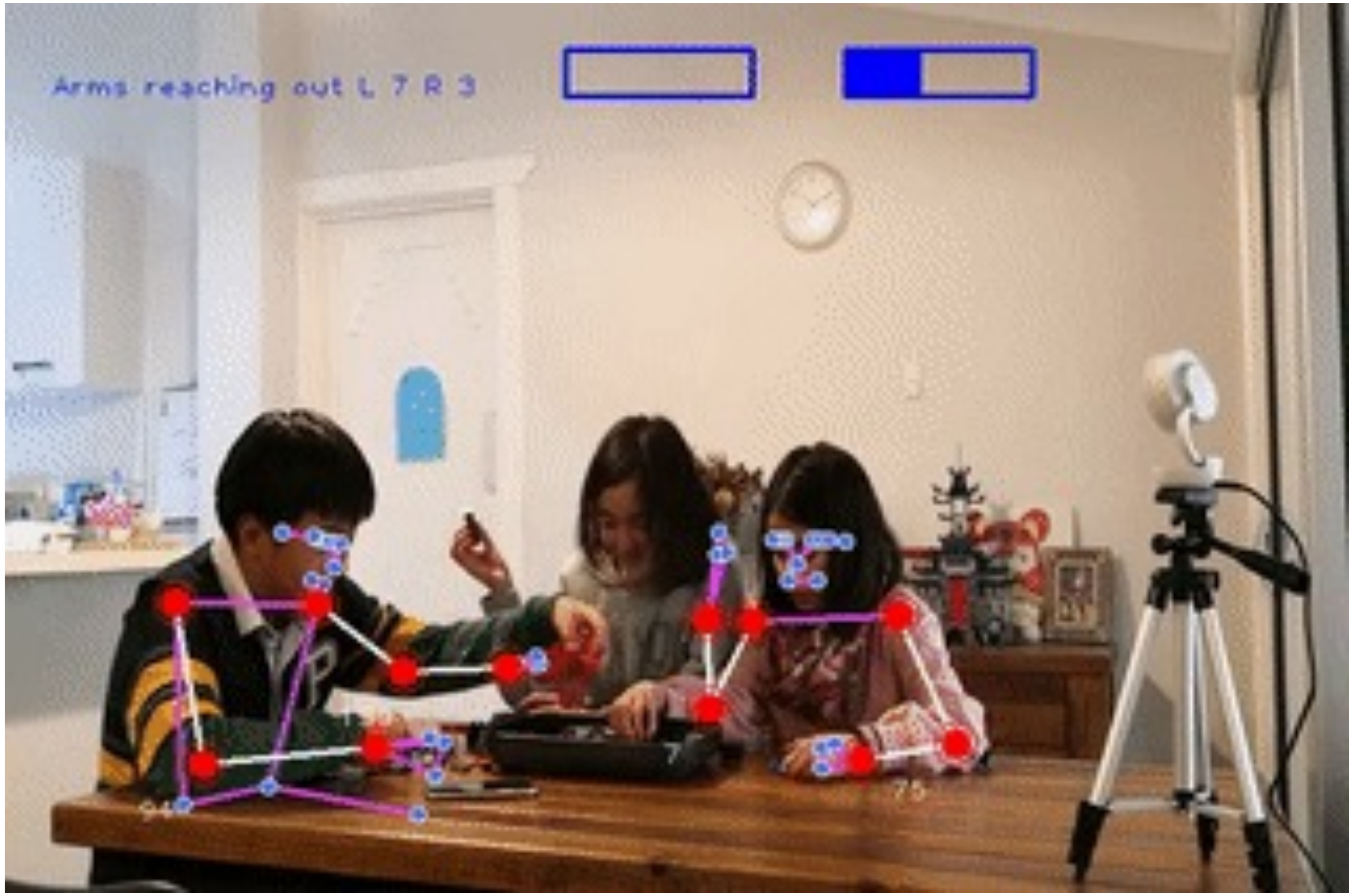
- Learning analytics to analyze user data and report to teacher
  - Task engagement & progress
  - Assessment outcomes
  - Social learning and teamwork



AI playground:

- Real-time video to teacher with augmented measurements
  - Aggregated from body landmarks and pose
  - Spatial analyses: reaching out for Lego or scanning camera

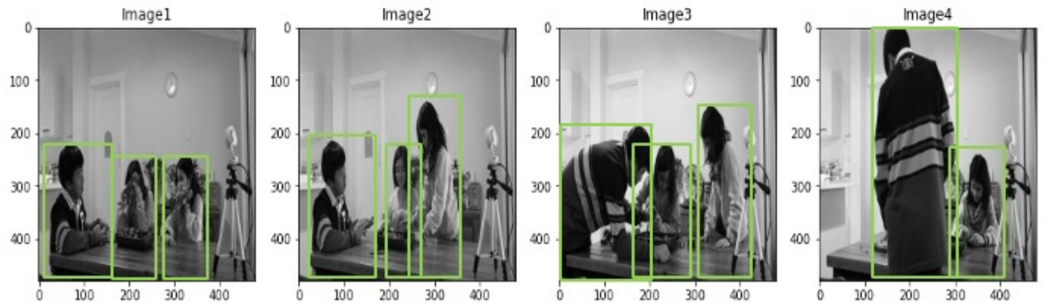
- Overall group dynamics
  - Engagement
  - Collaboration



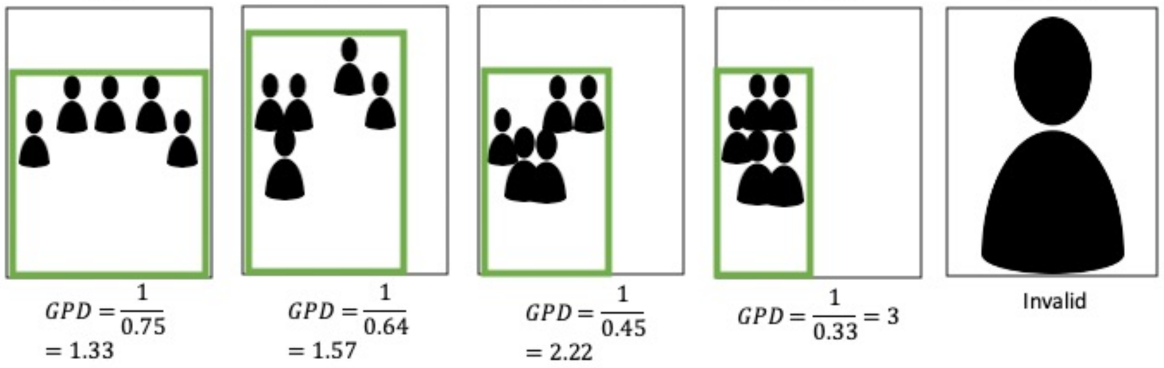
AI playground:

- Overall group dynamics
  - Engagement
    - Temporal – group on/off task time
    - Spatial (visual) – group physical density (GPD)
    - Audio – signal value (SV)
    - Text – group conversations (GC)

- Human-AI Collaboration
  - Spatial (visual) – engagement detection
  - Text – group conversations (GC)



In this example, GAHs from Image1 to Image4 are 270, 308, 313, 375 respectively.



In this example, GPDs from Layout1 to Layout4 are 1.33, 1.57, 2.22, 3 respectively.

Mind wandering:

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Flow/ Engagement

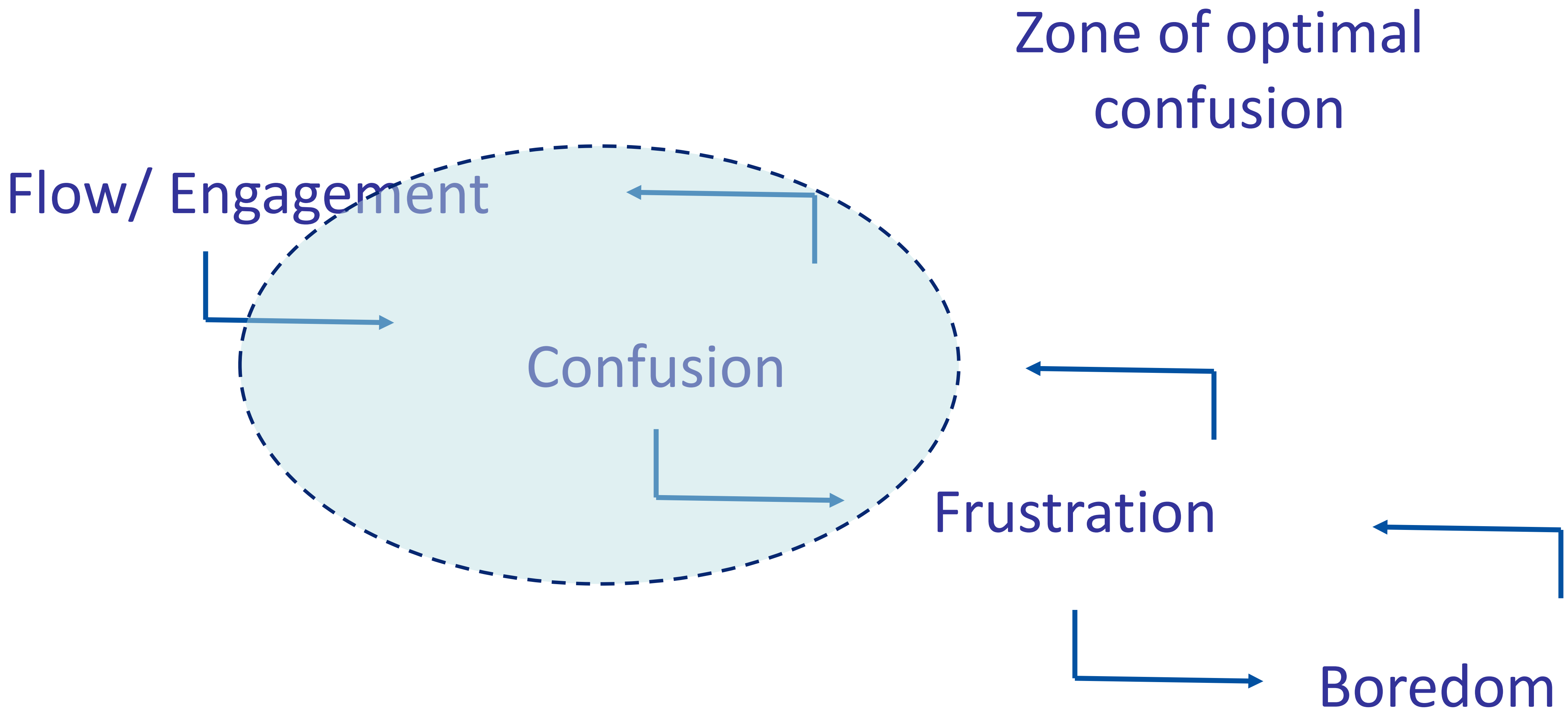
Confusion

Frustration

Boredom

D'Mello, S., Lehman, B., Pekrun, R., & Graesser, A. (2014). Confusion can be beneficial for learning. *Learning and Instruction*, 29, 153–170.

Mind wandering:



Arguel, A., Lockyer, L., Lipp, O. V., Lodge, J. M., & Kennedy, G. (2017). Inside Out: Detecting Learners' Confusion to Improve Interactive Digital Learning Environments. *Journal of Educational Computing Research*, *55*(4), 526-551.

Mind wandering:

University of South Australia

Flow/ Engagement

Confusion

Frustration

Boredom

Rich conditions for mind wandering

Mind wandering:

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- Lecture recordings – 40%
- Shorter videos – 40%
- Videos with set engagement tasks – 20%
    - Note taking
    - Quizzes

Kane, M.J., Smeekens, B.A., Von Bastian, C. C., Lurquin, J.H., Carruth, N.P. and Miyake, A., (2017). A Combined Experimental and Individual-Differences Investigation into Mind Wandering During a Video Lecture. *Journal of Experimental Psychology: General*.

Mind wandering:

- Mind wandering is a significant issue in learning
- More so in digital learning – requires more self regulation

Szpunar, K. K., Moulton, S. T., & Schacter, D. L. (2013). Mind wandering and education: from the classroom to online learning. *Frontiers in psychology*, 4.

Mind wandering:

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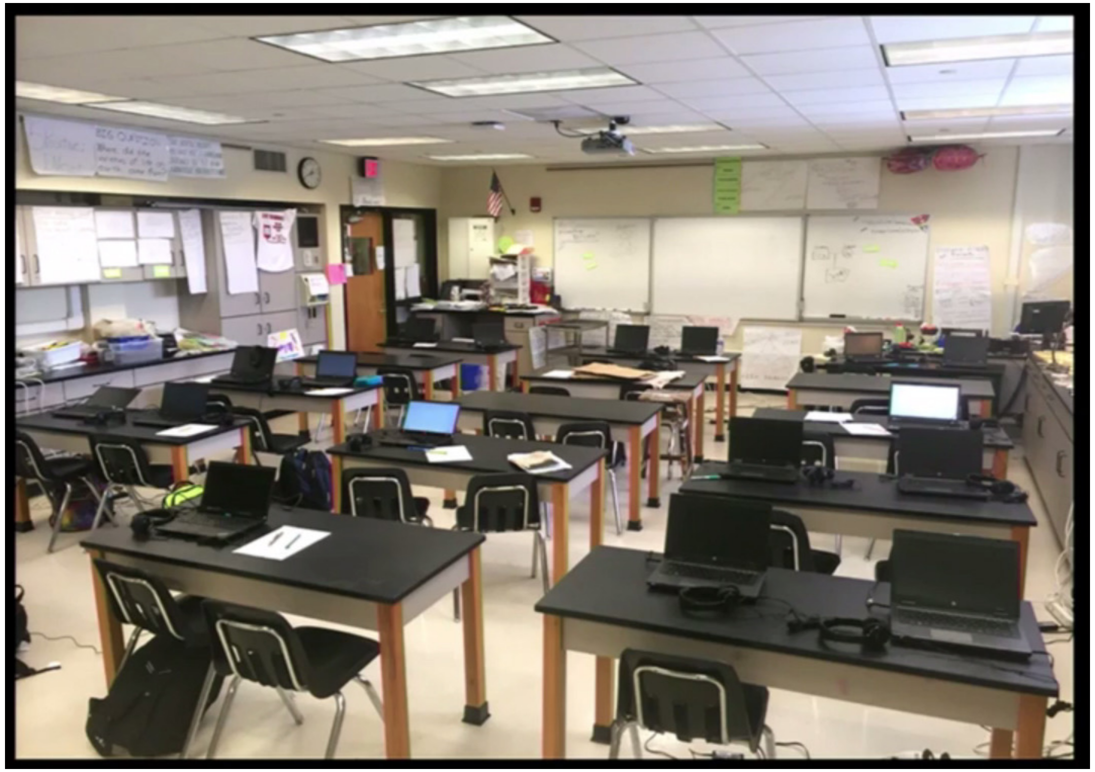
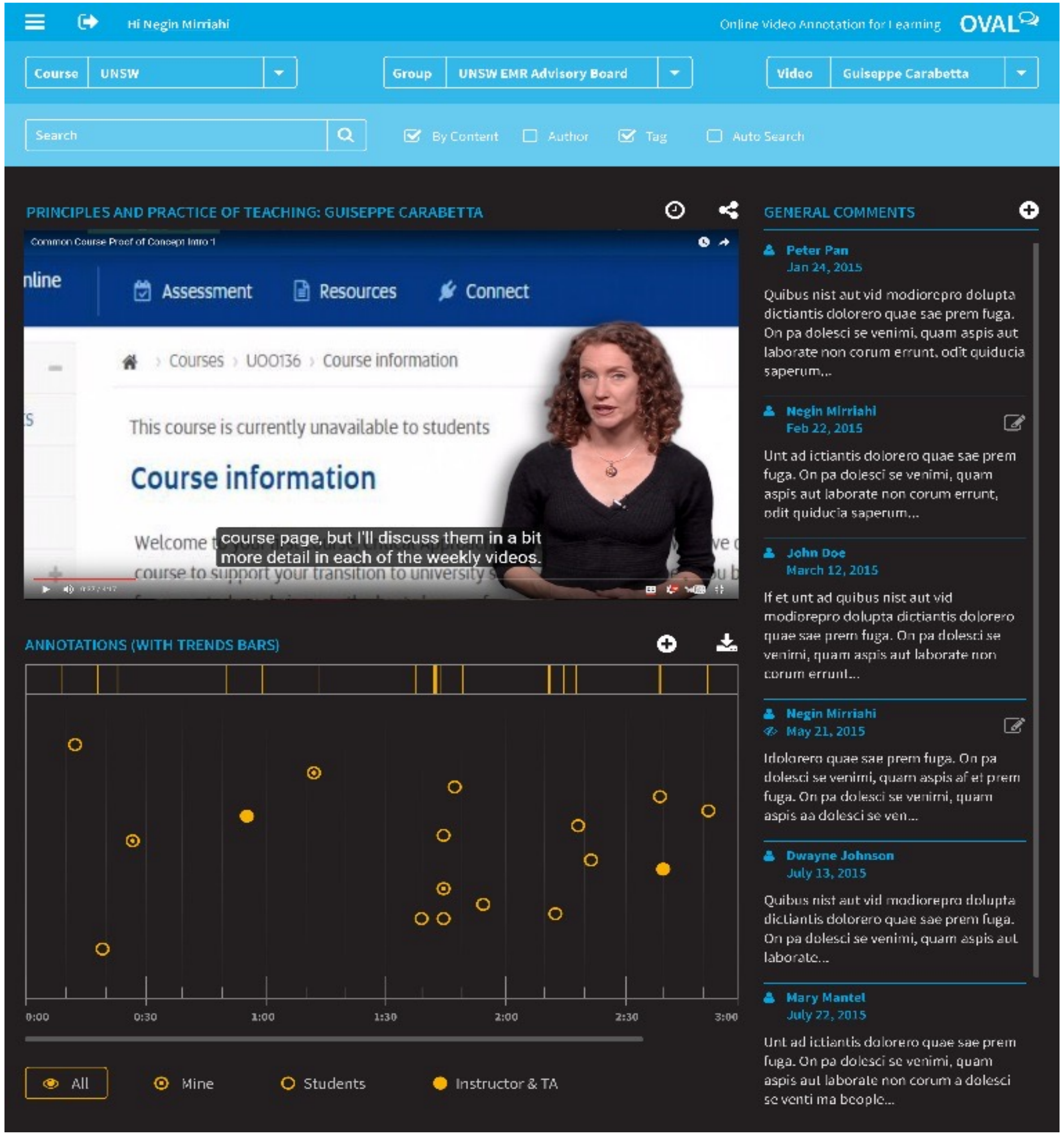


- Detection and intervention approach

D'Mello, S. (2017). Multimodal Classroom Analytics, *Keynote Learning Analytics and Knowledge* conference, Vancouver, Canada

C3L



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Designing for learning

- Proactive engagement
- Link to task motivations

C3L

Employability:

Master of Teaching (MMET)

Overview | Jobs | Skill matching analysis summary | Assessment Profile

The number of courses in the program : 69

All Courses

FILTER

COURSE DETAILS

Course Level	Course Name	AQF
4.5	Arts Education M	
4.5	Arts for Secondary Teaching 1	9
4.5	Contemporary Practice in Education Research	
4.5	Critical Perspectives of Education	9
4.5	Critical Perspectives on Curriculum, Pedagogy and Assessment	9

Analysis of curriculum:

Course aims, objectives, descriptions, and assessment

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Mapping curriculum with job descriptions

1. Discrete "hard" skills
2. Enterprise skills

Skill matching analysis summary

The following analytics were performed based on the public available data.

Match against skills gained from Course & Assessments

FILTER

MATCHED HARD SKILLS (OVERALL: 24)

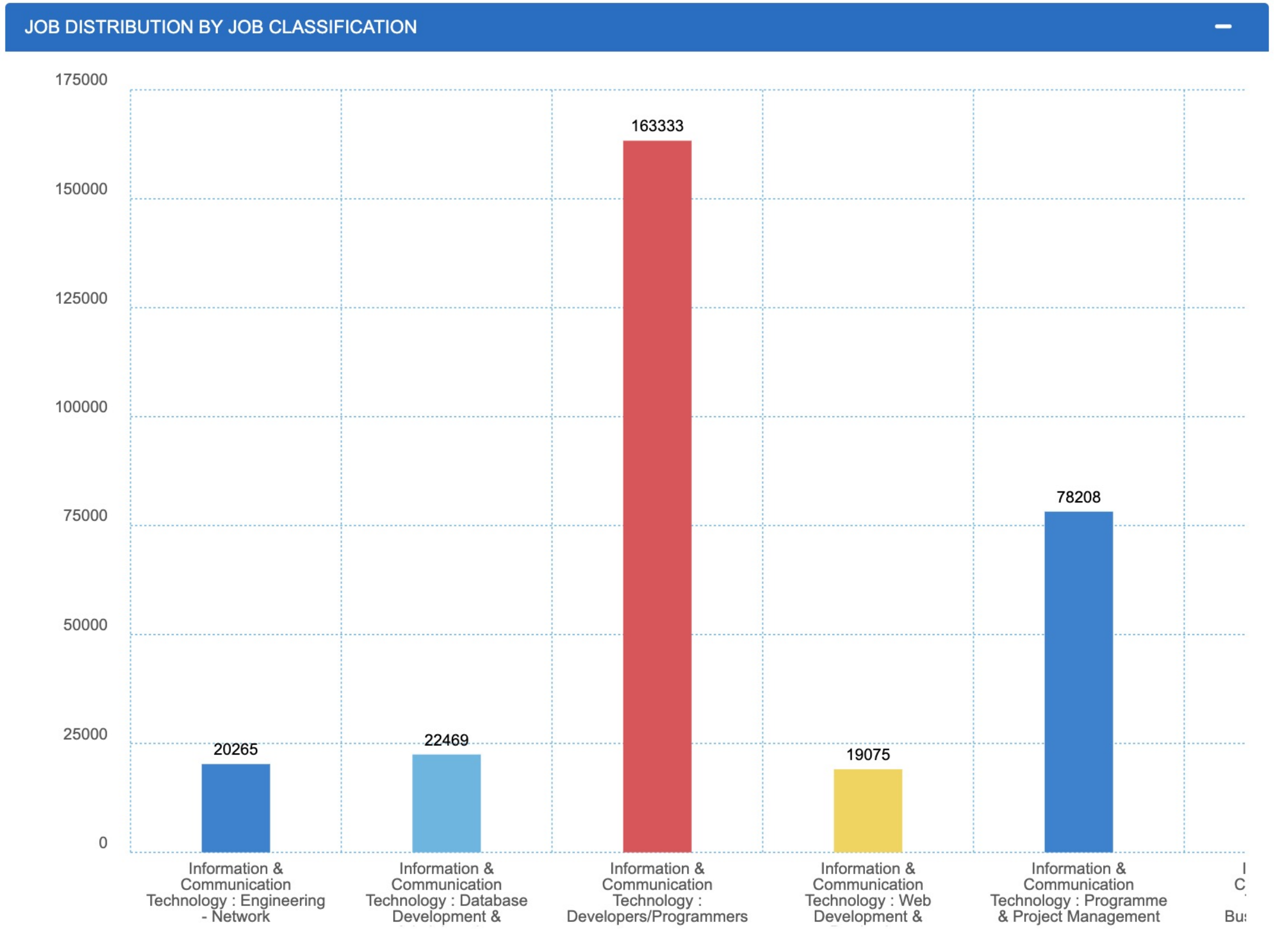
UNMATCHED HARD SKILLS (OVERALL: 8)

MATCHED SOFT SKILLS (OVERALL: 10)

Show 10 **entries**

Search:

TITLE	SKILL IN COURSE FREQUENCY	SKILL IN JOB FREQUENCY
problem solving	251 (51.02%)	54225 (22.91%)
communication	219 (44.51%)	55259 (23.34%)
experience	210 (42.68%)	77351 (32.68%)
professionalism	203 (41.26%)	71837 (30.35%)
self-management	149 (30.28%)	66136 (27.94%)
teamwork	129 (26.22%)	68425 (28.91%)
leadership	92 (18.70%)	44734 (18.90%)
responsibility	26 (5.28%)	42277 (17.86%)
courtesy	25 (5.08%)	29689 (12.54%)
flexibility	9 (1.83%)	13568 (5.73%)



Job trends

- Time
- Locality
- Classification

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As Student

Overview | Jobs | Skill matching analysis summary | Assessment Profile

The number of courses in the program : 22

All Courses

COURSE DETAILS

Course Level	Course Name	AQF
4.5	Advanced Research Methods	
4.5	Applications for Social Media Data	7C
4.5	Applying Social Research Methods	7C
4.5	Colonial Experiment: Australian History 1788 - 1918	7B
4.5	Foundations of Law	7A

Student lens

- Progress towards career goals and skills
- Identify gaps
- Recommend alternatives

Assessment Profile

Assessment

- Current course and program view
- External and accredited options?

Next generation:

LA is predominantly model focused. Yet current models fail to account for the complexity.

Next generation:

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The complexity of the education system is ignored.

LA is doing the same – we need methods and approaches that embrace complexity science (systems research) to *understand* learning and to *optimise*.

Next Generation:

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- The results demonstrate that overall there is little evidence that shows improvements in students' learning outcomes (9%) as well as learning support and teaching (35%).

Review

The current landscape of learning analytics in higher education

Olga Viberg [a], Mathias Hatakka [b], Olof Bälter [a], Anna Mavroudi [a]

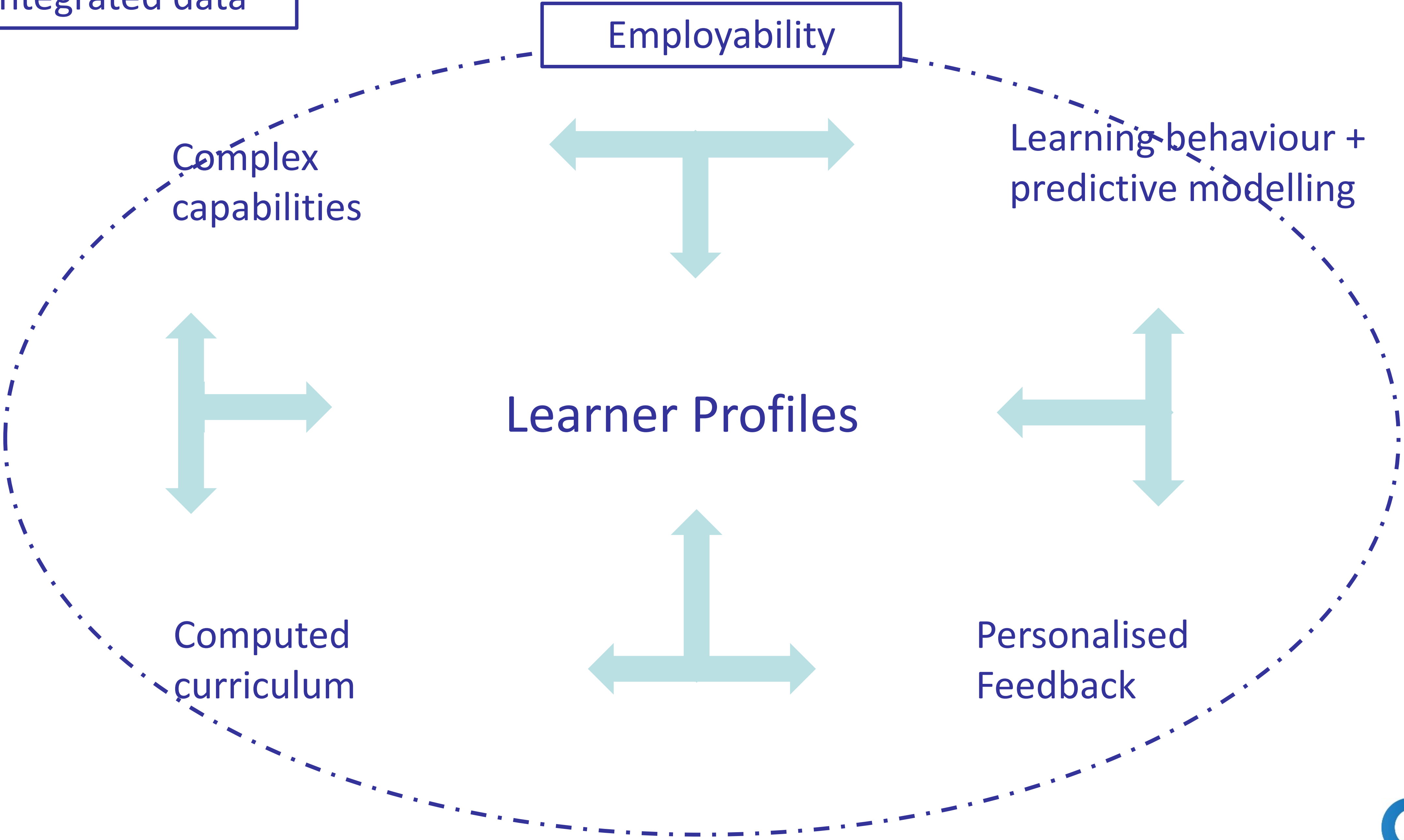
Show more

https://doi-org.access.library.unisa.edu.au/10.1016/j.chb.2018.07.027 Get rights and content

Highlights

- Most learning analytics research undertake a descriptive approach.
- Interpretative and experimental studies prevail.
- Overall there is little evidence that shows improvements in learner practice.
- The identified potential for improving learning support and teaching is high.
- There is a shift towards a deeper understanding of students' learning experiences.

Integrated data



Leadership

LA - Focus on leadership and capability development is more important then data solutions and innovations

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Thank you

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