

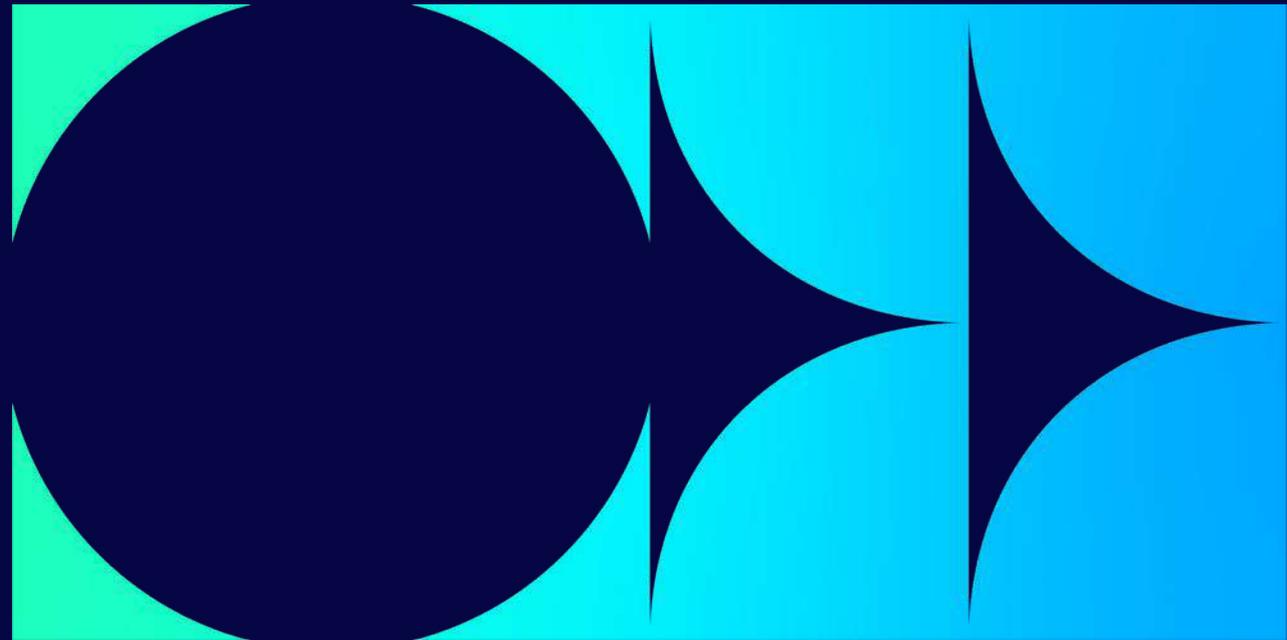
Moving Forwards with Learning Analytics

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Learning Analytics at the Institute of Educational Technology

Research

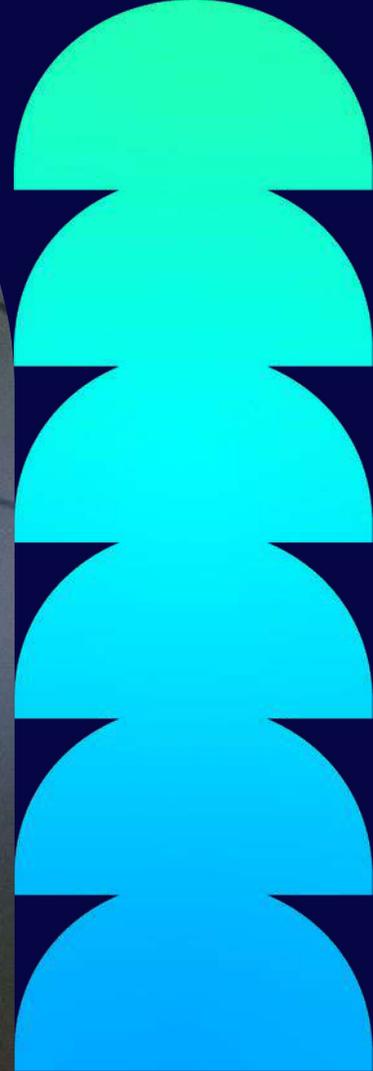
Teaching

Quality Enhancement
and Innovation



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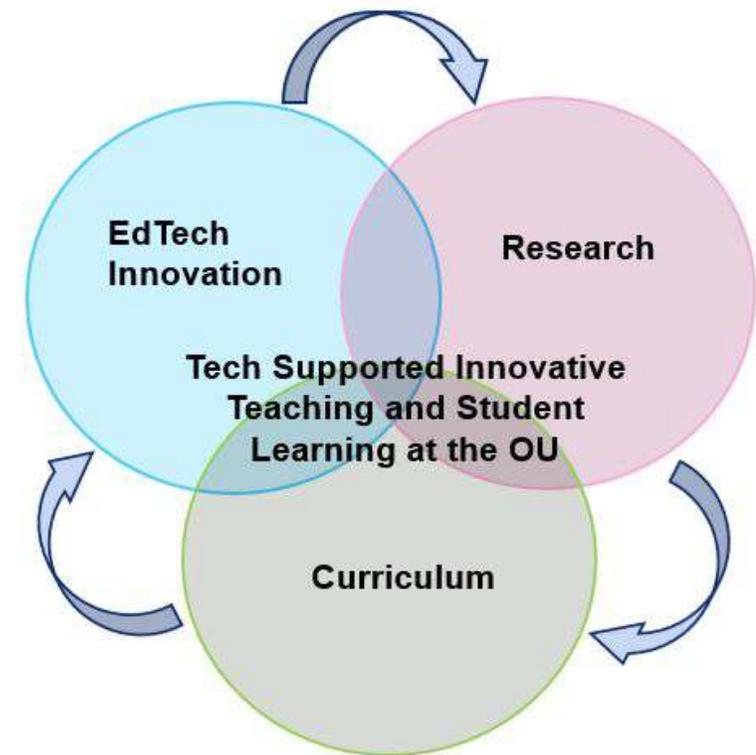
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IET Innovation through pedagogically driven technology

Learning Analytics Research Tools migrated to Main Stream Use

- 1. Research** - drives internal and external innovation, supported by KE work.
- 2. Innovative Curriculum** – instantiates and tests research outcomes.
- 3. Quality Enhancement with Innovation in EdTech** – evaluates and feeds innovative curriculum including Learning Analytics. Offers opportunities for further Research funding.



Moving Forwards with Learning Analytics Reviewing User FEEDBACK is essential

- What is Learning Analytics?
- Where are we now?
- Predictive dashboards
- Student facing feedback
- Generative AI
- Challenge FEEDBACK



LEARNING ANALYTICS: DEFINITION

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.



What and Why ?

What is Learning Analytics for ?

Assists with identifying and finding patterns in the data and then making sense of them!

Why use Learning Analytics?

To improve teaching Learning and Learning environments

What we have learned in 10 years in terms of benefits of LA?

Learners	<p>Enhance engagement of students</p> <p>Personalization of learning</p> <p>Enrich personalized learning environments</p> <p>Increase self - reflection & self-awareness</p> <p>Parents (Monitoring students' activities)</p>	<p>Improve learning outcomes</p> <p>Increase in students adaptivity</p>
Faculty	<p>Enhance Assessment services</p> <p>Get a real - time feedback</p> <p>Understand students learning habits</p> <p>Monitoring students' activities</p> <p>Provide warning signal</p> <p>Improve instructor performance</p> <p>Get a deeper understand teaching/learning</p> <p>Researchers (Increase efficiency Education & serious games, Identify knowledge gaps)</p>	<p>Make efficient interventions</p> <p>Get a real - time insight</p> <p>Modify content for students' desire</p> <p>Predicting student performance</p> <p>Improve teaching strategy</p> <p>Sources recommendation</p>
Institutions	<p>Identifying target course</p> <p>Improve learning design</p>	

1. Support access and inclusion
2. EDI

1. Improved pedagogical awareness
2. Improved data literacy and confidence
3. Driver for change based upon evidence

1. Identify good practice/teachers/modules
2. Alignments between modules/qualifications
3. Indications of good practice between/across institutions

Case-studies included from Arizona State University (USA), Dublin City University (IRE), Georgia State University (USA), Northern Arizona University (USA), New York Institute of Technology (USA), **The Open University (UK)**, Open Universities Australia (AUS), Purdue University (USA), Rio Salado College (USA), Sinclair Community College (USA), Tecnológico de Monterrey (Mex), University of Alabama (USA), University in Ankara (TUR), University of Maryland (USA), University of Michigan (USA), University of Wollongong (AUS)

What we have learned in 10 years in terms of challenges of LA?

- 1 **Ethics and privacy.** Various questions arise here, e.g., who has access to the data and personal information, how long it is kept, how much data is safe and who owns the data.
- 2 **Scope and quality of data.** Questions that arise include how much data should be collected, how much data should have variety, what type of data has value for learning and how much reliable predictions can be made.
- 3 **Theoretical and educational foundations.** There is a lack of attention to learning and teaching theories. *LA* should be based on pedagogical and epistemological assumptions.
- 4 **Research.** More research is needed to establish the foundations of *LA* (Dollinger & Lodge, 2018).
- 5 **Practice.** There is a lack of transference of *LA* theory to practice (Dollinger & Lodge, 2018). A user center design methodology as well as include the final user in the design process is needed to develop *LA* systems and applications (Dominguez F et al., 2020).
- 6 **Institutions.** It is essential to align the points of view of researchers, educators, learners, educational technologists and administrators regarding *LA* (Leitner & Ebner, 2019).
- 7 **Measurement of impact.** It is well known that *LA* can impact students learning by supporting teaching and learning strategies (Knight, Gibson, & Shibani, 2020).

OU has Ethics LA policy since 2014

Data Governance

Actual adoption and sense making

OU #1 in Europe, #2 in world

Actual adoption and sense making

LA embedded in design and practice

Good evidence within a module, more needed across qualifications and diversity

Ethics and Privacy: More to do

7 Principles

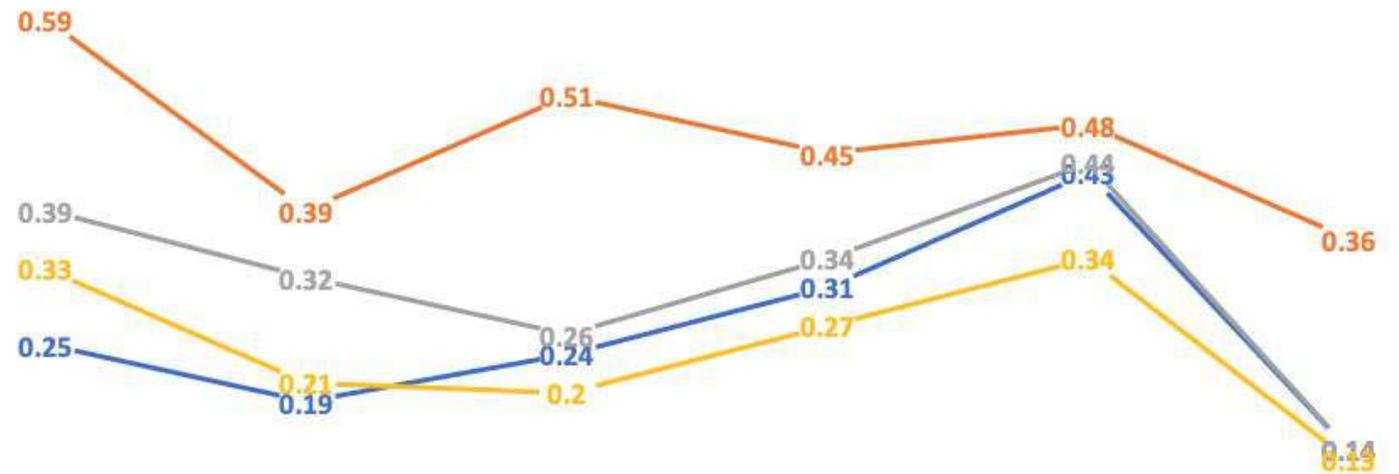
1. Improving conditions for learning and teaching
2. Support services for all students
3. Transparent handling of data
4. Critical handling of data
5. Human control
6. Managerial responsibility
7. Commitment to continuing training

Hansen, J., Rensing, C., Hermann, O., & Drachsler, H. (2020). **Verhaltenskodex für Trusted Learning Analytics: Entwurf für die Hessischen Hochschulen**. Frankfurt am Main, Germany. https://bit.ly/German_CoC_LA

OU Analyse Predictive Analytics

- 200K+ students at the Open University
- EAID supporting 86% of students
- EAID in more than 500 modules
- Publicly endorsed by VCE as a means to support student retention

PROPORTION OF ACTIVE USERS TO GIVEN ACCESS PER FACULTY



2018/2019

2019/2020

2020/2021

2021/2022

2022/2023

2023/2024

— FASS — FBL — STEM — WELS



New **OU Analyse** in top four in UNESCO awards

OU Analyse, the OU's Predictive Learning Analytics system, was selected as a finalist and among the four best projects for the 2020 edition of the UNESCO Prize in Education



Recognised by the Open University by receiving the Research Excellence Award 2019

for Outstanding Impact on Teaching, Curriculum and Students.



Winners at the DataIQ 2020 Awards

September 2020 - winners of the DataIQ 2020 Awards in Best use of data by a not-for-profit organisation.



Excellence in enhancing teaching and learning at the Open University

April 2020 - OUAnalyse awarded Recognition of Excellence in Teaching at the OU.



Shortlisted for THE awards 2019

5 September 2019 - OU Analyse was shortlisted for the Times Higher Education Awards 2019 in the category Technological or Digital Innovation of the Year.



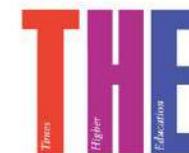
OU students' progress to be monitored by software

28 July 2015 - OU Analyse was featured on the BBC News website.



Students under surveillance

24 July 2015 - Predicting at-risk students at the Open University was part of the weekend article in The Financial Times.



The week in higher education - 30 July 2015

30 July 2015 - Times Higher Education mentioned OU Analyse in their weekly overview in academia.

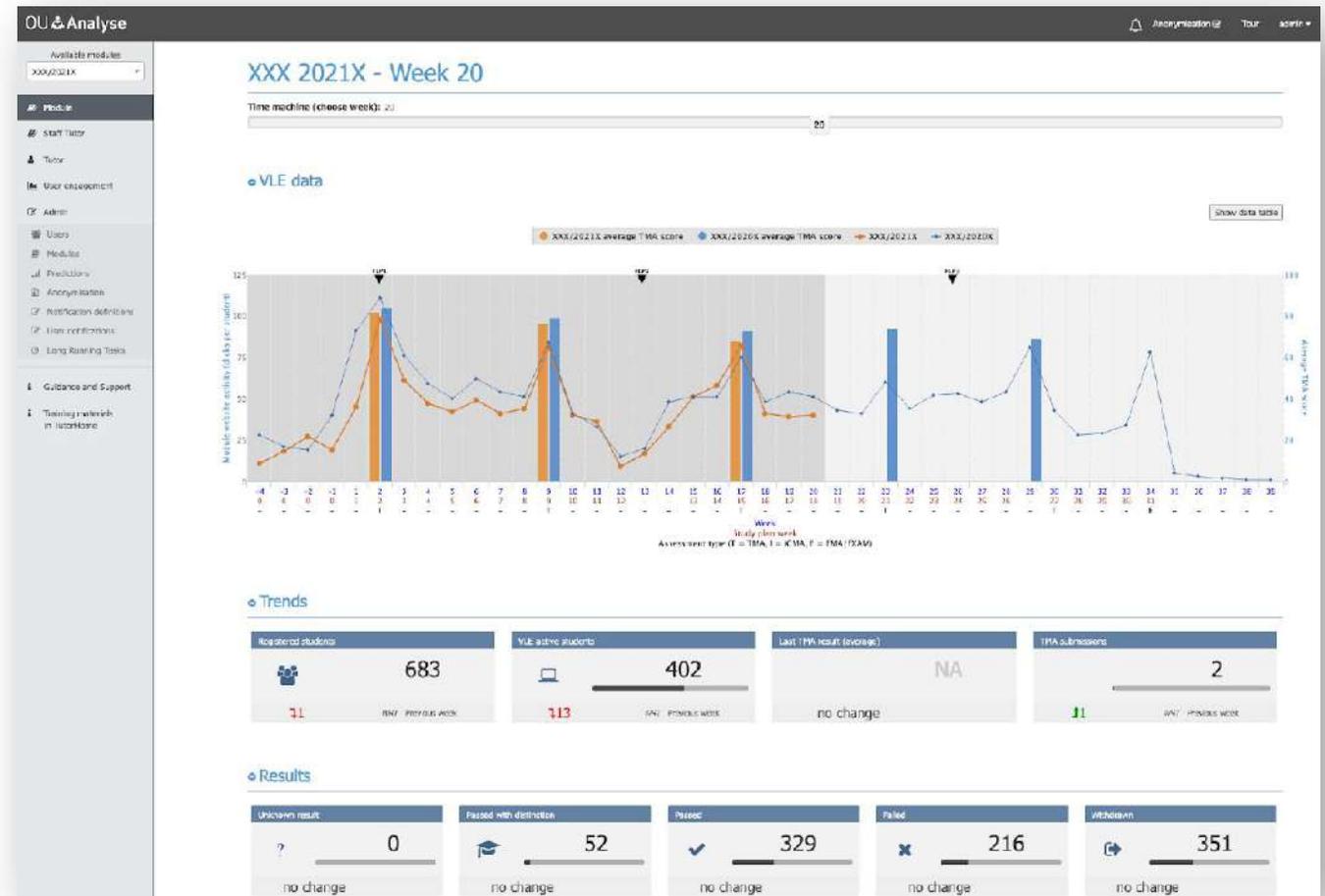
Two systems:

- **OU Analyse (OUA):** Short –term predictions of submitting course assignments (based on machine learning)
- **Student Probabilities (SPM):** Long-term predictions of completing and passing a course (based on regression analysis)

OUA & SPM produce predictions as to whether students are at risk of failing their studies

OUA: The model predicts on a weekly basis whether or not a given student will submit their next course assignment.

OUA: The model predicts on a weekly basis whether or not a given student will submit their next course assignment.



Dashboard information

timely interventions

Student Information						Next TMA predictions Generated: 07/11/18 (7 days ago) Week: 5			Long term predictions Generated: 22/10/18 (23 days ago) Week: 3	
Student PI	Name	Tutor PI	Staff tutor PI	TMA	Submission	Risk of NS	Grade	Completion	Passing	
A0000000	Mara Rempel	36363055	33650217	● ● ● ●	Submit	<div style="width: 100%;"></div>	Pass 3	70-80%	80-90%	
A0000000	Kian Wisoky	80489403	62763544	● ● ● ●	Submit	<div style="width: 20%;"></div>	Pass 3	70-80%	70-80%	
A0000000	Lambert Harvey	08627544	99976574	S ● ● ●	N/A	N/A	N/A	80-90%	80-90%	
A0000000	Craig McGlynn	07319920	46831221	S ● ● ●	N/A	N/A	N/A	70-80%	70-80%	
A0000000	Bradford Bins	94514471	26920693	● ● ● ●	Submit	<div style="width: 100%;"></div>	Pass 3	80-90%	90-100%	
A0000000	Adam Bosco	33720208	37534639	● ● ● ●	Submit	<div style="width: 100%;"></div>	Pass 3	60-70%	60-70%	
A0000000	Hollie Fisher	36044157	53930445	● ● ● ●	Submit	<div style="width: 100%;"></div>	Pass 2	80-90%	80-90%	
A0000000	Blanche Bode	19208845	24052581	● ● ● ●	Not Submit	<div style="width: 30%;"></div>	Not Submit	40-50%	50-60%	
A0000000	Frida Kiehn	78191699	38103031	● ● ● ●	Submit	<div style="width: 30%;"></div>	Pass 3	80-90%	80-90%	
A0000000	Eulah Mraz	86995088	89187335	● ● ● ●	Not Submit	<div style="width: 30%;"></div>	Not Submit	60-70%	50-60%	
A0000000	Jocelyn Bartell	74240344	31486517	● ● ● ●	Submit	<div style="width: 10%;"></div>	Pass 3	50-60%	40-50%	
A0000000	Deborah Watsica	99359149	61217869	● ● ● ●	Submit	<div style="width: 100%;"></div>	Pass 3	80-90%	70-80%	
A0000000	Frieda Kunze	87156737	26155957	● ● ● ●	Submit	<div style="width: 30%;"></div>	Pass 3	80-90%	80-90%	
A0000000	Kip Nolan	49604671	28613777	● ● ● ●	Submit	<div style="width: 30%;"></div>	Pass 3	60-70%	50-60%	
A0000000	Ignacio Reinger	49019365	31486117	S ● ● ●	N/A	N/A	N/A	90-100%	90-100%	

Student details

Short-term predictions
(Assignment Submission)

Long-term propensity of success



OUAnalys

SPM

Evidence Predictive Analytics is making a difference

Paper: Educational Technology
Research and Development, 2019

 59 ALs  1325 Students

 9 OU Courses

Paper: British Journal of
Educational Technology, 2019

 559 ALs  14K Students

 15 OU Courses

Paper: Int. Conf. on Artificial
Intelligence in Education, 2021.

 1500 Students

 3 OU Courses

World-class research,
with large-scale studies
and over 30 publications

**The more ALs use OUA, the
more retention is increased**

**More students pass courses
(~7-8% more) where ALs
regularly use OUA than
when they don't**

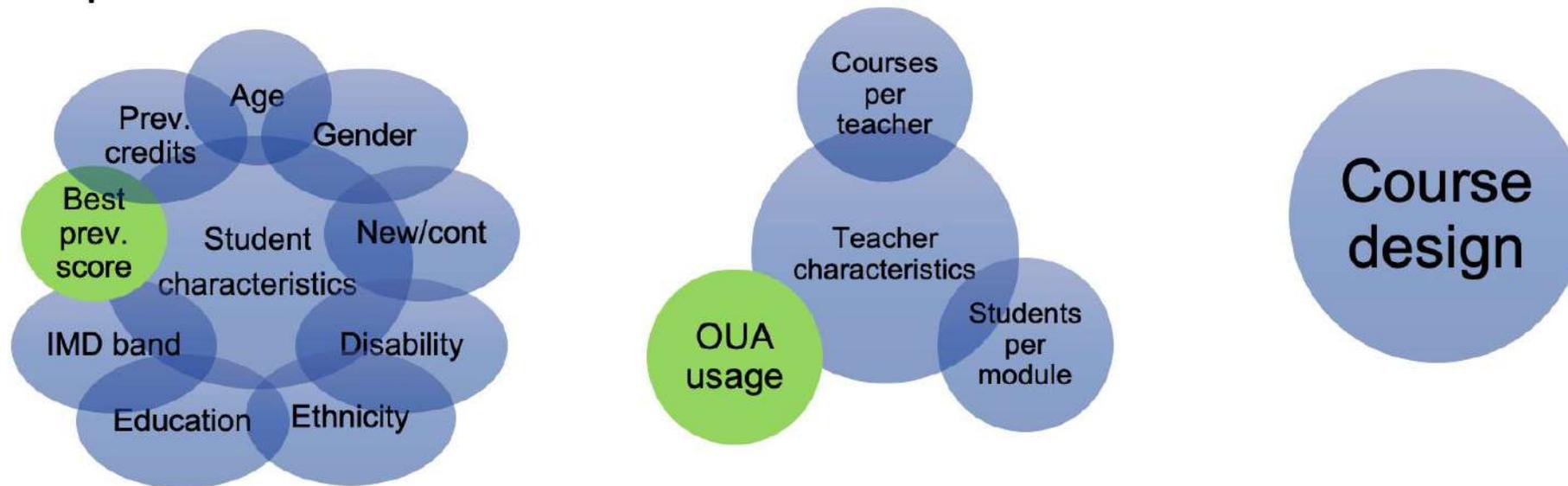
**Retention of ethnic minority
students increases by ~10%
with the use of OUA**

Does OU Analyse use by tutors lead to better student OU performance?

What are the factors best explaining student pass and retention rates?

Sample: 59 teachers, 1325 students, 9 year 1 courses across all Faculties.

Findings: OUA usage and best previous score as best predictors of student pass and completion rates.



Herodotou C., Rienties B., Borooa A., Zdrahal Z., Hlosta M. A large-scale implementation of Predictive Learning Analytics in Higher Education: The teachers' role and perspective. Educational Technology Research and Development, <https://link.springer.com/article/10.1007/s11423-019-09685-0> [

Is OUAlyse better than other ways of monitoring students' progress?

- **54 teachers who taught the same courses in the academic year 2015/16 and 2016/17. Access to EAID only in 2016/17.**
- **No statistically significant differences in previous best performance between groups of students in the two academic years. Observed differences not related to students' variation in academic ability.**
- **Significant differences in student performance for teachers who made EAID use the year they were using OUA.**

What are tutors' views about OU Analyse?

OUA complements existing teaching practices and empowers teachers to become more proactive and engaging with their students.

Teachers who tend to check on students and their progress often:

- OUA systematized their practices and made it easier to identify what students were doing at certain times.

For others:

- it influenced their practices positively by making them more proactive in contacting students

Can OU Analyse use help specific student groups?

Impact of Predictive Learning Analytics on Course Awarding Gap of Disadvantaged students in STEM

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Václav Bayer^{0000-0001-8263-6305}, and Miriam Fernández^{0000-0001-5503-4201}

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Abstract. In this work, we investigate the degree-awarding gap in distance higher education by studying the impact of a Predictive Learning Analytics system, when applying it to 5 STEM (Science, Technology, Engineering and Mathematics) courses with over 1,500 students. We focus on Black, Asian and Minority Ethnicity (BAME) students and students from areas with high deprivation, a proxy for low socio-economic status. Nineteen teachers used the system to obtain predictions of which students were at risk of failing and got in touch with them to support them (intervention group). The learning outcomes of these students were compared with students whose teachers did not use the system (comparison group). Our results show that students in the intervention group had 7% higher chances of passing the course, when controlling for other potential factors of success, with the actual pass rates being 64% vs 61%. When disaggregated: 1) BAME students had 10% higher pass rates (55.5% vs 45%) than BAME students in the comparison group and 2) students from the most deprived areas had 4% higher pass rates (58% vs 54%) in the intervention group compared to the comparison group.

Keywords: Predictive Analytics · Course Awarding Gap · BAME · SES

1 Introduction

Historically, the performance of some demographic groups of students has been persistently worse than others. The impact of low socio-economic status (SES) on learning has increased over the last 50 years across countries, including the UK [3]. The attainment of ethnic minorities is consistently worse than White students. In the UK, in the past decade, 57% of Black students gained an upper second or first in their undergraduate degree, compared with 81% of White students [10]. There may be a significant overlap between Black, Asian and Minority Ethnic (BAME) students and low SES students. Recent post-pandemic statistics show that nearly half of BAME households (46%) live in poverty as opposed to 26% of White households [11].

Predictive Learning Analytics (PLA) focuses on forecasting the future students' outcomes using Machine Learning (ML) models and provide actionable

- Impact of dashboard on the course awarding gap of students from black & minority ethnic backgrounds and low socio-economic status (SES)
- Students from black and minority ethnic groups in the intervention group better passing rates (62%) as opposed to similar students in the control group (52%)
- Students from low SES (in intervention group) better outcomes (pass and overall score) than similar students in the control group
- Students found in disadvantaged contexts such as poverty are more likely to benefit from the EAID dashboard.

Predictive Dashboard Co-designed with OU students

- **Based on the OU Analyse Early Alert Indicators dashboard**
- **Focus groups with 20 students**
- **Data points endorsed by students related to”**
 - descriptive (assignment scores, engagement with VLE, material accessed),
 - predictive (score prediction),
 - prescriptive data (material recommendations and contact information).
- **Students’ choices of data points driven by a desire to better understand their study progress and take appropriate action.**

Student facing dashboard :

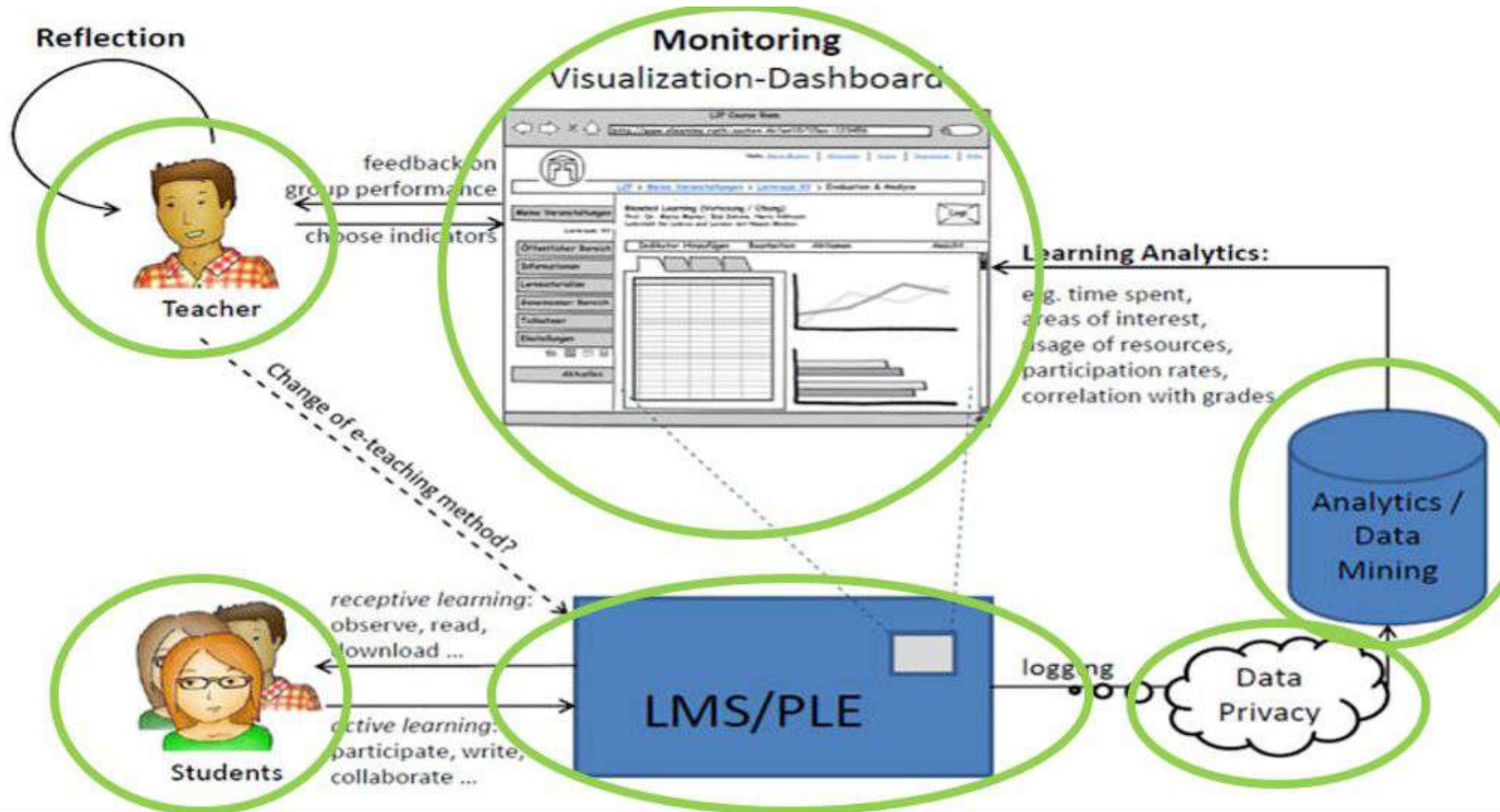
- Students can monitor their own performance on a module
- Raises awareness of study progress
- Provides material recommendations
- Provides support options (email tutor, contact SSTs)
- Enables students to take action to improve their performance

The screenshot shows the 'OU Analyze' student dashboard for module A111/20231. The dashboard is titled 'Discovering the arts and humanities' and is for 'Week 20/23'. It features a 'VLE Course Activity' chart showing course activity over time, with a peak around week 11. Below the chart are buttons for 'Provide feedback' and 'Report technical issues'. The 'Highlights' section includes four cards: 'Latest Prediction' (Week 20 Prediction), 'Upcoming TMA' (TMA04), 'Latest Achievement' (Searched Out For Help), and 'Recommendations'. The 'Reach Out For Support' section includes a message and two cards for 'Contact Tutor' and 'Contact SST'. The 'My Learning' section includes 'Recommended material' and 'Recommendations using past data'. The 'Achievements' section includes five cards: 'Searched Out For Help', 'Completed Recommended Items', 'Increased VLE Activity', 'Submitted TMA', and 'Passed TMA'. The footer includes the OU logo and the KM1 logo.

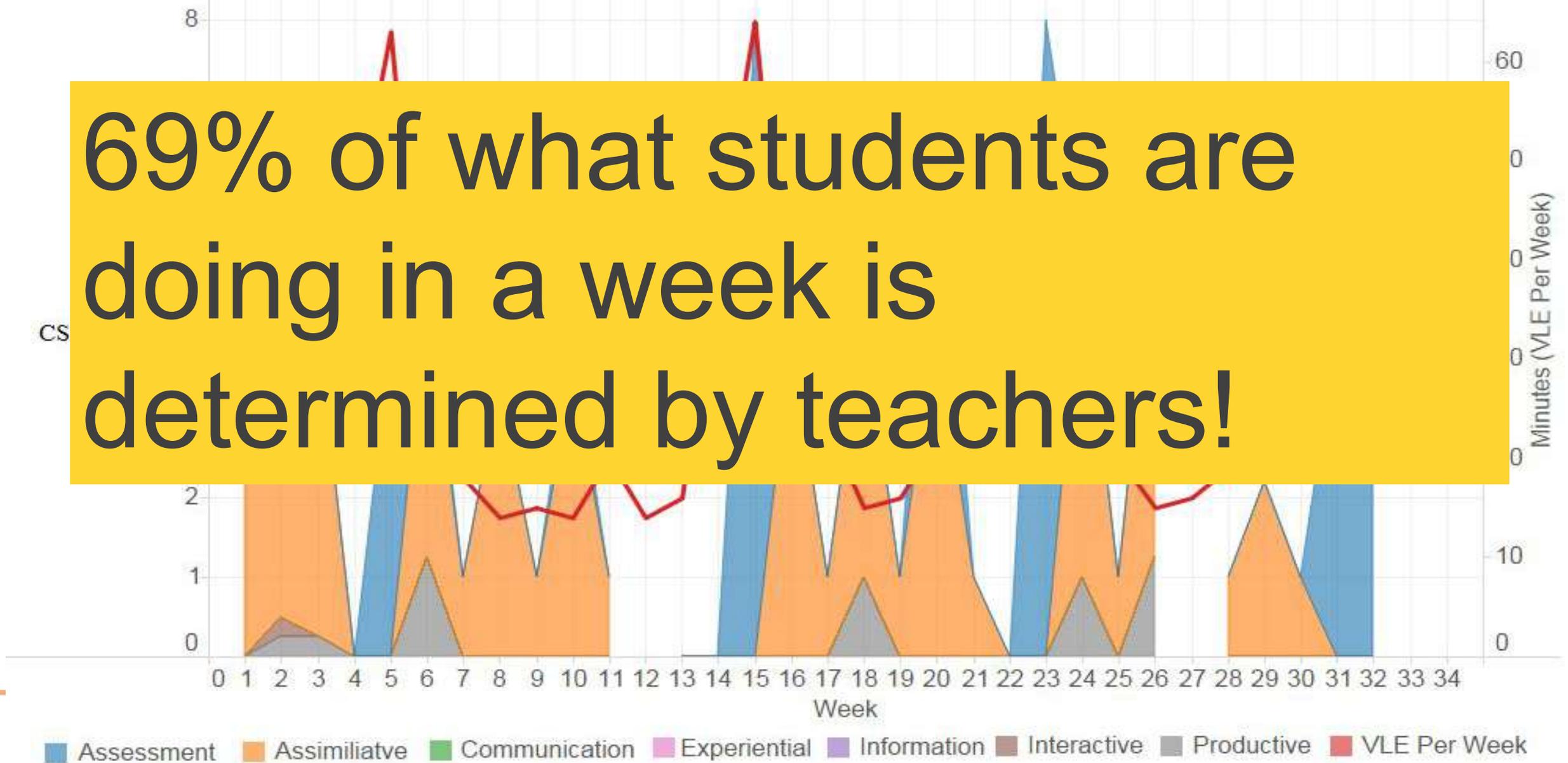
IET Authors for OU Analyse :Herodotu and Rienties

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Model of LA Usage with Staff and Students



69% of what students are doing in a week is determined by teachers!



Learning Analytics and Learning Design

Magic of learning design (does not come easy)

TechTrends
<https://doi.org/10.1007/s11528-020-00498-0>

AECT

ORIGINAL PAPER



Learning Design: European Approaches

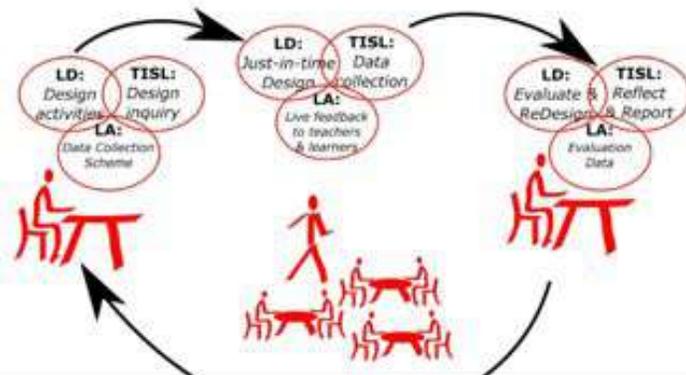
Barbara Wasson¹ · Paul A. Kirschner²

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Abstract

Research on instructional and learning design is 'booming' in Europe, although there has been a move from a focus on content and the way to present it in a formal educational context (i.e., instruction), to a focus on complex learning, learning environments including the workplace, and access to learner data available in these environments. We even see the term 'learning experience design' (Neelen and Kirschner 2020) to describe the field. Furthermore, there is an effort to empower teachers (and even students) as designers of learning (including environments and new pedagogies), and to support their reflection on their own practice as part of their professional development (Hansen and Wasson 2016; Luckin et al. 2016; Wasson et al. 2016). While instructional design is an often heard term in the United States and refers

Fig. 7 Teacher-led design inquiry of learning and innovation cycle (Wasson et al. 2016)



"Research on **the relationship between learning design and learning analytics** has also been a focus in European research in recent years. For example, in their research at **the Open University UK**, Toetenel and Rienties combine learning design and learning analytics where learning design provides context to empirical data about OU courses enabling the learning analytics to give insight into learning design decisions. **This research is important as it attempts to close the virtuous cycle between learning design to improve courses and enhancing the quality of learning, something that has been lacking in the research literature.** For example, they study the impact of learning design on pedagogical decision-making and on future course design, and the relationship between learning design and student behaviour and outcomes (Toetenel and Rienties 2016; Rienties and Toetenel 2016; Rienties et al. 2015)."

Teaching entrepreneurial competences¹

COURSE DETAILS

PLANNING

ANALYSIS

Learner workload



Mode of delivery



Get your free account

<https://learning-design.eu/>

Total workload

Competence

660 min



Item count

Teacher not present



Workload

Teacher not present



Developed by Faculty of Organization and Informatics, Learning Analytics Laboratory

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Rienties, B., Balaban, I., Divjak, B., Grabar, D., Svetec, B., Vonda, P. (2023). Applying and translating learning design approaches across borders. *Practicable Learning Analytics*. O. Viberg and A. Gronlund (Eds). Springer Nature.

Rienties, B., Divjak, B., Eichhorn, M., Iniesto, F. Saunders-Smiths, G., Svetec, B., Tillmann, A., Zizak, M. (2023). Online professional development across institutions and borders. *International Journal of Educational Technology in Higher Education*.

Balanced Design Planning

learning-design.eu

1600+
USERS

30+
COUNTRIES

1500
COURSES



RAPIDE e-course on relevant pedagogies and LA

COURSE DETAILS

PLANNING

ANALYSIS

EXPORT

Edit TLA

Name ⓘ

Peer-assessment

Description ⓘ

Solutions to the problem assignment are peer-assessed.

Learning type ⓘ

Assessment

Description

Use this category to allocate time to activities which are directly assessed, either by a tutor, a peer or a computer. Assessment includes both formative and summative assessment.

Example usage

Quizzes, tests, written assignments, peer assessment activities,...

Workload in minutes ⓘ

60

Activity delivery ⓘ

Online

On-site

Hybrid

Synchronous

Asynchronous

Teacher-present

Teacher not present

Collaboration ⓘ

Work in groups ⓘ

Feedback ⓘ

Feedback provider ⓘ

Teacher

Automated

Peer

Other

Assessment ⓘ

Assessment type ⓘ

Summative

Assessment provider ⓘ

Teacher

Automated

Peer

Self

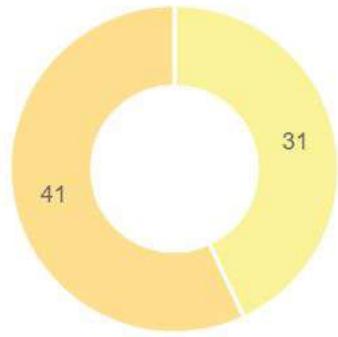
Other

Assessment points ⓘ

10

Feedback

■ Activities with feedback
■ Activities without feedback



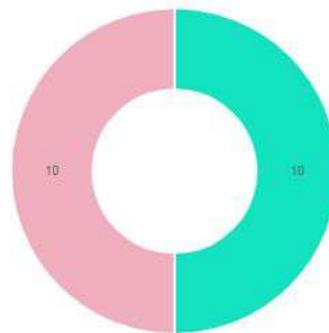
Item count

■ Teacher
■ Automated
■ Peer
■ Other



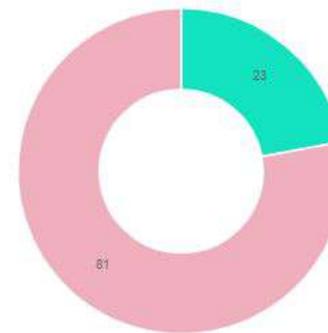
Assessment

■ Formative
■ Summative



Assessment types count

■ Formative
■ Summative



Assessment types by points



iLed
 Innovating Learning Design
 in Higher Education

Assessment and learning outcomes

Topic	Assessment		🗨️ Describe the concept of innovative teaching approaches (8)	✅ Design and implement FC and WBL in online environments (12)	✅ Design and implement assessment methods related to... (12)	✅ Implement peer-assessment and student project assessment (10)	📊 Analyse aspects in which learning analytics can be... (10)	📊 Analyse LA models and dashboards that support student... (10)	📄 Interpret LA data taking into account ethical aspects (10)	✅ Choose appropriate assessment methods, taking into... (8)	📊 Estimate the impact of innovative pedagogies on the... (10)	📊 Relate LA to the social impact and informed decisions (10)
	Formative	Summative										
Innovative pedagogies (FC & WBL)	6	30	90%	90%	10%						10%	
Assessment related to innovative pedagogies	4	11	10%	10%	90%	100%				100%		
Learning analytics and dashboards	11	20					100%	100%	90%			20%
Impact of innovative pedagogies	2	20							10%		90%	80%
Total	23	81	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	104											

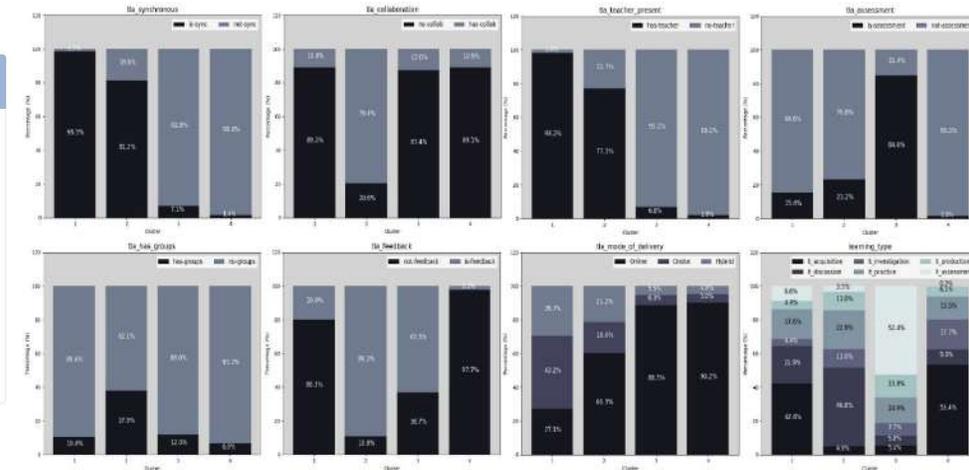
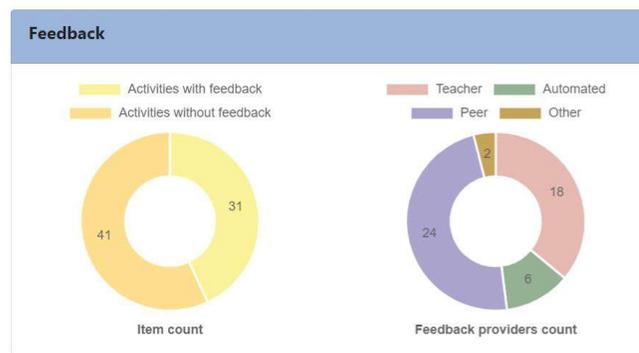
Divjak, B., Grabar, D., Svetec, B., & Vondra, P. (2022). Balanced Learning Design Planning: Concept and Tool. *Journal of Information and Organizational Sciences*.

Rienties, B., Balaban, I., Divjak, B., Grabar, D., Svetec, B., & Vonda, P. (2023). Applying and translating learning design approaches across borders. In O. Viberg & A. Gronlund (Eds.), *Practicable Learning Analytics*. Springer Nature.

How can we improve our automatic advice to educators to design better learning opportunities?

1. European project iLED aims to enhance digital readiness, resilience and capacity of HE through purposeful use of innovative digital pedagogies, tools and learning design
2. Rienties et al explored how 165 educators across 40+ institutions in Europe designed and integrated 12,749 teaching and learning activities (TLA) in 218 Learning Designs using freely available learning-design.eu tool
3. The findings suggest educators use only a combination of four common learning design activities (i.e., Generating independent learning, Traditional classroom activities, Assessment, Collaboration).
4. Next step will be to include AI for automatic recommendations

RAPIDE e-course on relevant pedagogies and LA



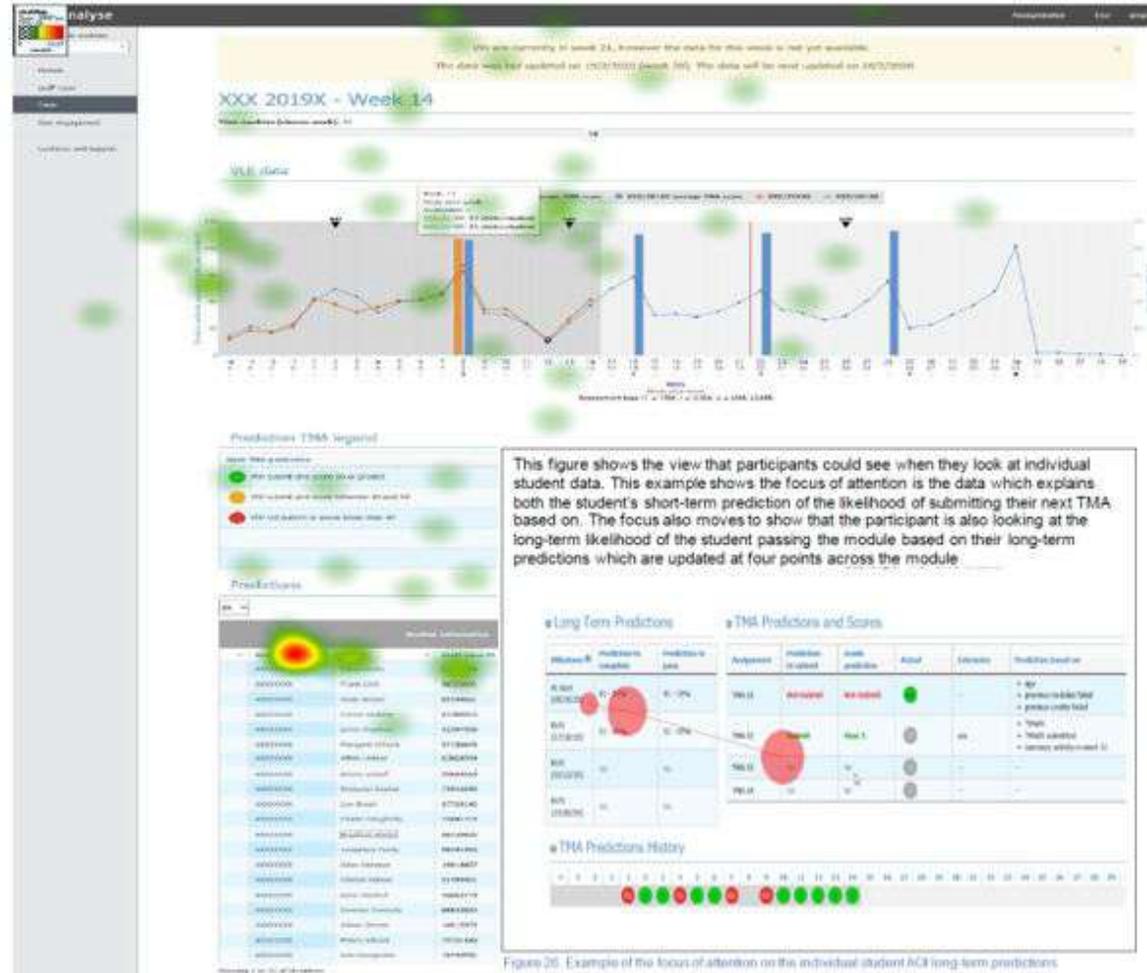
Effective Learning Analytics: **Feedback** for Effective Learning



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Reading Dashboards: Is this the best type of Feedback?

Figure 22. Heat map example of the density of the fixations on stimuli



- Eye-tracking combined with think-aloud protocol of experienced teachers using PLA
- Most teachers comfortable with main dashboard, but worried about ethics/data
- Some erroneous interpretations and sense making of actual data
- Uncertainty about what options to address identified issues

Short text for illustration of Rainbow Diagrams

Text (Extract from online FAQ about foxes)

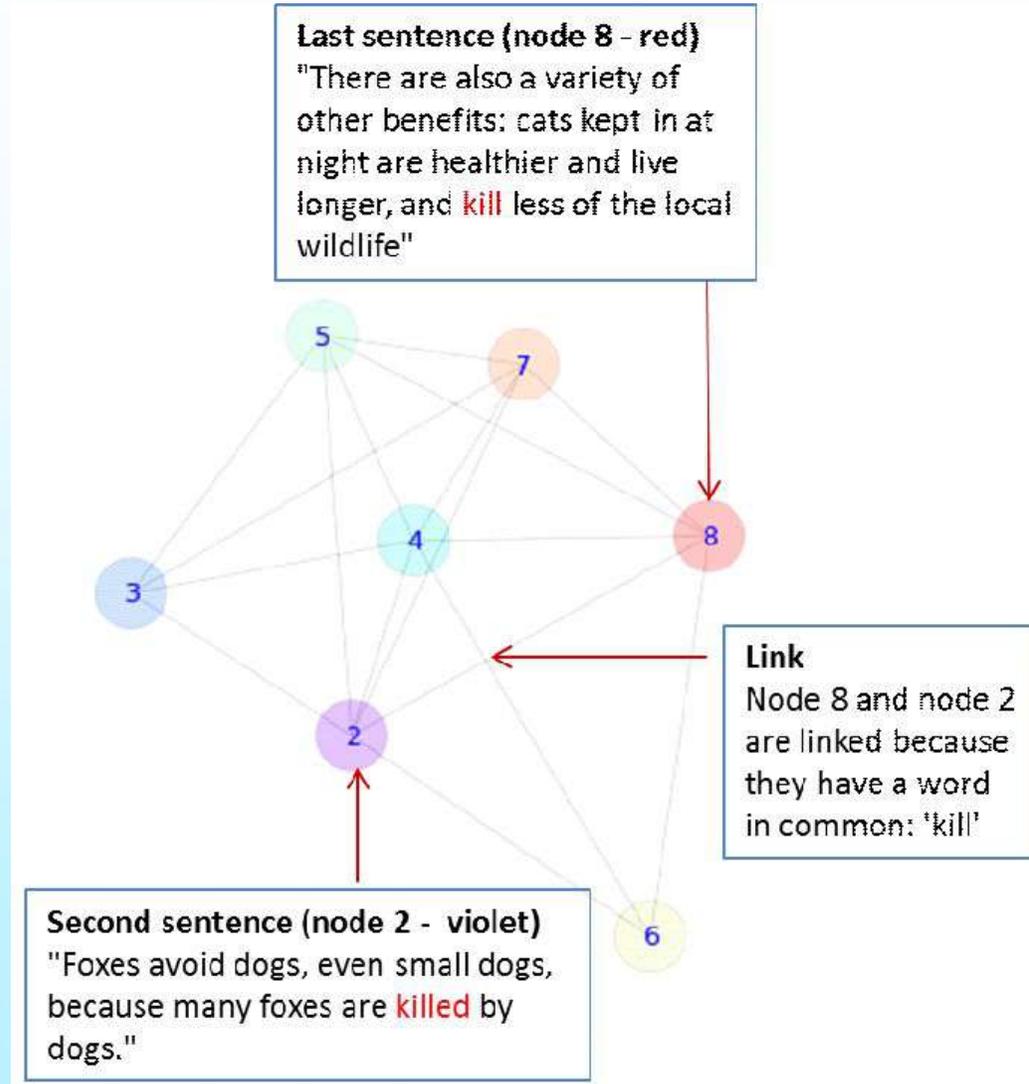
Will the foxes in my garden attack my dog or cat?

This is extremely unlikely. *2. Foxes avoid dogs, even small dogs, because many foxes are killed by dogs.*

So it is much more likely that your dog will attack the fox, not the other way round. Attacks on cats are equally rare: cats and foxes are roughly the same size, and cats are very capable of defending themselves against foxes. So it is hardly surprising that foxes generally give cats a wide berth and flee when threatened by a cat. Occasionally small kittens are killed, but this is rare. Keeping your cat indoors at night greatly reduces the chances of an encounter with a fox. *8. There are also a variety of other benefits: cats kept in at night are healthier and live longer, and kill less of the local wildlife.*

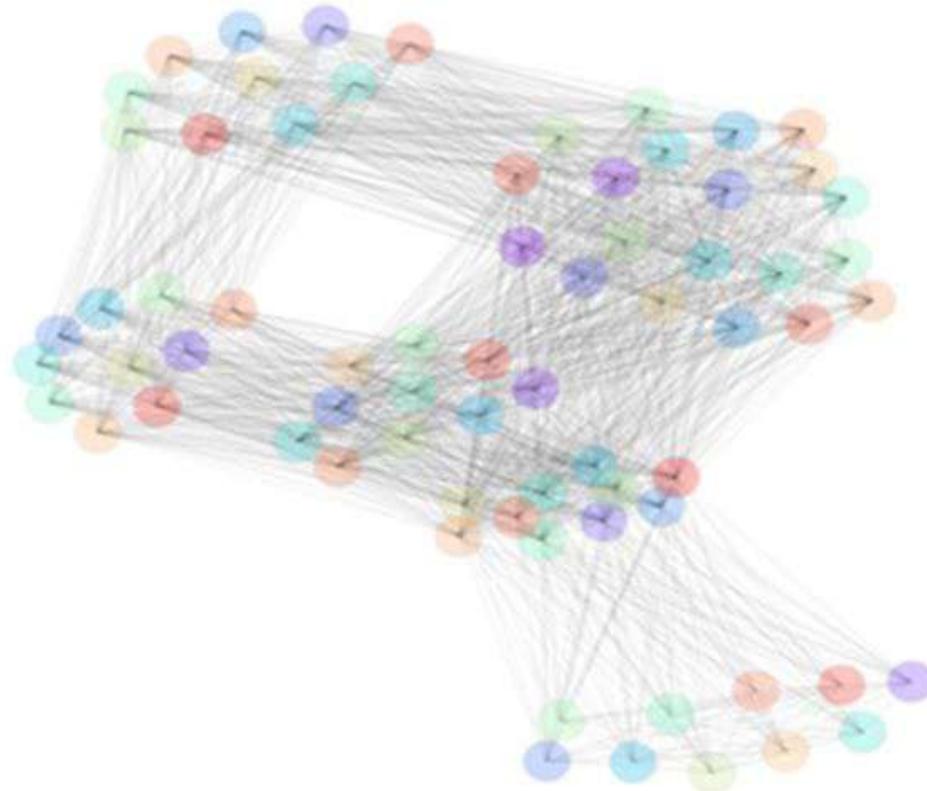
Researchers

Sentence graph of short text



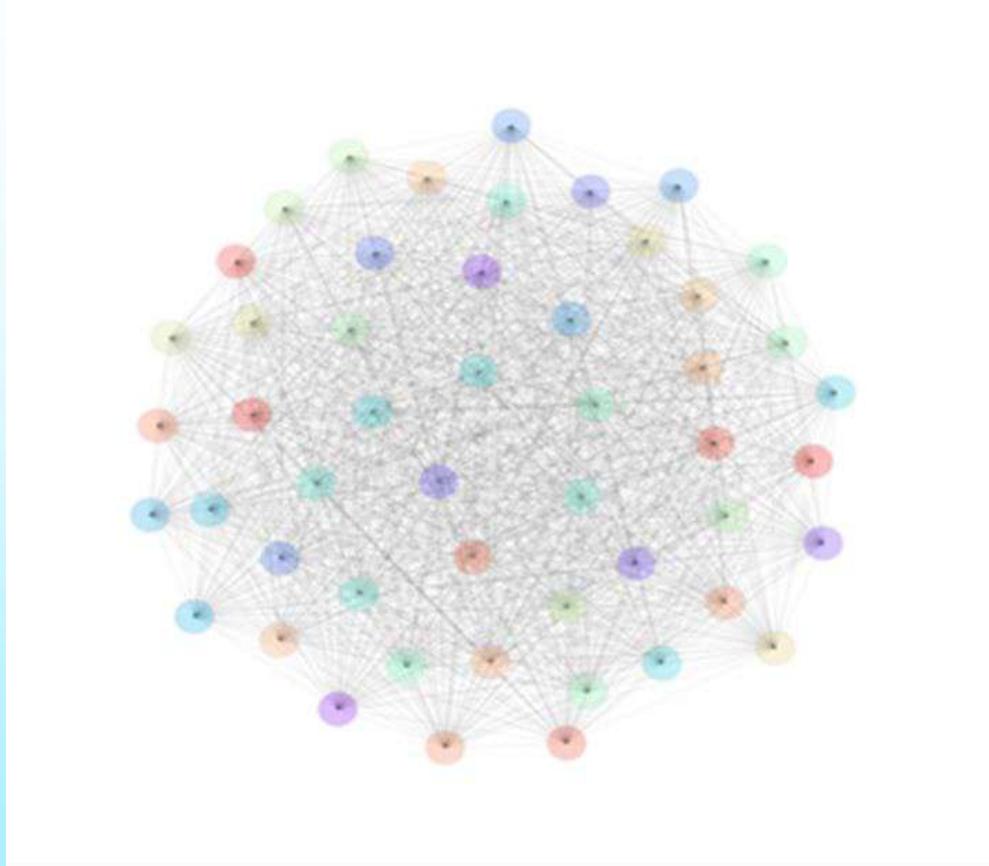
Researchers

Pretend essay: 10 identical paragraphs



Researchers

Pretend essay: 50 identical sentences



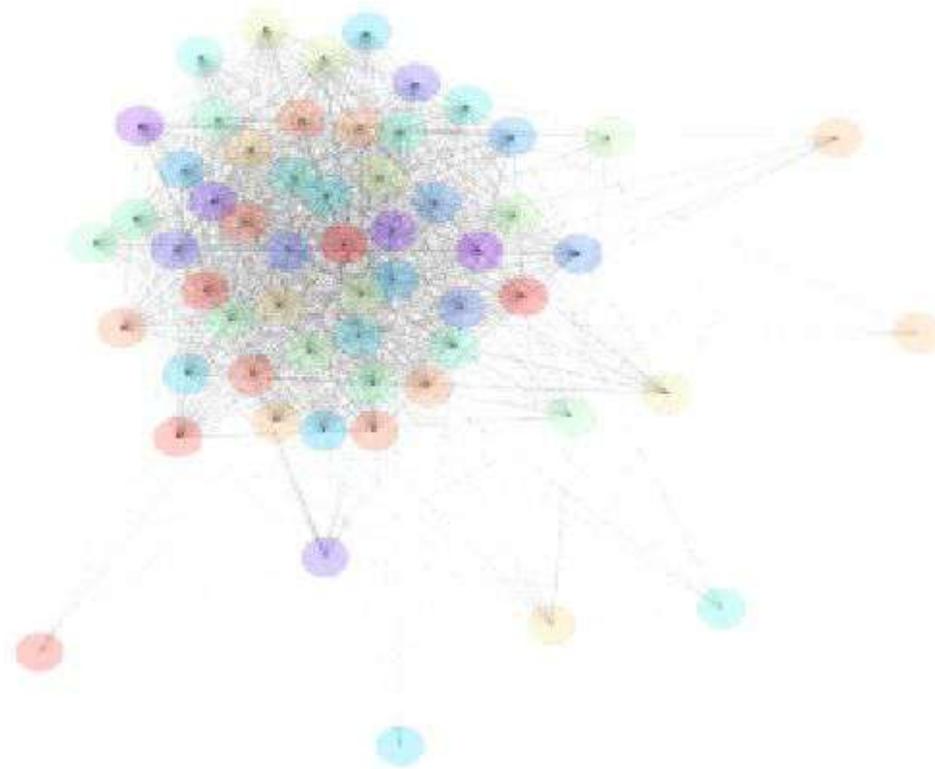
Researchers

Stanford University Boothe Prize essay



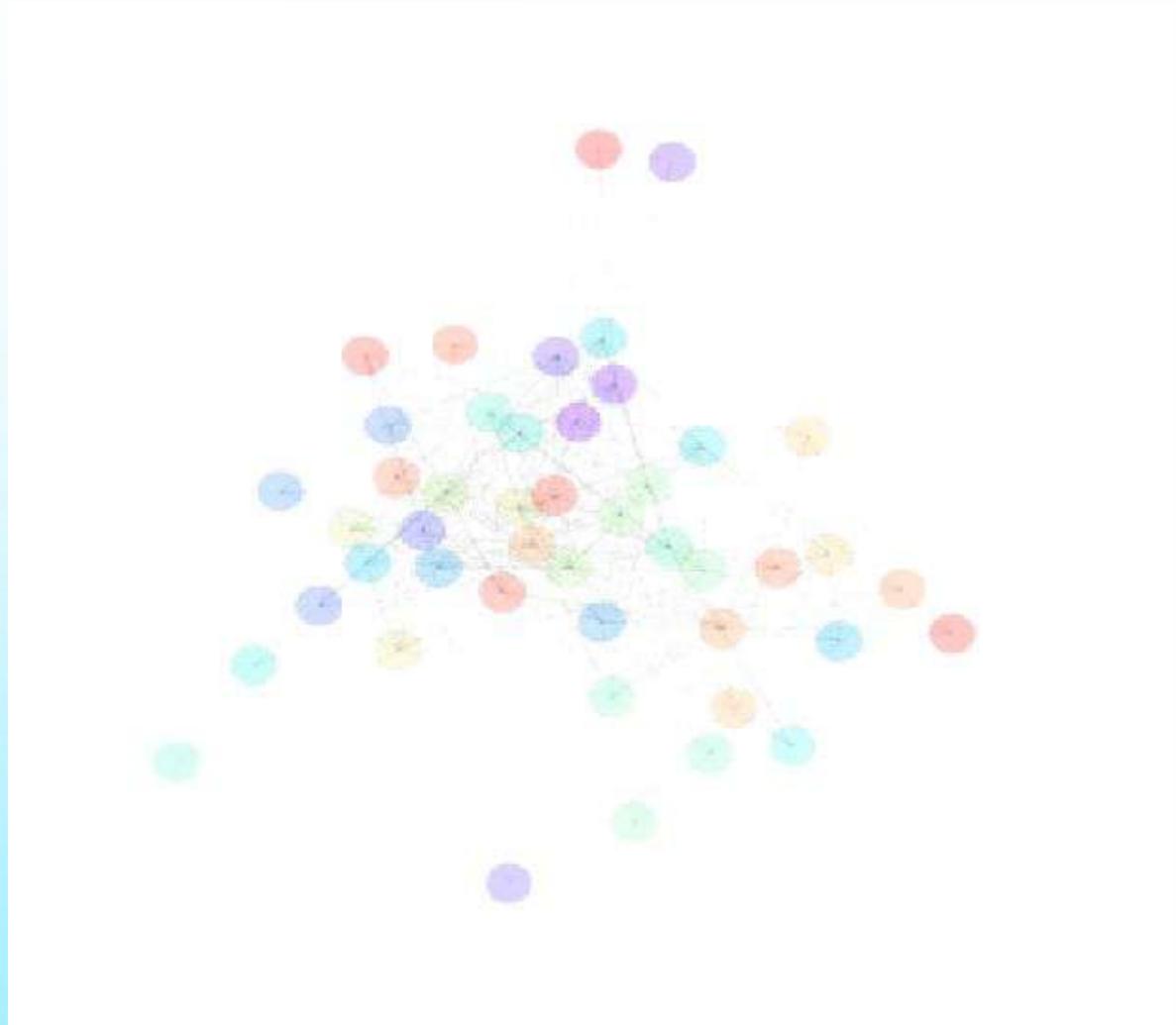
Researchers

OU Essay awarded high grade



Researchers

OU essay awarded low grade

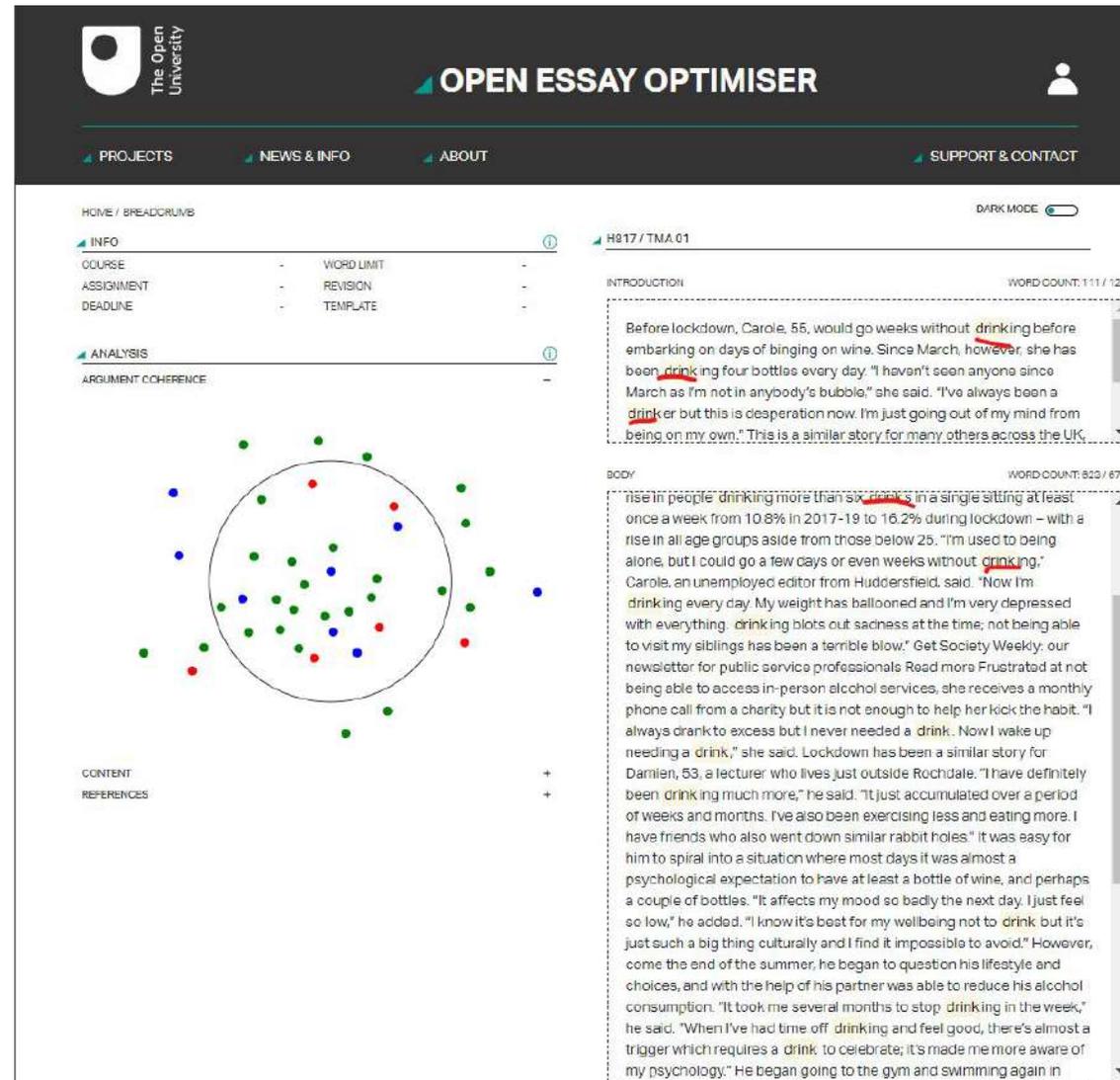


Researchers

Rainbow diagrams related to mark awarded

- Multivariate analysis of variance on marks awarded to 45 students
- Submitted two essays
- Rainbow diagrams produced from these essays and rated as high, medium or low attainment
- Covariate showed a significant relationship with the marks
- $F(1, 43) = 5.92, p = .01$ using a directional test
- Essays rated as high would be expected to receive 8.56 percentage points more than essays rated as medium
- 17.2 percentage points higher than essays rated from rainbow diagrams as low

- Summarisation through different visualisations
- Using Key words and key phrases
- Mean grade for overall module for students in cohort who used Open Essayist (64.2) and students previous cohort (53.7) p0.4



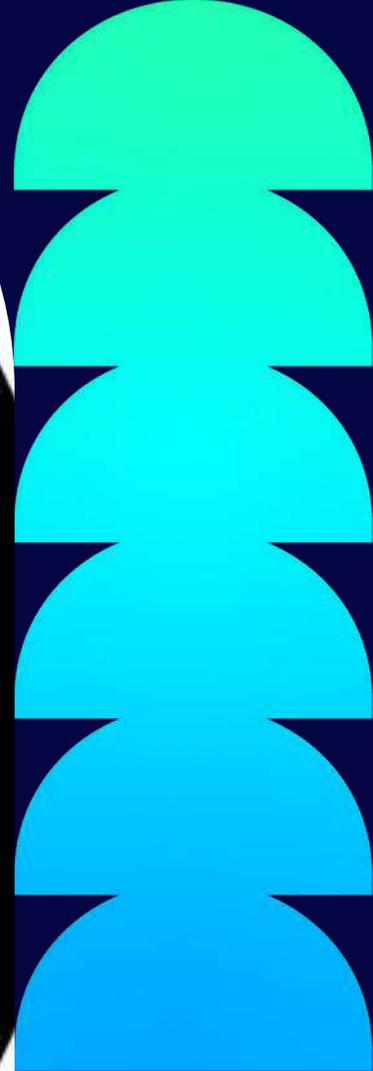
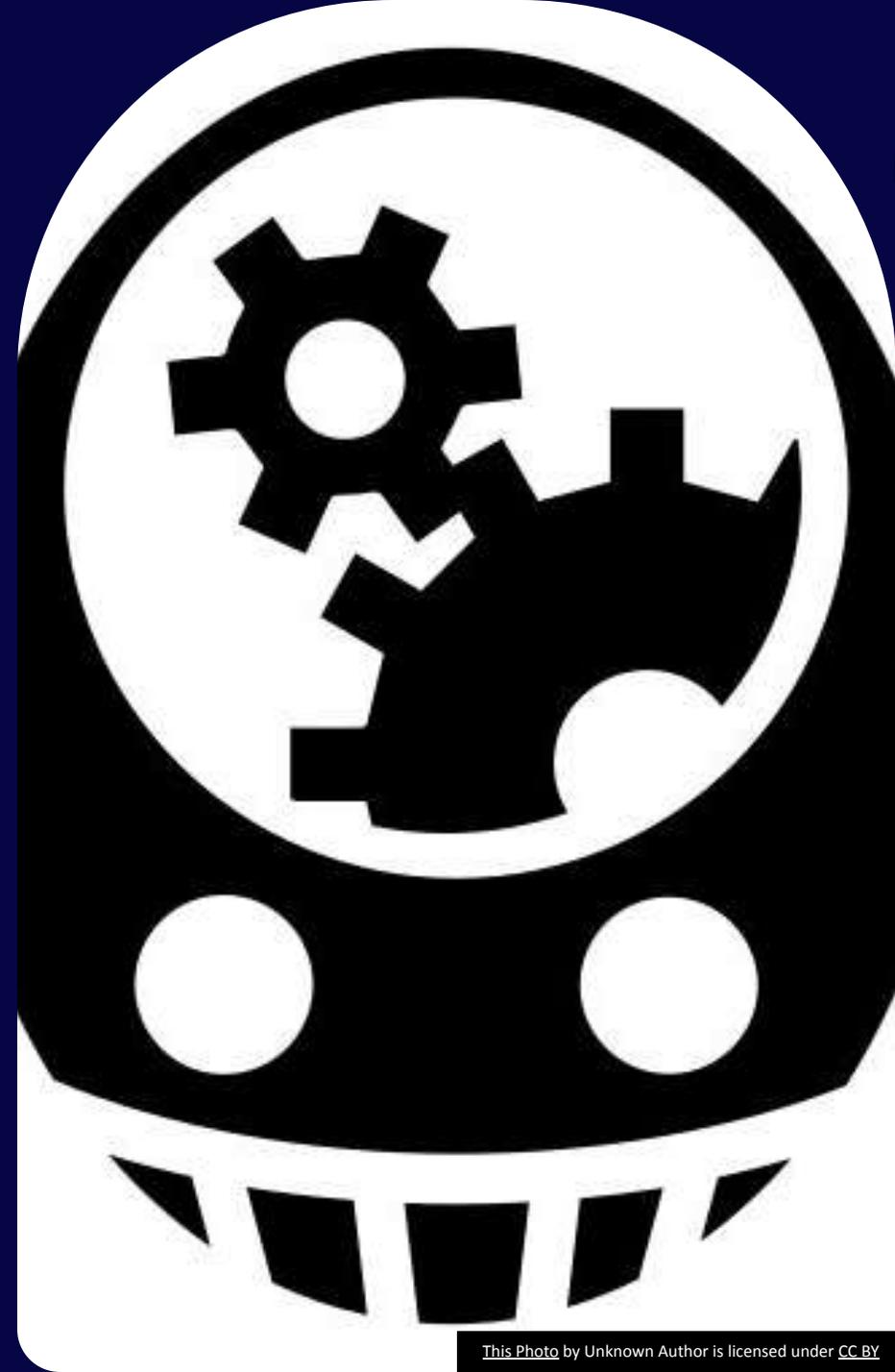
The screenshot displays the 'OPEN ESSAY OPTIMISER' interface. At the top, there is a navigation bar with 'PROJECTS', 'NEWS & INFO', 'ABOUT', and 'SUPPORT & CONTACT'. Below this is a sidebar menu with 'HOME / BREADCRUMB', 'INFO', 'ANALYSIS', 'CONTENT', and 'REFERENCES'. The main area is divided into two sections: 'H817 / TMA.01' and 'INTRODUCTION'. The 'INTRODUCTION' section shows a text editor with the following text: "Before lockdown, Carole, 55, would go weeks without drinking before embarking on days of bingeing on wine. Since March, however, she has been drinking four bottles every day. 'I haven't seen anyone since March as I'm not in anybody's bubble,' she said. 'I've always been a drinker but this is desperation now. I'm just going out of my mind from being on my own.' This is a similar story for many others across the UK." The text is highlighted with red and green markers. Below the text editor is a 'BODY' section with the following text: "rise in people drinking more than six drinks in a single sitting at least once a week from 10.8% in 2017-19 to 16.2% during lockdown - with a rise in all age groups aside from those below 25. 'I'm used to being alone, but I could go a few days or even weeks without drinking,' Carole, an unemployed editor from Huddersfield, said. 'Now I'm drinking every day. My weight has ballooned and I'm very depressed with everything. drinking blots out sadness at the time; not being able to visit my siblings has been a terrible blow.' Get Society Weekly, our newsletter for public service professionals Read more Frustrated at not being able to access in-person alcohol services, she receives a monthly phone call from a charity but it is not enough to help her kick the habit. 'I always drank to excess but I never needed a drink. Now I wake up needing a drink,' she said. Lockdown has been a similar story for Damien, 53, a lecturer who lives just outside Rochdale. 'I have definitely been drinking much more,' he said. 'It just accumulated over a period of weeks and months. I've also been exercising less and eating more. I have friends who also went down similar rabbit holes.' It was easy for him to spiral into a situation where most days it was almost a psychological expectation to have at least a bottle of wine, and perhaps a couple of bottles. 'It affects my mood so badly the next day. I just feel so low,' he added. 'I know it's best for my wellbeing not to drink but it's just such a big thing culturally and I find it impossible to avoid.' However, come the end of the summer, he began to question his lifestyle and choices, and with the help of his partner was able to reduce his alcohol consumption. 'It took me several months to stop drinking in the week,' he said. 'When I've had time off drinking and feel good, there's almost a trigger which requires a drink to celebrate; it's made me more aware of my psychology.' He began going to the gym and swimming again in

- Coherence related to mark awarded now available with Open Essay Optimiser Whitelock et al (2022)

Whitelock, D., Twiner, A., Richardson, J.T.E., Field, & Pulman, S. (2018). What does a 'good' essay look like? Rainbow diagrams representing essay quality. In: E. Ras & A. Guerrero Roldan (Eds.) Technology Enhanced Assessment (TEA2017). Communication in Computer and Information Science, Springer, Cham, 829, 1-12.

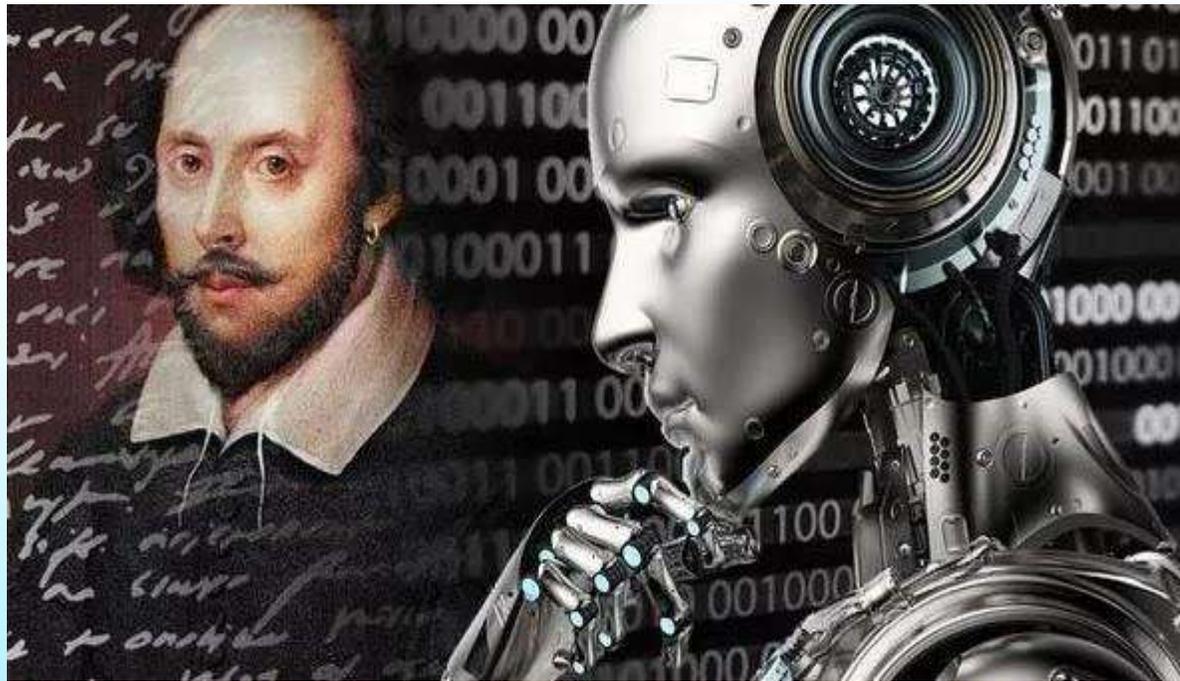
Generative Artificial Intelligence

Moving Forward



Disrupter

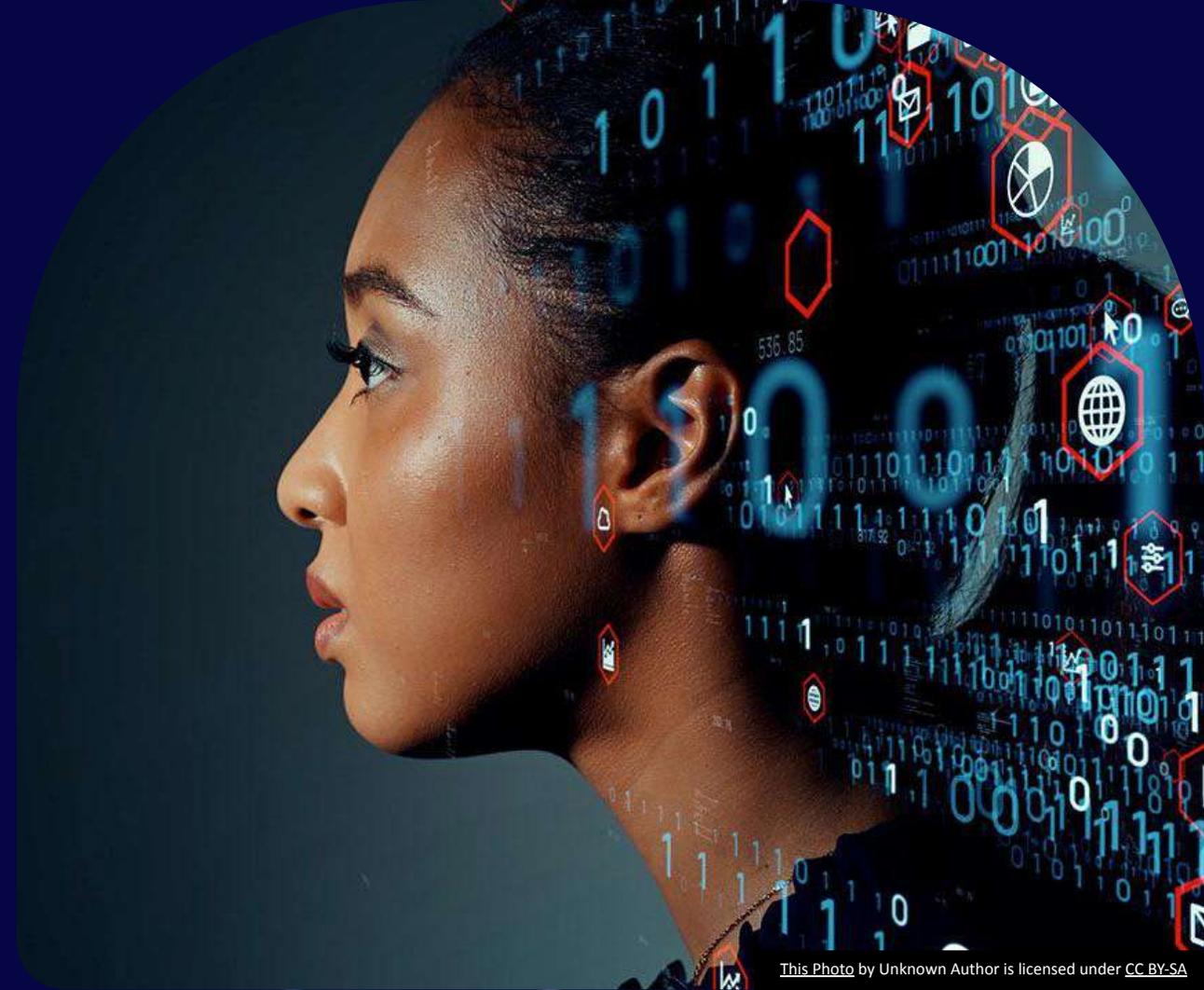
Generative AI



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- Generative AI models are trained by toggling 'weights' or the strength of connections between different variables
- Applied statistics not such a good term as AI?
- Can generate academic text rapidly
- Chat GPT 4 Improving but not for journal abstract
- Hallucinates
- Amoral and Biased

Generative Artificial Intelligence And Learning Analytics

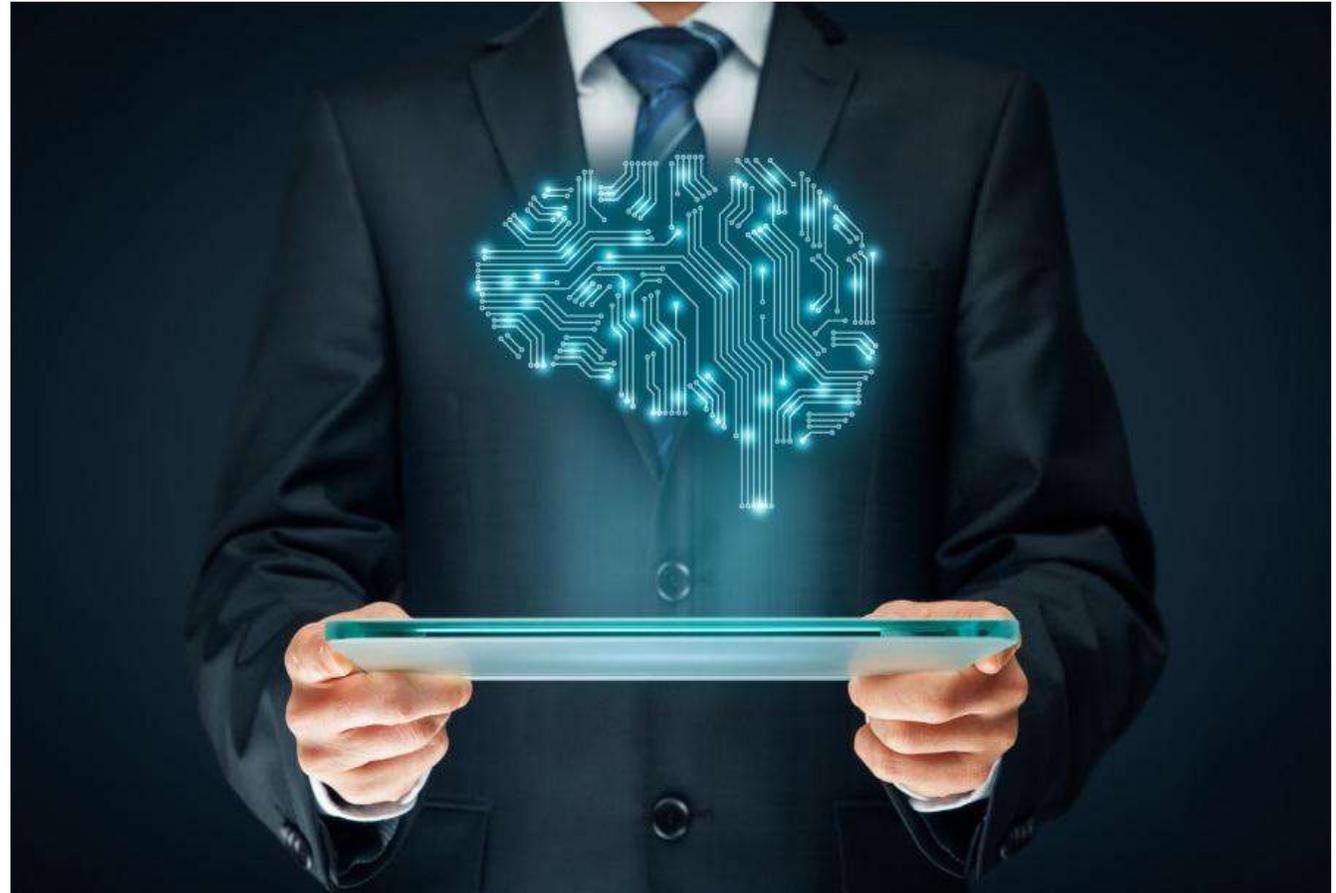


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AI and Learning Analytics

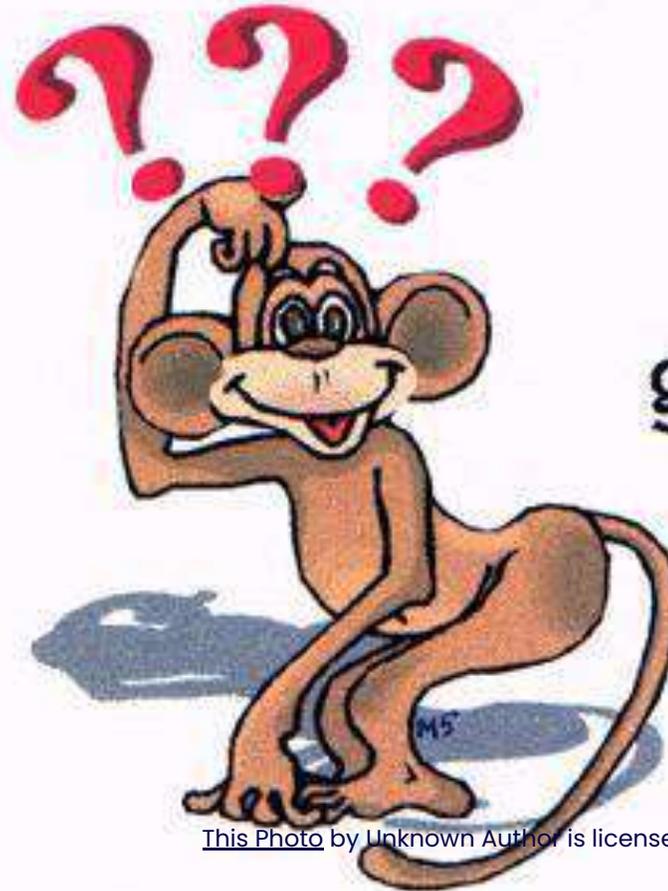
- Finding patterns in data sets for student success
- Recommender system
- Highlight best outputs to user with:
audio and visual feedback
- User interrogate feedback
/dashboard with an audio dialogue
- Give more control to users by AI
finding the relevant questions they
want answered



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Questions

1. What is the effect of different LA feedback types for effective learning?
2. How does feedback literacy affect teachers' pedagogical strategies?
3. What is the relevant data to affect student outcomes?
4. How does student feedback literacy influence their interpretation and then their reaction to feedback?



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Questions
are
guaranteed in
life;
Answers
aren't.

Research Agenda for Learning Analytics

Ethics revisited

Co design with students feedback
dashboards or

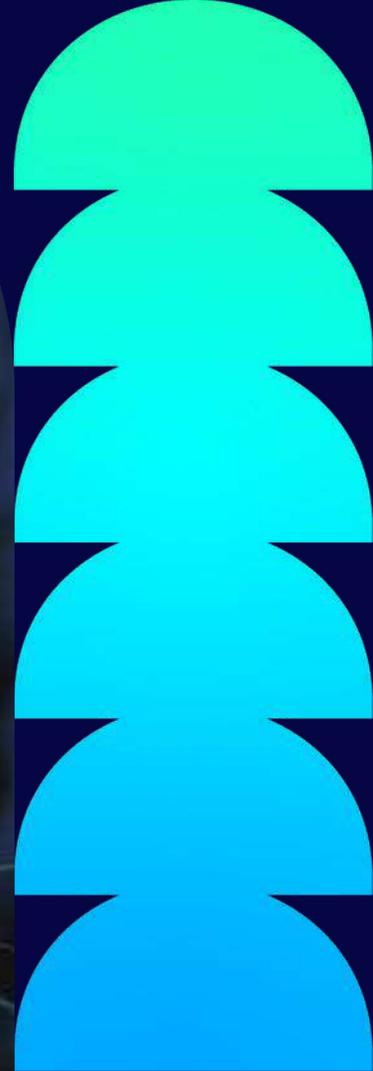
Models of feedback with embedded AI
tools

Integration AI Tools means
re-evaluation of Course Design Learning

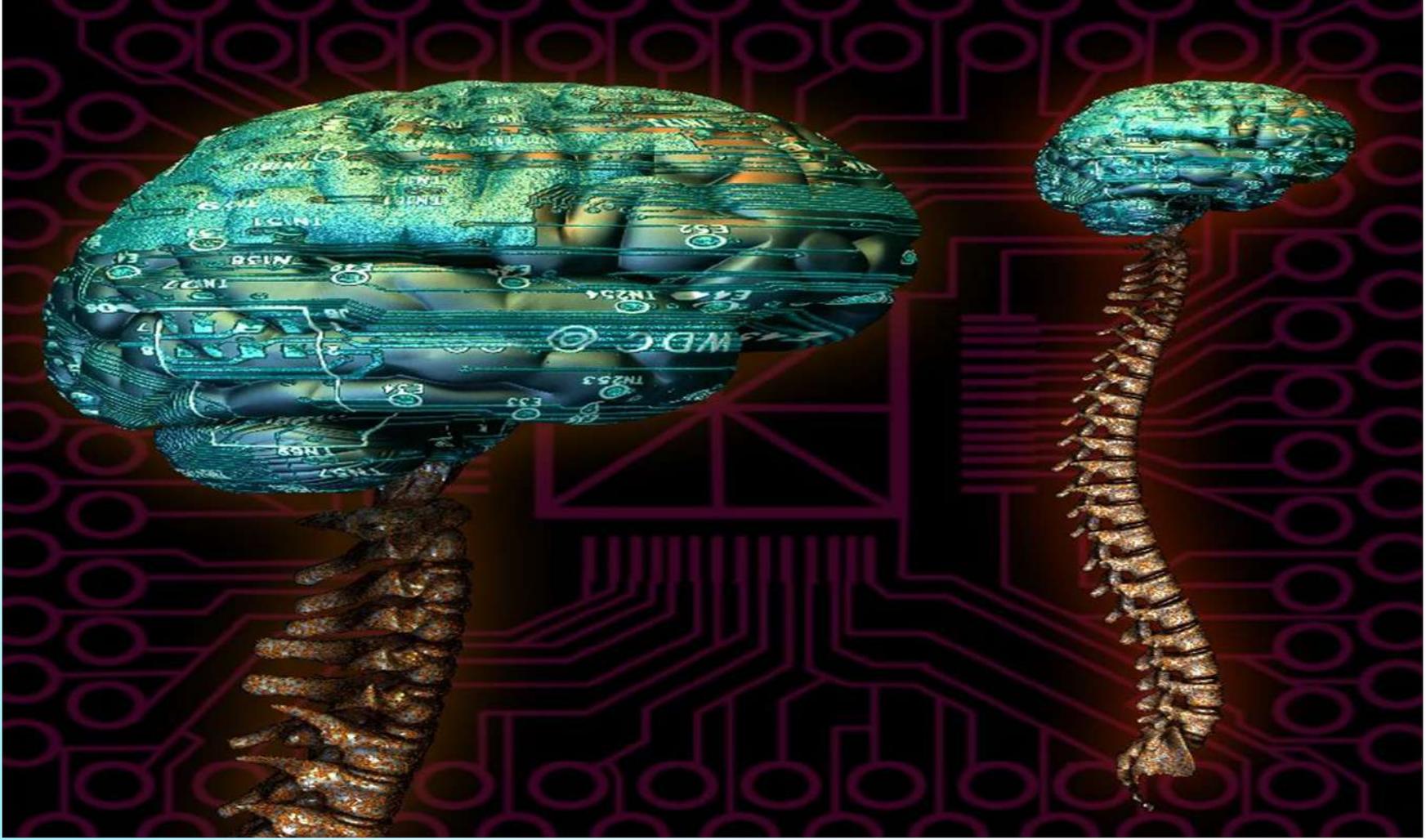
Data Analytics Literacy for students and
teachers

Investigate multimodal models and
theories of Learning that will guide the
missing loop of critical feedback that
will enhance Learning with Analytics

Mobile feedback to students / equitable
systems



Grand Challenge for Learning Analytics: what does it mean to assess human learning that can be readily understood by students and teachers? Moving Feedback Forwards





**The Open
University**