READY FOR LEARNING ANALYTICS?

Lessons from the coalface

Kevin Mayles
Head of Quality Enhancement and Learning Analytics
“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.

Review of learning analytics in Australian HE found two trajectories for the implementation of learning analytics:

1. A predictive or measurement tool for identifying students at risk
2. Developing understanding of, and improvements in, learning and teaching

Sclater (2017): Learning Analytics Explained
Four applications of learning analytics:

1. Early alerts and student success
2. Course recommendations
3. Adaptive learning
4. Curriculum design

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Learning analytics implementation directly linked to strategic objectives
Which area of your institution are you from?

- Teaching and learning enhancement: 26%
- Faculty / School: 21%
- IT / CIO: 21%
- Strategic planning: 32%
- Student support: 21%

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LESSONS LEARNED AND RECOMMENDATIONS

Key tips from lessons learned during the OU’s learning analytics implementation journey

- Executive sponsorship
  - Create the coalition

- Be clear on your purpose / objective
Early alert indicators using predictive analytics

Using operational and experience data

Partnering with researchers

Data visualisation and ‘dashboards’

Policy on the ethical use of student data for learning analytics

Analytics for action evaluation framework

Impact of learning design on outcomes

Data warehousing and management

Adapted from Barton and Court (2012)
Big Data Analytics
What was the first thing that came to mind?

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PRINCIPLES
for the ethical use of student data for learning analytics

01
Learning analytics is an ethical practice that should align with core principles, such as open entry to undergraduate level study.

02
The OU has a responsibility to all stakeholders to use and extract meaning from student data for the benefit of students where feasible.

03
Students should not be wholly defined by their visible data or our interpretation of it.

04
The purpose and boundaries regarding the use of learning analytics should be well defined and visible.

05
The University is transparent regarding data collection, and will provide students with the opportunity to update their own data at regular intervals.

06
Students should be engaged as active agents in the implementation of learning analytics (e.g., personalised learning paths, interventions, etc.).

07
Modelling and interventions based on analysis of data should be sound and free from bias.

08
Adoption of learning analytics with the OU requires broad acceptance of the values and benefits (organisational culture) and the development of appropriate skills across the culture.

INFORMATION FOR STUDENTS

Ethical use of Student Analytics Policy

This policy aims to set out how the University of the Open University (OU) uses student data to support the student support provided. The policy includes particular aspects of learning analytics.

For more information, see How the OU uses student data.

For more information, see How the OU uses student data.

Charter Principle: We treat each other with dignity and respect.

Learning analytics and you

Univeristy staff look for the best ways to support you in getting good results. But it’s not always easy to know when we should offer extra help.

- Our excellent tutors are there for you when you need support in your studies.
- Our student support teams (SSTs) are highly trained in providing study advice to fit your circumstances.
- Our IT staff have developed sophisticated systems and statistical methods to help us be proactive in offering individual support when we think it might be needed.

The techniques of learning analytics help us to select specific types of information from the data we have and use it to personalise what we work out for students. That way, you don’t get messages that aren’t relevant to you, and we try to send helpful ones at all the right times.

To do this we use data gathered when you are registered – such as your previous educational experience – along with the information we record during your studies, such as when you submitted an assignment.

Your analytics of past students also help us to decide what might be helpful. For example, you’re studying several modules at once and we know it’s worth getting in touch to check what you’ve done and let you know about support you might need.

Because we’re using your data in this way, we’ve produced a separate policy document, Ethical use of student data for learning analytics.

We developed it by reviewing research on learning analytics and consulting with students through a student forum. The policy itself is primarily aimed at staff, but there’s also an executive summary for students.

How we use learning analytics

Student data is used in three main ways:

- Monitoring: The way we want our students to meet certain criteria, such as submission of assignments or self-engagement with their studies.
- Daily warning indicators: This approach is based on statistical analysis of past students and is an indication of the expected threshold of something happening. It isn’t an absolute prediction but an indication of how likely we think it is based on the information we know that a student will be unsuccessful at a particular point.
- Policy model: student outcomes with absolute certainty, and there will always be factors that affect students’ progress that are beyond the University’s control.

However, the predictive models used contain the effects of multiple factors to create the probabilities and have been shown to provide an acceptable level of accuracy across the individual student level. We contract students who are not doing as well as they should with an email or contact details. However, when you report the problem to us, we should be able to identify and provide support to students who may benefit from a letter that can offer additional support or encouragement.

It’s expected that the overall use of the analytics data is being considered and is one of the data that will impact the University’s ethical and data protection policies.

Evaluating our teaching: We evaluate our teaching and learning design and technology by aggregating data to help us make improvements. For example, the assessment strategy for a module.
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- Foreground the “should we” arguments
  Involve your students
FACTOR ANALYSIS – END OF MODULE EVALUATION SURVEY

Factors of student satisfaction

Student Experience

Tutor Guidance & Support

Assessment Feedback

Value

Module Content

Factors:
- Student Experience
- Tutor Guidance & Support
- Assessment Feedback
- Value
- Module Content

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The OU has developed several approaches to the development and application of predictive analytics.

**Pass rates model generating explanatory factors**

*Student probabilities generated for the various milestones including completion, pass and return*

**Pass rates model generating explanatory factors**

*Greater understanding of student success variables for BAU processes*

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**Conventional Modelling**

- OUTPUTS
  - SSTs and SRSCs
  - Associate Lecturers

**Machine learning**

- OUTPUTS
  - TMA submissions
  - Recommend
  - Students
VISION FOR EARLY ALERT INDICATORS

Proactive and personalised support to students

Associate lecturers, staff tutors, SRSC and SST staff, data interpreters

Student view with recommender

Predictive engines

At risk indicators

Recommended action is ... / Student at risk because ...

Ongoing interaction

Student data

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# OU ANALYSE DASHBOARD

## Predictions

<table>
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<tr>
<th>Student PI</th>
<th>Name</th>
<th>TMA</th>
<th>Risk of non-submission</th>
<th>Next TMA prediction</th>
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<td>William Smith</td>
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<td>George Wilson</td>
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<td>Thomas Evans</td>
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<td>Not submit</td>
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</tr>
</tbody>
</table>
DEPLOYMENT PILOTS

2 AL Super users recruited

- **2015-16**
  - **Number of Modules**: 10
  - **Number of Tutors**: 240
  - **Participation**: Voluntary or access available under test (A/B Tests and Randomised Control Trials) conditions
    - **Number of Students**: (~) 4800

- **2016-17**
  - **Number of Modules**: 26
  - **Number of Tutors with access to OUA**: 1163
  - **Number of Tutors who actually accessed OUA**: 251
  - **Participation**: Voluntary / Randomised Control Trials on a few modules
    - **Number of Students**: (~) 28,000

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OU ANALYSE DEPLOYMENT EVALUATION OUTCOMES

Evaluation of pilot deployments has shown the affordances of early alert predictive indicators

• The two studies show that the best predictors of student performance were:
  • Degree of OU Analyse usage by the tutor ~ *What level of support does the student receive? OR How active is the tutor?*
  • Best previous score achieved by the student ~ *Does the student know how to learn?*

• Tutors who accessed/used OU Analyse 51% or more of the relative module length had higher Assignment Submission Rates and Completion Rates.

• Interviews with Tutors suggested that OU Analyse enhanced and facilitated their teaching practice

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“I love it it’s brilliant. It brings together things I already do [...] it’s an easy way to find information without researching around such as in the forums and look for students to see what they do when I have no contact with them [...] if they do not answer emails or phones there is not much I can do. OUA tells me whether they are engaged and gives me an early indicator rather than waiting for the day they submit”
OU in Scotland conducted a random control trial of a targeted intervention using predicted probabilities.

**Random Control Trial of Targeted Intervention**

Scottish Cohort with 31-40% probability of completion (n=410)

- **SMC (HC)**
  - 318 (200)
  - 312 (210)
  - Register
  - Start
  - 25% FLP
  - 50% FLP
  - 100% FLP
  - Completion
  - Pass

**Control – M2 intervention only**

**Test – M2 intervention with new Scottish intervention**

*This band was selected for targeting as it is one in which improvement in student outcomes.*

**3 weeks**

- **Text**
  - Initial notification of upcoming phone call by text message

- **Phonecall**
  - How do you feel about starting? Do you have concerns? Do you where to look for help?

- **Email**
  - Follow up email for those who were not contactable by phone
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- Eat the elephant one bite at a time – look for quick wins

- Foreground the “should we” arguments
  Involve your students

- Create your super-users, grow organically

- Compelling case studies outcomes and stories

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Rate on a scale of 1 to 6 (where 1 is really easy and 6 is nearly impossible) how easy it is for you to access data for analysis at your institution.

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- 1: 20%
- 2: 7%
- 3: 20%
- 4: 7%
- 5: 20%
- 6: 27%
SUPPORTED BY REAL-TIME ACCESS TO MANAGEMENT INFORMATION

Procurement of a new data visualisation tool integrated with our data warehouse enabled the development of new, self-service, real-time views of student data.

Definitions workshops
Agreed global student terms

Identifying the right data sources
Student Data Sets from Strategy and Information Office
New Qual Data Mart
Establishing Qual/Mod relationships

Expanded Data Warehouse

SAS Visual Analytics
Interactive, Drill down, Real Time Reporting

STUDENT PROGRESSION REPORTS
Real Time Dashboards showing student progression within qualifications, across OU study, in module

Faculty Workshops
Gathering Retention Reporting Requirements

Student Progression Reporting Framework

Workshops With:
Student Services
IET
Strategy and Information Office
Awards Ceremonies and Qualification
University Secretary’s Office

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Plot your institution in terms of maturity of data provision and literacy of users

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SCAFFOLDING ACTION

We developed an evidence based framework for scaffolding module teams’ engagement with data – the Analytics 4 Action Framework and Toolkit

1. PERFORMANCE MEASURES AND DRILL DOWNS
2. MENU OF RESPONSE ACTIONS
3. METHODS OF GATHERING EVIDENCE
4. EVALUATION PLANS
5. EVIDENCE HUB
6. DEEP DIVE ANALYSIS AND STRATEGIC INSIGHT

COMMUNITY OF INQUIRY FRAMEWORK: UNDERPINNING TYPOLOGY

Implementation/testing protocols with evaluation plans
- Randomised control trials
- A/B testing
- Pilot study with sub-sample
- Quasi-experimental
- Apply to all

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LEARNING DESIGN LINK TO SUCCESS

Through systematic mapping of the learning design of modules we can look for links to student outcomes.
Constructivist Learning Design

Assessment Learning Design

Balanced-variety Learning Design

Socio-construct. Learning Design

Learning Design 150+ modules

Rienties and Toetenel (2016)
Constructivist Learning Design

Assessment Learning Design

Balanced-variety Learning Design

Socio-construct. Learning Design

Learning Design 150+ modules

VLE Engagement

Week 1
Week 2
Week 30+

Student Satisfaction

Student retention

Communication

Rientes and Toetenel (2016)
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- Don’t underestimate the guidance required

- Find and nurture your champions and stars

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Rank these applications for Learning Analytics in priority order for your institution

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- Early alert indicators and student success: 1st
- Curriculum and learning design: 2nd
- Adaptive learning: 3rd
- Course recommendation: 4th
Text mining and sentiment analysis

Adapting models for new teaching framework

Cloud based analytics platforms

CRM analytics

Embedding within new QA/QE process and alignment with TEF

New systems for collecting student feedback

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# LESSONS LEARNED AND RECOMMENDATIONS

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<tr>
<td>Don’t underestimate the guidance required</td>
<td>Find and nurture your champions and stars</td>
<td>Integrate, review, repeat…</td>
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ACKNOWLEDGEMENTS

This has been just a small slice of the work undertaken by a large network of colleagues at the Open University.
Useful references


Rienties, Bart; Boroowa, Avinash; Cross, Simon; Kubiak, Chris; Mayles, Kevin and Murphy, Sam (2016). Analytics4Action Evaluation Framework: A Review of Evidence-Based Learning Analytics Interventions at the Open University UK. Journal of Interactive Media in Education(1), article no. 2. [http://oro.open.ac.uk/44932/]


THANK YOU
ANY QUESTIONS?