The Open University

Learning Analytics @ The Open University

JISC Networking Event 11th May 2016

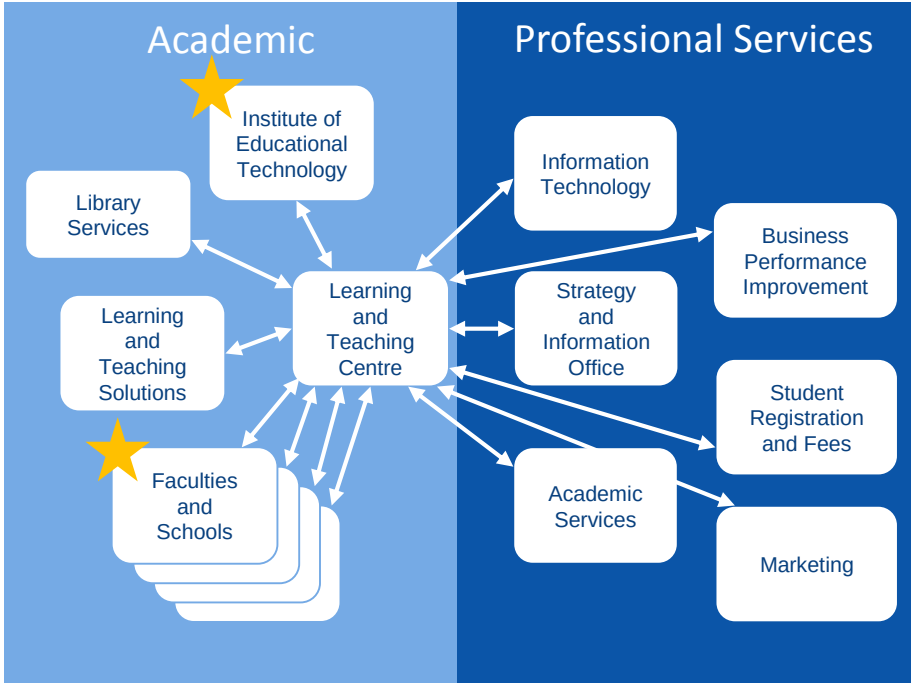
Kevin Mayles, Head of Analytics, The Open University

Life-changing Learning

Learning Analytics @ The Open University

Where are you from?

- PVC Learning & Teaching
- CIO / IT
- Planning Office
- Student Support
- Faculty



The Learning and Teaching Centre

kevin.mayles@open.ac.uk | @kevinmayles

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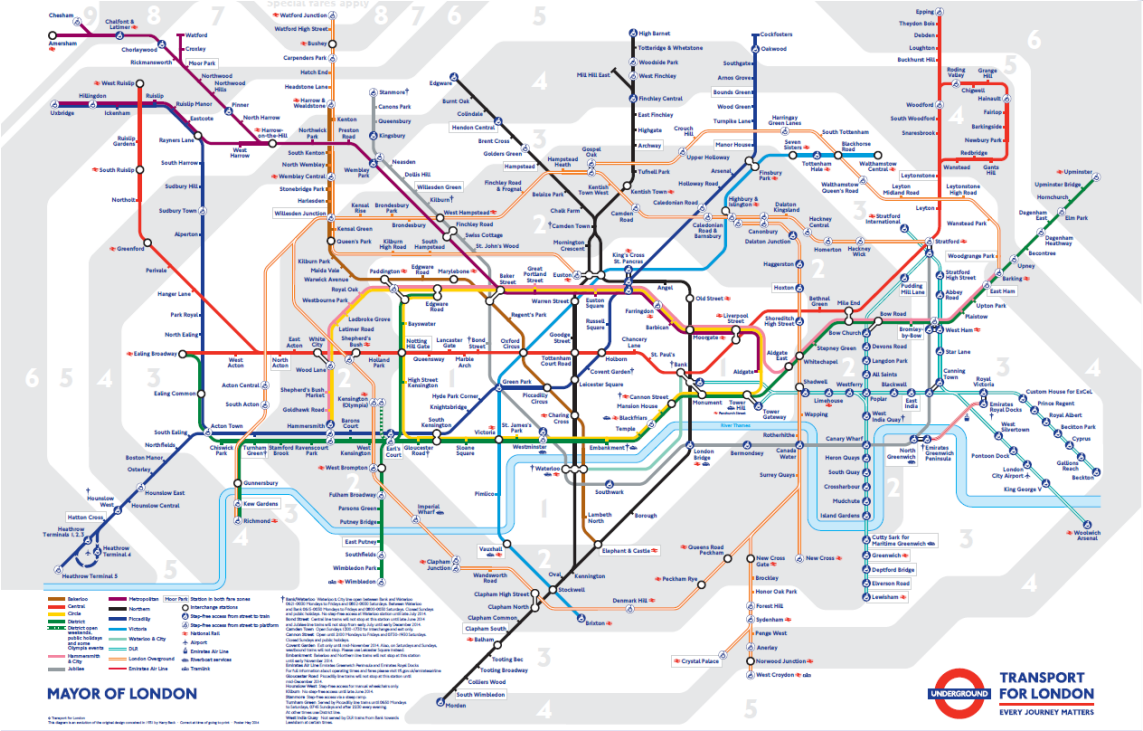

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OU Context

2014/15

174k students

The average age of our new undergraduate students is 29

40% new undergraduates have 1 A-Level or lower on entry

Over 21,000 OU students have disabilities

868k assessments submitted, 395k phone calls and 176k emails received from students

Analytics for student success vision

A clear vision statement was developed to galvanise effort across the institution on the focused use of analytics

Vision

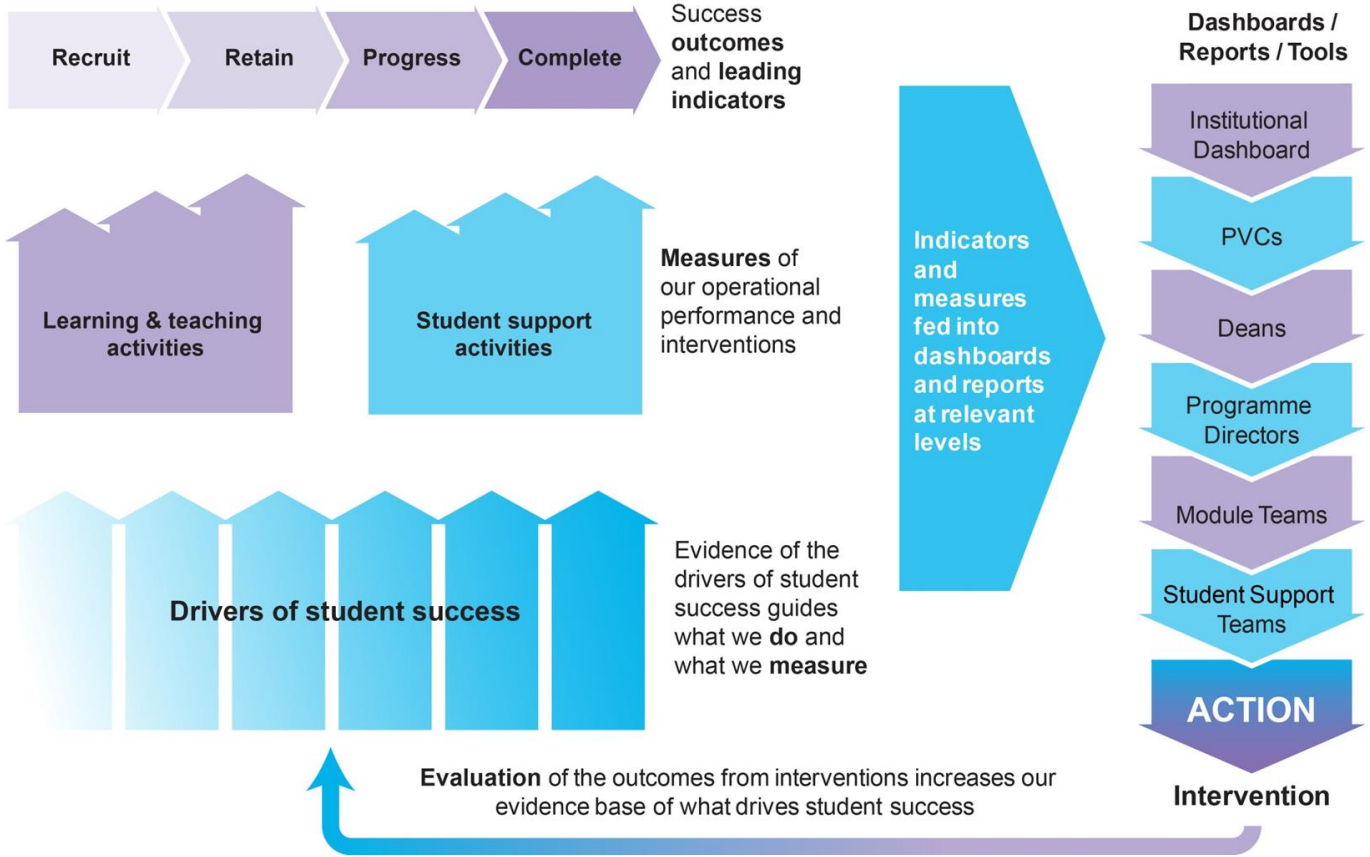
To use and apply information strategically (through specified indicators) to retain students and progress them to complete their study goals

Mission

This needs to be achieved at :

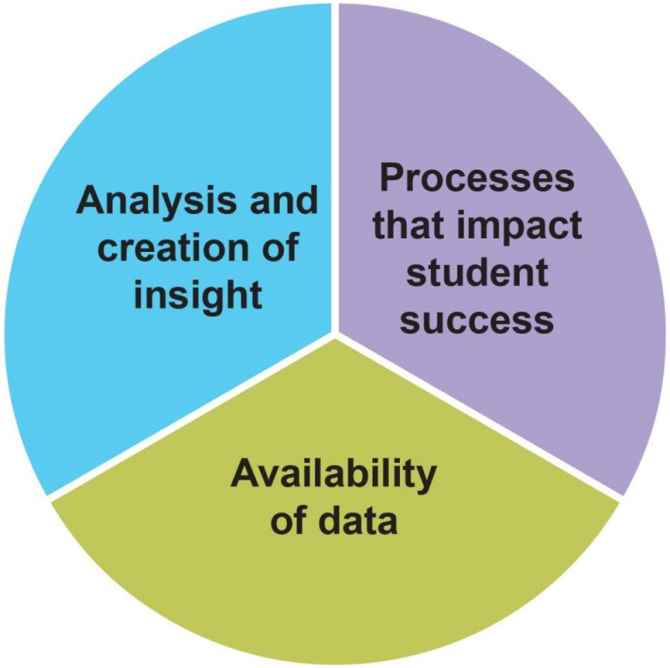
- a macro level to aggregate information about the student learning experience at an institutional level to inform strategic priorities that will improve student retention and progression
- a micro level to use analytics to drive short, medium and long-term interventions

Vision in action



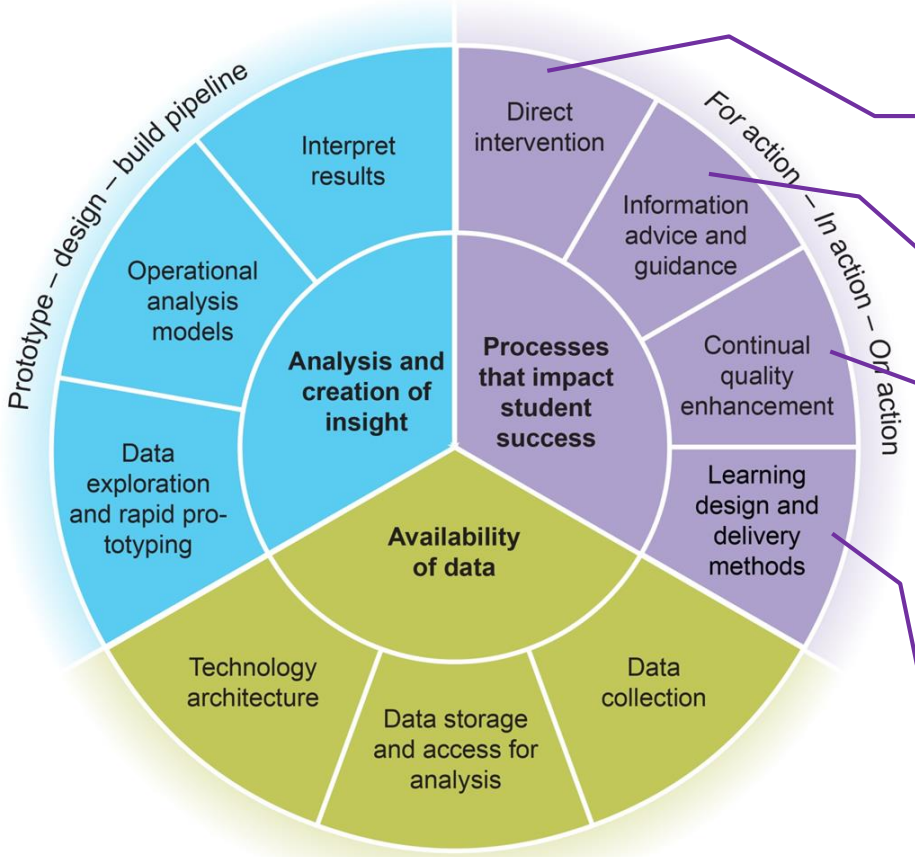
Analytics enhancement strategy

The OU recognises that three equally important strengths are required for the effective deployment of analytics



Adapted from Barton and Court (2012)

Analytics enhancement strategy



Early alert indicators using predictive analytics

Policy on the ethical use of student data for learning analytics

Analytics for action evaluation framework

Impact of learning design on outcomes

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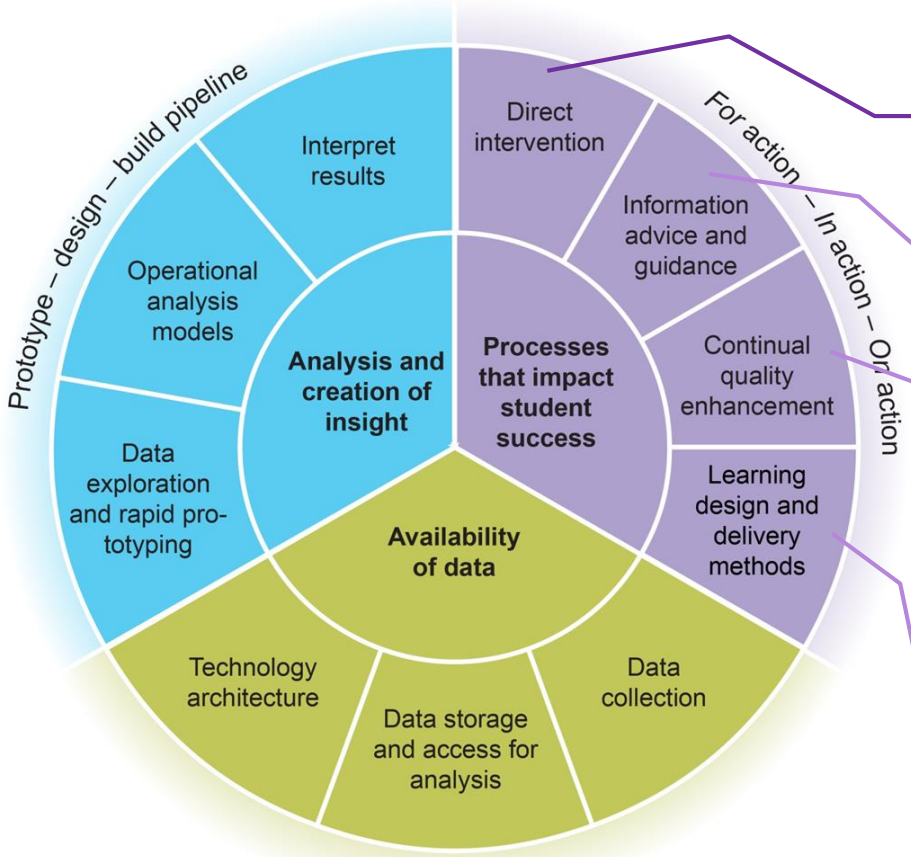
Analytics enhancement strategy



Early alert indicators using predictive analytics

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Analytics for action evaluation framework

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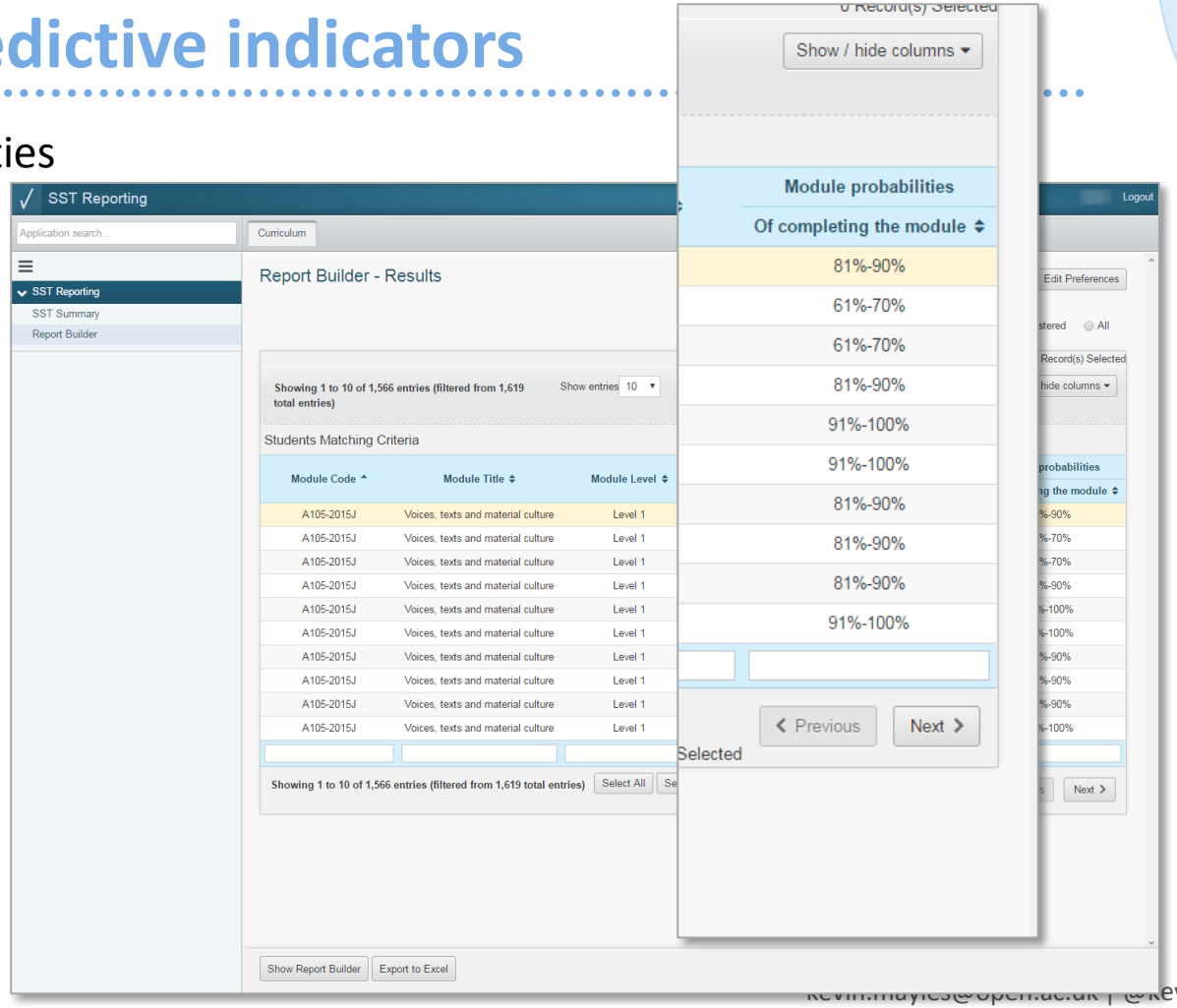
Current predictive indicators

Module probabilities

Integrated into the Student Support Intervention Tool

Predicts the probability of a student completing and passing the module

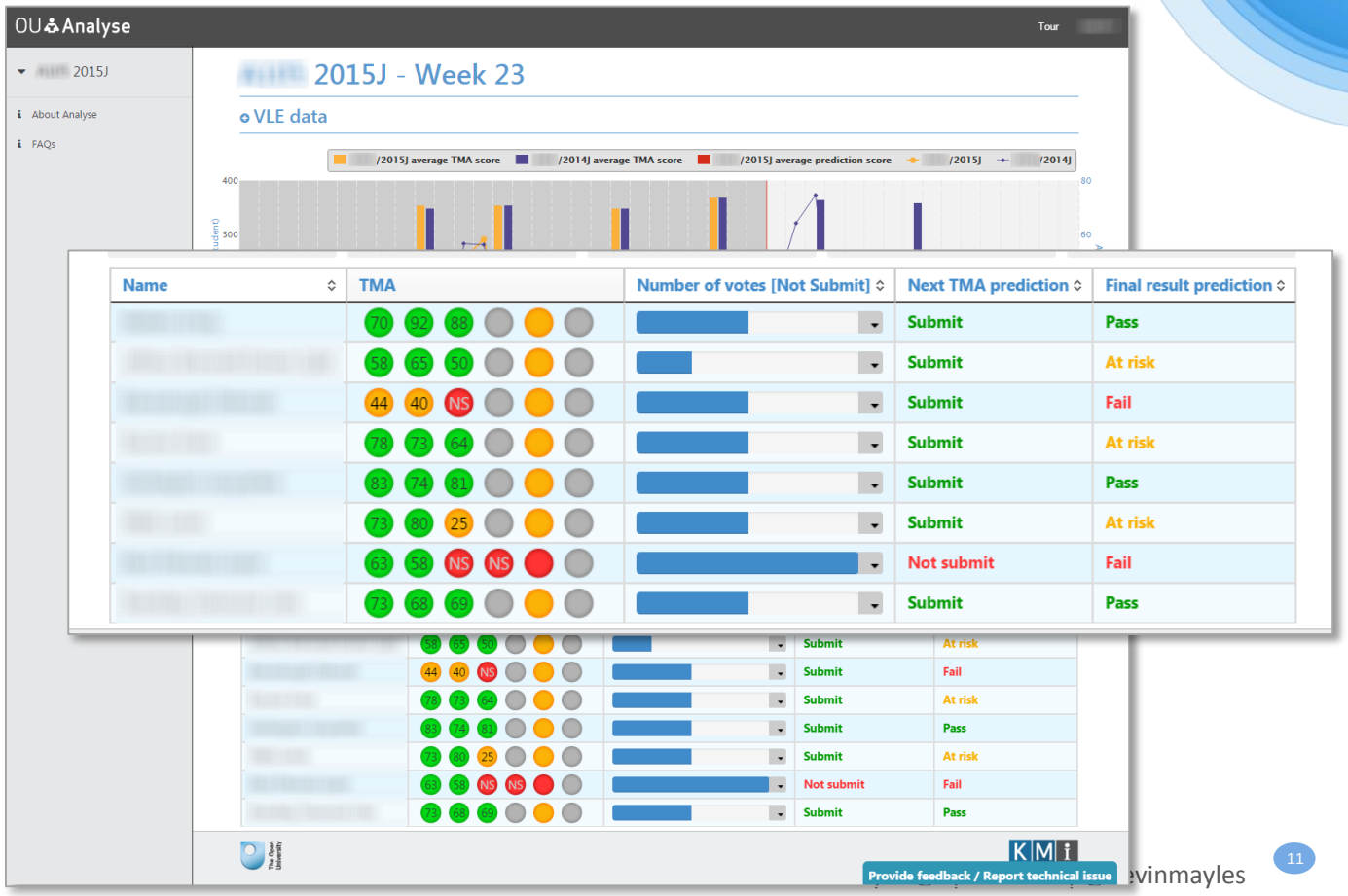


Current predictive indicators

OU Analyse

Predicts the submission of next assignment weekly

Deployed through OU Analyse Dashboard



Lessons

Create the right story for the user

Start small – find and nurture your champions

Don’t underestimate the guidance required

Create your super-users, create your case studies

Foreground the “should we” arguments

Repeat, repeat, repeat

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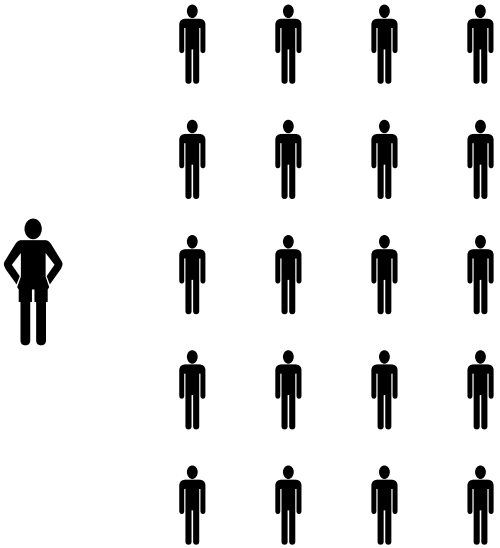
Intervention potential

We have been working to assess the intervention potential of using frequent indicators

Measures

- Accuracy of predictions
- Volume of predictions
- Timeliness of predictions



Accurate predictions at a manageable **volume** that are **timely** in relation to a student's decision to drop out

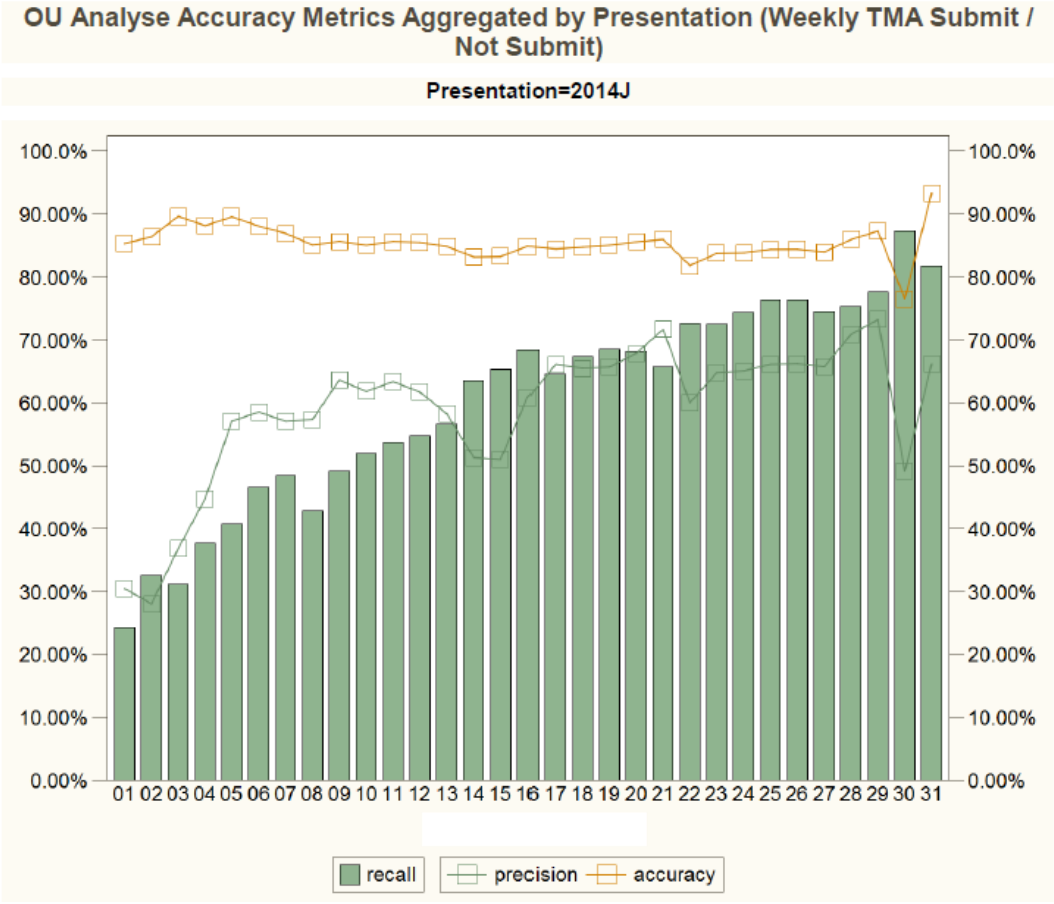
= Ability of Associate Lecturers (or others) to act on the information

Accuracy

- Using standard metrics where the condition we are predicting is the student NOT submitting (or completing/passing)

- **Accuracy** = % of all predictions that are correct
- **Precision** = % of non-submission predictions that are correct (the reverse of this is the false positive rate)
- **Recall** = % of actual non-submissions that are identified by the predictions (the reverse of this is the miss rate)

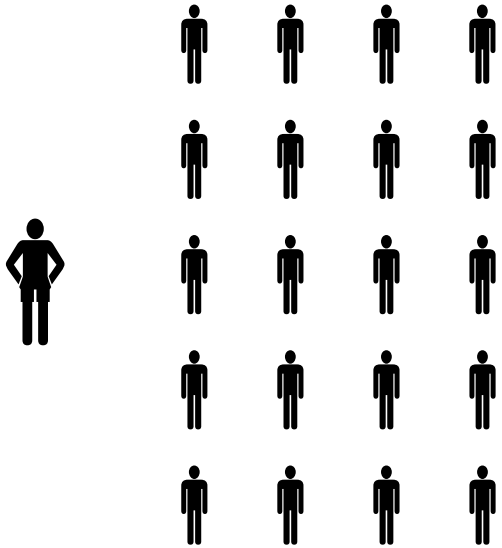
Accuracy


OU Analyse Accuracy Metrics Aggregated by Presentation (Weekly TMA Submit / Not Submit)
Presentation=2014J
100.0%
90.00%
80.00%
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31
recall
precision
accuracy

Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:

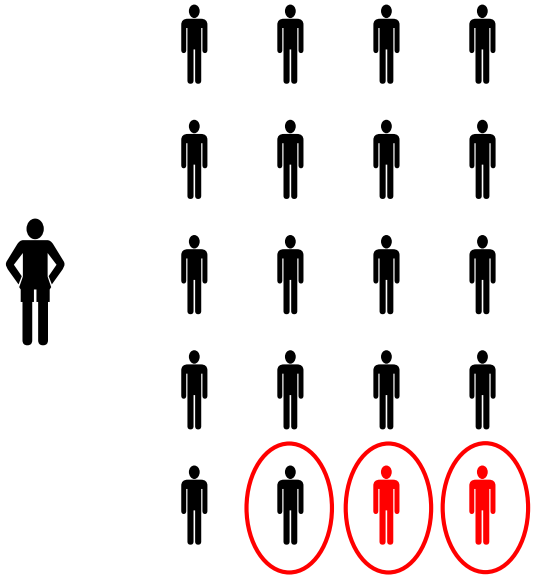


Predicted not to submit = New prediction this week = Actually did not submit =

Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:
By week 5, 2/3rds of predictions true, but …

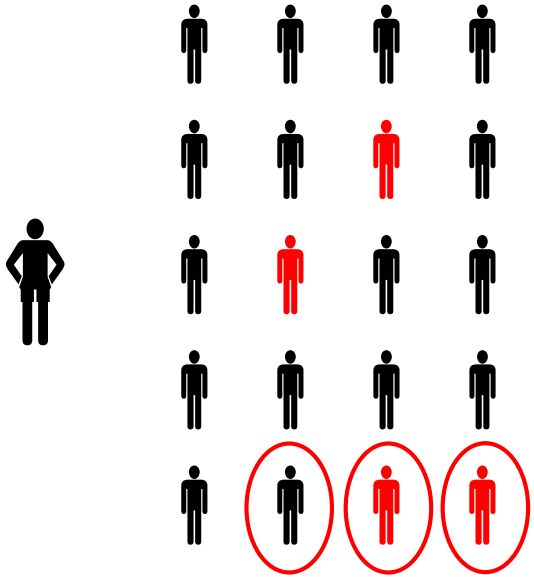


Predicted not to submit = New prediction this week = Actually did not submit =

Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:
By week 5, 2/3rds of predictions true, but only identify half of non-submitters



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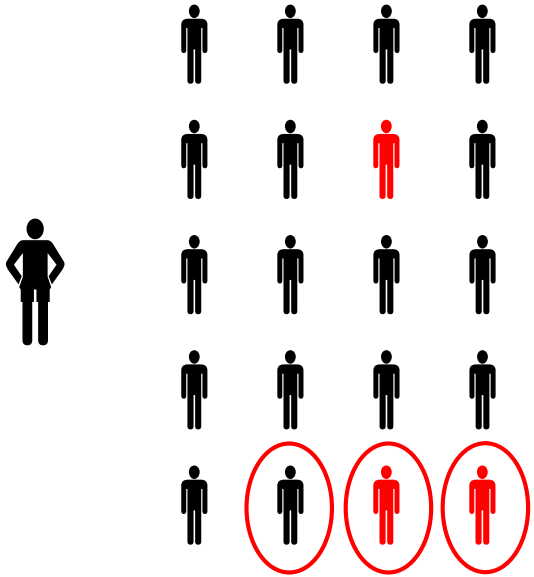
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:

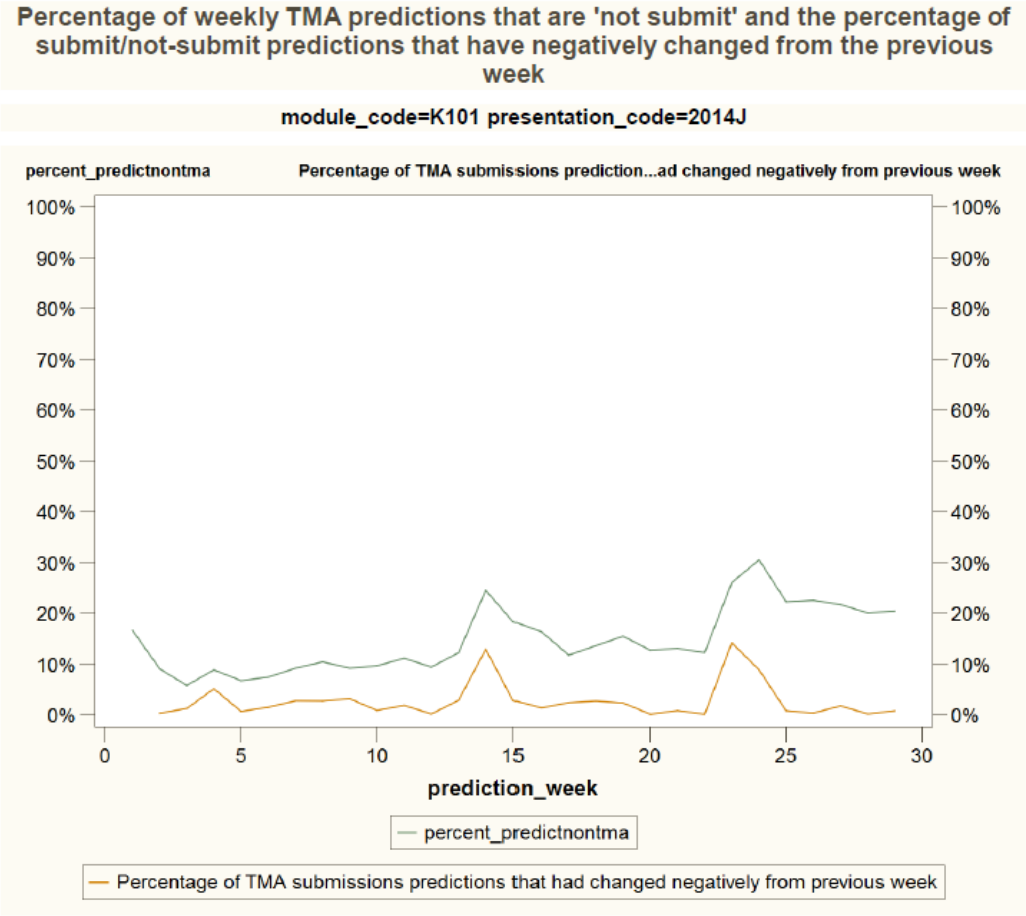
By week 5, 2/3rds of predictions true, but only identify half of non-submitters

By week 14, predictions identify 2/3rds of non-submitters



Predicted not to submit = New prediction this week = Actually did not submit =

Volume


Percentage of weekly TMA predictions that are 'not submit' and the percentage of submit/not-submit predictions that have negatively changed from the previous week
module_code=K101 presentation_code=2014J
percent_predictnontma
Percentage of TMA submissions prediction...ad changed negatively from previous week
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0
5
10
15
20
25
30
prediction_week
percent_predictnontma
Percentage of TMA submissions predictions that had changed negatively from previous week

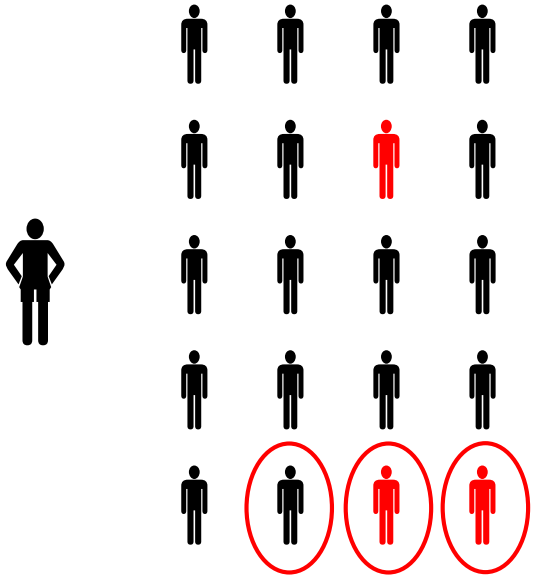
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:

By week 5, 2/3rds of predictions true, but only identify half of non-submitters

By week 14, predictions identify 2/3rds of non-submitters



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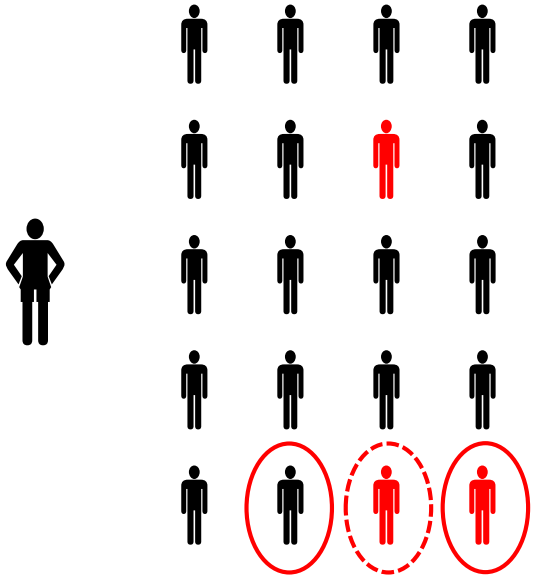
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:
By week 5, 2/3rds of predictions true, but only identify half of non-submitters
By week 14, predictions identify 2/3rds of non-submitters

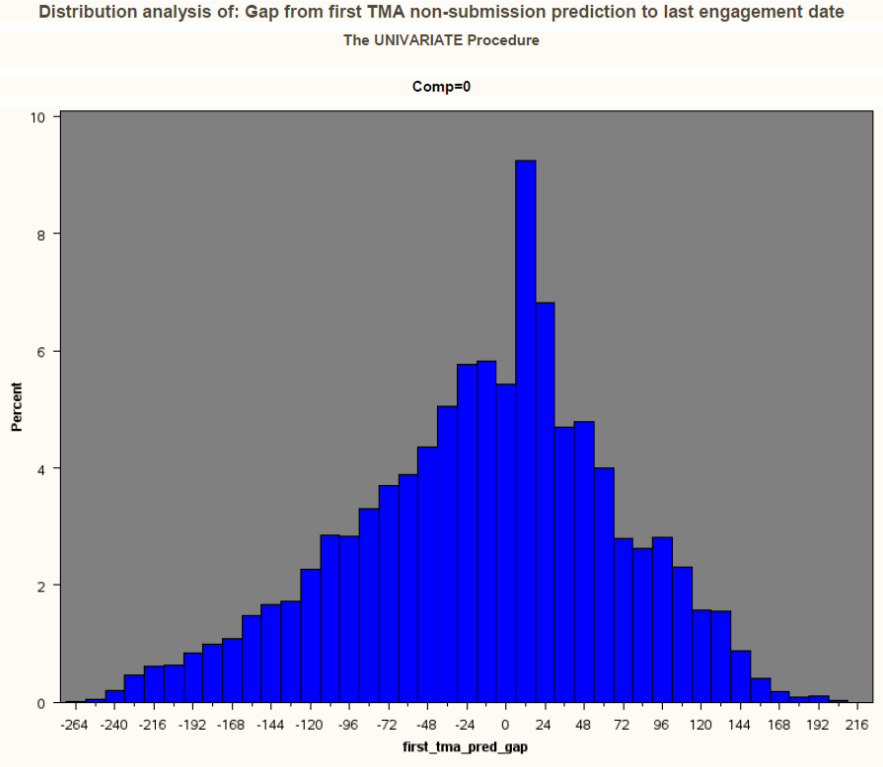
Volume:
Manageable – one new prediction per fortnight



Predicted not to submit = New prediction this week = Actually did not submit =

Timeliness

Gap from FIRST TMA non-submission prediction to last engagement



Mean: -14 days
St Dev.: 80 days

-30 days to 0: 15% of all first predictions
+1 days to +14: 9% of all first predictions

NB: last engagement date = Last date of either visit to VLE site, submit assessment, respond to study engagement check email

Caution – this is crude proxy measure

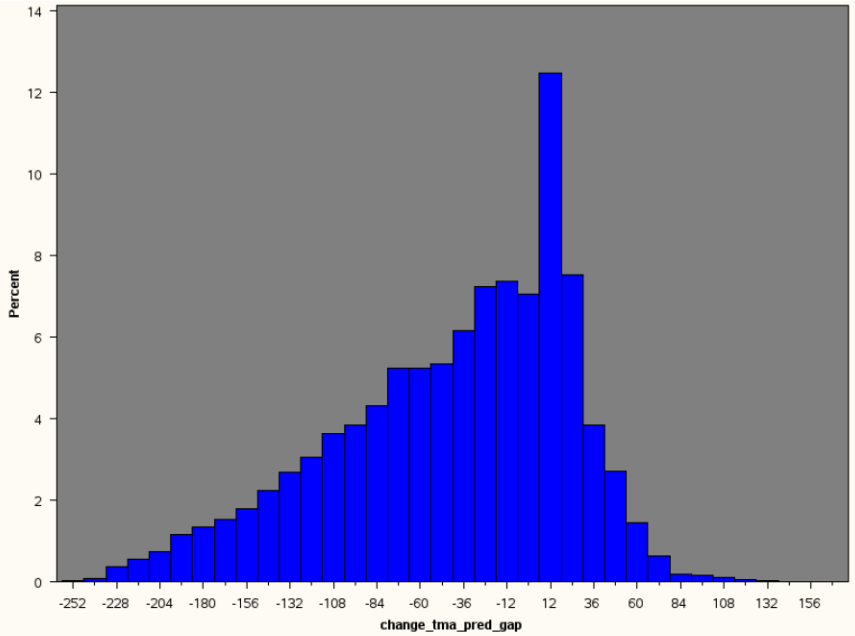
Timeliness

Gap from changes in TMA non-submission prediction to last

Distribution analysis of: Gap from each change to TMA non-submission prediction to last engagement date

The UNIVARIATE Procedure

Comp=0



Mean: -42 days
St Dev.: 65 days

-30 days to 0: 19% of all prediction changes
+1 days to +14: 12% of all prediction changes

NB: last engagement date = Last date of either visit to VLE site, submit assessment, respond to study engagement check email

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Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

Accuracy:
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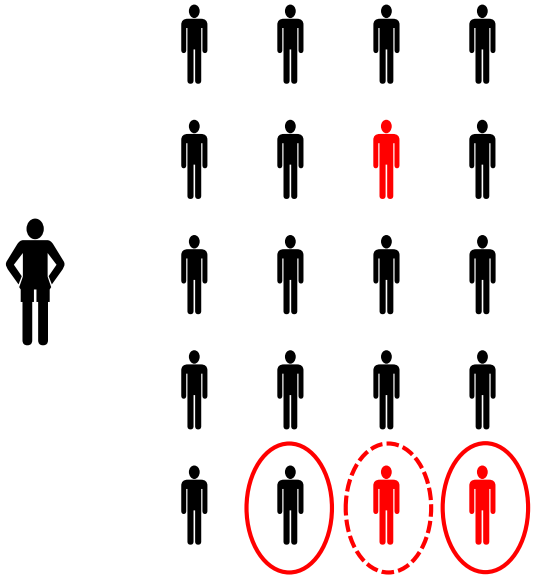

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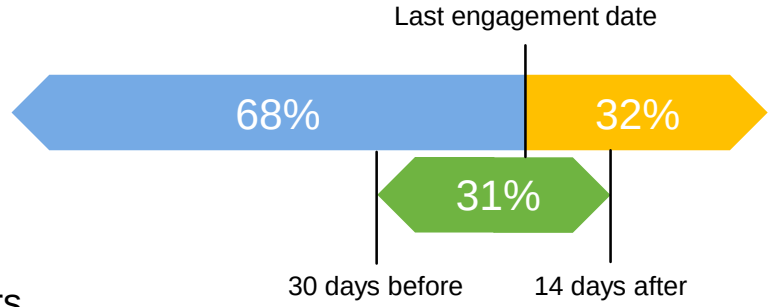
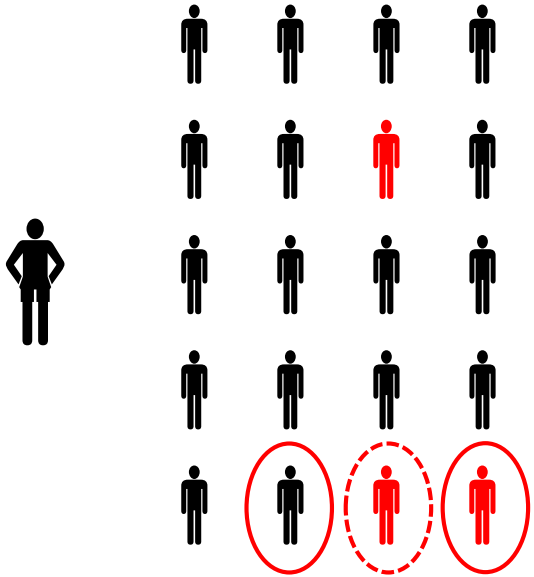
By week 14, predictions identify 2/3rds of non-submitters

Volume:
Manageable – one new prediction per fortnight

Timeliness:
One in three of all new predictions fall in a six week "window of opportunity" around the last engagement date based on an analysis of predictions for non-completers





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Lessons

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Start small – find and nurture your champions

Don’t underestimate the guidance required

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Foreground the “should we” arguments

Repeat, repeat, repeat

Champions

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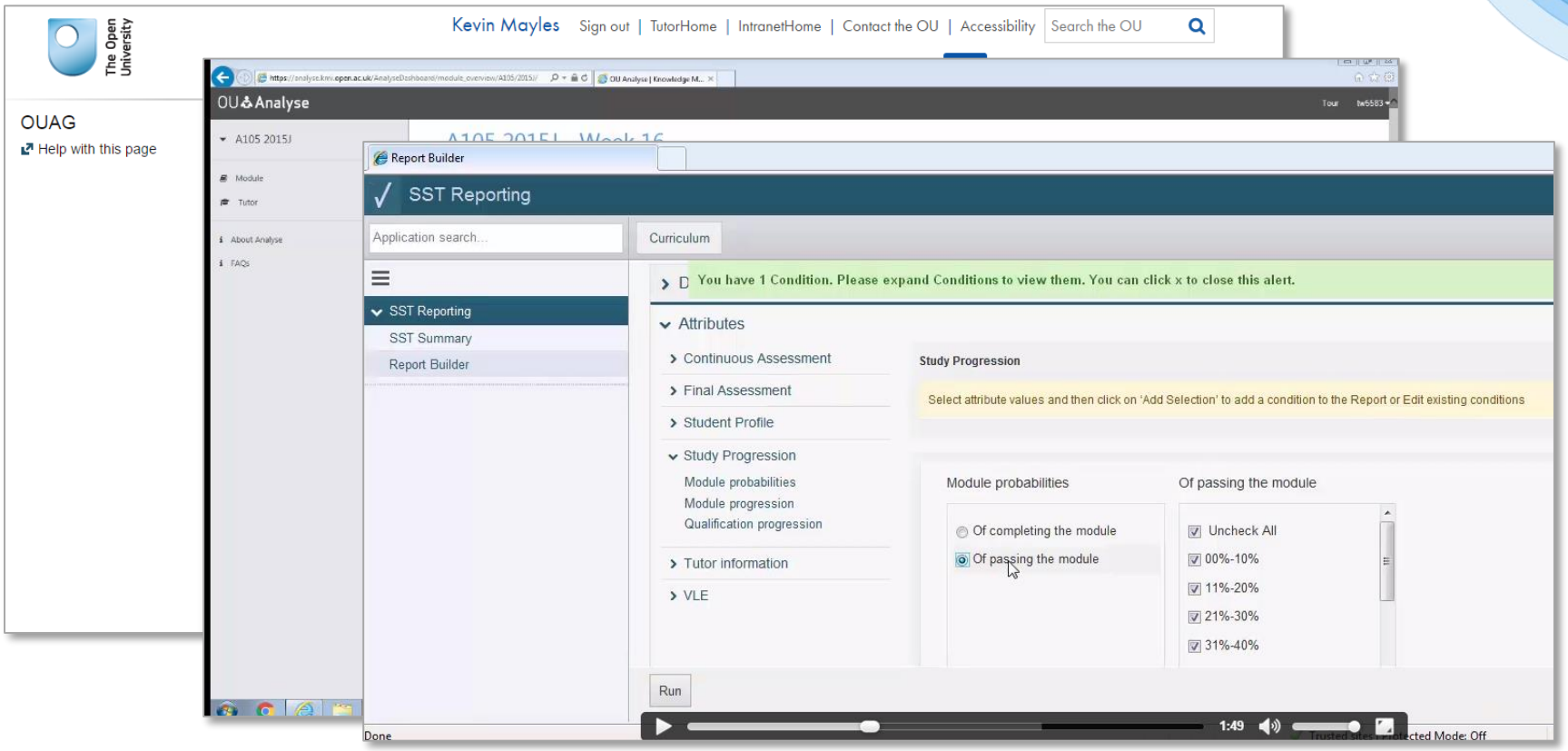
Guidance and help materials



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Super-users

Briefings

Catch-ups

Support and feedback

Outcomes of current pilots

Summary of the interim evaluation of piloting as at March 2016

- There is a mixed picture in the quantitative analysis on the impact in the pilot tutor groups on withdrawal rates and assignment submissions (note that tutors are self selected and the expectations to intervene are not consistent across the module piloting)
- It is a useful tool for understanding students and their participation
- Predictions generally agree with tutors' experience and intuitions of which students might potentially be at risk
- A (potential) USP of OU Analyse was the **information provided between the assignment** submission in relation to students' engagement with learning materials
- Overall, all tutors interviewed were positive about the affordances of OUA, and are keen to use it again (for a range of reasons) in their next module

Case studies and vignettes

"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"

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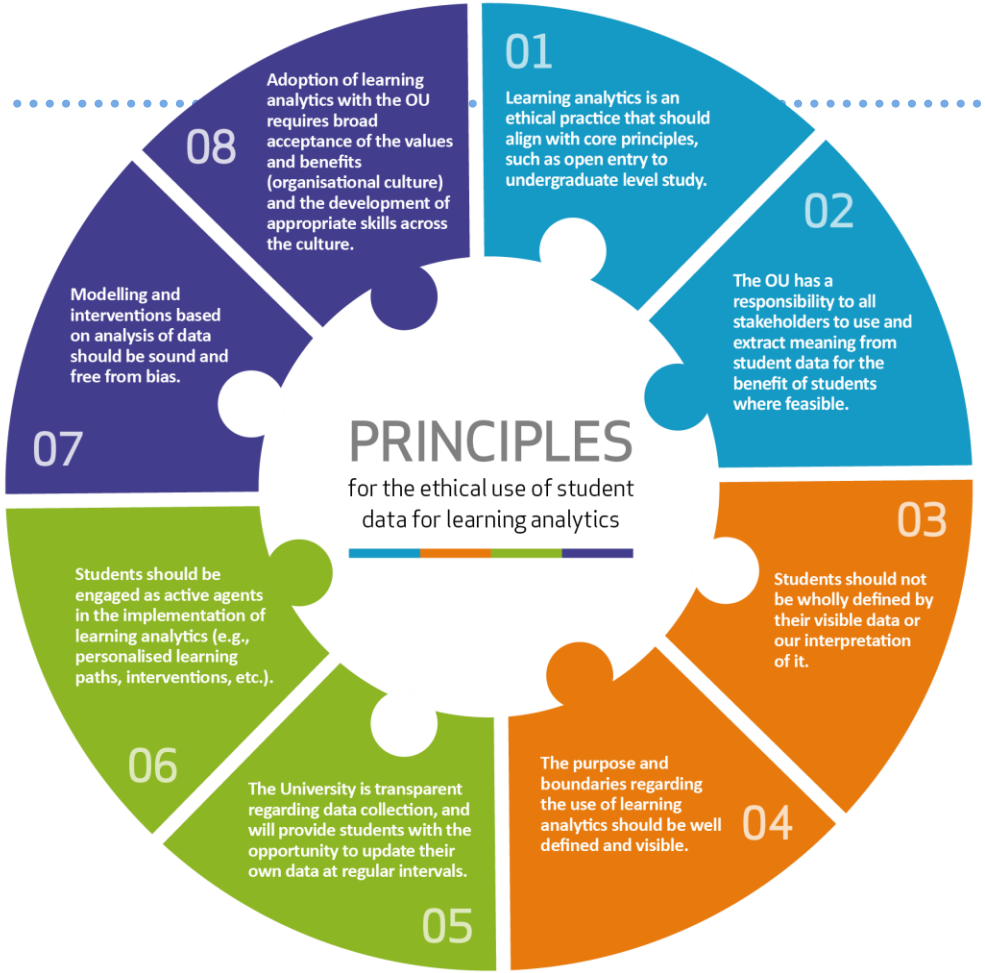

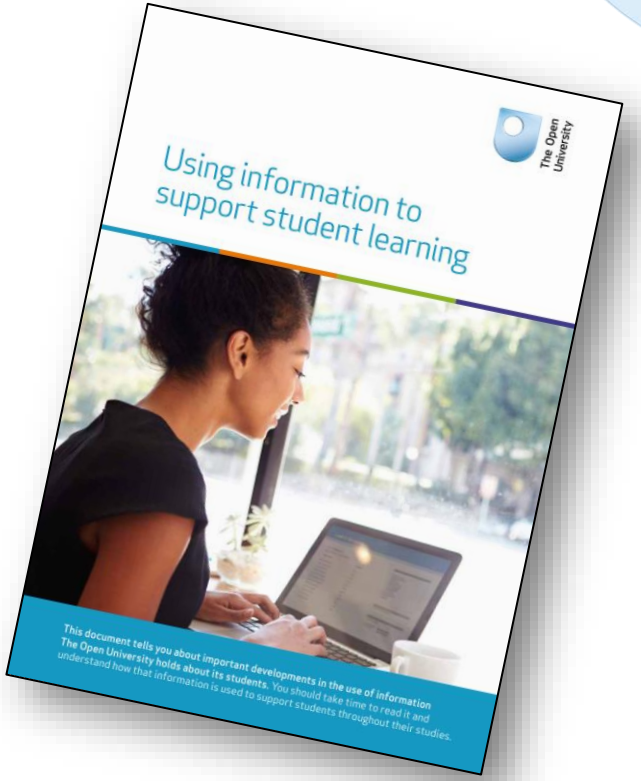

http://www.open.ac.uk/students/charter/essential-documents/ethical-use-student-data-learning-analytics-policy

Information for students

Accessibility | Mobile view | Kevin Mayles / Sign out | StudentHome | TutorHome | IntranetHome | Contact | Search the OU

The Open University

Essential documents

Ethical use of Stude
Analytics Policy

Also listed as:
Ethical use of Student Data for Learning

This policy aims to set out how the Univers
the student support provided. The policy is
particular aspects of learning analytics.

- Policy on Ethical use of Student Da
- Ethical use of Student Data for Lea
- Using information to support stude

For more information, see How the OU use

Charter Principle:
We treat each other with dignity and respe

Sign in | Contact the OU | Accessibility | Search the OU

Help Centre > Complaints, appeals and policies > Student policies > How the OU

How the OU uses student data

Note for staff. This page is targeted at the following audiences: student,

Page 1 of 5

This article explains how we collect and use your data and describes the policie

The Open University collects and uses personal student data to fulfil its legal o

You may have heard news reports of security breaches involving internet servic
systems. When something like this happens we usually assess the risk and if n

Policy

You can see the University's Data Protection Policy on Essential documents sit

> We are committed to the data-protection principles of good
> personal information is held in secure computer and manu
> the University on a 'need-to-know' basis so that we can sup
> you.

In addition, you may want to read about how we use learning analytics.

We have other information and security policies that staff must observe to keep
Protection Act.

Ensuring University policies are followed

Only staff who need to see students' records have access to them. The compu
members of staff with particular roles can view information.

All University staff must follow the University's Data Protection Code of Practic
staff and the procedures they should follow to ensure they are working within th
personal data on students must not be divulged outside the University and mus
staff would only look at your student record if, for example they were dealing w
you. Even then it's unlikely that they'd be able to see all the information held i

Page 1 of 5

Found what you're looking for? Yes No

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StudentHome Profile Dashboard Study Library Community Help Centre

Help Centre > Complaints, appeals and policies > Student policies > Learning analytics and you

Search within help...

Learning analytics and you

Note for staff. This page is targeted at the following audiences: student, public. Find out more

University 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 module.
- Our student support teams (SST) are highly trained in providing study advice to fit your circumstances.
- Our IT staff have developed sophisticated systems and statistical methods to help us to 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 send out to students. That way you don't get messages that aren't relevant to you, and we try to send helpful ones at the right time.

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

Our analysis of past students also helps us to decide what might be helpful. If, for example, you're studying several modules at once we know it's worth getting in touch to check that you're ok and let you know about support you might find you need.

Because we're using your data in this new 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 associated set of FAQs written from a student perspective.

How we use learning analytics

Student data is used in three main ways.

- **Monitoring**: We try to identify students who meet certain criteria, such as submission of assignments or active engagement with their studies.
- **Early warning indicators**: This approach is based on statistical analysis of past students and is an indication of the *expected likelihood* of something happening; it is not an absolute prediction but an indicator of how likely we think it is (based on the information we know) that a student will be successful at a particular point. No model can predict outcomes with absolute certainty, and there will always be things that affect students' progress that are beyond the University's control or knowledge.

  However, the predictive models used combine the effects of multiple factors to create the probabilities and have been shown to provide an acceptable level of accuracy at the individual student level. We contact students who are new to study to welcome them, explain about expectations of workload, and encourage them to plan ahead. We analyse information that we hold about all of our students to help us to identify and prioritise students who may benefit from a call that can offer additional support or encouragement. It should be noted that the ethical use of the predictive data is being considered and our use of this data will meet with the university's ethical and data protection policies.
- **Evaluating our teaching**: We evaluate our teaching and learning design and technology by aggregating your data to help us make improvements in, for example, the assessment strategy for a module.

Found what you're looking for? Yes No

Save this page

This article is part of:
Complaints, appeals and policies

Related help

- Changes to policy, terms and conditions
- How the OU uses student data
- Policy documents for students
- Social networking guidance
- Student charter
- Student consultation

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- Saved
- Contact us

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Are there any questions?

For further details please contact:

- Kevin Mayles – kevin.mayles@open.ac.uk
- @kevinmayles
- Slideshare: http://www.slideshare.net/KevinMayles
- OU Analyse: https://analyse.kmi.open.ac.uk/

References:

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CALVERT, C.E., 2014. Developing a model and applications for probabilities of student success: a case study of predictive analytics. Open Learning: The Journal of Open, Distance and e-Learning.

KUZILEK, J., HLOSTA, M., HERRMANNOVA, D., ZDRAHAL, Z. and WOLFF, A., 2015. OU Analyse: Analysing At-Risk Students at The Open University. Learning Analytics Review, no. LAK15-1, March 2015, ISSN: 2057-7494

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