Learning analytics
The evidence and the potential

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Jisc

UNIVERSITY OF AMSTERDAM

Sclater Digital

HEIR Conference 2017, Robert Gordon University, Aberdeen, 13th Sept 2017

"Digital exhaust"
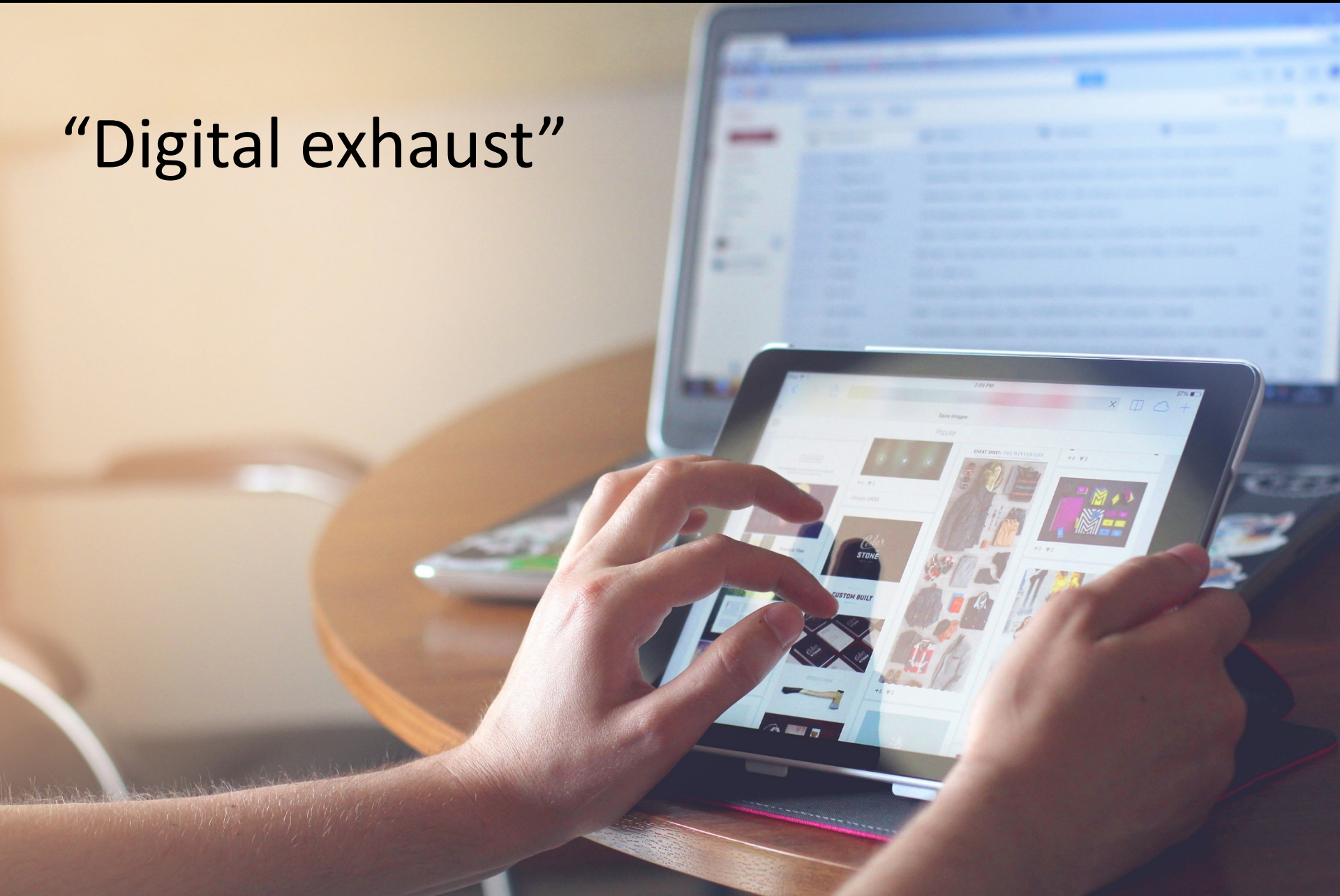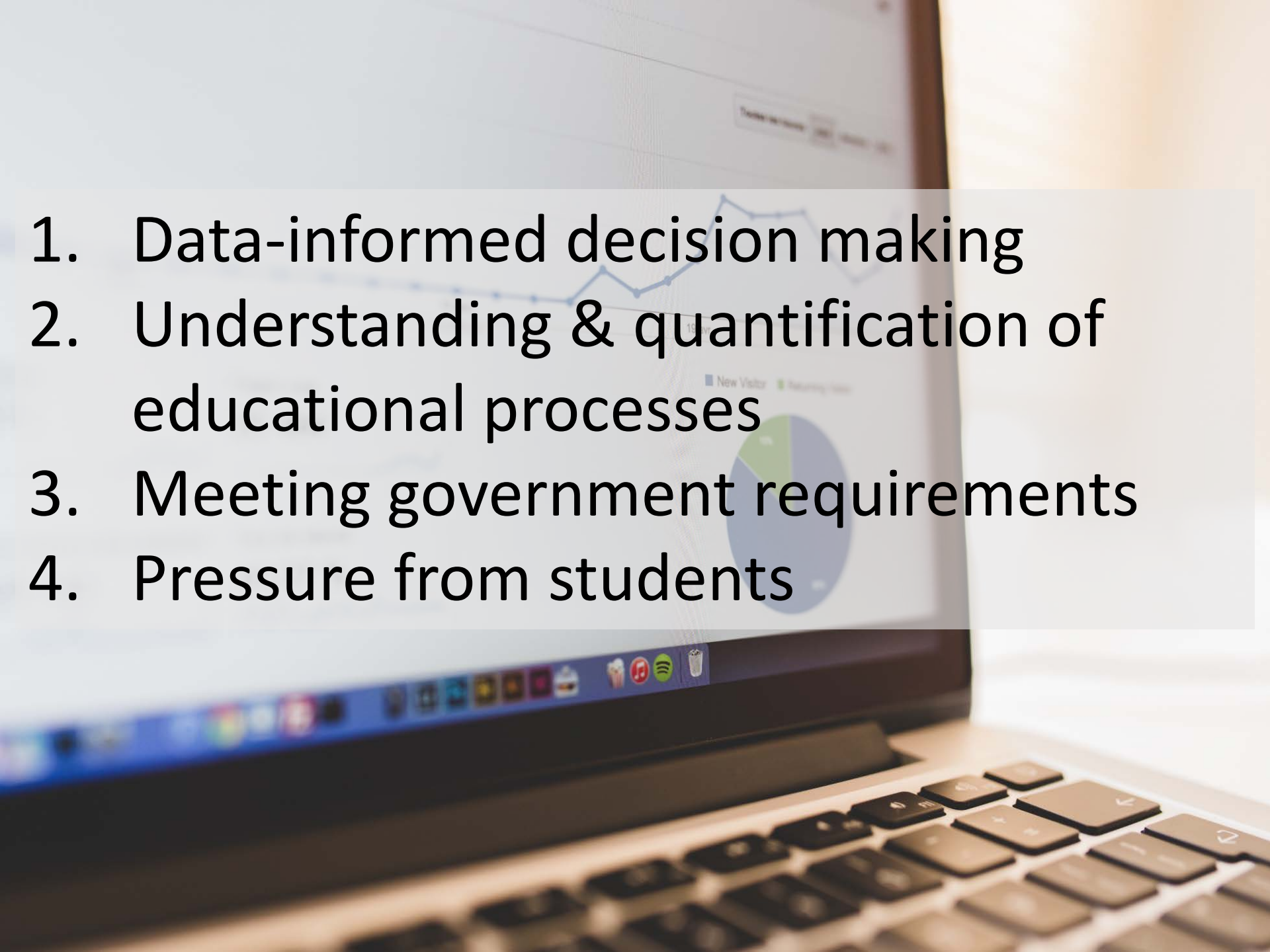
Big data.   Business intelligence.   Analytics.

"Datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse"

Manyika, J. et al., 2011, Big data: The next frontier for innovation, competition, and productivity, McKinsey Global Institute.

Learning analytics
The use of data about students and their activities to enhance education

Drivers

1. Data-informed decision making
2. Understanding & quantification of educational processes
3. Meeting government requirements
4. Pressure from students

Jisc

Learning analytics
## The current state of play in UK higher and further education

Niall Sclater

John Henry Brookes Building, Oxford Brookes University

1

Variety of motivations

» Enhancing the student learning experience

» Improving retention

» Providing students with better information on their progress

» Improving National Student Survey scores

» Enhancing teaching

» Building better relationships between students and staff

» Providing additional support to under-achieving groups
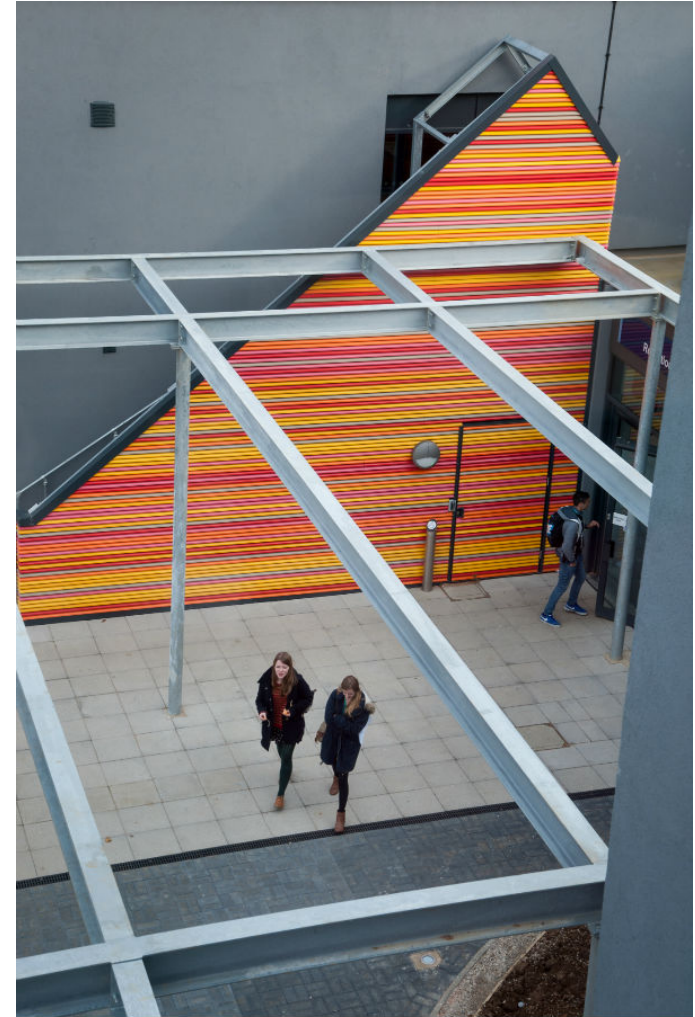
Nottingham Trent University

Project goals:

» to enhance retention

» to increase a sense of belonging within the course community particularly with tutors

» to improve attainment

University of Technology, Sydney

Project goals:

» provide information to reduce student attrition

» help understand the factors affecting low pass rates in 'killer subjects', i.e. those with high failure rates

» provide a dashboard to students showing their study and engagement patterns

» better understand how different types of interventions affect student success
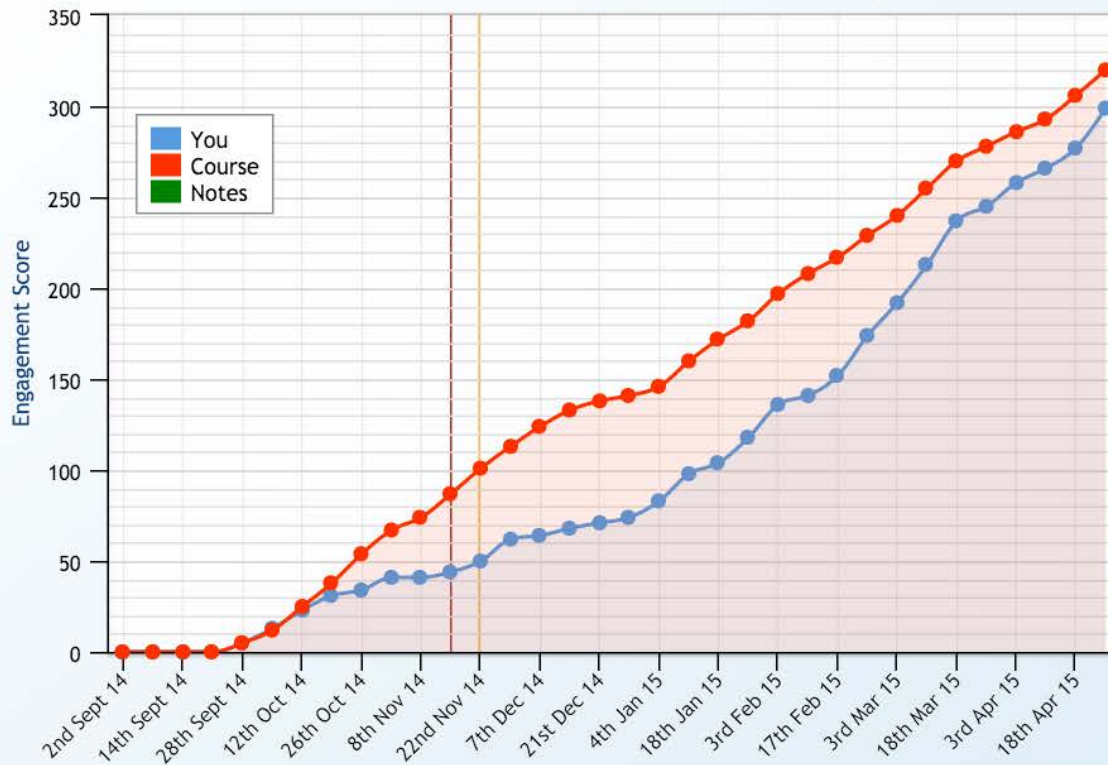
» help to develop more personalised adaptive learning

Applications

1. Early alert and student success

Student detail view - DTP SolutionPath

Detail	Student ID	First Name	Last Name	Home Address	Engagement Rating	Enrolment Status	Course Level	Course Year	Course	Study Mode
Detail	3242fcbe81	Sabine	Legarra	4908 Long Road Beijing	low	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	6b3a48cedf	Sheryl	Katsari	15371 Long Road Berlin	sat	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	ce92a24e45	Roldn	Berrocosa	19822 Long Road Dubai	low	Terminated	Undergraduate	1	Sociology	Full-Time
Detail	7411633792	Kimber	Banfi	13320 Long Road London	high	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	6971a16287	Sle	Godecke	7721 Long Road Dubai	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	eebc69cf53	Uasal	Edler	4431 Long Road Berlin	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	7890fbbcc9	Scott	Jashkov	4534 Long Road Madrid	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	b7025a8753	Laima	Feldstein	13609 Long Road Dubai	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	87d44b0071	Kelsey	Janka	16914 Long Road Paris	sat	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	f2b76caae2	Rachel	Nedellec	24157 Long Road Berlin	good	Enrolment	Undergraduate	1	Sociology	Full-Time

Tutor view from DTP Solutionpath

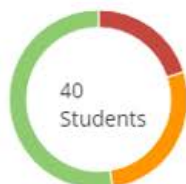# Blackboard Predict Student Risk Reports

Probability of Student Passing This Course

Summer 2016 Week 6 5/22/16 - 8/18/16 (12 weeks)

40 Students

8 High Risk — 20%
11 Medium Risk — 28%
21 Low Risk — 53%

Student	Probability of Passing	Last Activity	Degree Programs	Current Grade
High Risk				
David Devereaux 10480572	0%	5 days ago	Computer Science - BS	D / 64%
Richard May 10065669	0%	5 days ago	Information Systems - BS	D / 61%
Mary Peake 10269006	13%	5 days ago	HealthAdmin & Policy Prog - BA	C / 75%
Evan McLean 10623711	14%	5 days ago	HealthAdmin & Policy Prog - BA	B / 82%
Lucas Fraser 10893133	25%	5 days ago	Information Systems - BS	F / 57%

Signals at Purdue

» Problems identified in 2nd week of semester

» Interventions include:

› Posting signal on student's home page

› Emailing or texting them

› Arranging a meeting

» Courses that deploy signals see consistently better grades

» Students on Signals seek help earlier and more frequently

2. Course recommendation

Brightspace Degree Compass

3. Adaptive learning

LeaP Screenshot: D2L Corporation

Course Overview   Group Progress   **Learner Paths**

Medical Terminology Personalized Learning Course: Cardiovascular System - Advanced Path

Students Group

NVT Group

Less Filters

Concept Types
- ✓ Normal
- ✓ Test

Concept Status
- ● Not reached
- ✓ Understood

- ⊘ Skipped
- ✗ Didn't Understand

- ↗ Path Changed/Reset
- n Activities Performed

Course Completion Status
- ○ Any status
- ○ Students who have finished the course
- ◉ Students who haven't finished the course yet
- ○ Students who haven't started the course yet

Inactivity
- ○ Any status
- ○ Students who haven't seen an activity in the last 7 days
- ◉ Students who haven't seen an activity in the last 28 days
- ○ Students who haven't seen an activity in the last [365 ▾] days

Apply Filters

5 learners matched this criteria

Select a Learner	Pathways taken in the course	Badges Earned	Actions
○ Stewie Griffin ▾ Last Login : 31 Aug 2015 (30 days back)	Cumulative- All Paths ▾	○ ○ ○	↺ Rest Understanding Status

How to Use Cogbooks
Completed
6 concepts understood
2 tests skipped
1 concept not understood
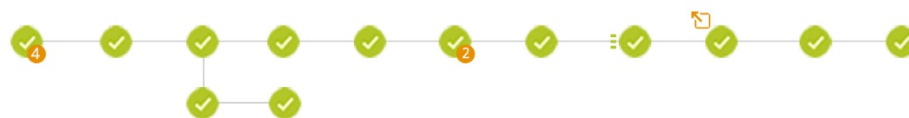
Cardiovascular Capstone Definitions
Completed

Cardiovascular Reference Material
Completed
6 concepts understood
2 tests skipped
1 concept not understood

Cardiovascular Capstone Definitions
Completed

Cardiovascular Reference Material
Completed

Course Overview | Group Progress | **Learner Paths**

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- ✗ Didn't Understand
- ↱ Path Changed/Reset
- ⓝ Activities Performed

Course Completion Status

Inactivity

Select a Learner

Stewie Griffin

Last Login : 31 Aug 2015 (30 days back)

Pathways taken in the course

Cumulative- All Paths

Badges Earned

Cardiovascular Reference Material
Completed

6 concepts understood
2 tests skipped
1 concept not understood

Cardiovascular Capstone Definitions
Completed

Cardiovascular Reference Material
Completed
6 concepts understood
2 tests skipped
1 concept not understood
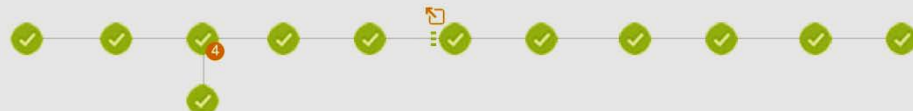
Cardiovascular Capstone Definitions
Completed

Cardiovascular Reference Material
Completed

4. Curriculum design
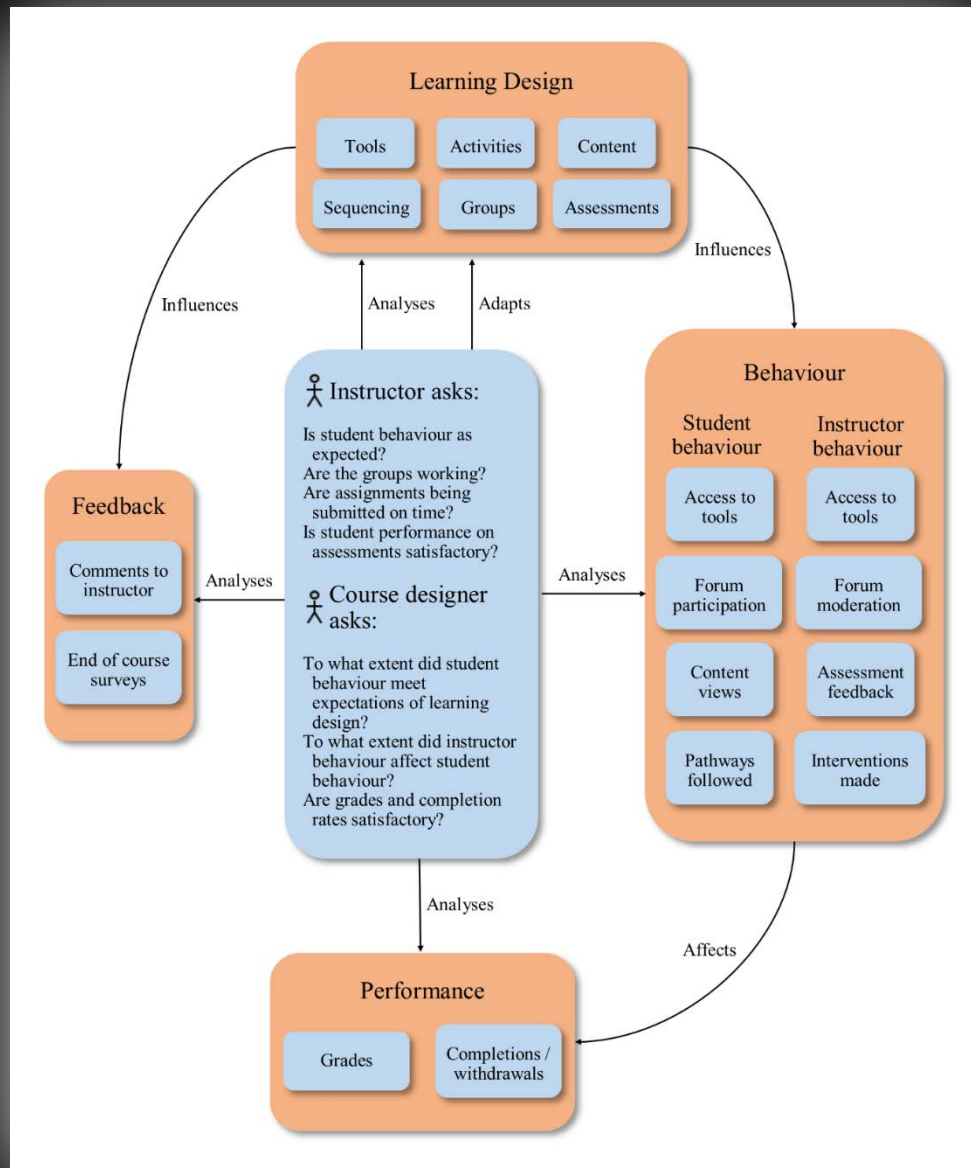
Is student behaviour as expected?
Are the groups working?
Are assignments being submitted on time?
Is student performance on assessments satisfactory?

To what extent did teacher behaviour affect student behaviour?
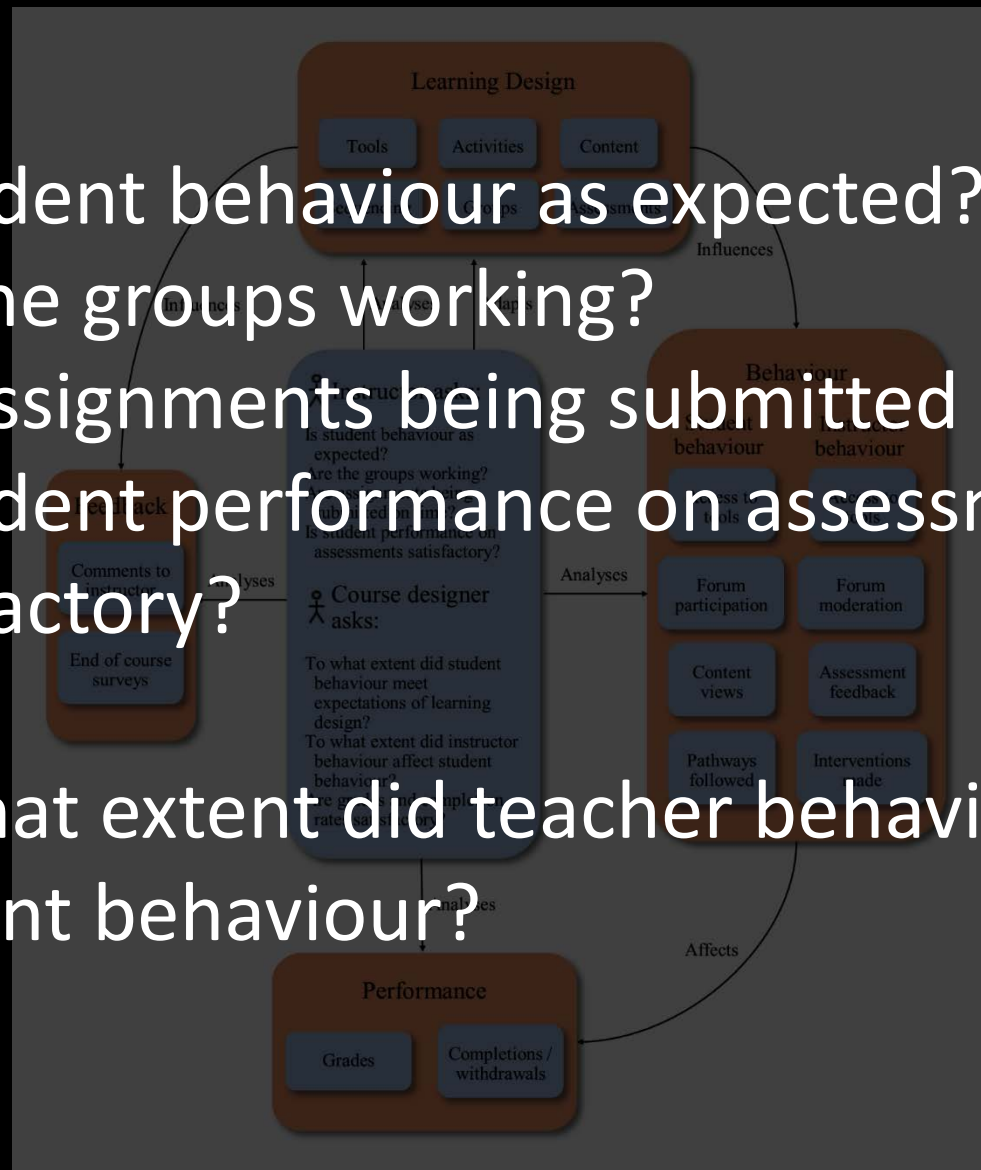
Issue identified: a key piece of learning content is not being accessed by most students

Questions: was the content too difficult, sequenced at the wrong time, or its importance not properly communicated?

Intervention: ask students why they're not accessing it; make content easier to find; communicate its importance better
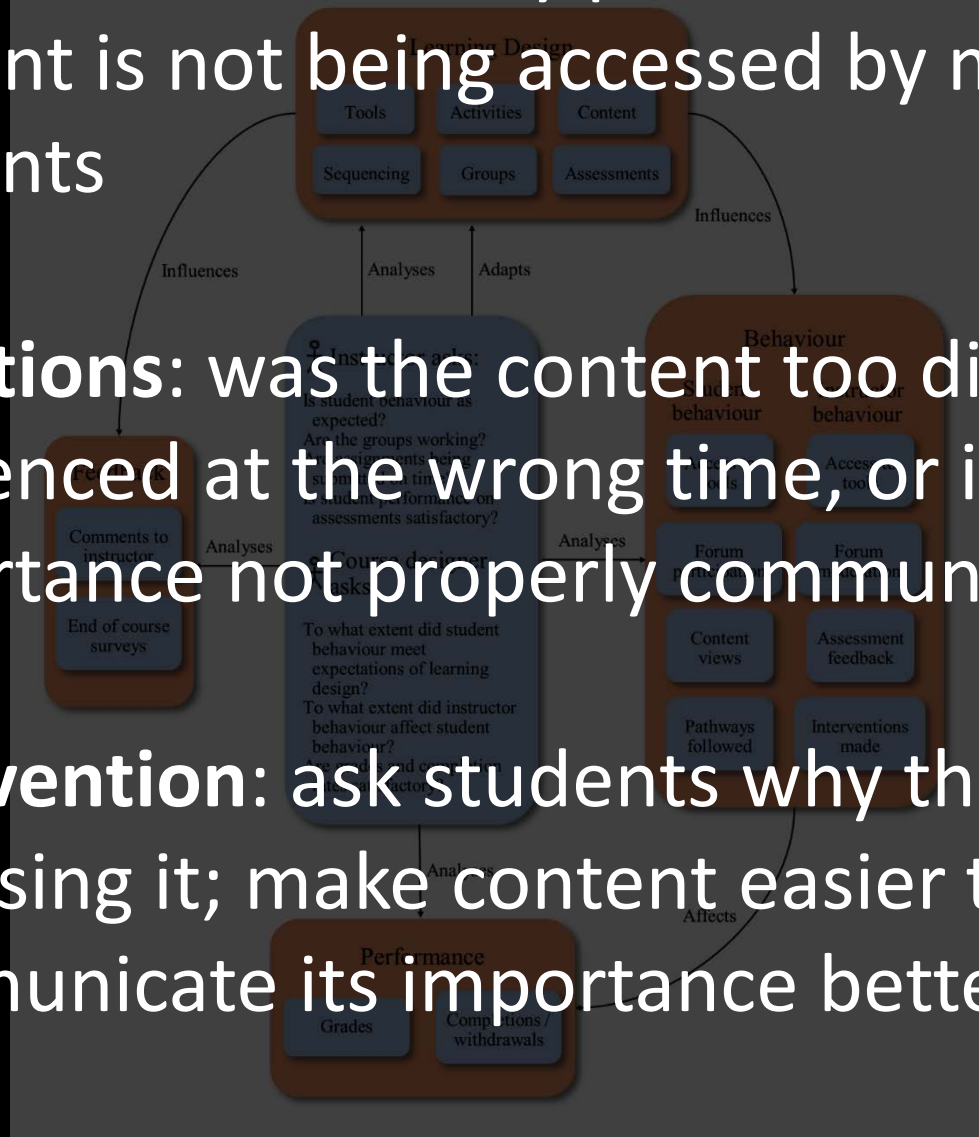
Issue identified: a particular minority group is not performing well in an aspect of the curriculum

Questions: is this due to linguistic or cultural issues, lack of prerequisite knowledge or skills, or financial issues?

Intervention: target additional support at the minority group
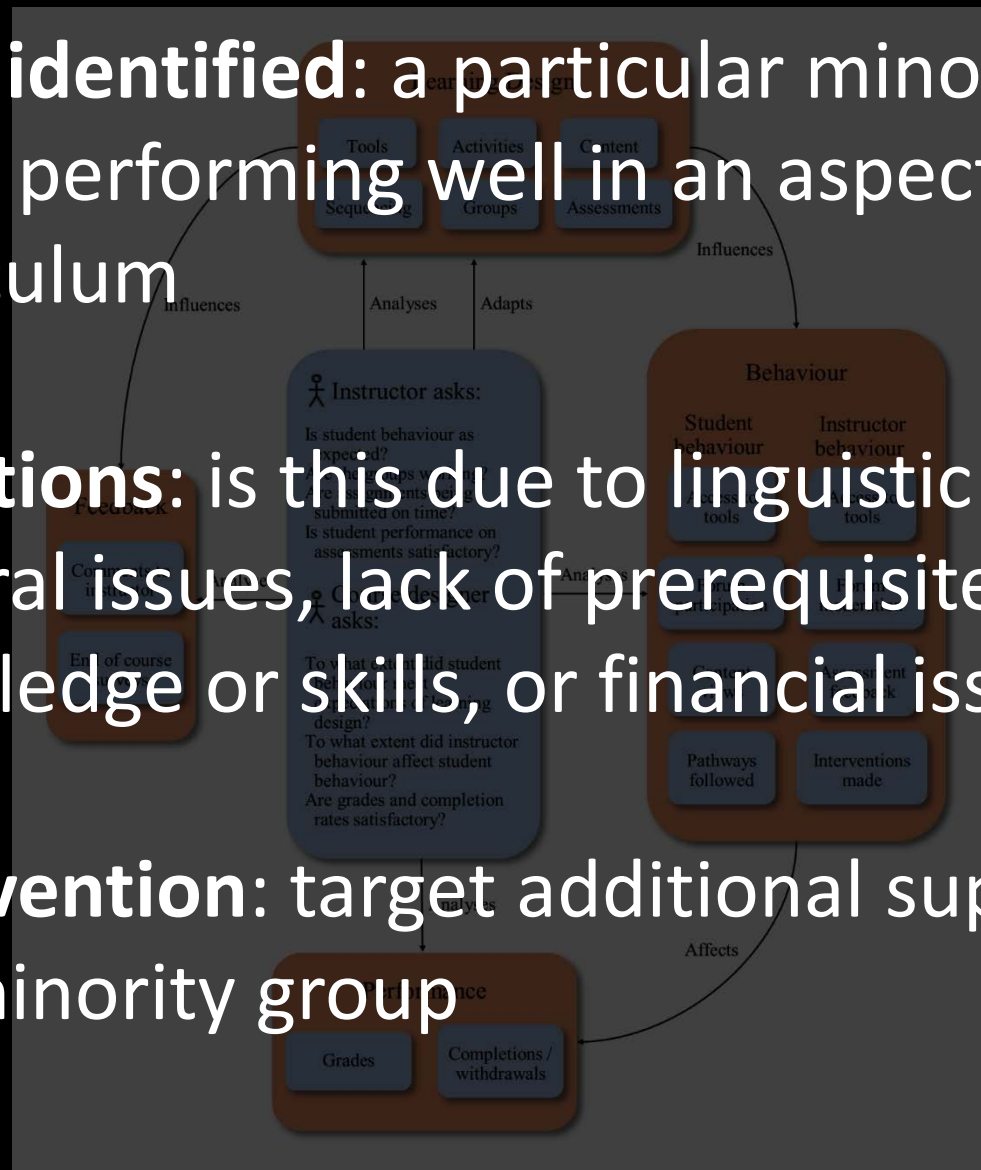
Ethical and legal issues

Technology

Privacy Fears Over Student Data Tracking Lead to InBloom's Shutdown

By Olga Kharif | May 01, 2014

SEND TO kindle

Photo illustration by 731; Photograph by Getty Images

Companies Mentioned

APO (Apollo Global Management LLC)
$23.24 USD   0.12   0.52%

If a student is al... lection and analysis could th... n their academic progr...

What should a s... are in conflict with their study...

How can institutions avoid overly simplistic metrics and decision making which ignore personal circumstances?

Available from Effective learning analytics blog: analytics.jiscinvolve.org

86 issues in 9 groups
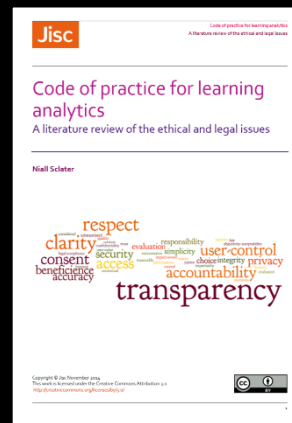
Group	Name	Question	Main type	Importance	Responsibility
2 Consent	Adverse impact of opting out on individual	If a student is allowed to opt out of data collection and analysis could this have a negative impact on their academic progress?	Ethical	1	Analytics Committee
7 Action	Conflict with study goals	What should a student do if the suggestions are in conflict with their study goals?	Ethical	3	Student
8 Adverse impact	Oversimplification	How can institutions avoid overly simplistic metrics and decision making which ignore personal circumstances?	Ethical	1	Educational researcher

What should a student do if the suggestions are in conflict with their study goals?

How can institutions avoid overly simplistic metrics and decision making which ignore personal circumstances?
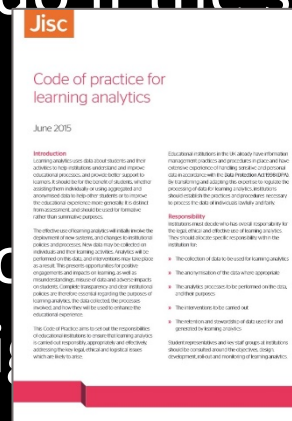
Code of practice for learning analytics

June 2015

Introduction

Learning analytics uses data about students and their activities to help institutions understand and improve educational processes, and provide better support to learners. It should be for the benefit of students, whether assisting them individually or using aggregated and anonymised data to help other students or to improve the educational experience more generally. It is distinct from assessment, and should be used for formative rather than summative purposes.

The effective use of learning analytics will initially involve the deployment of new systems, and changes to institutional policies and processes. New data may be collected on individuals and their learning activities. Analytics will be performed on this data, and interventions may take place as a result. This presents opportunities for positive engagements and impacts on learning, as well as misunderstandings, misuse of data and adverse impacts on students. Complete transparency and clear institutional policies are therefore essential regarding the purposes of learning analytics, the data collected, the processes involved, and how they will be used to enhance the educational experience.

This Code of Practice aims to set out the responsibilities of educational institutions to ensure that learning analytics is carried out responsibly, appropriately and effectively, addressing the key legal, ethical and logistical issues which are likely to arise.

Educational institutions in the UK already have information management practices and procedures in place and have extensive experience of handling sensitive and personal data in accordance with the **Data Protection Act 1998 (DPA)**. By transferring and adapting this expertise to regulate the processing of data for learning analytics, institutions should establish the practices and procedures necessary to process the data of individuals lawfully and fairly.

Responsibility

Institutions must decide who has overall responsibility for the legal, ethical and effective use of learning analytics. They should allocate specific responsibility within the institution for:

» The collection of data to be used for learning analytics

» The anonymisation of the data where appropriate

» The analytics processes to be performed on the data, and their purposes

» The interventions to be carried out

» The retention and stewardship of data used for and generated by learning analytics

Student representatives and key staff groups at institutions should be consulted around the objectives, design, development, roll-out and monitoring of learning analytics.

Group	Name		Importance	Responsibility
2 Consent	Adverse impact... out on individua...		1	Analytics Committee
7 Action	Conflict with stu...		3	Student
8 Adverse impact	Oversimplificati...		1	Educational researcher

jisc.ac.uk/guides/code-of-practice-for-learning-analytics

Techniques

Social network analysis
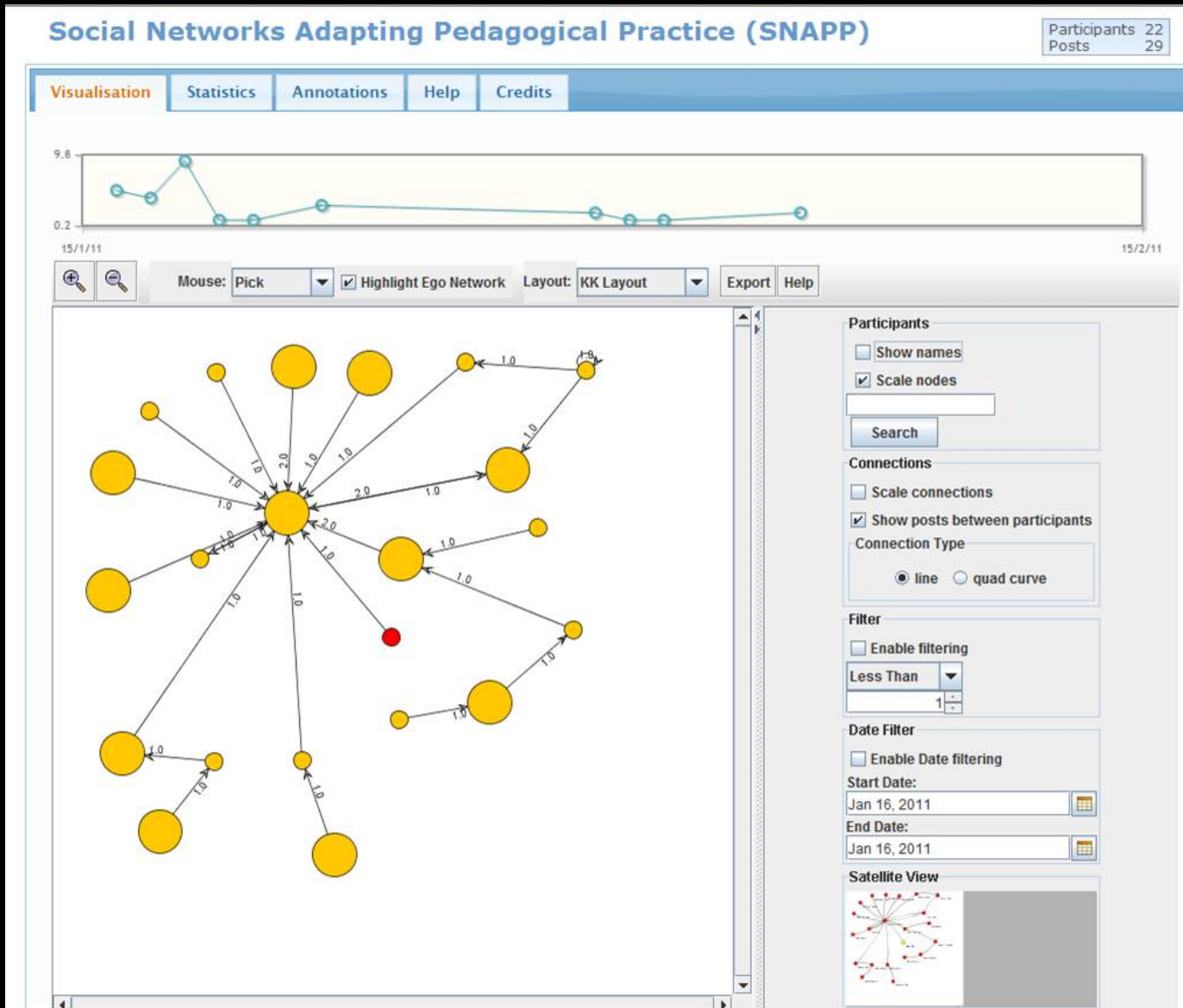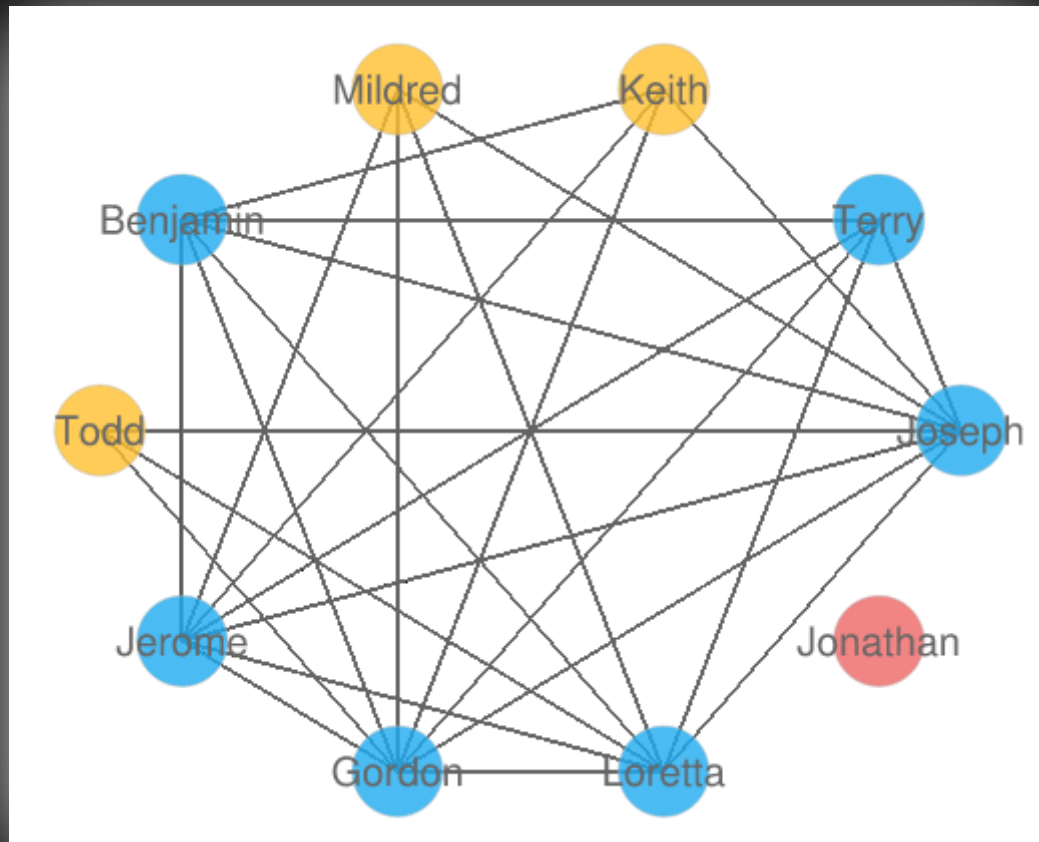
Interaction analysis – Blackboard X-Ray Learning Analytics

There's small, stocky horses and then there are the ponies and then the big, gigantic horses. So, I'm sure their surroundings probably played a role in their physical appearance over many hundreds of years.

Ming, N. C. & Ming, V. L., 2015, Visualizing and Assessing Knowledge from Unstructured Student Writing, Technology, Instruction, Cognition & Learning, 10(1), pp. 27-44.

Does the strawberry plant have numerous offspring? [Do] its traits contribute to high population growth? Is the strawberry found in variable, temporary or unpredictable environments, where the probability of long term survival is low? Is it non-competitive?

Ming, N. C. & Ming, V. L., 2015, Visualizing and Assessing Knowledge from Unstructured Student Writing, Technology, Instruction, Cognition & Learning, 10(1), pp. 27-44.

Sentiment and emotion analytics

Appreciation, Delight, Desire, Disappointment, Dislike, Emphatics, Enjoyment, Excitement, Fear, Frustration, Happiness, Hope, Humour, Irony / sarcasm, Like, Passion, Preference, Pride, Surprise, Thankfulness, Unhappiness, Wonder and Yearning.

Cleveland-Innes, M., 2012, Emotional presence, learning and the online learning environment, IRRODL: The International Review of Research in Open and Distributed Learning, 13(4), pp. 269-292.

Applications

- 1. Early alert
- 2. Course recommendation
- 3. Adaptive learning
- 4. Curriculum design

Techniques

- Predictive analytics
- Social network analysis
- Discourse analytics
- Sentiment & emotion analytics
- Textual analytics

Data

Demographic data (1)

ID: 313f8ed8
Sex: Female
Born: 1999-05-12

Sensitive data (1a)
Ethnicity: White Scottish
Disability: severe visual

Academic data ②

K101
2017 Semester 1
Assignment 1: 67%
Assignment 2: 71%

Prior performance ②a
2016 Scottish Highers
Economics: A
English: A
French: B
Maths: B
Physics: A

Learner-generated content ②b
Assignment 1: (Essay)
Assignment 2: (Group report)

Educational context data

④

K101
Start date: 2017-10-01
Duration: 15 weeks
Instructor: K. McDonald
Assignment 1
 Type: Essay
 Due: 2017-10-27

Jisc Survey: Data

» Wide variety of sources

» VLE and Student Information System are the main ones

» Attendance records

» Library systems

» Assignment handling systems

» Student survey data

Metrics

Signals at Purdue

» Performance

» Effort

» Prior academic history

» Student characteristics

Composite metrics

» use of library

» attendance

» VLE engagement

At-risk
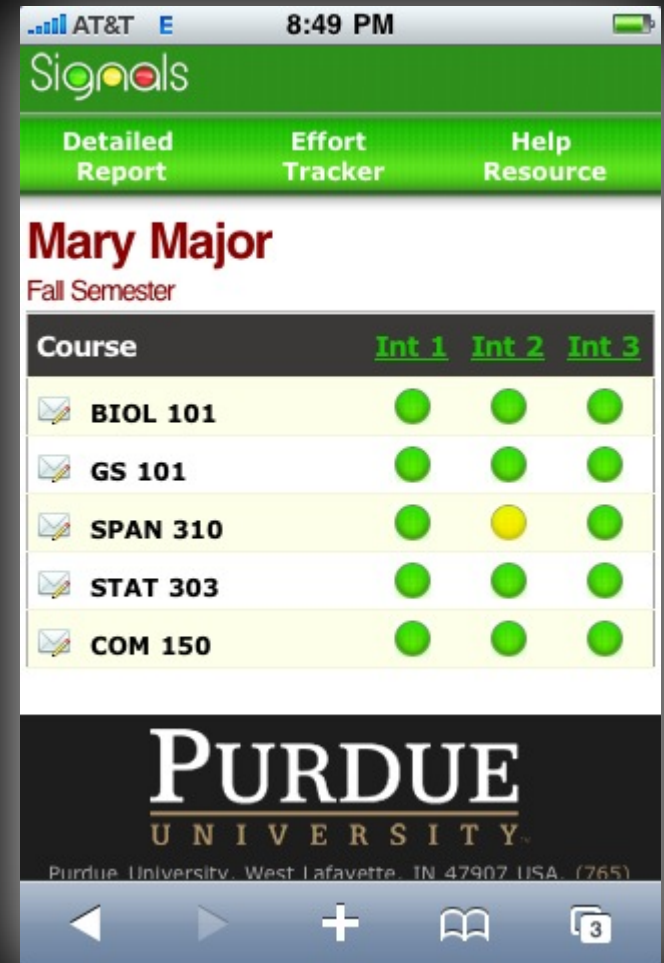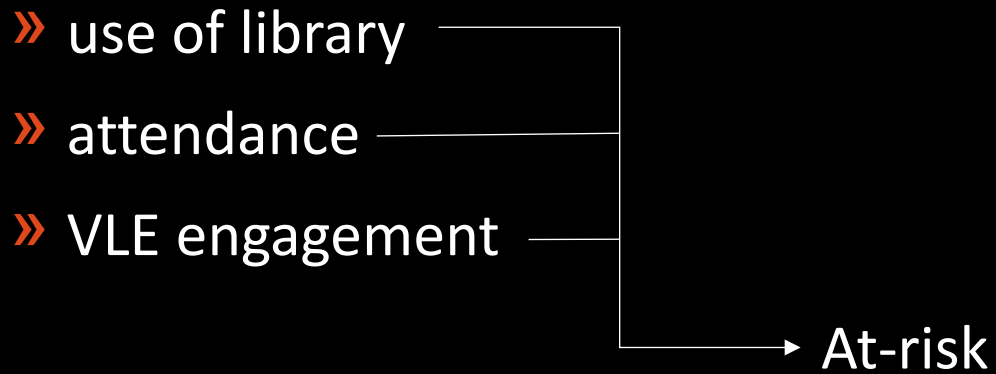
Predictive modelling

Linear regression

Student	LMS accesses (x)	Result (%) (y)
1	27	70
2	70	62
3	36	51
4	85	75
5	17	53
6	55	65
7	12	48
8	59	67
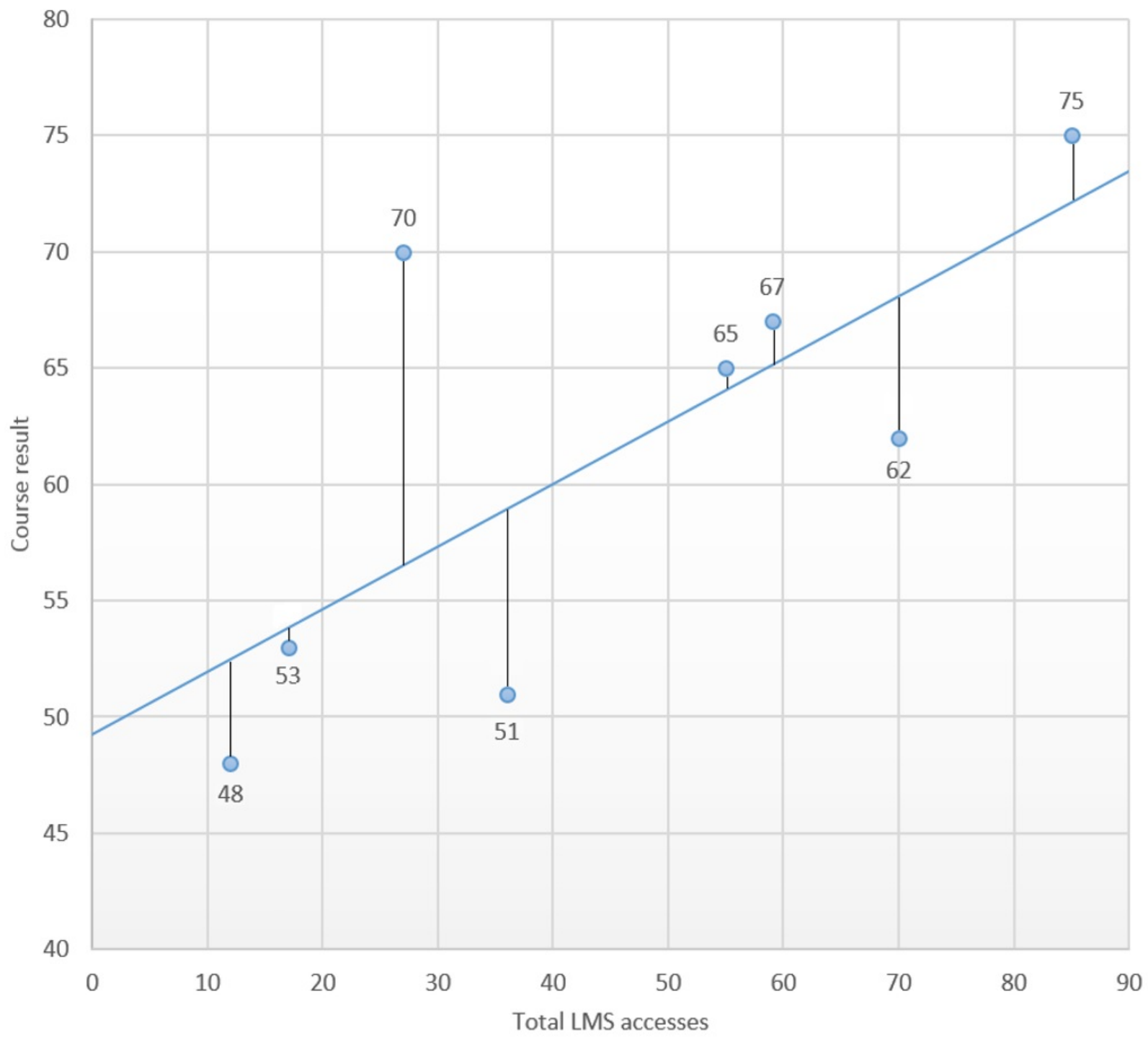
Naïve Bayes
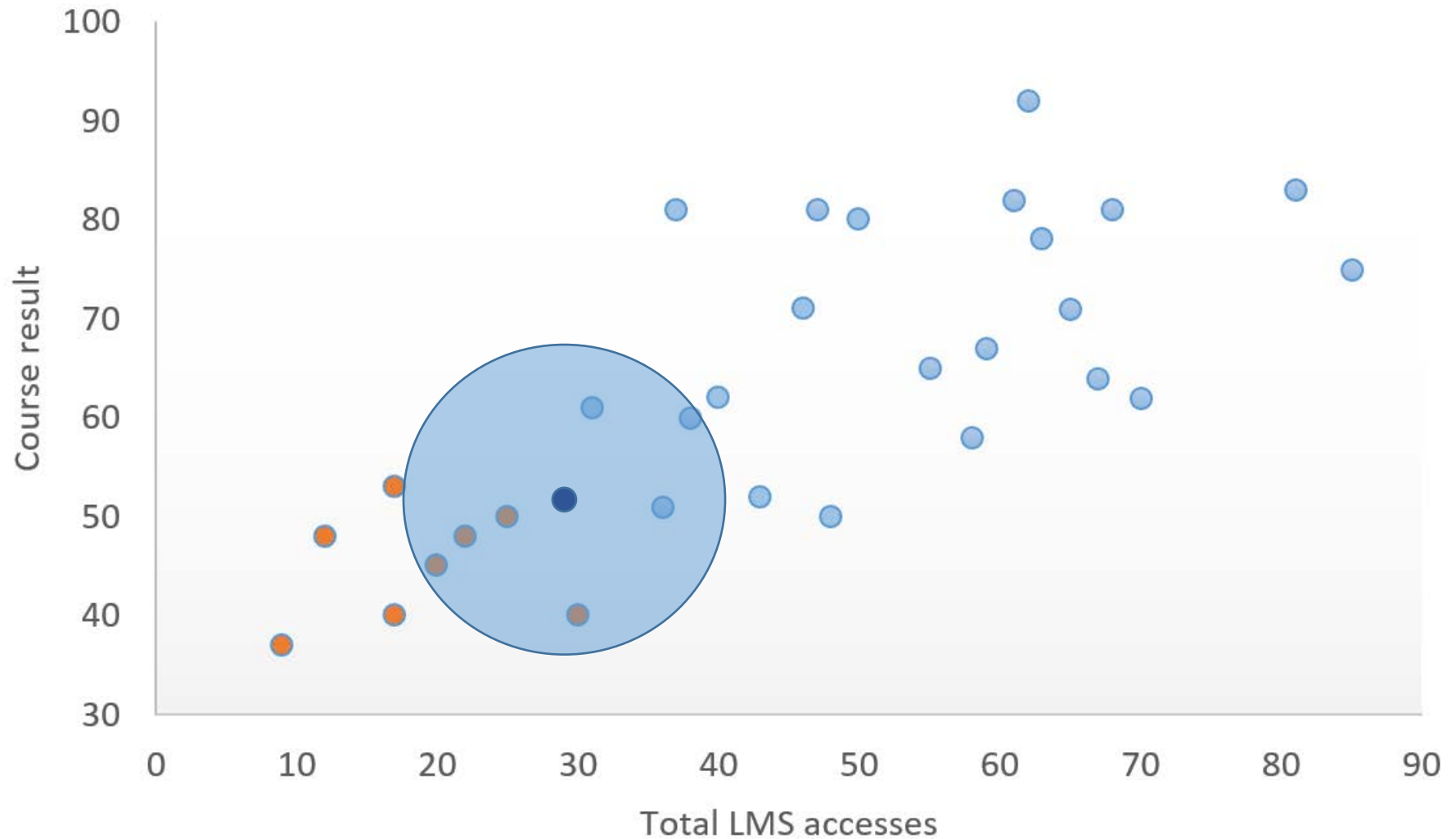
California State University - Chico

» Total hits is strongest predictor of success

» Assessment activity hits is second

» Metrics relating to current effort (esp VLE usage) are much better predictors of success than historical or demographic data.

John Whitmer

"a student with average intelligence who works hard is just as likely to get a good grade as a student that has above-average intelligence but does not exert any effort"

(Pistilli & Arnold, 2010)

Marist College, New York

» Predictive early alert model transferred to different institutions

» Around 75% of at-risk students were identified

» Most significant predictors were:

› Marks on course so far

› GPA

› Current academic standing

(Jayaprakesh et al.)

University of South Australia

» 730 students identified as at-risk

» 549 contacted:
  › 66% passed with av GPA of 4.29

» Those not contacted:
  › 52% passed with av GPA of 3.14

Student-facing analytics

Comparative – social – gameified – private by default – usable standalone - uncluttered

ACTIVITY FEED 👤 ⚙️

You have spent 7 hours in the library over the last 3 days.

🕐 2 min ago ●●●

John Doe spent 6 hours doing lab work yesterday.

🕐 8 min ago ●●●

Jane Doe scored in the top 10% in her assignment: "The Myth of Sisyphus".

🕐 18 min ago ●●●

Hong Gildong met his target to spend 15 hours last week working on his module "Theatre of the Absurd".

🕐 50 min ago ●●●

Luther Blisset says, "Which books off the reading list for next term's Nihilism course

| ☰ Feeds | 🖥 Stats | 🕐 Log | ⚑ Target |

4900
Activity points

Activity	Count	Points Awarded
Loggedin	263	526
Viewed	853	4265
Attended	109	109

This week	Overall

15:57

📖 Module	BASIC ODS 1 ▼
👤 Activity Type	Studying (arts) ▼
👤 Choose Activity	Reading ▼

⏱ Reminder to Take Breather After

00:00

00:00

Start   **Stop**

ACTIVITY LOG

All Activities

In Group Study for 6 hours for Introduction to Stats Module

Experimented for 1 minute for Introduction to Analytics Module

Read for 1 minute for Introduction to Analytics Module

Read for 1 minute for Introduction to Analytics Module

Read for 1 minute for Introduction to Analytics Module

Read for 1 hour and 30 minutes for Introduction to Analytics Module

Target

Prepare a dissertation 1 hour daily

Revise 0 hours and 5 minutes weekly

Study 1 hour daily

Blog 1 hour daily

Attend Seminars 32 hours monthly

Attend Seminars 2 hours daily

Attend Seminars 2 hours daily

Alice Scott

Student ID : 50002

My Friends	0	›
Startup Screen	Stats	›
Trophies	10	›
Language	English	›
Report Feature / Bug		
Privacy Statement		

8932

1	2	3
4	5	6
7	8	9
	0	⊗

Send PIN

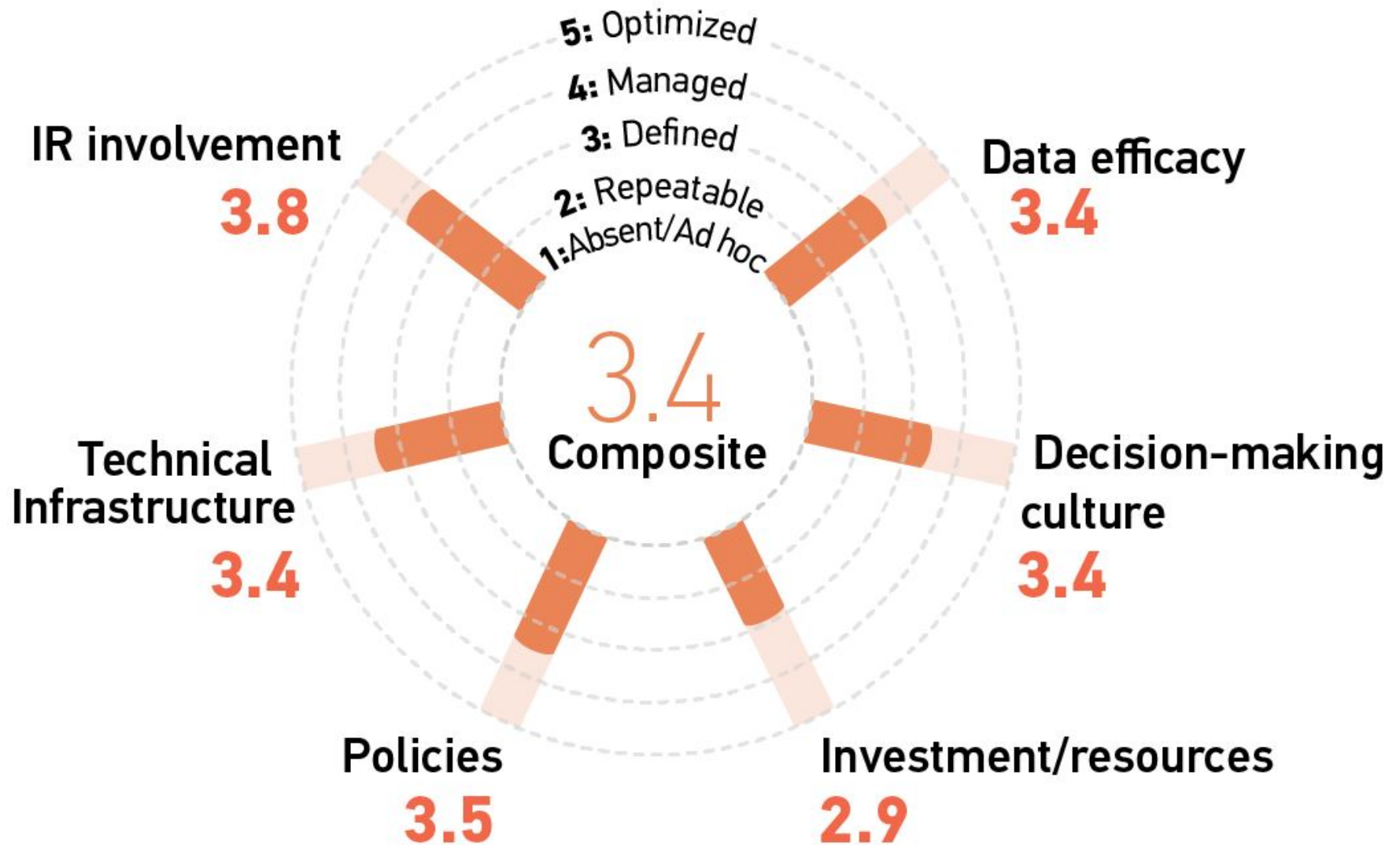# Readiness

Survey of 33 people in 9 North American universities

Rating from **strongly disagree** to **strongly agree** e.g.

"My institution has a culture that accepts the use of data to make decisions"

"My institution has professionals with knowledge and expertise in manipulating data from multiple sources and platforms to conform to institutional specifications"

Arnold, Lonn & Pistilli, 2014

2015

5: Optimized
4: Managed
3: Defined
2: Repeatable
1: Absent/Ad hoc

IR involvement
3.8

Data efficacy
3.4

3.4
Composite

Technical
Infrastructure
3.4

Decision-making
culture
3.4

Policies
3.5

Investment/resources
2.9

- a strong vision and belief in the importance of learning analytics from senior managers in order to enhance the student experience
- interest in better reporting and dashboards, rather than simply predictive analytics at this stage
- interest in enhancing both progression and attainment
- the agent of change seen primarily as the personal tutor mediating the data rather than automated, unmediated, student-facing dashboards

Andy Ramsden, Blackboard

"A focus on technological issues merely generates 'urgency' around technical systems and integration concerns, and fails to address the complexities and challenges of institutional culture and change."

Macfadyen & Dawson, 2012

"Absolutely vital to success was having a leader with a deep scholarly understanding of learning analytics principles and practices and the mechanics of creating predictive models."

Arnold, Lynch, Huston, Wong, Jorn & Olsen (2014)

Tips

1. Start on a small scale
2. Support and empower the key stakeholders
3. Transparency and openness are key to success
4. Distribute learning analytics governance power structures (datasets, technical infrastructure & interventions)
5. Minimise possibilities for conflict between different stakeholders by defining principles around the collection and use of the data

Elouazizi (2014)

Sclater, 2017 *Learning Analytics Explained*
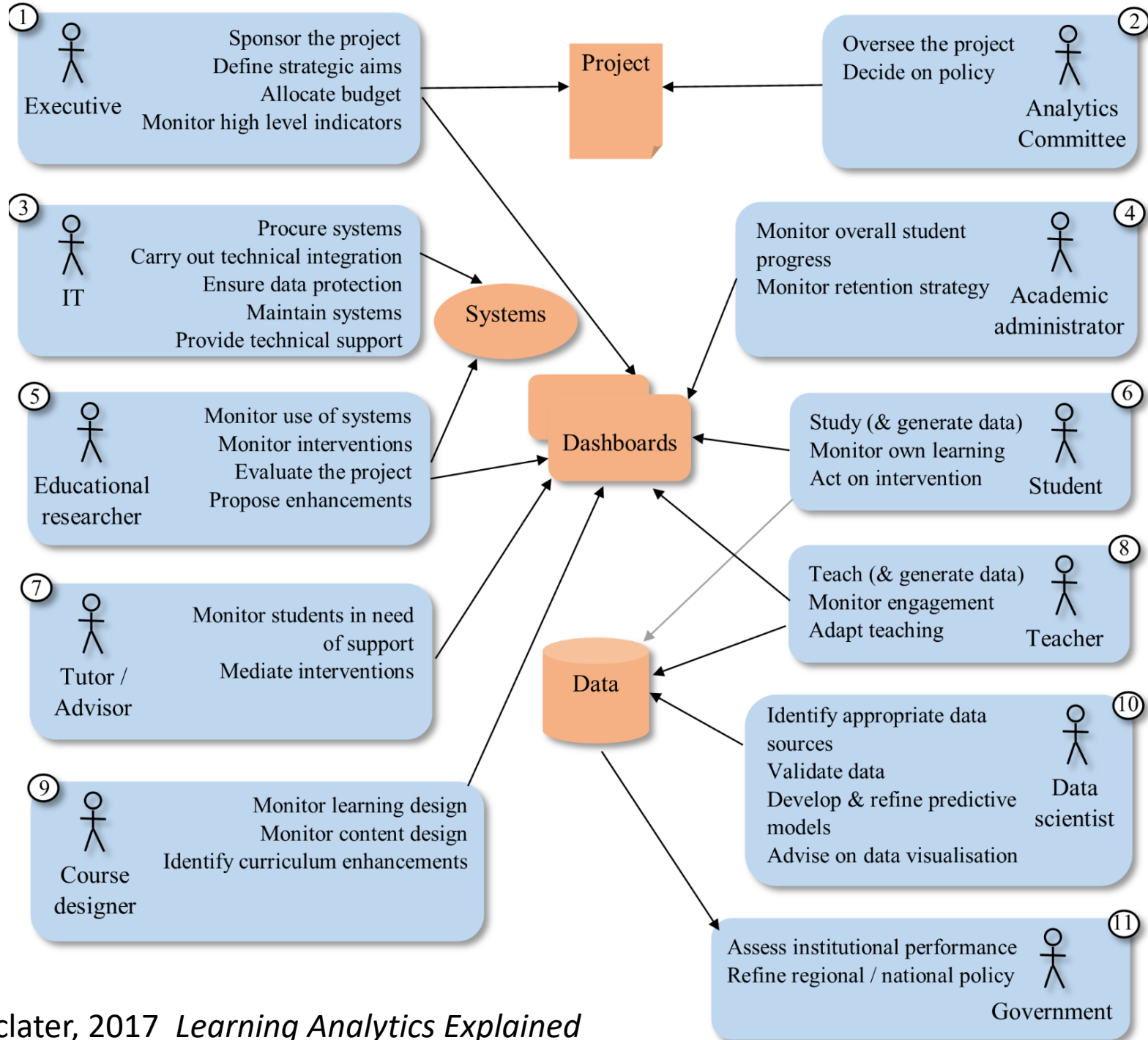
What next?

"ORU offers one of the most unique educational approaches in the world by focusing on the whole person - mind, body, and spirit."

President William M. Wilson, Oral Roberts University

Student › News

Oral Roberts University criticised for making new students wear 'grade-issuing' Fitbit trackers

Eating disorder campaigner says: 'This is the most shameful idea I have ever seen'

Aftab Ali Student Editor | Monday 18 April 2016 | 💬 3 comments

16 shares

2. Analytics as normal practice

"learning analytics becomes as common as a chalkboard is to a classroom today"

Dr Jeff Grann, Capella University

3. Personalisation

"Analytics can identify the shape of every module … and knows exactly which kind of path students have to take, and then provides a completely personalised path for our students."
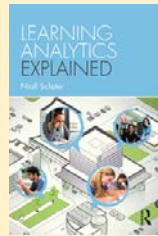
Dr Bart Rienties, Open University

we may have to redesign our courses in order to motivate students to communicate more

Prof. Dragan Gašević

@sclater

analytics.jiscinvolve.org

Book:

Learning Analytics Explained

Niall Sclater (Routledge, March 2017)

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UNIVERSITY OF AMSTERDAM

Sclater
Digital