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Educational Analytics

A systematic review of empirical studies

Professor Peter Francis

Carly Foster

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Overview

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- Background and Rationale
- Research Questions and Criteria
- Methodology
- Results
- Analysis
- Discussion

Background and Rationale

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- Northumbria University is developing an Educational Analytics Framework to support the University Strategy 2018-23
- Systematic review provides evidence and insight for:-
  - The design and evaluation of an initial pilot project with Civitas Learning International (2017/18)
  - The design of Phase 2 (2018/9) – scale, tools, culture and reach
- Implementation of Education Strategy 2018-23

Research Aim and Questions

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To systematically review the primary research literature on the deployment and effectiveness of Learning Analytics and Academic Analytics methods to improve student outcomes in Higher Education Institutions.

RQ1: Where, how, and in what ways, have Learning Analytics and Academic Analytics been deployed in the studies progressed?

RQ2: How effective are Learning Analytics and Academic Analytics methods in improving student outcomes?

RQ3: What methodologies are used to evidence and report the effectiveness of Learning Analytics and Academic Analytics?

RQ4: How valid and reliable are the methodologies and evidence in the studies progressed?

Methodology: Terms

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<u>In Scope</u>

- **Learning analytics** methods are defined as the generation of **targeted personal, pastoral, wellbeing or other support interventions, delivered by academic or professional support staff** through the application of Educational Data Mining (EDM)

- **Academic analytics** methods are defined as the generation of **academic interventions such as changes to course or curricula design, assessment and feedback, pedagogies, or other Learning and Teaching enhancement activities** through the application of Educational Data Mining (EDM)

<u>Out of Scope</u>

- Educational Data Mining (EDM)
- Learner Analytics
- Institutional Analytics
- Adaptive Analytics

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Methodology: Process

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Searching

- 9 x Databases
- 5 x Primary terms

= 45 searches

- Bibliography searches (ongoing)

Platform	Database
EBSCO	British Education Index
EBSCO	Education Abstracts
EBSCO	Education Administration Abstracts
EBSCO	Education Resources Information Center
EBSCO	Business Source Premier
EBSCO	Library, Information Science & Technology Abstracts
EBSCO	Teacher Reference Center
Proquest	Australian Education Index
Scopus	All

Sifting

- Applying predefined criteria linked to the research questions

Primary	Secondary	Tertiary
Learn* Analytics Education* Data Mining Education Big Data Academic Analytics Educational Analytics	Outcomes OR Retention OR Progression OR Achievement OR Performance OR Engagement OR Intervention OR Teaching OR Active OR Predict OR Satisfaction OR Learning OR Attainment OR Adaptive	Student OR Higher Education OR Universit* OR HE OR Data Science OR Data Analytics

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Methodology: Sifting Criteria

- An original primary research study in English
- Published between 2007-2017
- Including:
  - Conference Paper
  - Journal Article
  - Article (including those in press)
  - Reports – Evaluative and Research
  - Case Study
  - Dissertation, Thesis or Doctoral Dissertation
- Relevance to scope

High Level Results

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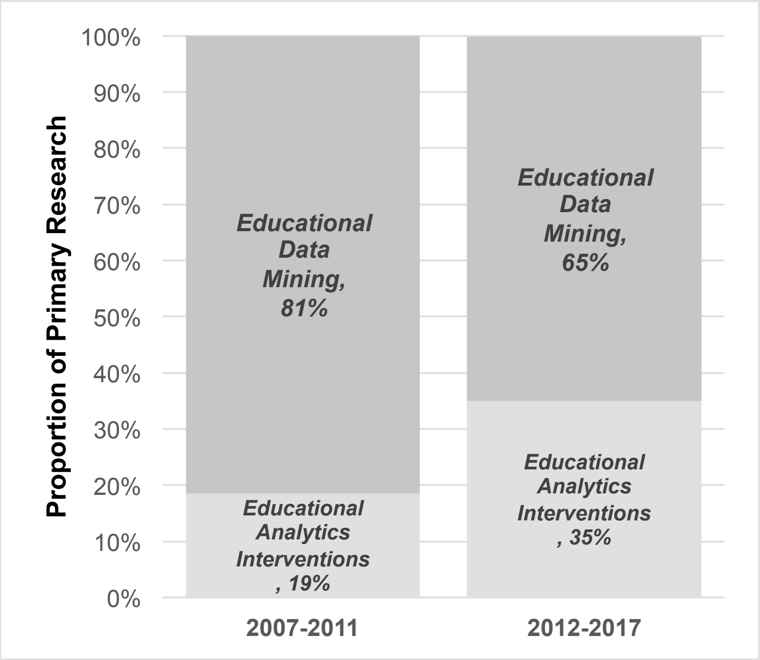
Initial Search

Full search (n = 3,427)

After applying structural criteria (n = 2,010)



Abstract Review

Progressed (n = 125)

Rejected

Full Text Review

Learning Analytics (n = 8)

Academic Analytics (n = 10)

0.5%

Not Applicable on Final Review

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RQ1: Where, how, and in what ways, have Learning Analytics and Academic Analytics been deployed in the studies progressed?

Characteristic		Studies (n)	Proportion (%)
Period of Publication	2007-2012	4	22%
	2013-2017	14	78%
Geographic Location	USA	9	50%
	Australasia	4	22%
	ROW	3	17%
	UK	2	11%
Variables Used	Demographic, Academic, Engagement, Behavioural	5	28%
	3/4	1	6%
	2/4	7	39%
	1/4	5	28%
Delivery Method*	On Campus	8	44%
	MOOC/ Distance Learning	8	44%
	Blended Learning	2	11%
Primary Outcomes Measured	Retention	4	22%
	Academic Performance	8	44%
	Engagement	6	33%
Secondary Outcomes Measured	Retention	3	17%
	Academic Performance	5	28%
	Engagement	0	0%
	N/A	10	56%

- Momentum
- Majority of studies in the United States
- Increasing focus towards On Campus Activities
- Academic Performance is most common application
- 8 studies attempt to improve multiple outcomes
- Most studies report the use of at least two *types* of predictive variables

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RQ2: How effective are Learning Analytics and Academic Analytics methods in improving Retention?

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Retention

Study	**Intervention Method**	**Evidence of Effectiveness**
Burgos, C., Campanario M., Peña, D., Lara, J., Lizcano, D., Martínez, D. (2017)	A predictive model using Moodle data highlights students at risk of dropping out and a tutoring action plan sets out prescribed actions including emails and telephone calls for two academic roles; the course instructor (course issues) and the degree programme tutor (social, cognitive, affective issues). The model is deployed in weeks 4, 7 and 10.	There was a significant improvement in retention rates of 14% plus a 6% improvement in final grades compared to the previous year.
Cambruzzi, W., Rigo, S.J., Barbosa, J.L.V. (2015)	A predictive model is used to support the planning, design and development of specific and targeted pedagogical actions. The goal of the intervention was to improve interaction between educators and students.	A positive retention impact of 23% and 6% between classes within the same discipline.
Grant, M., R. (2012)	There were three types of interventions based on LMS usage reports. Learning Interventions: links to additional resources, changes in the planned assignment structure; Design Changes: developing practical strategies to further engagement, easier access to assessment, adding voiceovers to resources; and Content Revisions: Clarity in the presentation of the LMS	Quantitative: This study reports that the courses in which interventions were made had a better retention rate (2.8%) compared to other online courses (3%) and face to face courses (4.7%) Qualitative: A survey was carried out with students; the majority reported that the course met their needs and felt the online experience was more effective.
Liu D.Y.T., Taylor C.E., Bridgeman A.J., Bartimote-Aufflick K., Pardo A. (2016)	Instructors had access to the datasets and were able to query them based on student characteristics. They then delivered personalized interventions in the form of emails or phone calls.	The improvement in both the retention rate and students' overall academic performance are stated in this paper but not quantified or evidenced.

RQ2: How effective are Learning Analytics and Academic Analytics methods in improving Academic Performance?

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Academic Performance

Study	Intervention Method	Evidence of Effectiveness
Arnold, K.E., Pistilli, M.D. (2012)	Course Signals (CS): A student success system - allows meaningful feedback to be provided to students based on predictive algorithmic models. Personalised student interventions include: posting a traffic light signal on a student home page; email correspondence; text messaging; referral to an academic tutor; face to face meetings with support staff	Qualitative: A 10.37 % point increase in A's and B's awarded between CS students and students from previous semesters of the same course not using CS; A 6.41 % point decrease in D's, F's and withdrawals awarded to CS users compared to previous semesters of the same course not using CS. Qualitative: Student and faculty feedback from survey and focus group provided supporting evidence of positive impact on student attitude and behaviour
Jayaprakash, S M., Moody, E., W., Lauria, E. J. M., Regan, J., R., Baron, J, .D. (2014)	Course Signals (CS): A student success system - allowed notification interventions, but with a new concept of awareness interventions, whereby students receive email 'nudges' and have access to an online community designed to promote academic support available, peer to peer engagement, access to self assessment tools, and educational scaffolding. Subsequent engagement can include online and face to face as needed.	6% improvement in final grades amongst those students in the two treatment groups over non interventionist controls. In addition statistically significant impact on students who demonstrate exceptional financial need.
Smith, V.C., Lange, A., Huston, D.R. (2012)	STARS: An automated, systematic, early alert system - allowed instructors to launch proactive interventions at any point in the course to assist students who show signs of struggling. Resulted in Faculty outreach to students at risk; and an automated course welcome email.	Faculty designed outreach programmes did not generate significant improvements in success rates; although evidence to suggest that students who received direct contact succeeded more often than students who received non direct contact. Some impact on drop out rate reported related to welcome email.
Tanes, Z; Arnold, K., King, A. S., Remnet, M., A. (2011)	Signals: A student success system - enabled Faculty staff to send asynchronous motivational / formative and summative students feedback, including feedback sent by email. Students also receive traffic light visualisation to in their CMS	Results of two studies reported: The first is on instructor feedback. Study 2 reported that rather than frequency of messaging, the type of feedback provided within a message made a difference to students success, as did feedback that compared student performance to cohort performance, and feedback that was outcome orientated.
Wright, M. C., McKay, T., Hershock, C., Miller, K., Tritz, J. (2014)	E2 Coach: Delivered tailored advice and study support to students, involving emails at the beginning of term, personalised messages throughout the semester, and advice on performance and future activities. E2Coach also provided comparative performance data and information to students	Students who used the system performed 'better than expected' (against predicted performance) significantly more often than those who did not. Assessed actual performance of students against predicted performance, and found that students who used E2Coach had significantly improved performance against predicted performance, while non users of E2Coach showed no difference.
Corrigan, O., Smeaton, A.F., Glynn, M., Smyth, S. (2015)	Predicted: A predictive analytics system - enabled weekly automated emails to students predicting their exam performance	Nearly a 3% improvement (58.4% to 61.2%) on exam performance for those students who opted in to the programme.
Dodge, B., Whitmer, J., Frazee, J.P. (2015)	Targeted interventions in the form of email nudges sent to students via Blackboard suggesting ways to improve their performance, and included online and in-person resources that could help improve performance.	No significant difference between the experimental and control groups on course achievement. Interventions were associated with a higher final grade in one course, but only for a particular demographic group
Herodotou, C., Heiser, S.,Rienties, B. (2017)	Interventions consisted of an email message from Student Support Team reminding students to choose an assessment slot; an outbound call from the Learner Support staff regarding end of module assessment and any help; and an email sent to the students' Associate Lecturer informing them that the student had not picked their end of term exam date	No significant effect of support intervention on students' end-of-module performance. No significant differences between the three intervention types and control conditions was reported in relation to support provided to at-risk students before the end-of-module assessment.

RQ2: How effective are Learning Analytics and Academic Analytics methods in improving Engagement?

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Engagement		
Study	**Intervention Method**	**Evidence of Effectiveness**
Lonn, S., Aguilar, S.J., Teasley, S.D. (2015)	Student Explorer: An early warning system - used by academic advisors in a Summer Bridge programme (delivering intensive academic preparation, individualised academic advising, and community based living environment) to deliver face to face student support with the aim of improving motivation and goal orientation (using Achievement Goal Theory).	The impact of the interventions was to statistically decrease students' reported pre-bridge mastery scores and post bridge mastery scores, and that elements of the intervention programme may have moderately decreased students' mastery goal orientations
DeMonbrun, R.M., Brown, M.G. (2017)	Student Explorer: An early warning system - and E2Coach - a digital coaching system - used to deliver tailored advice and study support to students, involving weekly help messages, exam preparation, and reflection tools, along with a weekly check list of tasks, a grade calculator and online mechanisms for reviewing academic material.	Assessment of student performance on a week-to-week basis (rather than final grade performance), which identified that engagement in the online digital tools reduced 'risk' levels of students in the sample.
Lu, O.H.T., Huang, J.C.H., Huang, A.Y.Q., Yang, S.J.H. (2017)	Students in the experimental group received adaptive learning interventions (online, email and face to face) from an instructor (informed by learning analytics) when their engagement fell below a specific threshold. Students in the control group received interventions based on the instructors observations	There was an improvement in the learning outcomes and engagement of students on the module with learning analytics, as interventions from instructors helped. There was also some improvement in learning outcomes of the experimental group.
Corrigan, O., Glynn, M., McKenna, A., Smeaton, A., Smyth, S. (2015)	The intervention consisted of sending students weekly information about their engagement and regarding the predictions of their attainment for modules they were studying, based on their Moodle engagement, and the provision of a dashboard for academic staff to monitor their students' engagement.	Quantitative: There was an average increase in grades of 2.9% when comparing the grades of participants in this study with grades of non participants across the various modules. Qualitative: Student feedback indicated that 33% of them had changed their engagement with Moodle / VLE.
Shimada, A., Mouri, K., Ogata, H. (2017)	Use of an e-learning system and an e-book system that allowed academic tutors to monitor student engagement in the module, and to adapt accordingly etc., and thus allow students to catch up quickly.	The synchronization ratio of the experimental group was significantly better than the control group (77% to 60%). This meant that students who received the interventions were better engaged with the online resources.
Yen, C. H., Chen, I. C., Lai, S. C., Chuang, Y. R. (2015)	Instructional strategies were changed and adapted by instructors (according to the results of statistical, discourse and qualitative analysis of learning analytics data drawn from student engagement in LMS and social media) to help learners develop a cognitive load that is conducive to learning and to enhance students' germane cognitive load	The strategies had an effect on the level of interaction as part of asynchronous discussions and also the quality of that discussion. This was evidenced by increased views and the classification of discussion content based on the cognitive processing level. Both are reported to be higher post intervention. Finally students took a pre test and post test which showed performance significantly increased.

RQ3: What methodologies are used to evidence and measure the effectiveness of Learning Analytics and Academic Analytics?

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- Retention
  - Drop outs
  - Academic Failure Rates
- Academic Performance
  - End of year mean test results
  - Pre test / post test
- Engagement
  - Log data
  - Cognitive Load
  - Synchronization Ratio
  - Motivation Surveys

Characteristic		Studies (n)	Proportion (%)
Research Population	< 100 students	2	11%
	> 100 students	16	89%
	Average	2,053	
	Range	59–14,340	
Data used to evaluate effectiveness	Quantitative	13	72%
	Qualitative	0	0%
	Mixed Methods	5	28%
Sampling techniques	Probability	3	17%
	Non Probability/ Not Mentioned	15	83%
Control Group	Yes	9	50%
	No	9	50%
Stated Effectiveness	Yes	15	83%
	No	3	17%

- Majority of studies reported to be effective
- All studies use quantitative analysis e.g. ANOVA, Regression, Chi-Squared, Pearson
- Some complement their findings with surveys and interviews with staff and students
- Very few probability sampling techniques adopted such as RCT although some studies do state the use of / desire for control groups

RQ4: How robust are the methodologies in the studies progressed?

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1. Measures and definitions of success differ

2. Theories of change are limited…
   - Expected benefits are presumed
   - Impact of interventions on student outcomes underdeveloped

… and there is a focus on demonstrating impact rather than evidencing effectiveness

3. The methodologies fail to fully…
   - Acknowledge limitations of statistical methods
   - Explore the value of mixed methods are the exception rather than the norm
   - Understand the student voice - limited qualitative data to capture the impact of interventions
   - Embrace sophisticated sampling strategies

4. Little understanding of the value added of Learning and Academic Analytics compared to other Learning and Teaching intervention strategies

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Northumbria Educational Analytics Framework

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A transformative and immersive experience evidenced through improved student outcomes enabled by ....

...a high quality, academically challenging learning community which delivers proactive and tailored support models enabled by...

*...**Adaptive Analytics** which drives a customised learning environment where programmes, staff, services, resources and technology are optimised...*

*... **Learner Analytics** which enables students to self-regulate their learning and benchmark their performance through targeted communication, visualisation tools and other enhancement activities...*

*... **Learning Analytics** which promotes targeted personal, pastoral, wellbeing or other support interventions ...*

*...**Academic Analytics*** which empowers staff to make academic, pedagogic or other Learning and Teaching interventions..

*...**Institutional Analytics*** which enables strategic interventions for improved utilisation of physical, spatial, technological or digital resources...

...as part of a personalised student experience which is built upon...

...an Educational Data Mining (EDM) platform which harvests, processes and analyses Big Data from the Learning Environment to identify patterns and generate insights facilitated by investment in...

Data | *Systems* | *Processes* | *Policies* | *People*

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A Realist Evaluation of a Learning Analytics Pilot Project

Lessons learned at Northumbria University

Carly Foster

Insight and Performance Manager

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Overview

- Why evaluate?
- Project Overview
- Research Questions
- Data and Analysis
- Plans for 2018-2019

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Why evaluate the project?

- Evaluations are expensive but so is institution-wide Educational Analytics!
- TEF student outcomes framework
- OfS –All students, from all backgrounds, receive value for money (Strategic Objectives 4)

Teaching Quality (TQ)
Impact and effectiveness of…
- schemes focused on monitoring and maximising students' engagement with their studies"
- innovative approaches, new technology or educational research
- feedback initiatives aimed at supporting students' development, progression and achievement

Learning Environment (LE)
Impact and effectiveness of initiatives aimed at
- supporting the transition into and through a higher education course
- understanding, assessing and improving retention and completion

Quantitative information demonstrating proportional investment in teaching and learning infrastructure

Use and effectiveness of learner analytics in tracking and monitoring progress and development

Student Outcomes and Learning Gain (SO)
- **Impact of** initiatives aimed at closing gaps in development, attainment and progression for students from different backgrounds, in particular those from disadvantaged backgrounds or those who are at greater risk of not achieving positive outcomes.

Table 8: Possible examples of evidence for each aspect (*Teaching Excellence and Student Outcomes Framework Specification, 2017, p.53-54*)

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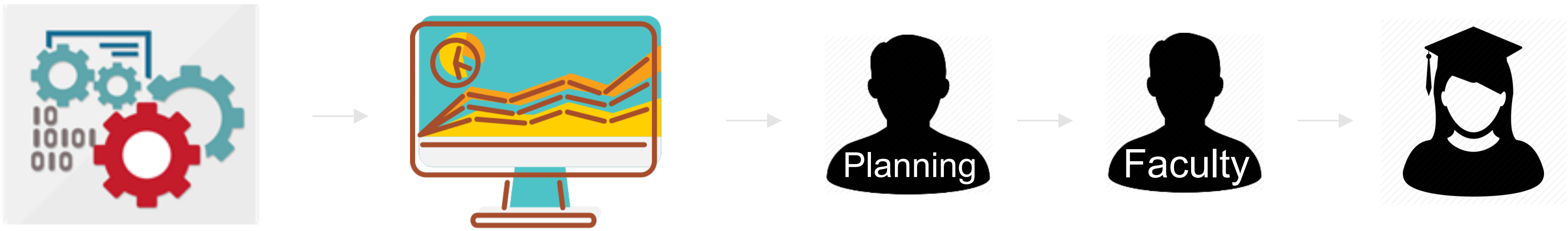
Project Overview



- Mined SITS and Blackboard data
- Utilised a commercial predictive model for **retention**- in partnership with Civitas Learning International
- Pilot Department – First Year, On Campus (Opt in rate of 85%)
- ‘Nudge the nudger’ approach
- Personal Tutors >>> students most at risk

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Research Questions

RQ1
Were the objectives of the project completed and what was learned?
RQ2
Did the project outputs lead to the expected outcomes?
RQ3
Did the project deliver the expected benefits?
RQ4
Were there any unexpected outcomes or benefits?
RQ5
Is there evidence to support further investment in Educational Analytics at Northumbria?

Evaluation >>> Recommendations

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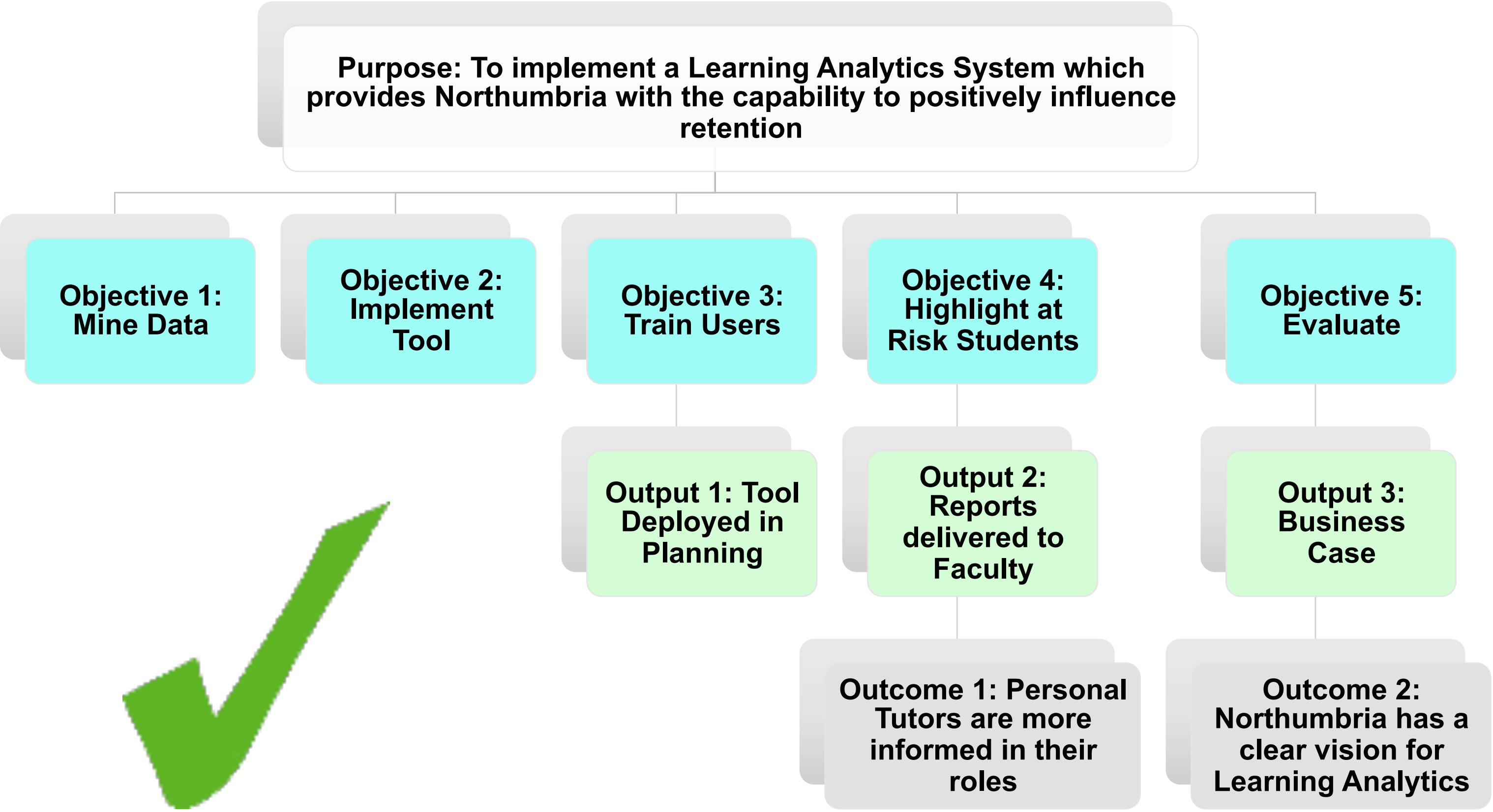
Outputs to Outcomes



RQ1 Were the objectives of the project completed and what was learned?

- Timeliness and data access- hosted data sets
- GDPR and policies
- Gather metadata

RQ2 Did the project outputs lead to the expected outcomes?

However… Projects don’t stop at outcomes they must deliver benefits…

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RQs 3 and 4 - Benefits

Even though…

- Predictions were made… (GDPR architecture)
- Engagement with faculty… (policies reinforced)
- Interventions were made... (All students still studying at NU)

The retention in the department did not significantly improve

Did we identify the right students?

Were staff prepared to act?

Were they the right interventions?

Data Sources

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	Data (Source)	Purpose/ Application	Method of Analysis
Context	Discovery Interviews [Qualitative]	To understand themes and context amongst key stakeholders	• Thematic
	Personal Tutor Surveys [Quantitative]	To measure attitudes towards the pilot project prior to implementation and after Semester 1 “***Were staff prepared to act?***”	• Descriptive • Comparative • Correlational
Mechanism	Predictive model metadata, attendance data [Quantitative]	“***Did we identify the right students?***”	• Descriptive
	Intervention data [Quantitative]	**“Were they the right interventions?”**	• PPSM
Outcome	In Year Student Enrolment Data [Quantitative]	To measure the impact on retention	• Significance testing on withdrawal rates
	Change of Circumstances Data [Qualitative]	To give context for outcomes	• Descriptive

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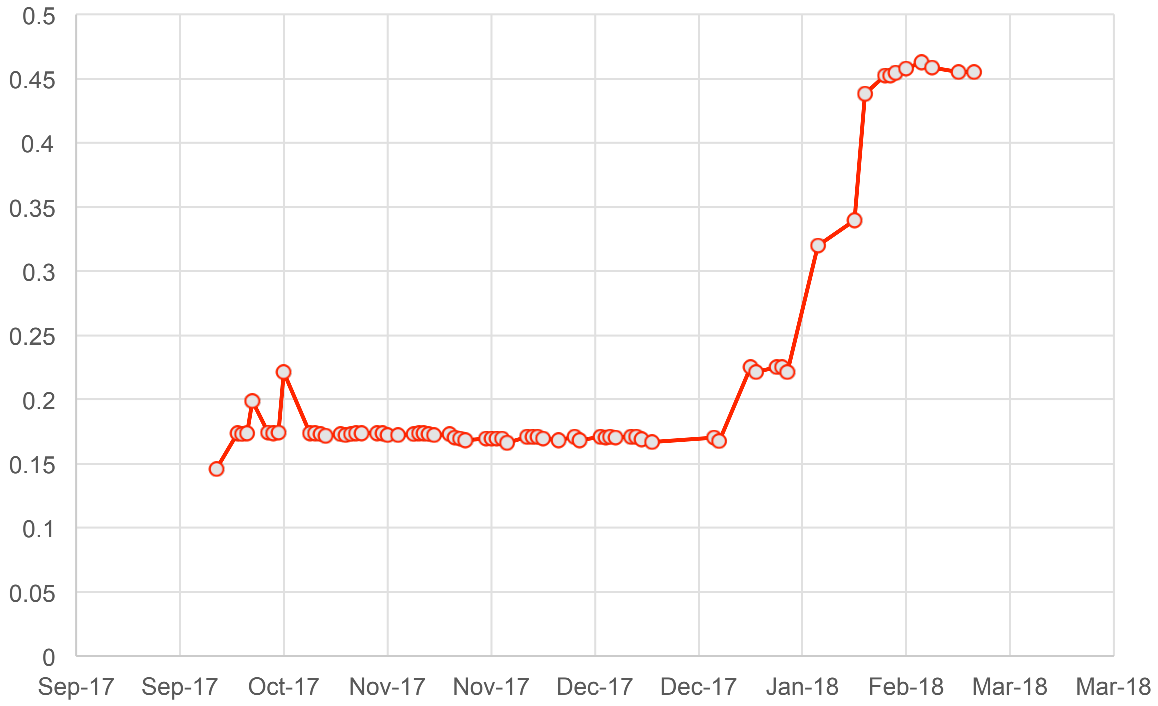
Did we identify the right students?

- Model was 83% accurate
- Literature suggests this is within range for Demographic and VLE data
- Better when first assessment data uploaded – more expected

Correlation Coefficient Throughout Pilot Project (Attendance vs Prediction)



Recommendations >>

- ***Engagement data required***
- ***Day 0 variables***

Were staff prepared to act?

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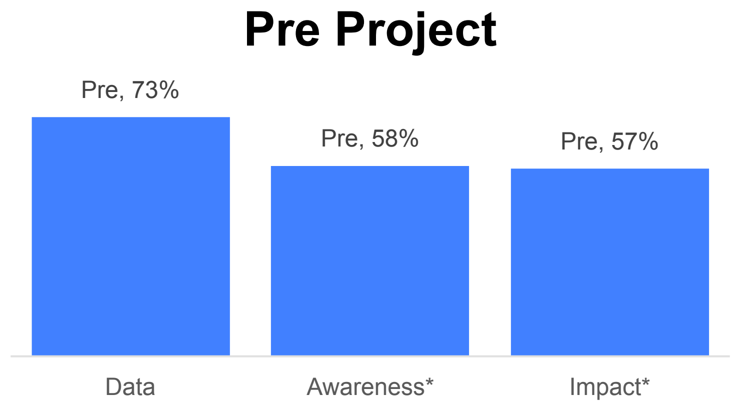

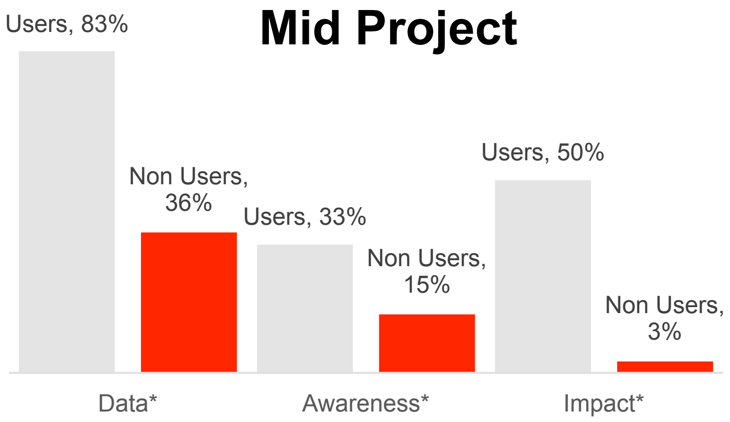

Outcome 1: Personal Tutors ~~are~~ ***feel*** more informed in their roles

Outcome 2: Northumbria has a clear vision for Learning Analytics

Benefit 1: Improved Retention

Benefit 2: Learning Analytics is embedded in Northumbria Culture

Shaw et al. (1978)-->
Role Adequacy- preparation and knowledge
Role Legitimacy – perception of responsibility
Role Support – training and support

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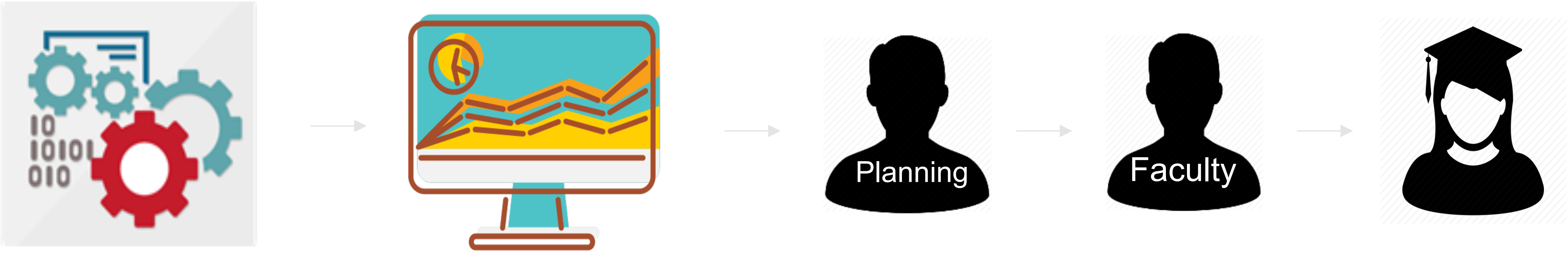
Were they the right interventions?



TOOL
Staff facing
Aligned to role
Student Level

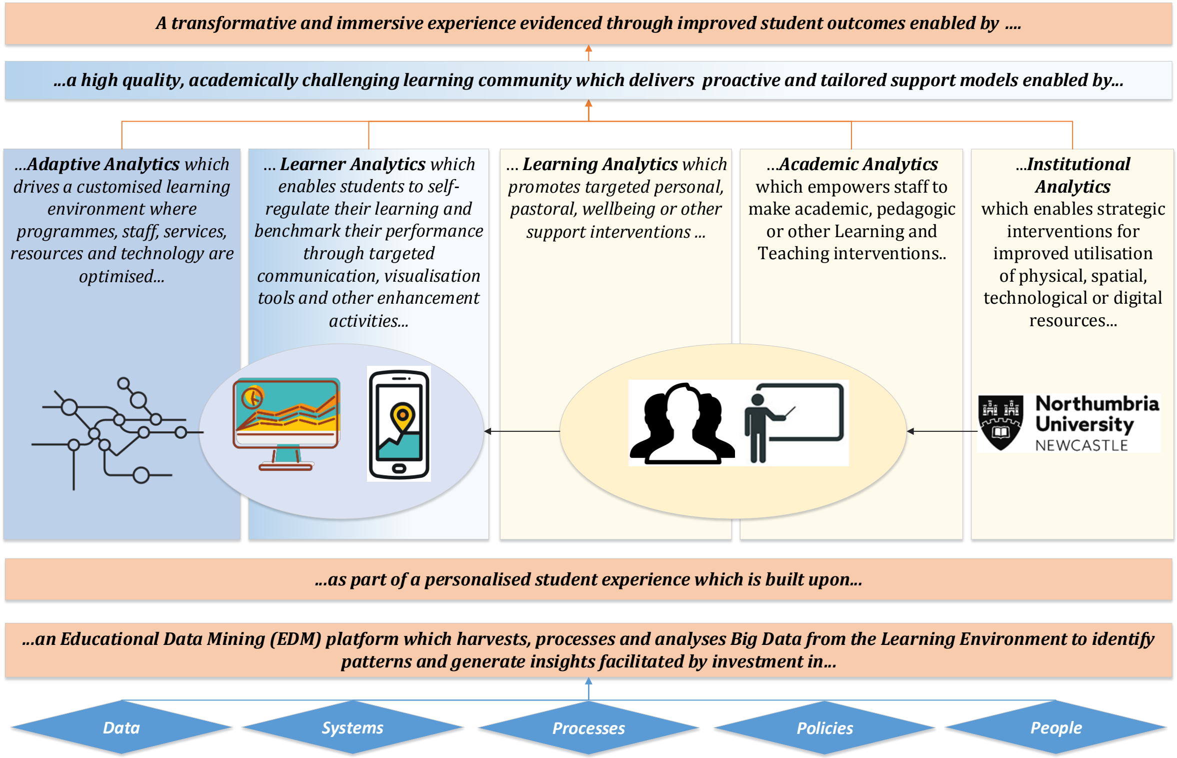
NUDGE
Method
Frequency
Content

DATA
Actionable Insights

AGENCY
Defined roles
Support

RQ 5 – Evidence

- Time to measure- 12 months vs 18 months
- Systematic Review
- Evaluation
- Framework
  - Learning Analytics
  - Academic Analytics
  - Institutional Analytics
  - Learner Analytics



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Next Steps

2018-2019

- Learning and Academic Analytics
- Learner Analytics
- RCT Sampling

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Northumbria University hosting Jisc event

19th September 2018