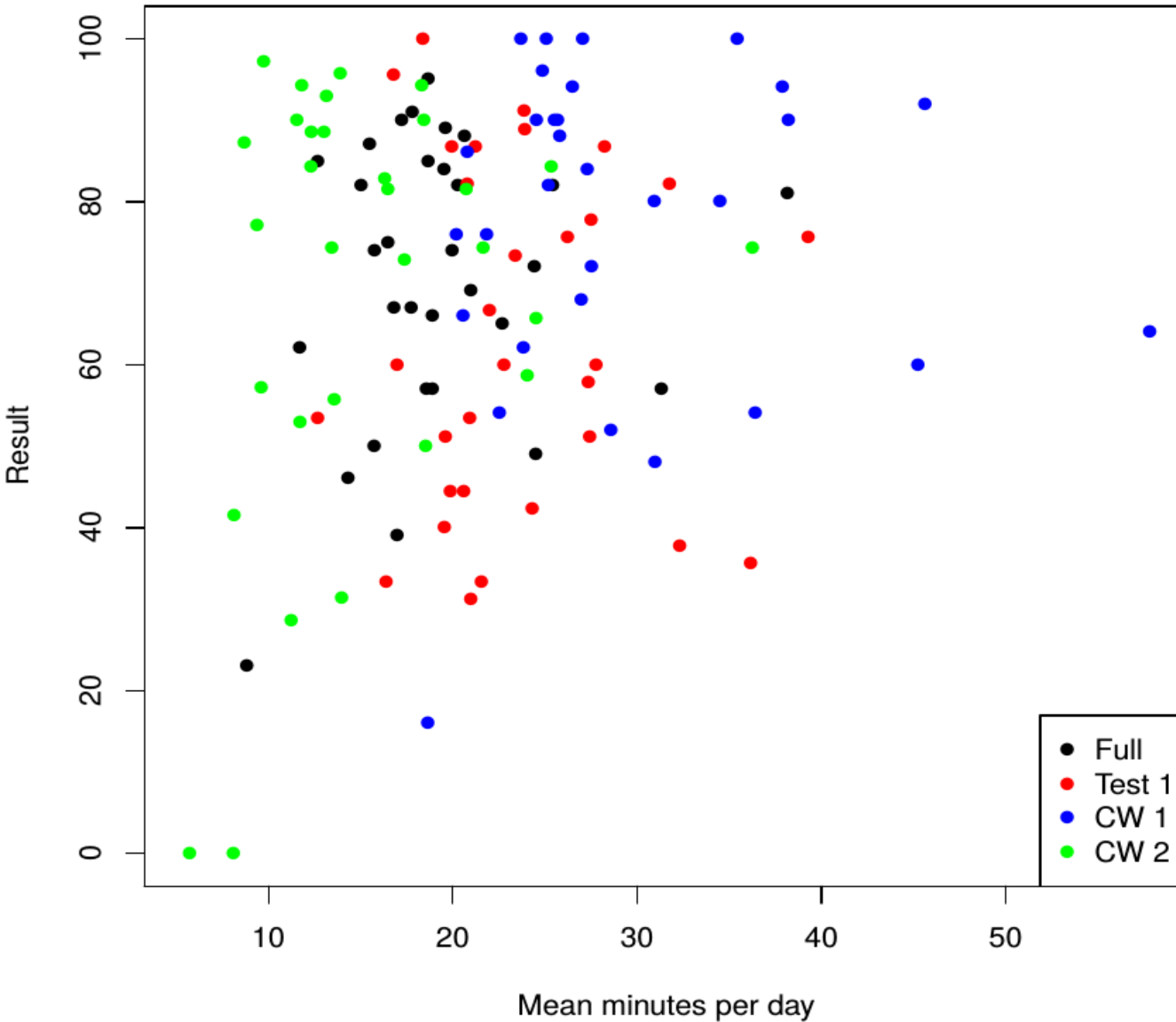


BIO2097, $r=0.159$, $p=0.127$

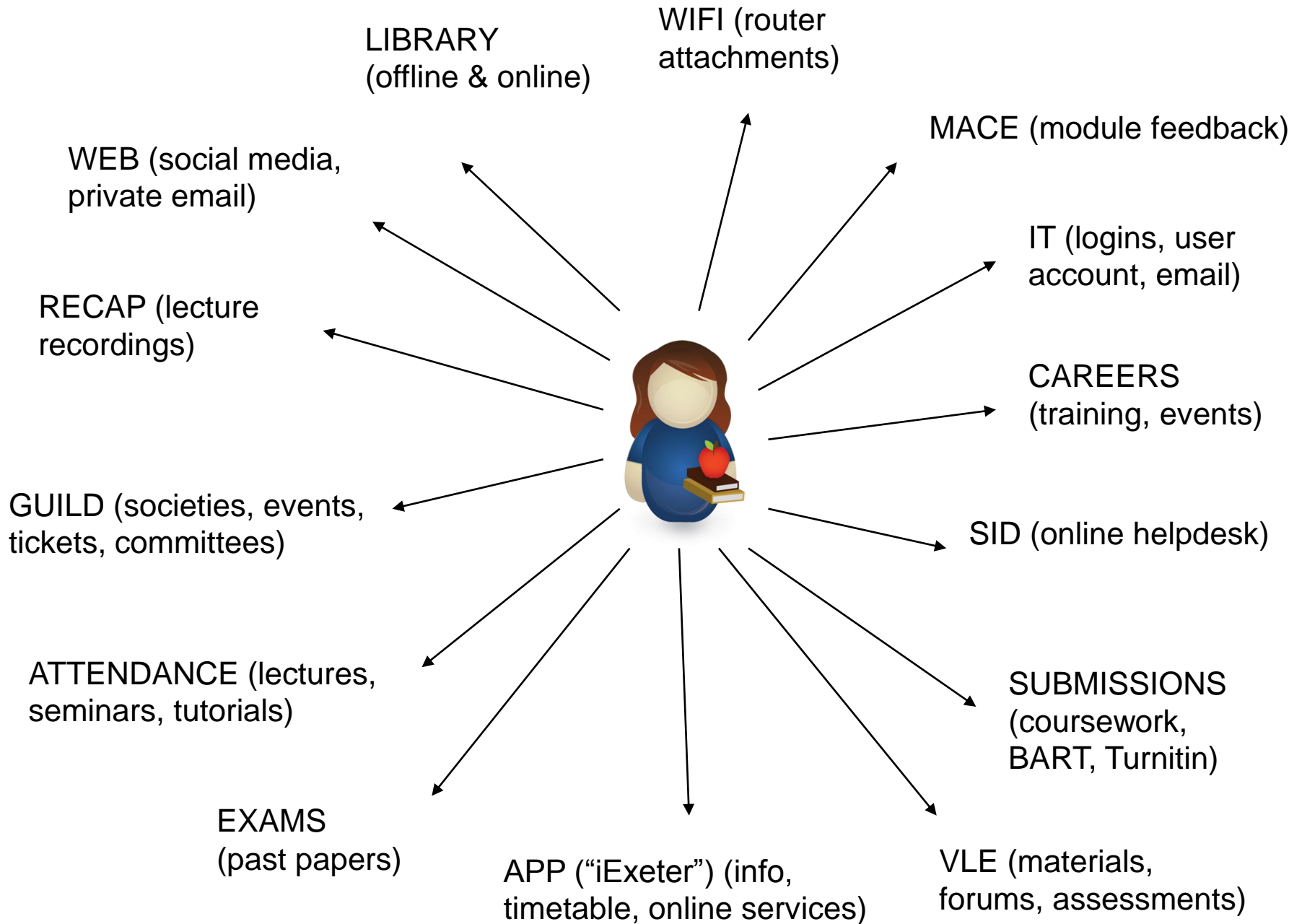


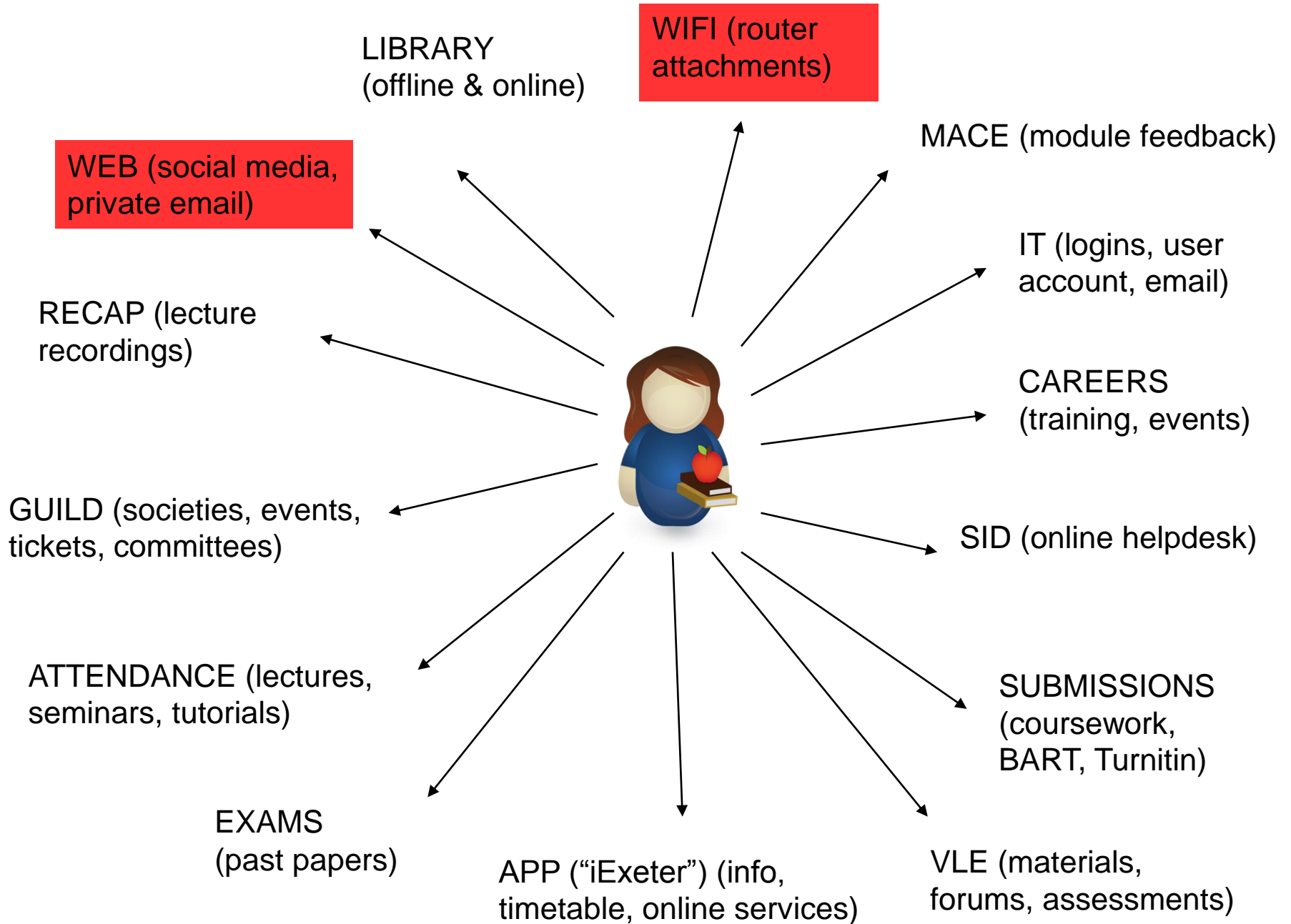
Engagement at BaM universities cannot be reduced to VLE use.

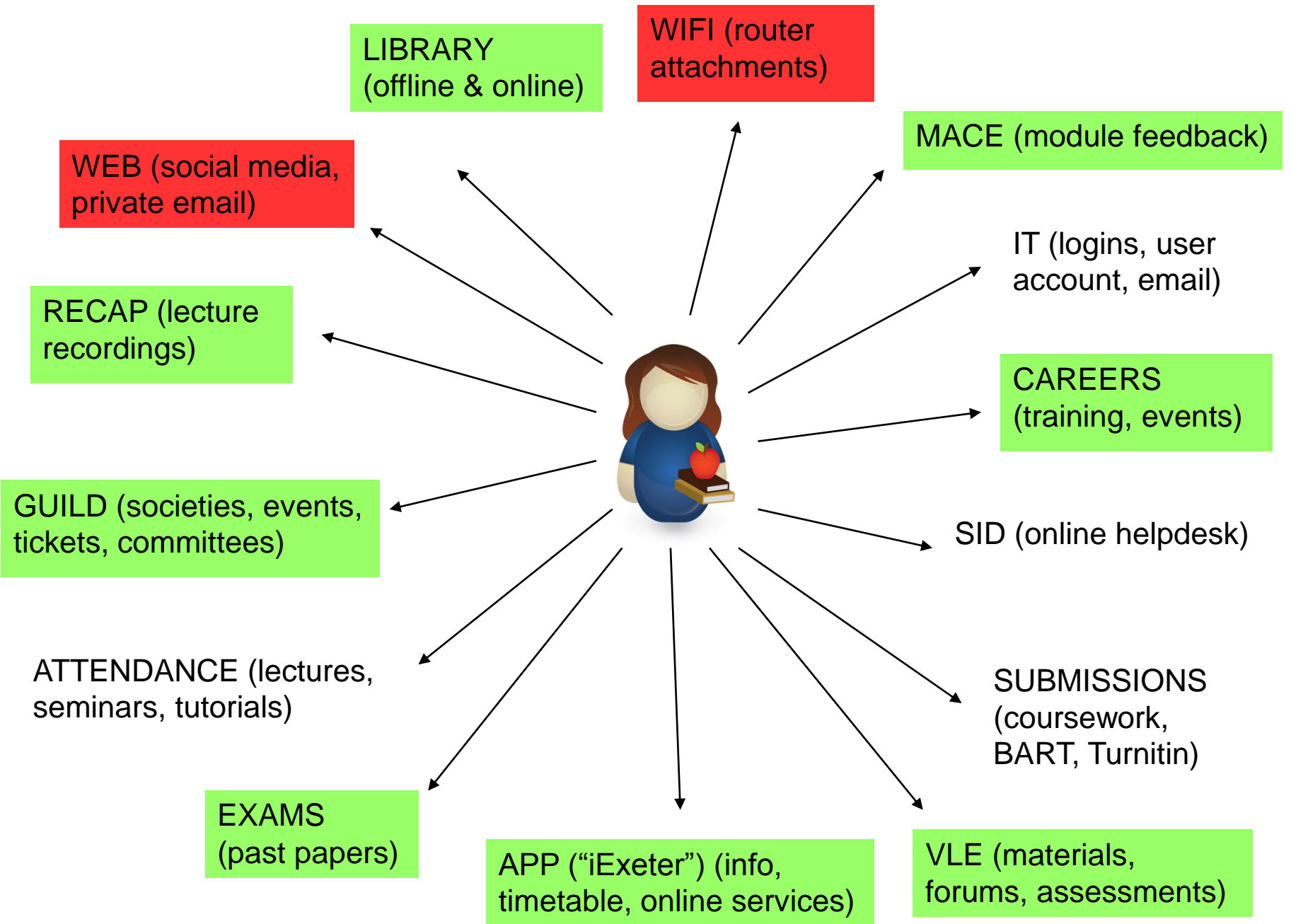
Is engagement at BaMs still predictive of student success?

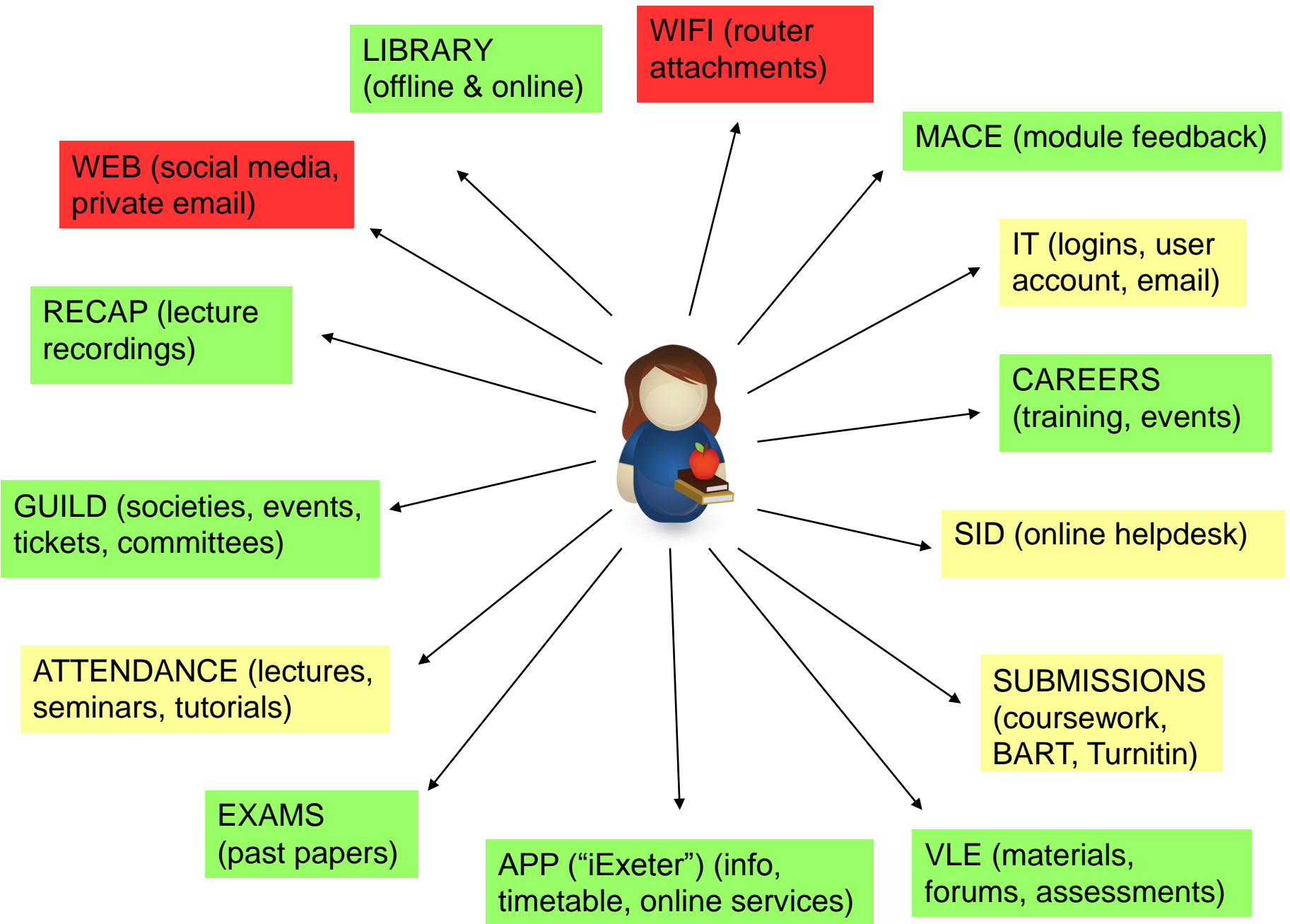
Measuring engagement

- Engagement has **many dimensions...**
 - Physical attendance at lectures
 - Interacting with staff
 - Being on campus
 - Student societies / sports / hobbies
 - Using digital resources (e.g. VLE, library)
 - Using external digital tools (e.g. social media)
 - ...
- Many of these leave **digital traces**
- **Pragmatic approach:** Focus on digital data that is routinely collected.
 - (Working closely with data warehouse project and IT managers.)



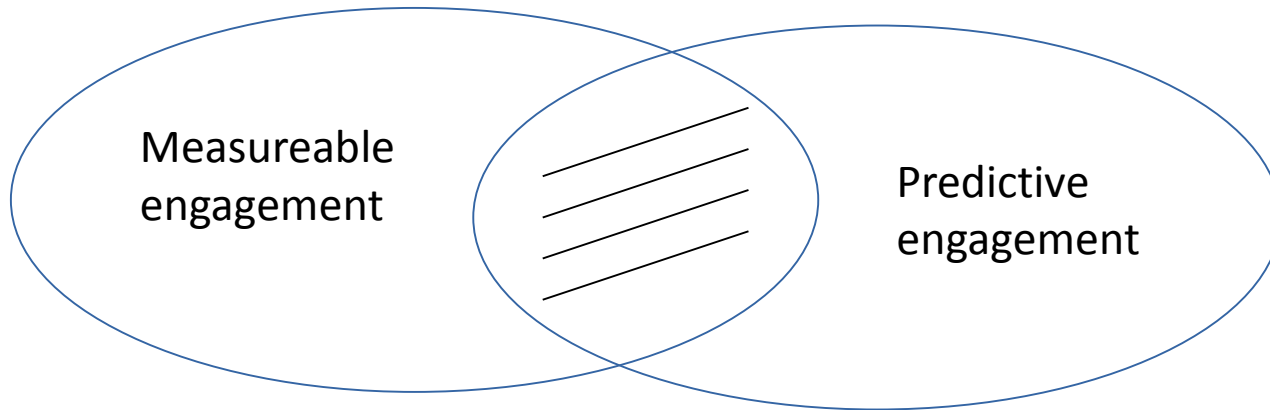






Data Source	Includes data about	Dates
Data warehouse	<ul style="list-style-type: none"> • Modules exams results • Students' Journey (incl. end of withdrawals, ending reason, transfers etc.) • Interruptions • Enrollment, Registration, Programs, Modules variables • Demographics • WP rules • Assessment Types & results • Students entry qualification (TBD) 	continuously updated
Committee Interactions	Memberships in committees and tickets' purchasing	2013-14-15
Guild (Careers Events System)	Signups and attendance for career events	2013-14-15
Mitigations biosciences (Manually curated)	Requests of mitigations and their status (only bioscience students)	2014-15-16
Systems' interactions	Time stamped logins from ELE, MACE, Inter Library Loans (Library ILL), Library fees, Exam's archival system	12/10/2012 - 3/2/2016
iExeter	Clicks on menu items & loading of pages	Term2 2014 – Term1 2016
Recap	Video views	Term 1 2016
ELE	Timestamps of all interactions with ELE from which we can calculate the usage per day (minutes, counts, active 10 minute intervals)	7/2015 – 1/2016
	Full logs, classified into resource type and activity type	8/2015 – 12/2016
Survey	Offline interactions, digital interactions outside of the university's systems, students' subjective perception of engagement and of their performance in learning, learning strategies	Term 2 2016
DLHE	Self reported employability variables	
BART	Due and actual dates of assignments, type of assignments (paper / online)	
SID	SID calls, categorized	2013,14,15

Measuring engagement



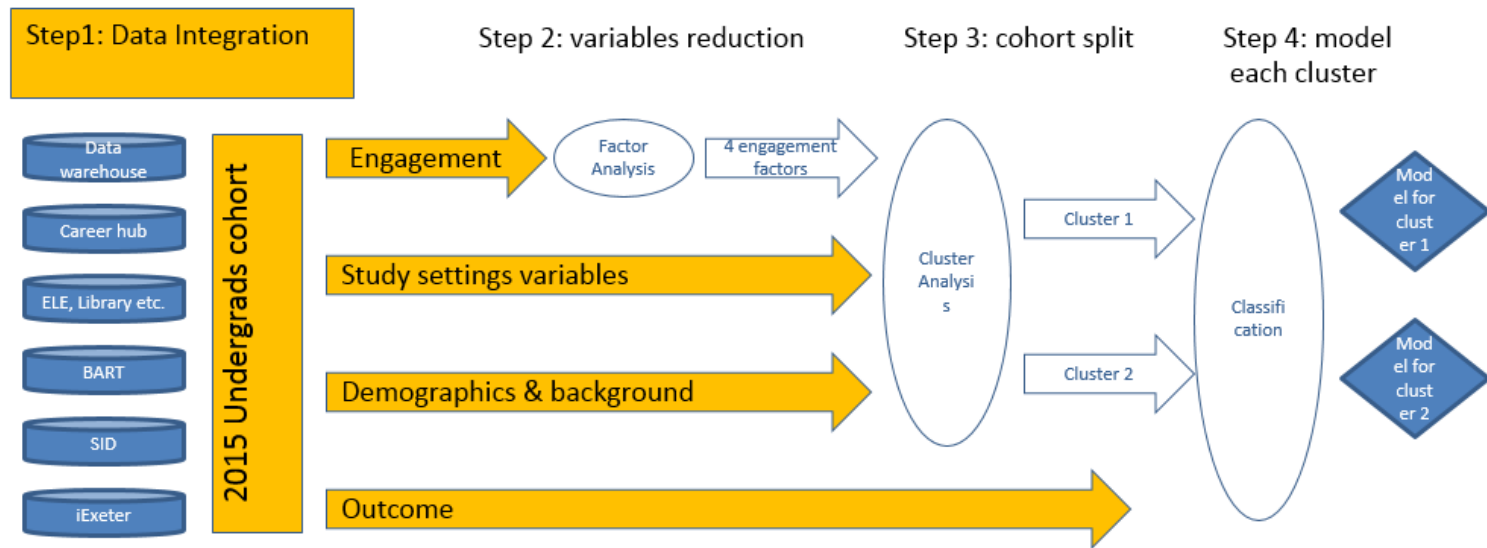
- Which forms of engagement are useful?
 - → need to be both **measurable** and **predictive**
- Focus on digital data may introduce bias
 - → running a complementary engagement survey (results are being written up)

Entire cohort – predictors of average credit-weighted module grade

Demographic	Engagement
Gender [U = 231120953.50**]	MACE evaluations [r = 0.250**]
Away from home [U= 152140073.00**]	MACE logins [r = 0.262**]
Disability type [H(10) =168.02**]	
Disability [H(3)=73.89**]	
Country of domicile [H(140)=1,554.98**]	
Ethnicity [H(18)=627.97**]	
National identity [H(7)=360.69**]	
Nationality [H(187)=1,880.03**]	
Parents' occupation [H(326)=869.74**]	

Statistics: r – Spearman's, U – Mann-Whitney, H – Kruskal-Wallis, ** - significant $p < 0.01$
 Sample: n=30,781 students in three years 2013-2015.

Kent, Boulton, Williams (2017) Towards Measurement of the Relationship between Student Engagement and Learning Outcomes at a Bricks-and-Mortar University. Proc. 2nd Cross-LAK Workshop at LAK 2017.

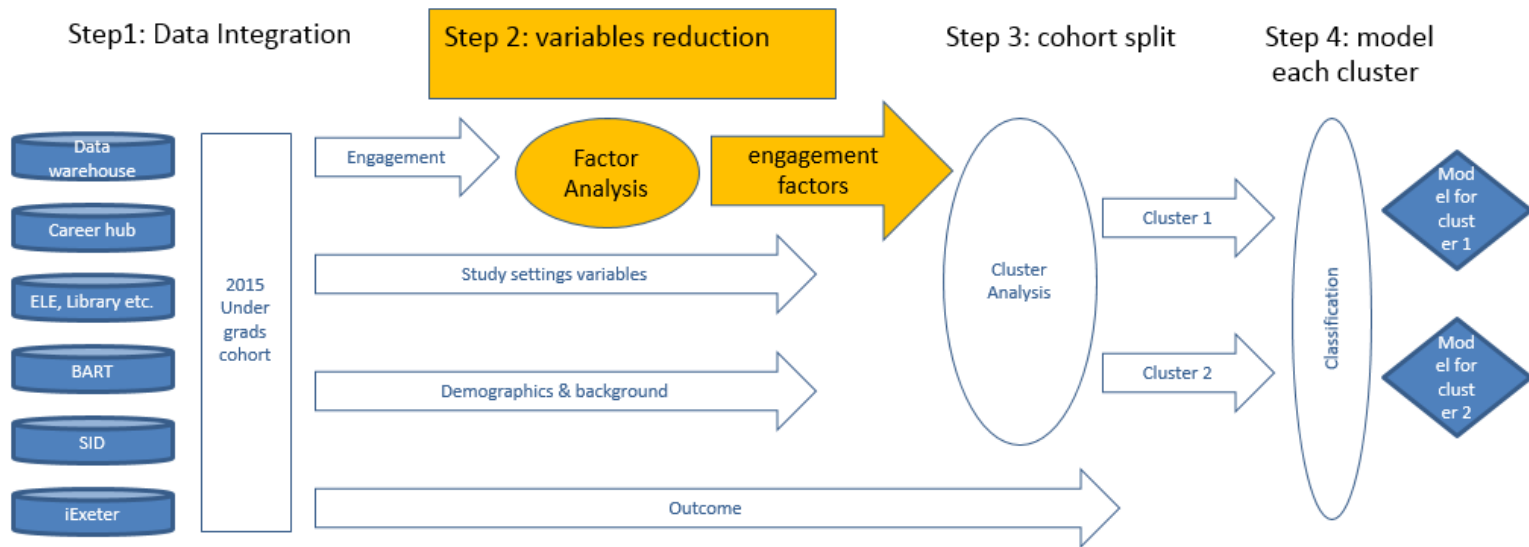


Data integration – Integrating, normalising and cleaning data from multiple data sources to create as complete a picture as possible of an individual’s experience

Variables reduction – Reduce the dimension in variables for simplicity and to minimise multicollinearity

Cohort split – Cluster students by grouping them by engagement, demographics and study settings

Modelling – Model the outcome/success of each cluster

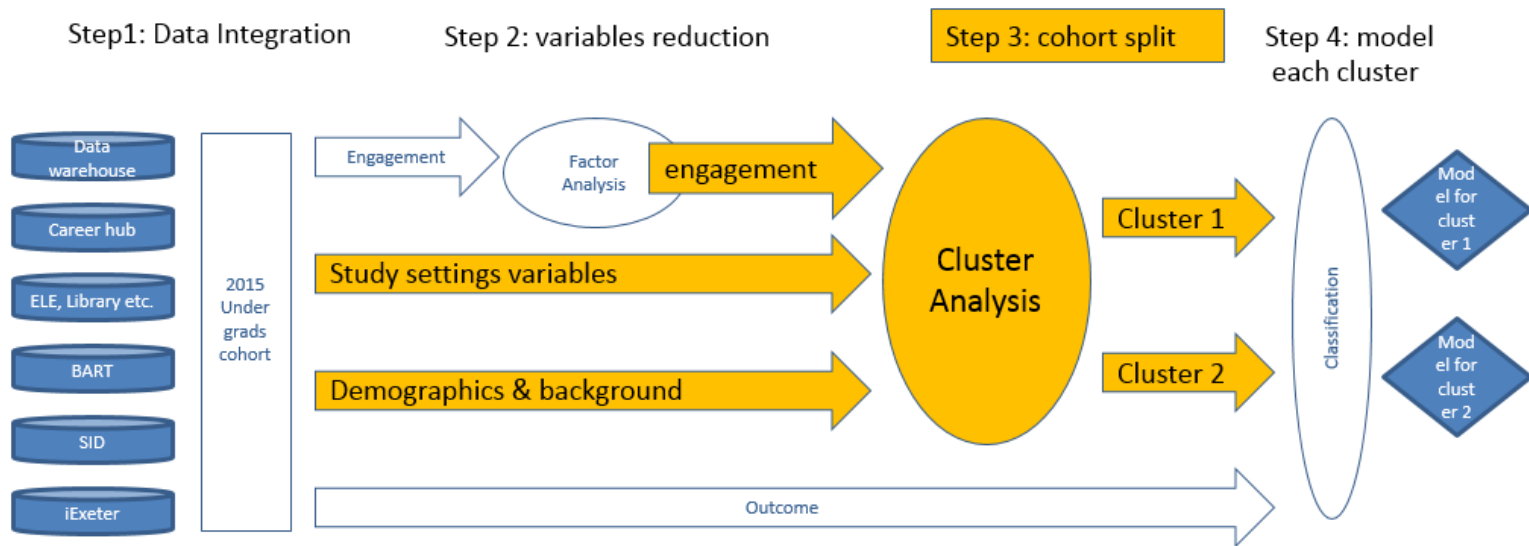


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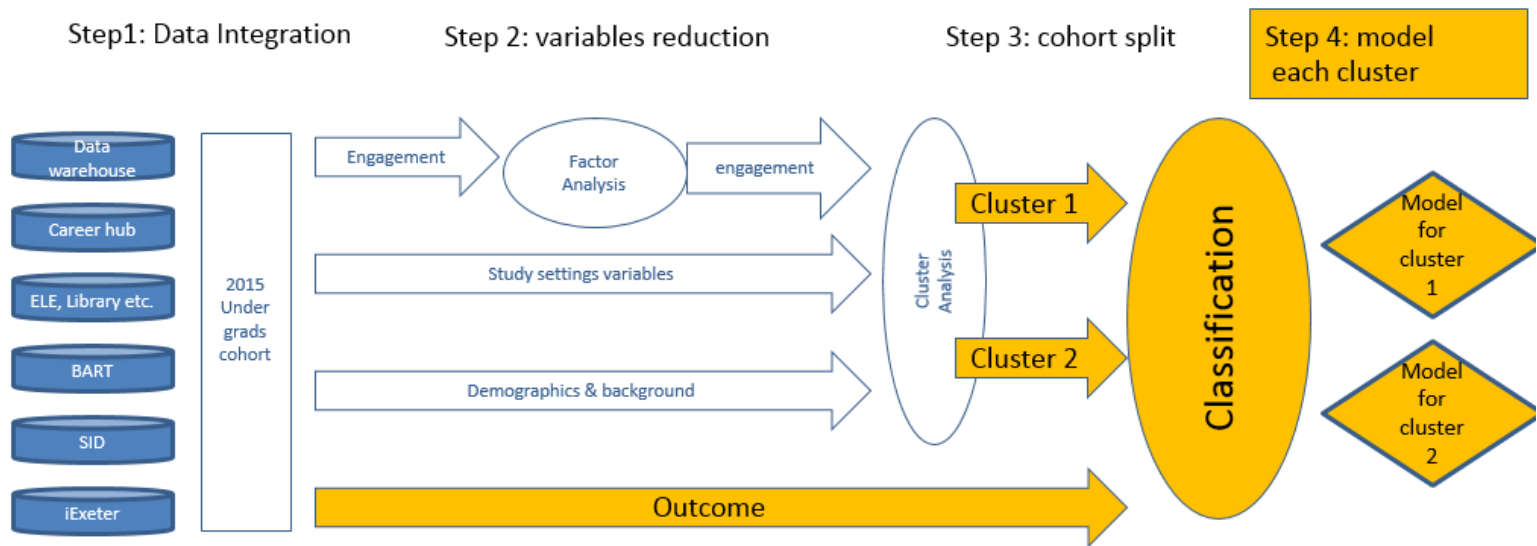


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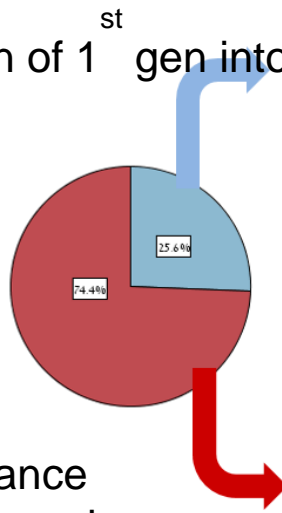
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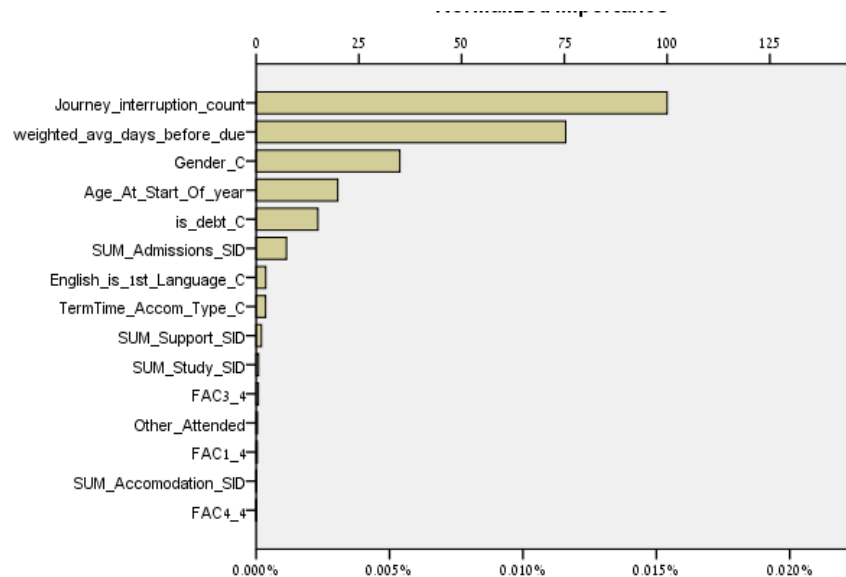
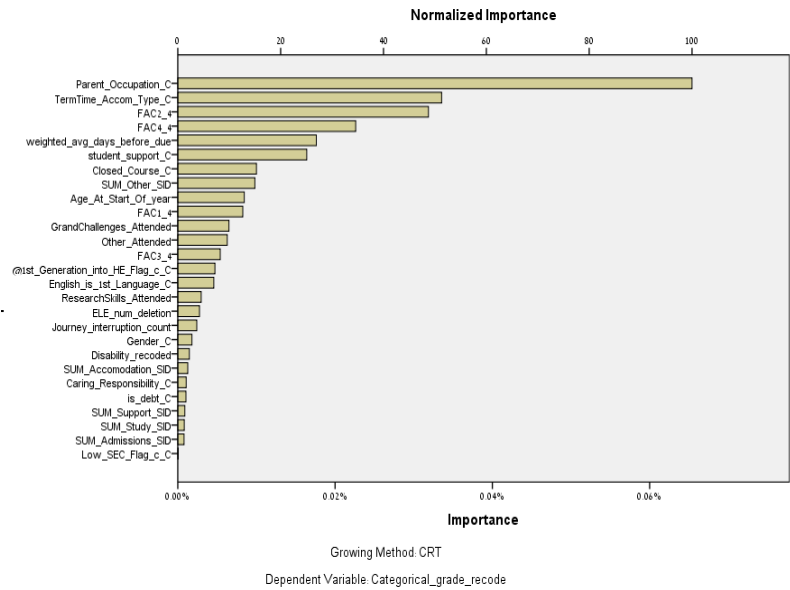
Cohort split – Cluster students by grouping them by engagement, demographics and study settings

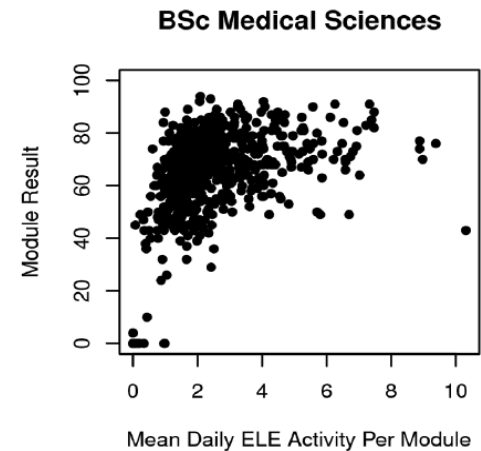
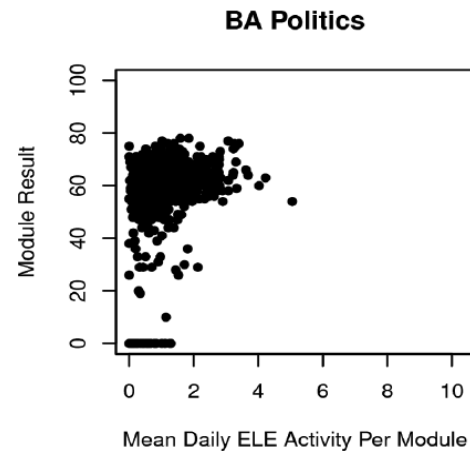
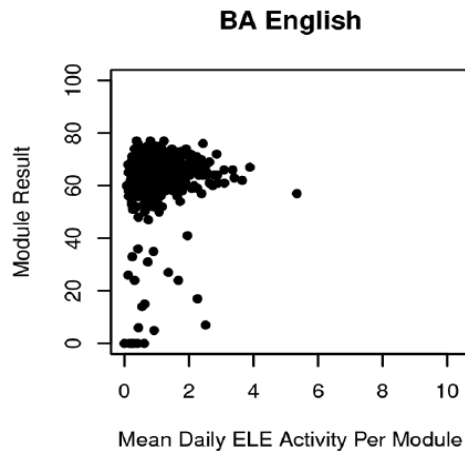
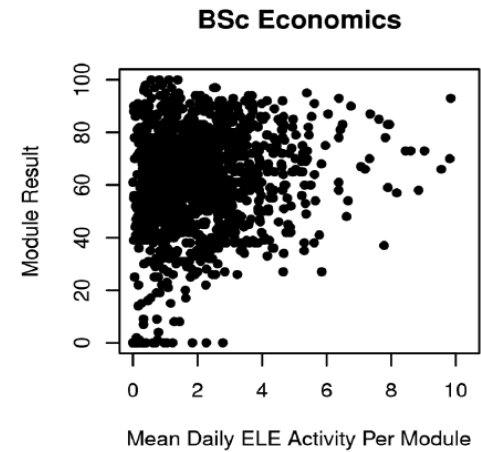
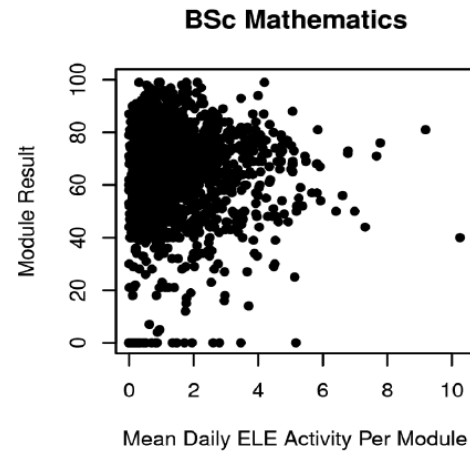
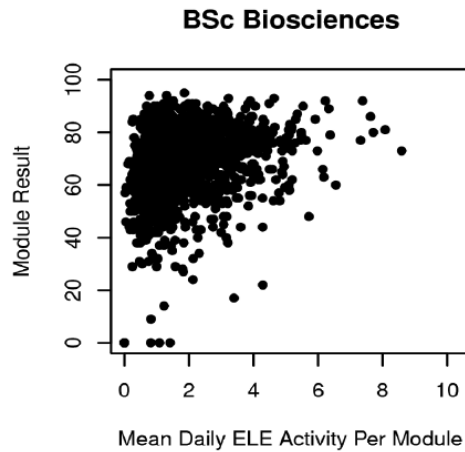
Modelling – Model the outcome/success of each cluster.

Lower performance
 Non-native English speakers
 Older
 Later assessment submission
 More SID calls
 Lower use of digital systems
 More career events attended
 Less student support
 More debts
 Higher proportion of 1st gen into university



Higher performance
 Native English speakers
 Younger
 Early assessment submission
 Less SID calls
 Higher use of digital systems
 Less career events attended
 More student support
 Less debts
 Lower proportion of 1st gen into university



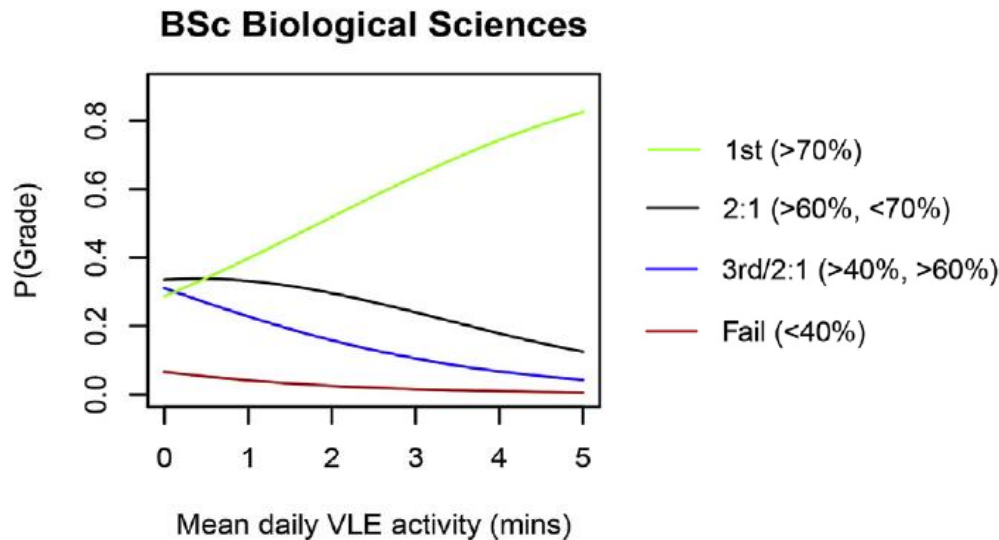


Engagement through ELE system is weakly predictive of module grades (with variation between disciplines).

Boulton, Kent, Williams (2018) Virtual learning environment engagement and learning outcomes at a 'bricks-and-mortar' university. Computers & Education

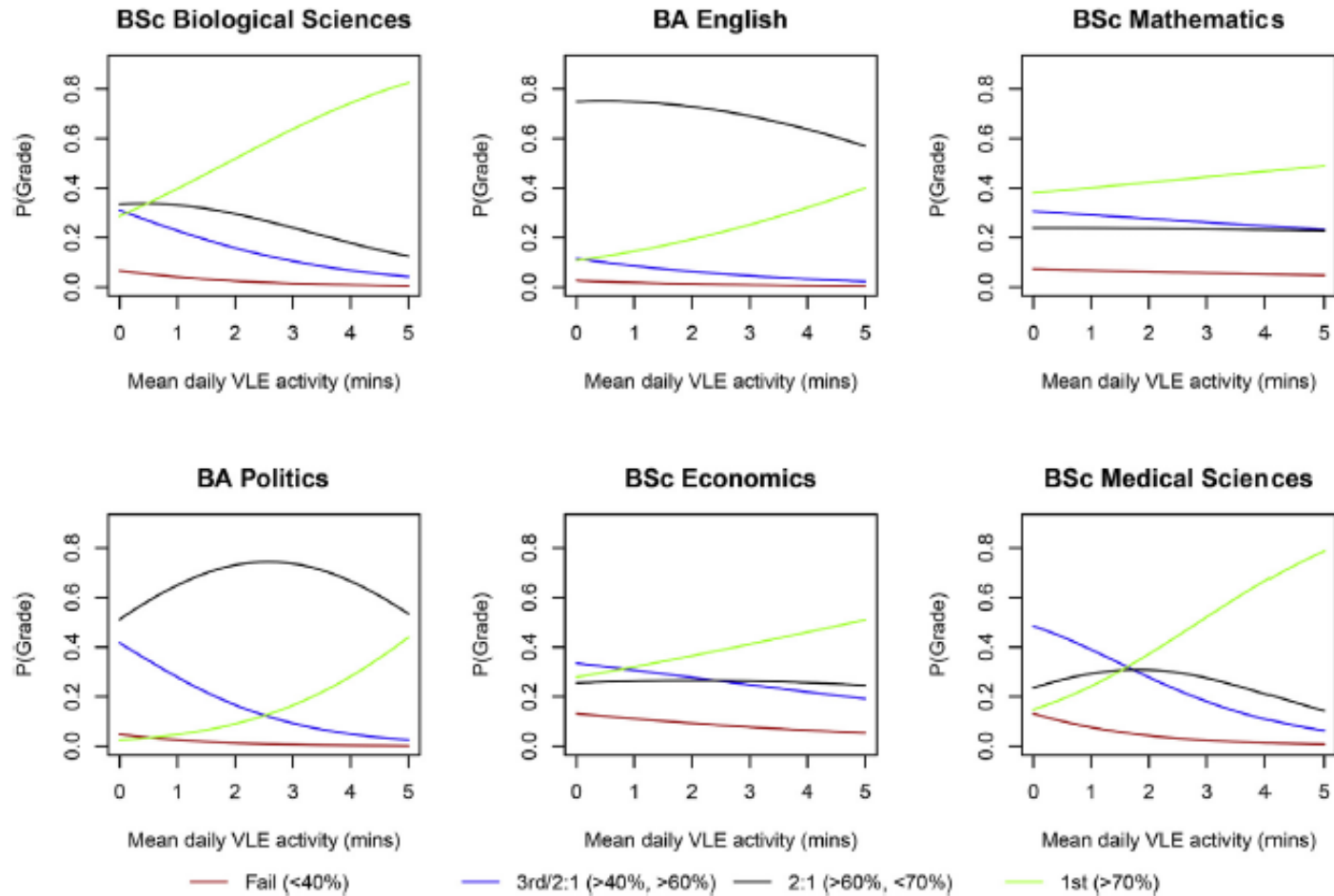
OLR models

- Can use ordinal linear regression (OLR) models as predictors of result based on engagement.
- After classifying results into degree classification categories, model outputs a probability of being in each category.



- Very low chance of failing but this decreasing with VLE usage.
- Equal probability of other categories with increase in getting a 1st with ELE usage.

Boulton, Kent, Williams (2018) Virtual learning environment engagement and learning outcomes at a 'bricks-and-mortar' university. Computers & Education

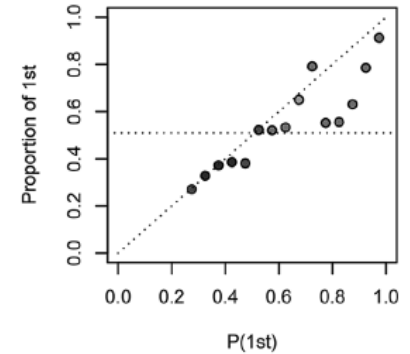
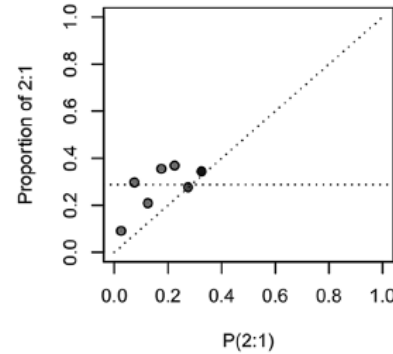
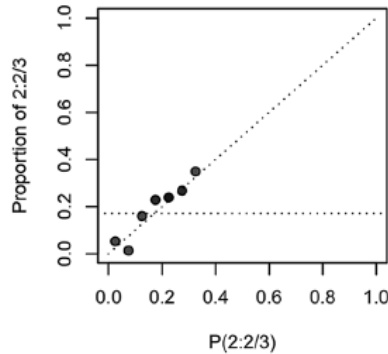
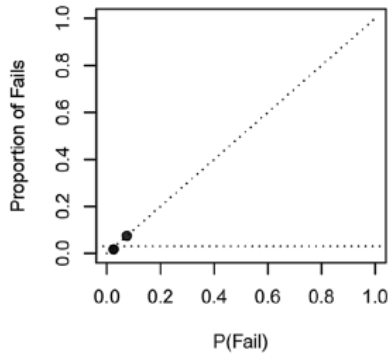


Different relationships predicted for different courses. Highlights differences in importance.

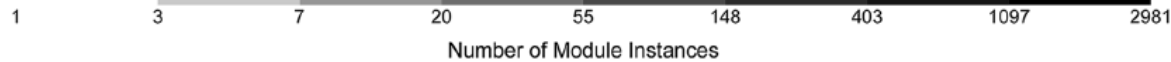
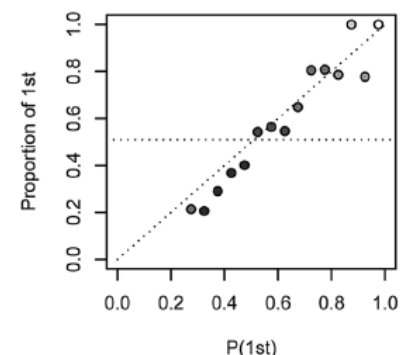
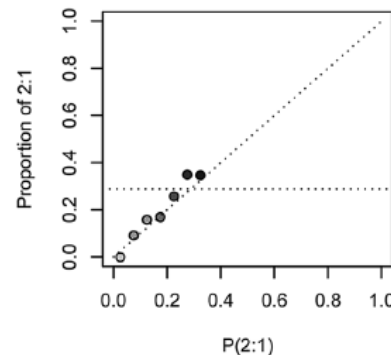
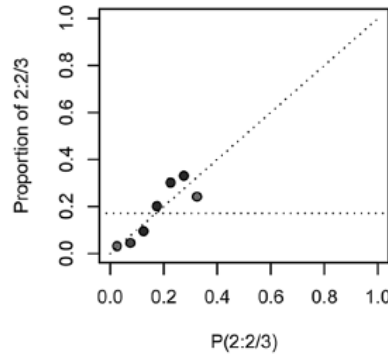
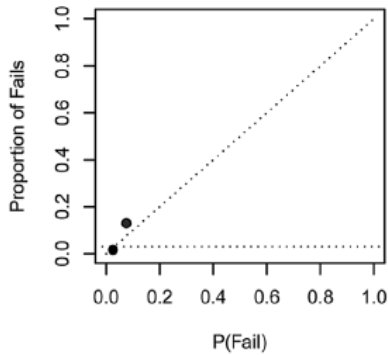
Boulton, Kent, Williams (2018) Virtual learning environment engagement and learning outcomes at a 'bricks-and-mortar' university. Computers & Education

Using OLR models for real time prediction

Week 5



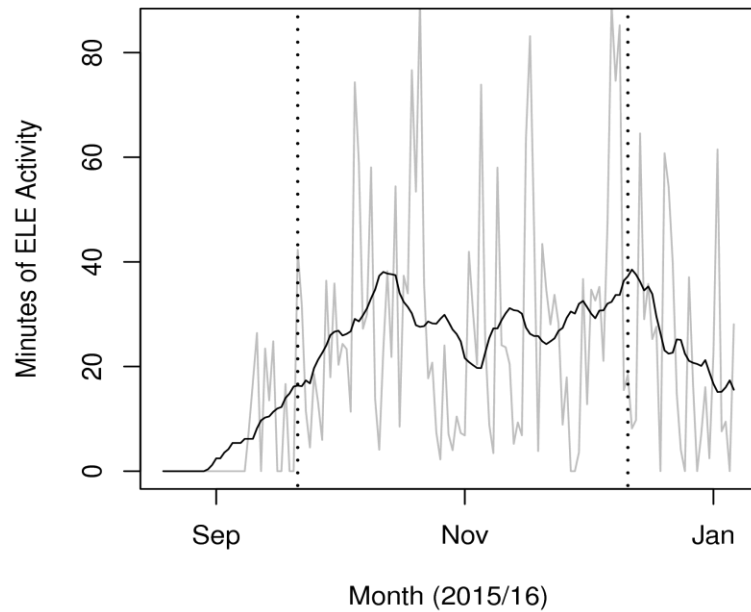
Week 10



- Use coefficients from last year's models to predict this year's outcomes.
- Useful prediction can be made after 5 weeks, at least identify students who could need intervention.
- Note that 10% of instances given a 10% of failing, do fail!

Can we spot interrupting students before it happens?

Non-interrupting student



Interrupting student

