



## Evidence for Enhancement: Improving the Student Experience

### Learning Analytics Hot Topic: Evaluating interventions

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There has been very little research work carried out to evaluate interventions, and the studies that have been carried out are inconclusive; see Sclater (2017), Whitmer et al (2017).

Ferguson and Clow (2017) examined issues around evidence that learning analytics improves learning by reflecting on the experiences gathered in evaluation work carried out in medicine and psychology. They used these experiences to illustrate some of the methodological and ethical lessons that learning analytics should seek to use or avoid during evaluation. These include:

- Although quasi-experimental techniques such as randomised control trials (RCTs) are thought to be the 'gold standard' in medical research and are commonly used in learning analytics evaluation, these can promote a 'simplistic view' that an intervention acts alone on a subject and in a context where all other variables are controlled. In other words, the intervention and nothing else causes any change in student behaviour (Pawson & Tilley (1997)).
- Correlation is not causation. Data can sometimes indicate that there may be a relationship between two variables (for example, an intervention of some kind and an uptick in student performance), but unless a causal link is identified between the two, one cannot be said to cause the other.
- For enhancement purposes, identifying what causes an improvement is as important as observing an improvement. For enhancement to adhere to its central definition - that is, the continuous improvement of the student experience - it is important to understand how the improvement has happened. This allows the relevant practice to be replicated, transferred to other contexts and further developed.
- Ethical issues may exist around withholding 'treatment' that may be beneficial to subjects in control groups: is it ethical to withhold a learning support tool to struggling students, even if its benefit is not known?

- Metrics and predictive models being used as proxies for student behaviour need to be robust, reliable and accurate.
- Publication bias (where evidence of impact is published, but the evidence to the contrary is not). Ferguson and Clow (2017) note in their analysis of the practice collected in the Learning Analytics Community Exchange (LACE) Hub that there was very little evidence that reported negative or no impact.

Ferguson and Clow (2017) emphasise that quantitative analysis alone will not suffice, and that analysis must consider the context in which the student is learning:

'Good quality quantitative research needs to be supported by good quality qualitative research: we cannot understand the data unless we understand the context.'

Dawson et al (2017) evaluated the effects of a predictive model with a large cohort of students (over 11,000) that was designed to detect students at risk of withdrawal and then offer interventions that aimed to improve their performance. Their evaluation showed that the interventions offered to students identified by the model did not have significant effect on retention. What makes this study particularly interesting is that preliminary statistical analysis showed a significant difference between students who received an intervention and those who did not, but that the difference (size effect) was very small. More sophisticated statistical analysis showed that there was no significant difference. The paper highlights several important points about evaluating interventions:

- the need for rigorous and robust statistical analysis, particularly in light of the constraints of the quasi-experimental methodologies mentioned above
- the need for more work to investigate the best methodologies to use when evaluating interventions that have been informed by learning analytics
- the need for predictive models to draw on information about individual 'differences such as motivation, employment, prior studies and self-efficacy' (in other words, the context in which students learn).

Evaluations of interventions will become more and more complex and difficult as institutions roll out learning analytics tools and increase the number of interventions that they inform. It may, for example, become difficult to evaluate whether a particular intervention has been effective, as it may have been implemented along with a plethora of other interventions and finding the causal relationship between intervention and effect might be difficult. This is particularly problematic for large institutions with large cohorts and complex support systems, which may issue multiple interventions from different sources. For these institutions, there is an added complexity: if interventions are not coordinated centrally, students may be inundated with interventions from different support systems within the institution, potentially reducing their effectiveness. It may be important for the institution to consider interventions from the students' point of view to ensure that this does not happen and to develop a holistic, institution-wide approach to interventions.

The Open University has attempted to address this issue in part by developing an Analytics4Action Evaluation framework (Rienties et al, 2016). It is described as a holistic framework for using and evaluating learning analytics which sought to include all stakeholders (but not students) as a core feature.

The framework identifies **six key steps**:

- 1 Key metrics and drill down: this involved bringing stakeholders together (staff involved directly with learning analytics; administrators; academics) in 'data touch point meetings' to look at all the data available from the University systems and ensure that all understood that data. The figure below reproduces which University data sources that were used:

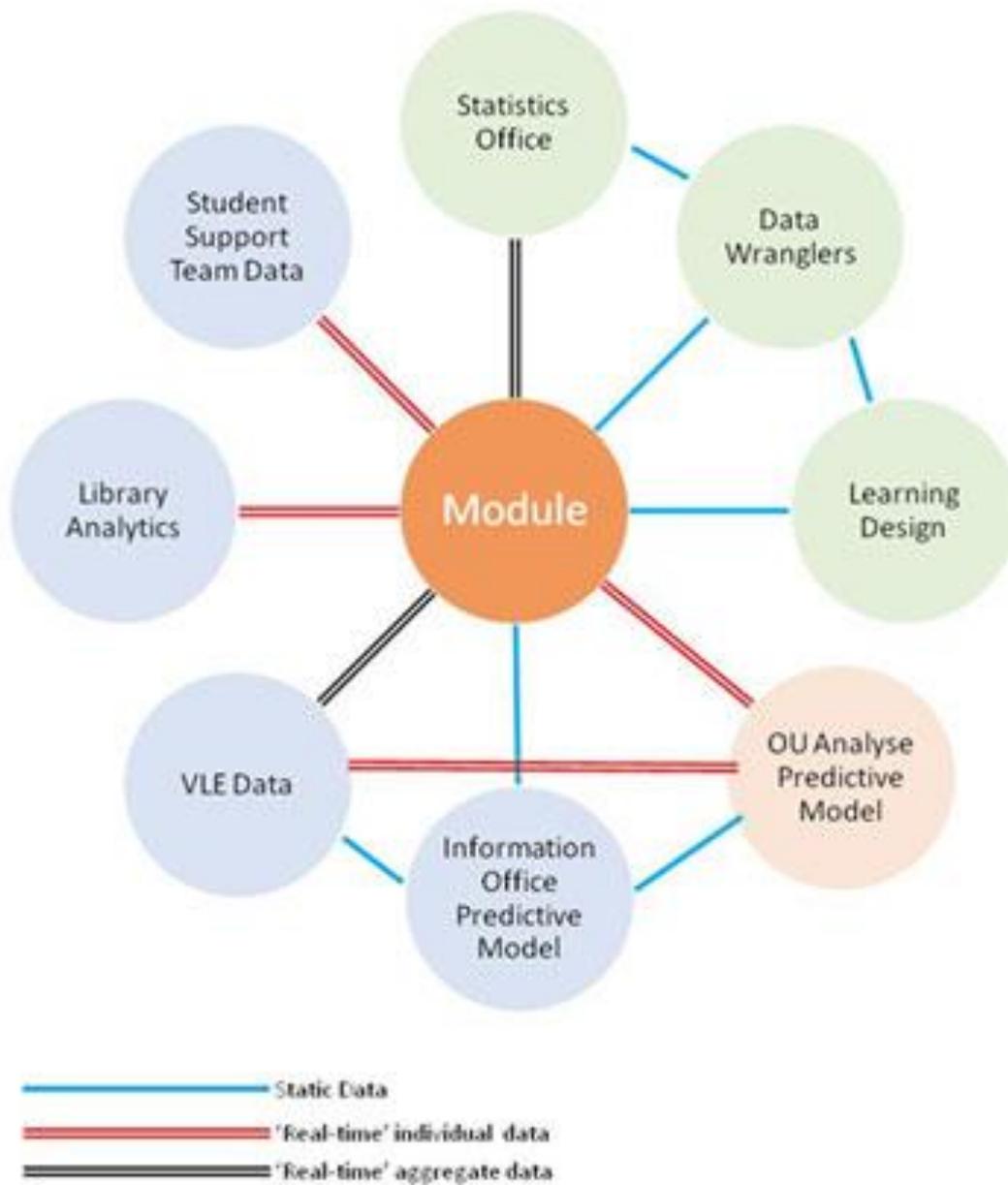
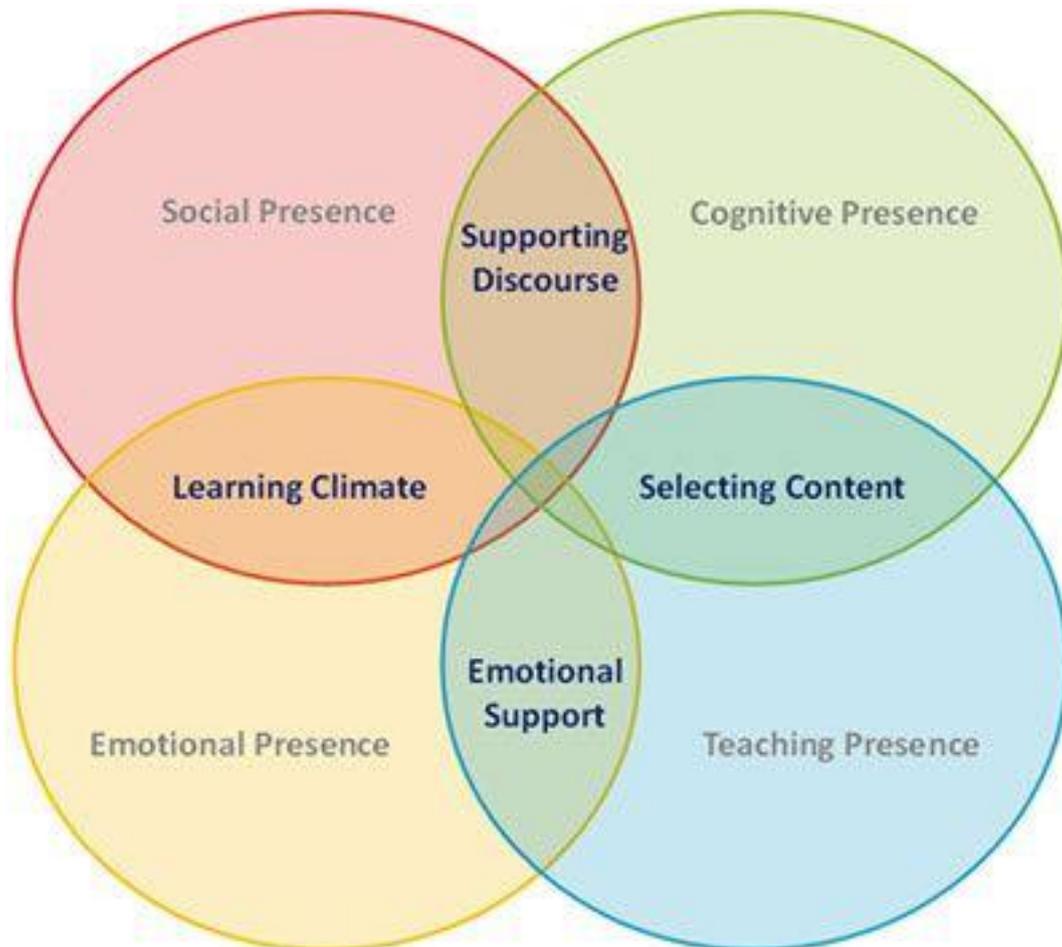


Figure 1: Data sources used in data touch point meetings (from Rienties et al, 2016)

- 2 Menu of response actions/interventions: academics are encouraged to consider a range of intervention/response options that are achievable within the institution. The menu is based on a Community of Inquiry model, articulated below. This attempted to define the teaching and learning context.



**Figure 2: Community of Inquiry Model (from Rienties et al, 2016)**

Figure 3 on page 5, also maps particular interventions to each domain of presence articulated in the Community of Inquiry model.

Potential intervention options (learning design vs. in-action interventions).		
	Learning design (before start)	In-action interventions (during module)
Cognitive Presence	<ul style="list-style-type: none"> <li>* Redesign learning materials</li> <li>* Redesign assignments</li> </ul>	<ul style="list-style-type: none"> <li>* Audio feedback on assignments</li> <li>* Bootcamp before exam</li> </ul>
Social Presence	<ul style="list-style-type: none"> <li>* Introduce graded discussion forum activities</li> <li>* Group-based wiki assignment</li> <li>* Assign groups based upon learning analytics metrics</li> </ul>	<ul style="list-style-type: none"> <li>* Organise additional videoconference sessions</li> <li>* One-to-one conversations</li> <li>* Cafe forum contributions</li> </ul>
Teaching Presence	<ul style="list-style-type: none"> <li>* Introduce bi-weekly online videoconference sessions</li> <li>* Podcasts of key learning elements in the module</li> <li>* Screencasts of “how to survive the first two weeks”</li> </ul>	<ul style="list-style-type: none"> <li>* Organise additional videoconference sessions</li> <li>* Call/text/skype student-at-risk</li> <li>* Organise catch-up sessions on specific topics that students struggle with</li> </ul>
Emotional Presence	<ul style="list-style-type: none"> <li>* Emotional questionnaire to gauge students emotions</li> <li>* Introduce buddy system</li> </ul>	<ul style="list-style-type: none"> <li>* One-to-one conversations</li> <li>* Support emails when making progress</li> </ul>

**Figure 3: Potential intervention options (reproduced from Rienties et al, 2016)**

- 3 Menu of protocols: this helps academics determine which research protocol will underpin the evaluation of the impact of the actions decided in step two. These include subjecting all students to the intervention, carrying out RCTs and pilot studies.
- 4 Outcome analysis and evaluation: evaluation of interventions is carried out using the research protocol identified in step three, although work is carried out in order to refine what variables will be affected by the intervention, and to control confounding factors. Effect size is also considered.
- 5 Institutional sharing of evidence: this is facilitated by sharing reports and outcomes on an Evidence Hub using a common template.
- 6 Deep dive analysis and strategic insight: regular meta-analysis of evidence base that might be able to help determine what works, why it works and when it works. This also allows the institution to examine whether existing metrics are fit for purpose and to change if necessary.

Other tools that have been developed to assist the evaluation of learning analytics interventions include the Learning Analytics Evaluation Framework developed by LACE.<sup>1</sup> This uses a series of Likert scale templates to determine users' experiences of using a learning analytics tool.

For the reasons articulated by Ferguson and Clow (2017), the effective evaluation of interventions arising from learning analytics still requires development. Major questions revolve around the ability of data to reflect learning behaviour. What can data from learning analytics tell us? What are the limits of the data's usefulness? How can qualitative data be usefully collected and utilised at scale to help determine what is happening? The field has attempted to address some of these questions by linking learning design and learning analytics (see below), but more work could be done to perhaps investigate how existing evaluation methodologies (such as social practice methods, realistic evaluations, and action theory) could be adapted and used with learning analytics.

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<sup>1</sup> [www.laceproject.eu/evaluation-framework-for-la](http://www.laceproject.eu/evaluation-framework-for-la).

## References

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