

# Learning analytics: let's get real...

*Work in progress...*

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# Learning analytics: let's get real...

## Structure

- How can we think about how generalisable (or not) our scholarship projects are?
- Propose a critical realist approach to evaluation
- Illustrative example – evaluation of learning analytics in OU STEM



## What is critical realism?

A family of approaches to with three general commitments:

### Ontological realism

There is a reality independent of our knowledge about it (unlike strong post-modernism/interpretivism)

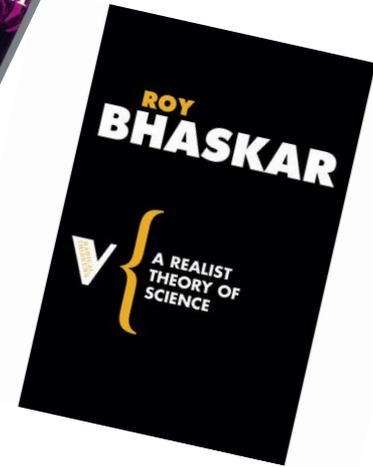
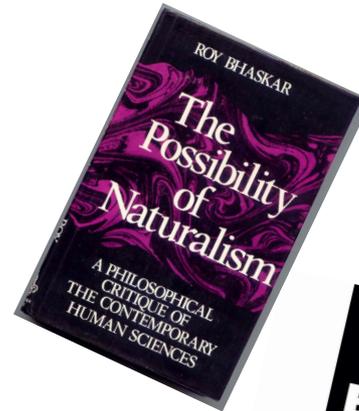
### Epistemological relativism

Our knowledge of that world is always mediated by our theories and is socially/historically/culturally situated (unlike positivism, 'scientism')

### Judgemental rationalism

We can still make judgements about whether alternative accounts of the world are better or worse (not all accounts are equal)

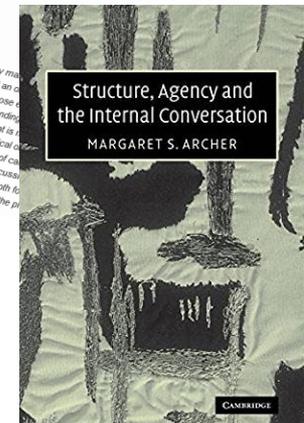
*An aside:* there is no single 'critical realist methodology'. It tends to favour multiple methods.



Techné: Research in Philosophy and Technology  
Volume 12, Issue 1, Winter 2009  
Clive Lawson  
Pages: 48-84  
DOI: 10.5840/techné200912114

An Ontology of Technology  
Artefacts, Relations and Functions

*Ontology tends to be held in deep suspicion by many technologists. The aim of this paper is to suggest an acceptable to ontology's critics and useful for those who want to sustain a conception of technology that is due weight to those features that distinguish technical activity aimed at harnessing such powers. Such discussions, however, require talk of different kinds of causal technological debates, but turn out to be significant both to the recasting of some more traditional debates within the p*



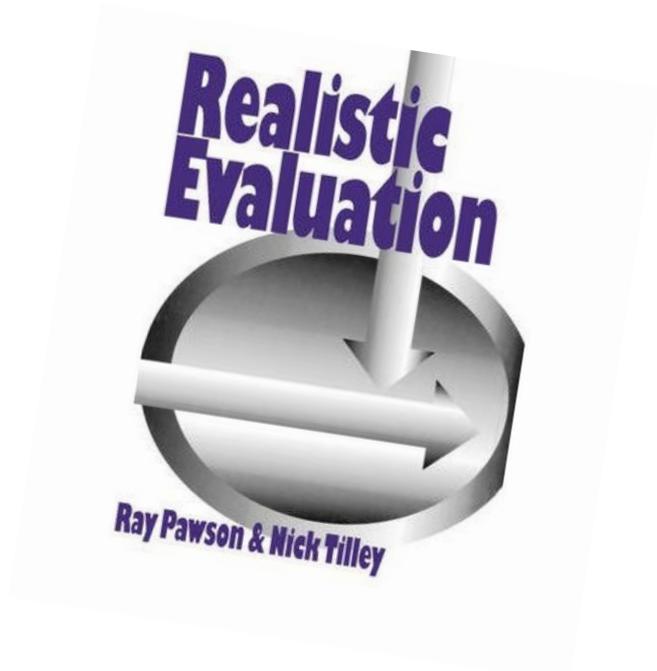
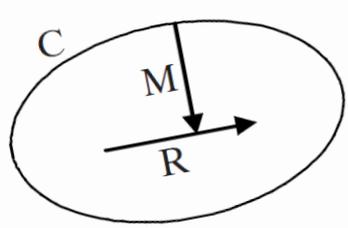


Figure 1: Basic ingredients of realist social explanation



C = context  
M = mechanism  
R = regularity

Source: Pawson and Tilley 1997, p. 72.

### Realist evaluation

A realist approach to applied **social research**  
(Pawson & Tilley, 1997, 2005)

- Underlying structures and mechanisms not generally observable directly (e.g. we can't see racism, sexism, class directly)
- Mechanisms may be enabled or suppressed by context
- Outcomes are often highly sensitive to context
- Look for regular configurations of context, mechanisms and outcomes (CMOC)
- **Infer mechanisms** (abduction – what, if it existed, would explain...)

Generate 'mid-range' theories in a domain/ context rather than universal laws.

Aims at explanations for why things happen.

## OU Analyse context

### Levels of context



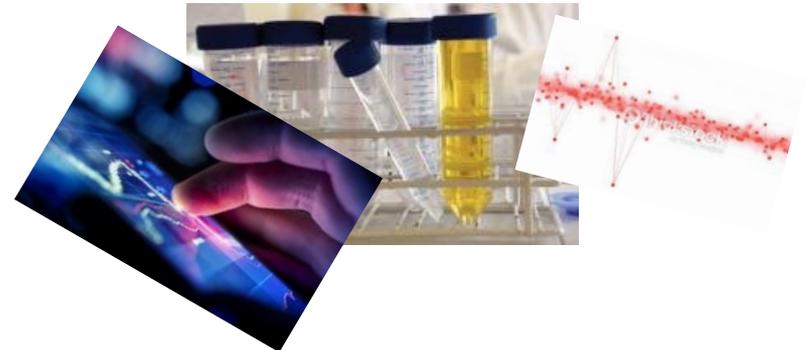
Global:  
technological  
change,  
technological  
rhetoric



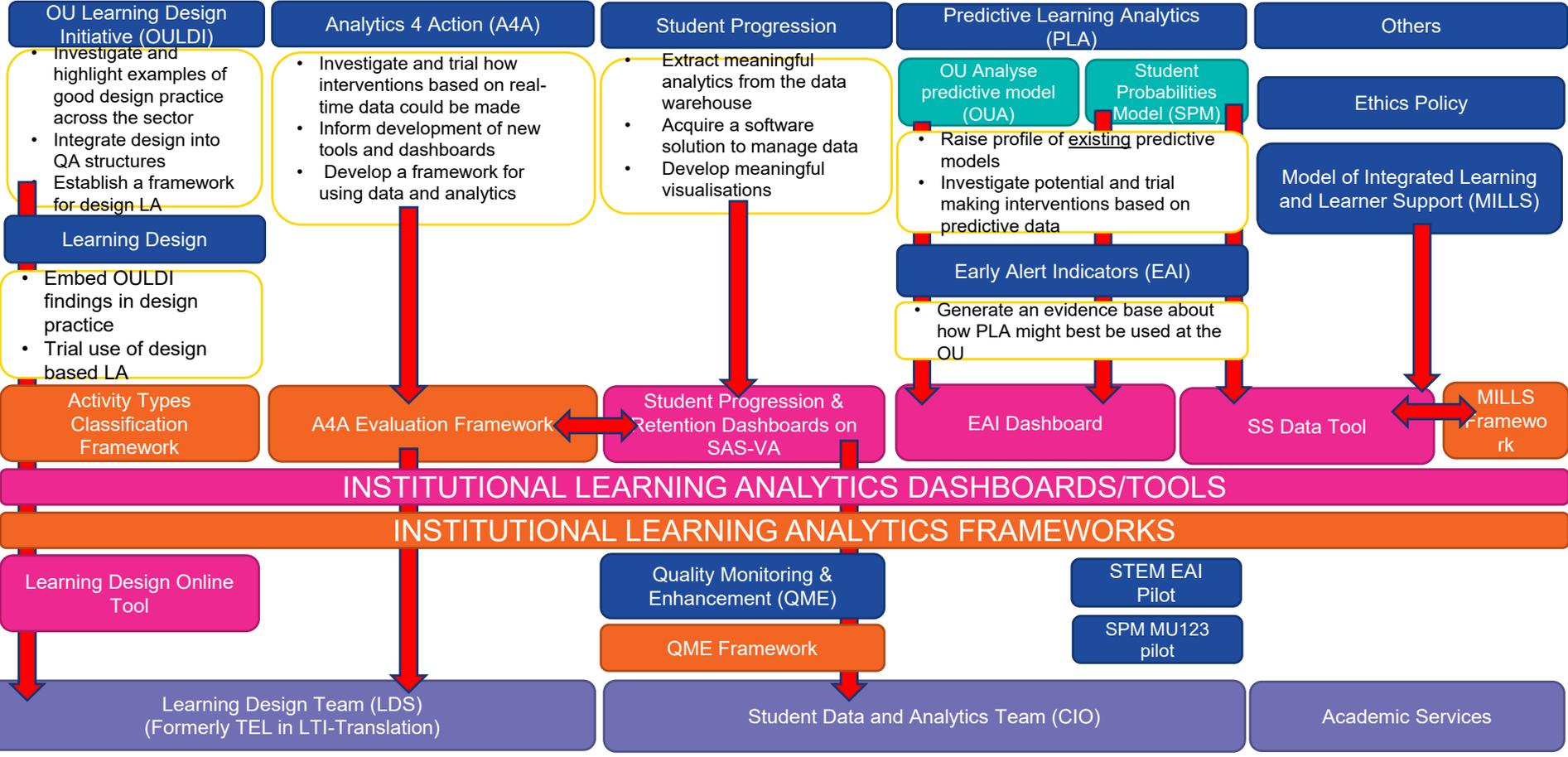
OU:  
2017 – Digital by  
design  
Technological  
innovation not  
closely linked to  
tuition/pedagogy



Curriculum:  
Discipline, level,  
Maturity of module;  
experience of AIs  
Volunteer modules and  
(mostly) ALs

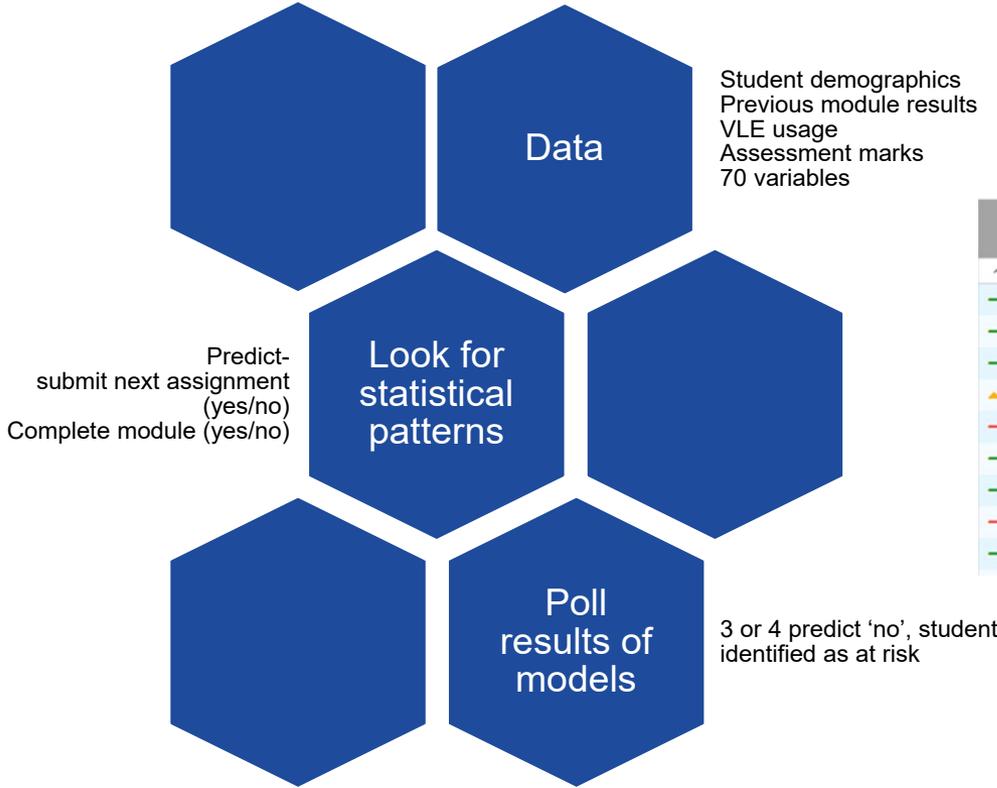


# INSTITUTIONAL LEARNING ANALYTICS PROJECTS



# INSTITUTIONAL LEARNING ANALYTICS MANAGEMENT

# OU Analyse dashboard



Student Information					Next TMA predictions Generated: 06/02/19 (yesterday) Week: 18		
Student PI	Name	Tutor PI	Staff tutor PI	TMA	Submission	Risk of NS	Grade
-				95 95 <span style="color: green;">●</span>	Submit	<input type="text"/>	Pass 1
-				95 95 <span style="color: green;">●</span>	Submit	<input type="text"/>	Pass 1
-				92 95 <span style="color: green;">●</span>	Submit	<input type="text"/>	Pass 2
▲				45 95 <span style="color: orange;">●</span>	Submit	<input type="text"/>	Pass 4
-				95 NS <span style="color: red;">●</span>	Not Submit	<input type="text"/>	Not Submit
-				95 95 <span style="color: green;">●</span>	Submit	<input type="text"/>	Pass 1
-				97 95 <span style="color: green;">●</span>	Submit	<input type="text"/>	Pass 2
-				95 NS <span style="color: red;">●</span>	Not Submit	<input type="text"/>	Not Submit
-				95 95 <span style="color: green;">●</span>	Submit	<input type="text"/>	Pass 2

## Case: evaluating learning analytics pilot in STEM

### Context:

How/why/were ALs using the OU Analyse?

2017 – digital by design, digital innovation...  
Modules (& generally, ALs) volunteered,  
took varied approaches

### Outcomes (regularities) for OUA included:\*

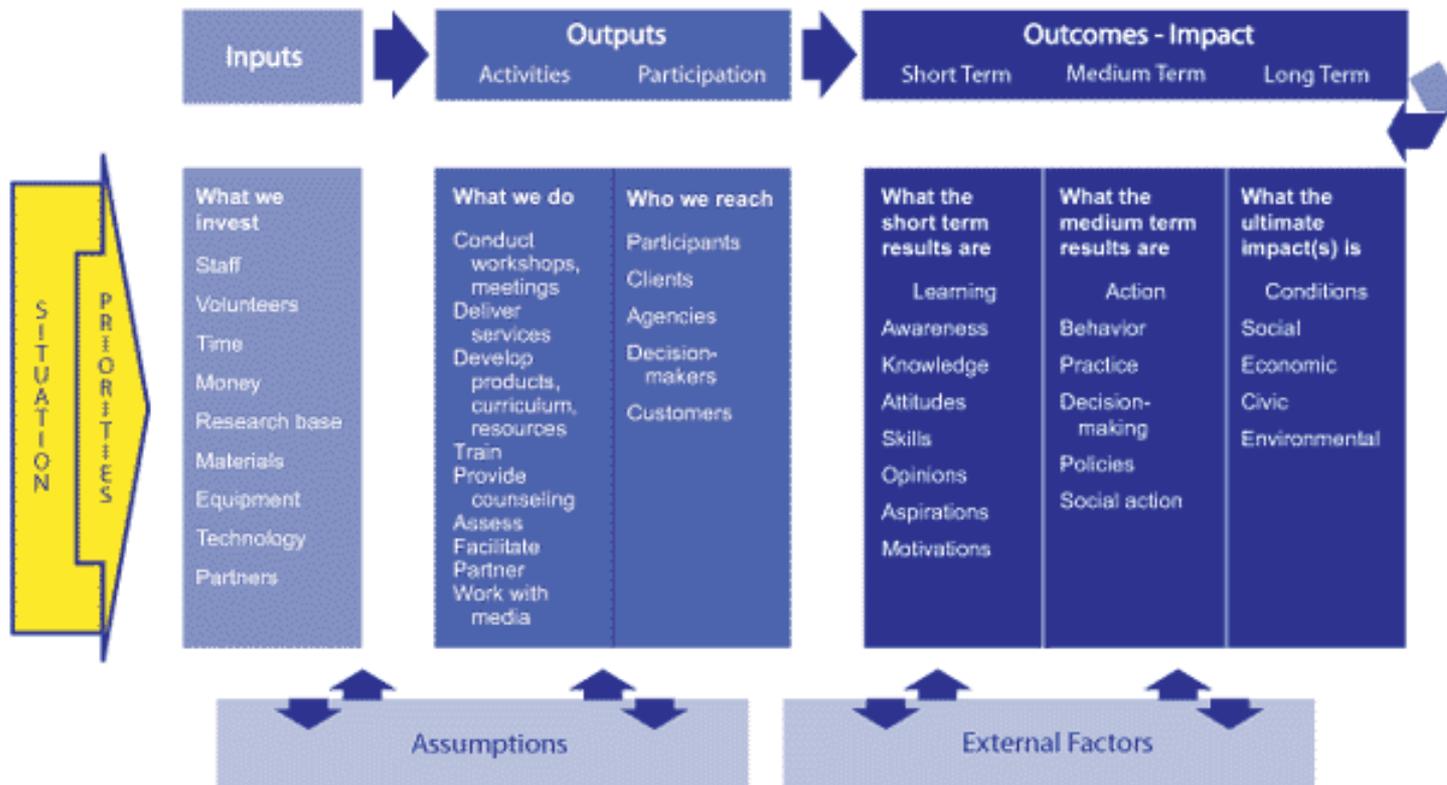
- Few outcomes intended by module teams were realised (especially retention)
  - Usage of the dashboard by ALs declined markedly through the presentation of every module
  - Tutors and module teams did not trust the data.
  - Tutors and module teams repeatedly emphasised the importance of communicating with students rather than the OUA information
- 
- See Olney et al (under preparation), Walker et al (2019); Piloting OU Analyse and the Student Probabilities Model on 12 STEM Modules Full Report



## 'Programme theory'

How, logically, did module teams expect their activities to lead to intended outcomes

# Logic Model

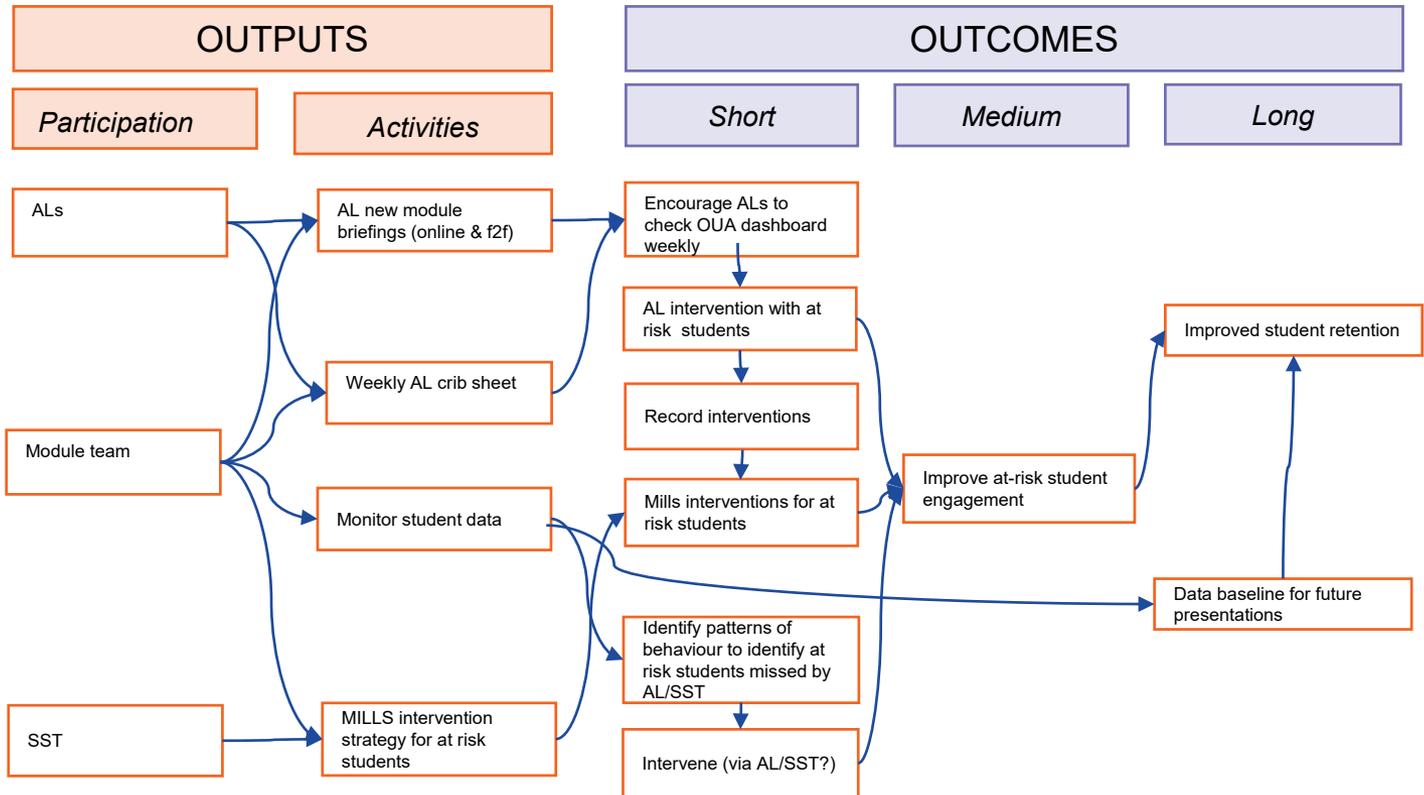


## INPUTS

- Associate Lecturers
- Students
- OUA dashboard
- SST

- Maria Velasco
- Helen Copperwheat

X123



### Assumptions

### External Factors/context (Summary)

First presentation  
Experienced ALs  
SCA (exam)

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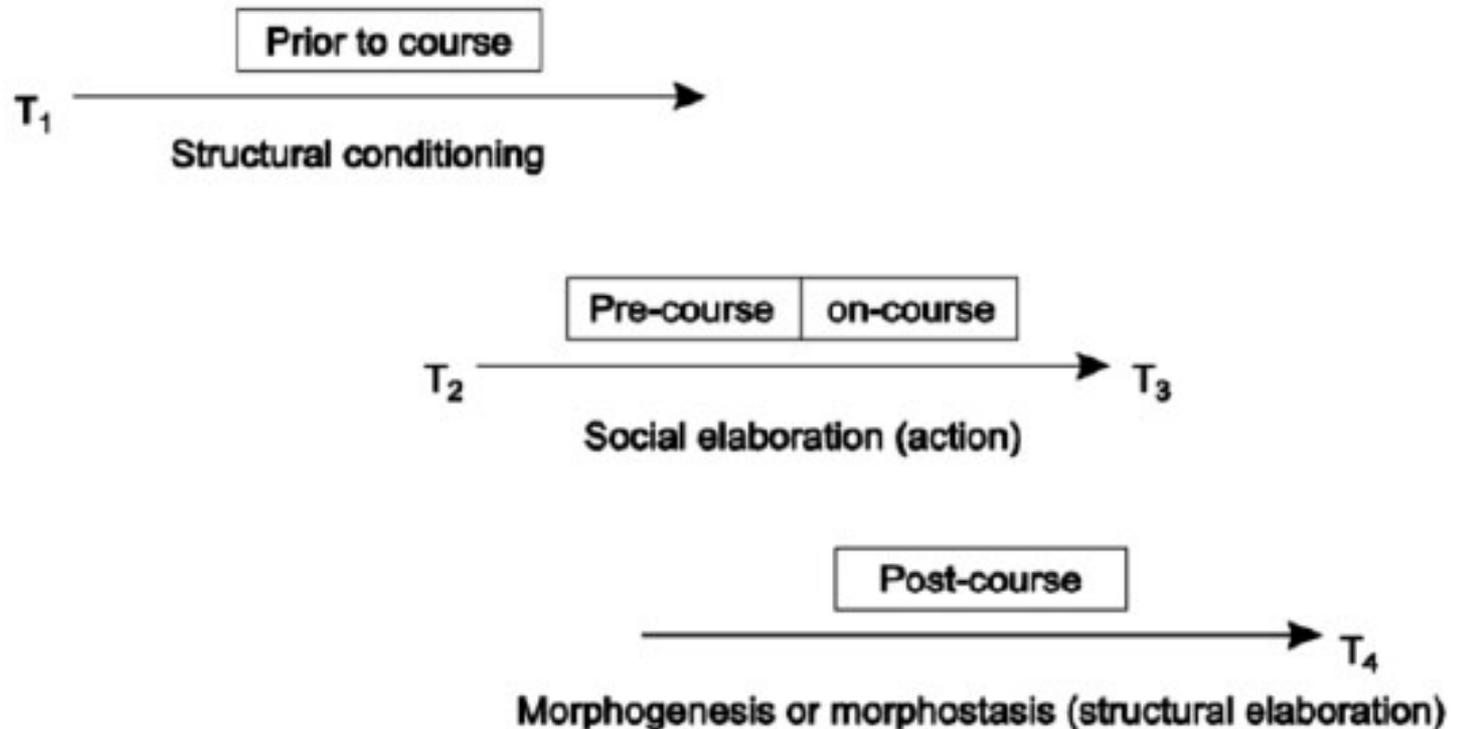
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Figure 3: The morphogenetic cycle with the change project mediation phases (Archer, 1995, p. 157)



## Types of mechanism

### Coleman, Archer etc

Macro->micro

(Structural conditioning)

Belief formation: initial briefing

*“I’m going to have to be honest and say that it’s been introduced in the briefing in <module> I didn’t quite understand what it was about or I came away thinking it must be a tool I’d have to get my head around but the explanation ... why I should use it or even how I should use it, especially when you’re having to take on other things new to the module anyway.”*

Micro->micro

(Social (sociotechnical) interaction)

Interpretation of data, personal histories

Micro->macro

(Structural elaboration)

Patterns of analytics use?

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*“You look at it and think; “I know that’s wrong!” Sometimes it gives you an orange for someone you know it doing the best they can but they might be finding that bit difficult so sometimes the predictions seem a bit odd and it gives you complete red dots at the start.”*

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Patterns of analytics use

*“It’s not something you think ‘oh i’ll go check OU analyse’ it’s not something that crosses my mind because it’s new. It’s not something that’s talked about on the tutor forums either so it’s about remembering.”*

## Candidate claims

	Macro->micro	Micro->micro	Micro->macro
Example	Belief formation <i>“I didn’t quite understand what it was about”</i>	Interpretation <i>You look at it and think; “I know that’s wrong!”</i>	Patterns of use <i>“It’s not something you think ‘oh i’ll go check OU analyse”</i>
Regularity	Lack of clarity about the purpose and use of OU analyse	Lack of confidence in dashboard data	Declining use across presentation
<u>Candidate</u> general statement (Context: technological innovation pilot in OU STEM)	In introducing innovation in OU STEM <ul style="list-style-type: none"> <li>- Why are we doing this?</li> <li>- What am I expected to do?</li> </ul>	In OU STEM <ul style="list-style-type: none"> <li>- If a tool (technology, data) doesn’t align with or contradicts tutors’ existing ‘craft’ knowledge, less likely to be used, especially where not transparent</li> </ul>	In OU STEM <ul style="list-style-type: none"> <li>- Individual choice to adopt/not adopt determines uptake</li> <li>- Individual choice about how to use it determines patterns of use</li> </ul>

## Possibilities

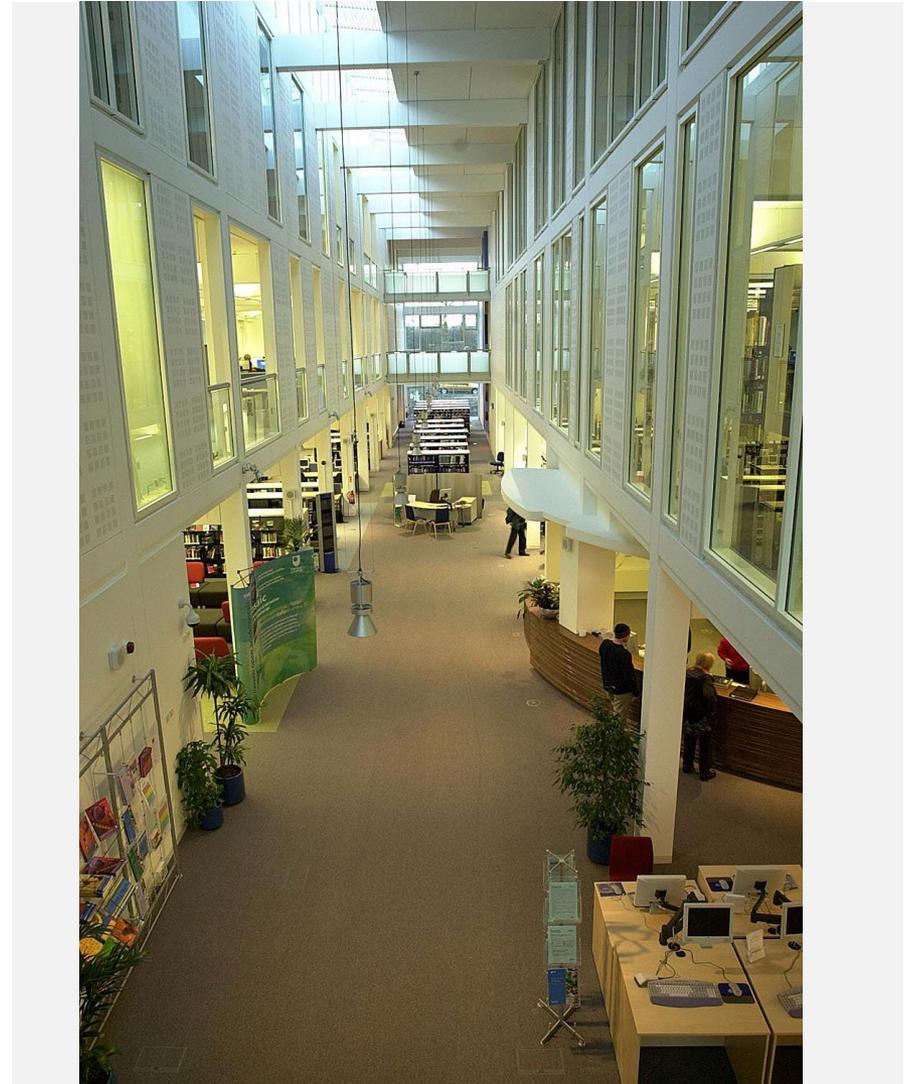
### Library of mechanisms?

Building a library of mechanisms that may be applicable across (e.g. edtech, esteem) contexts

*“This works (or not) for these people, in these contexts, and here’s why”*

Possible route to generalisability across contexts

- Some of the mechanisms identified more general than just learning analytics



**FIN**



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