EVIDENCE-BASED DECISION MAKING AS SÉANCE: IMPLICATIONS FOR LEARNING AND STUDENT SUPPORT

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South African Association for Institutional Research (SAAIR), **Cape Peninsula University of Technology**, Cape Town, 2015

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This presentation is based on a Chapter submitted for a forthcoming book “Institutional research in support of evidence-based decision making in Higher Education in South Africa” (provisional title)

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Evidence-based decision making as séance…

- The belief and practice that **the answer is out there**, hidden, in need of translation
- The belief and practice that it is possible to communicate with a world **unseen by the majority of us**
- The belief and practice that some have the ability to **translate the message** from ‘the other side’
- The reality that we need to know, want to know…

If only we would believe…

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The words/metaphors we use…

- Data analysis as “art” (Ibrahim, 2013)
- Data as “raw”, “cooked”, “corrupted”, “cleaned”, “scraped” “mined” and “processed” (Gitelman & Jackson, 2013)
- Student data as “the new oil” (Watters, 2013)
- Data analysis as a “black art” (Floridi, 2012)
- Data scientists as the “high-priests of algorithms” (Dwoskin, 2014), the “engineer[s] of the future” (Van der Aalst, 2014) and data scientists as “rock stars and gods” (Harris, Murphy & Vaisman, 2013)
- “Judged by the Tin Man” (Tene & Polonetsky, 2013) and the need for “algorithmic angels” (Koponen, 2015)

The words/metaphors we use…

… are not per se **benign,** they are **consciously chosen** not only to describe how we **understand** a phenomenon, and then **perpetuate particular understandings** of a phenomenon…

Metaphors are…

"… pattern-making devices that situate or locate patterns within their larger social contexts; they are [also] decentering devices"

(Bedoes, Schimpf & Pawley, 2014, p.3)

A well-chosen "metaphor is one of our most important tools for trying to comprehend partially what cannot be comprehended totally… (Lakoff & Johnson, 1980, p. 193)

Predictive analysis comparable to "the ancient practice of spilling the entrails of goats on the ground and reading messages from the patterns" (Trombley, 1998, in Birnbaum, 2001, p. 199)

"… the reading of goat entrails was an ancient, messy, low-tech, and low-cost precursor to environmental scanning" and this practice was "tough on the goat, but in the hands of a skilled shaman probably no less accurate or useful than many current practices based on today's technologies (Birnbaum, 2001, p. 1999)

Image credits: https://en.wikipedia.org/wiki/The_Scapegoat_%28painting%29

What do you get when you mix a context and drastic need for data/evidence, a hungry audience, a tool, and a medium or oracle?

But a question we don't ask – do we believe?

Image credits:
https://en.wikipedia.org/wiki/The_Scapegoat_%28painting%29
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My approach: A critical **techno-cultural discourse analytic (CTDA)** understanding of evidence-based decision making in higher education

- Understand the impact of the **surrounding culture and context** on a technological phenomenon – not only mediated by but also mediating…
- Investigate the **normative claims and assumptions** about the technologies and associated beliefs and practices
- Understand this techno-culture as a **set of inter-related narratives** and to unpack the semiotic and material connections between form, function, beliefs and associated practices
- "point to conceptual problematics that may be **resolved** through analysis, but not **'solved'** (Sweeney & Brock, 2014, par. 8; also see Brock, 2015; Dinerstein, 2006; Hutchby, 2001)

Evidence-based decision making is entangled in/at the intersection of the impatience of policy makers to find quick solutions (in line with their political agendas), stakeholders 'on the ground' and specialists who research the problems

(El-Khawas, 2000)

How do we then understand the hype, the practice, the failures, the enduring fascination and belief?

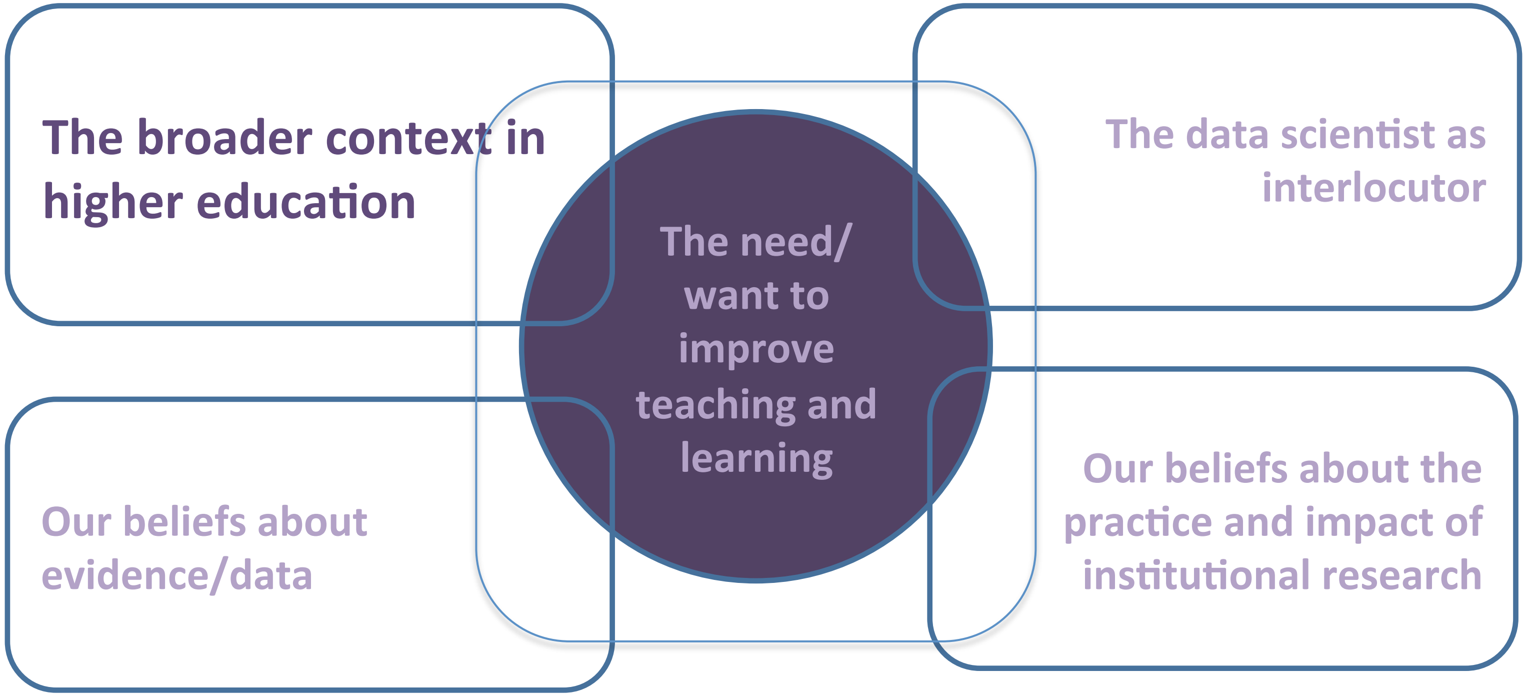
The broader context in higher education

The data scientist as interlocutor

The need/ want to improve teaching and learning

Our beliefs about evidence/data

Our beliefs about the practice and impact of institutional research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Evidence-based decision making *as fad or fashion*

Management fads are not only products, but also narratives in which there are “heroes, villains, and innocent victims involving change or transformation” and these fads resemble **magic** – “The consultant or fad champion, like the tribal shaman, appears to be in touch with the gods” (pp. 8-9)

It is also important to understand fads as **political** processes and as consequence of “the application of power by various interest groups at numerous levels” (p. 11)

As placebo, fads promise to cure an institutional illness…

(Birnbaum, 2001)

On the other hand: The need for evidence

Higher education should…

- Do more with less
- Expect funding to follow performance rather than then preceding performance
- Realise it costs too much, spends carelessly, teach poorly, plans myopically, and when questioned, acts defensively

(Hartley, 1995, p. 412, 861)

The McDonalidisation of higher education refers to Education as increasingly privatised and/or costly commodity, with an obsession on the return on investments, just-in-time products delivered by just-in-time labor aiming to get the products off the shelves in the fastest possible time…

(See Mahmud, 2015)

Enter data and evidence, and/but not necessarily understanding

- 'Efficiency' is "the new watchword" – not only are our criteria objective (sic), it is scientific (sic), progressive (sic) and the road to prosperity (whose prosperity?)… (Birnbaum, 2001, 15)
- "a neoliberal lexicon of numbers" (Cooper, 2104, par. 5) and a "quantification fetish"
- A "tyranny of numbers" or "measurement mania" (Birnbaum, 2001, p. 197)
- The audit society with its "rituals of verification" (Power, 1999, 2004)

Our technologies, algorithms, and artificial intelligence

- "To save everything click here" (Morozov, 2013)

- Technology as "white magic", as a secular theology leading to pure knowledge of the unknowable, leading us to the new Jerusalem (see Dinerstein, 2006)

Image credit: https://commons.wikimedia.org/wiki/File:N_icon_technology.png

Welcome to Auditland…

"The Stasi was the internal army by which the government kept control. Its job was to know everything about everyone, using any means it chose. It knew who your visitors were, it know who you telephoned, it knew if your wife slept around. It was a bureaucracy metastasised through East German society: overt or covert, there was someone reporting to their fellows and friends in every school, every factory, every apartment block, every pub"

(Funder, 2002 in Murphie, 2014, p. 10)

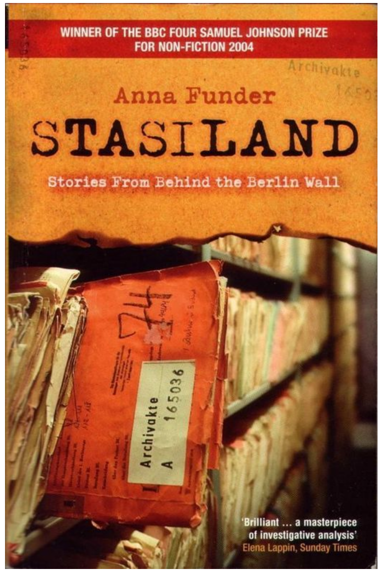


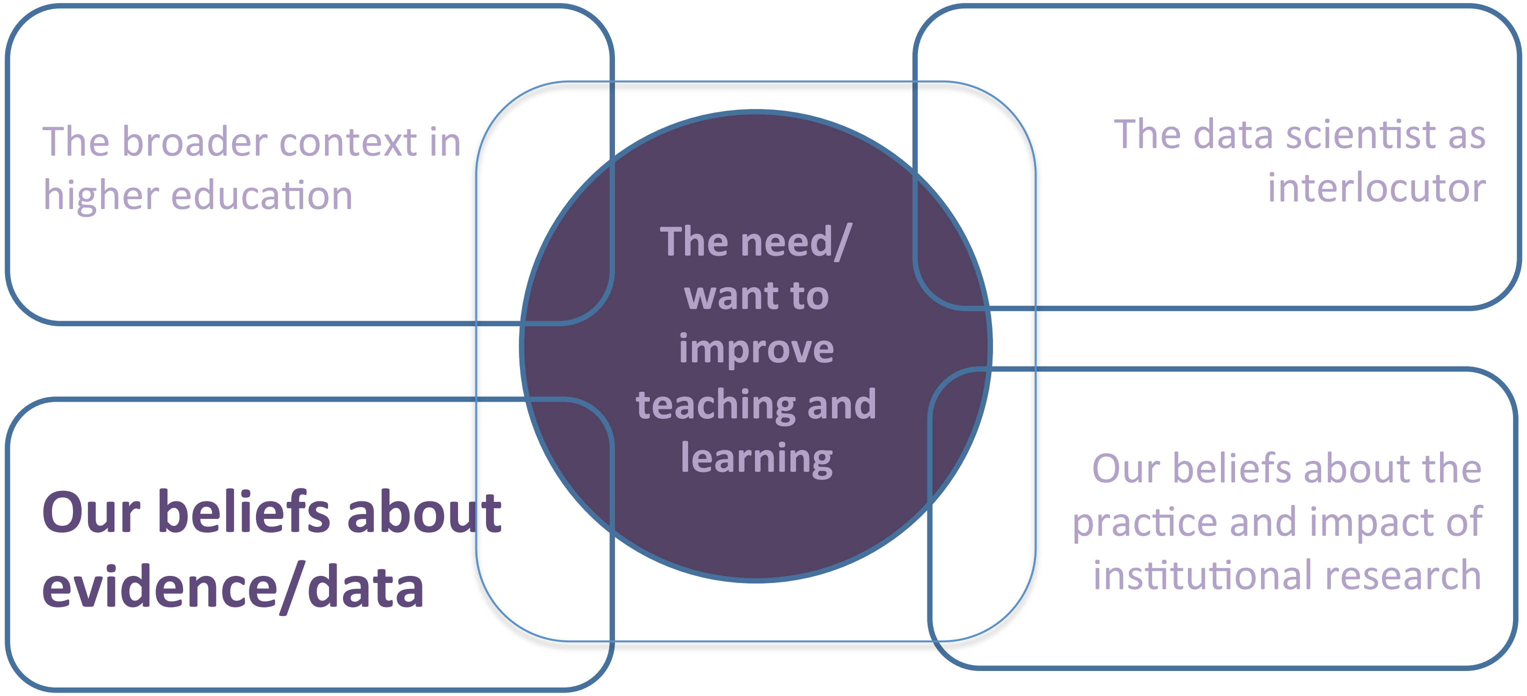
Image credit: http://sceneenough.com/2012/04/20/east-germany-again-in-word-and-film-stasiland-the-lives-of-others/

The ever, never fulfilled need for more data…

Metastasis, or metastatic disease, is the spreading of a disease (e.g. cancer) between organs or from one part of the body to other parts not directly connected to the original origin.

"Audit infests Learning and Teaching at all levels" (Murphie, 2014, p. 11)

Audit creates technical systems which serves, at the same time, as prosthetics and as parasitic– it supplements and replaces authentic learning and frantically monitors "little fragments of time and nervous energy" (Murphie, 2014, p. 19)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Our beliefs about evidence/data

We have access to ever **increasing volumes, velocity and variety of student** digital data, that **allows us to expand** not only on the traditional scope of institutional research with regard to student data, but **also to infer relations unthinkable ten years ago**. We may therefore be tempted to rush to look for patterns without considering our own assumptions and epistemologies

Silver (2012) warns **that in noisy systems with underdeveloped theory** – there is a real danger to mistake the noise for a signal, and not realising that the noise pollutes our data with false alarms and "setting back our ability to understand how the system really works" (p. 162)

Our beliefs about evidence/data

Data are not neutral, raw, objective and pre-analytic but framed "technically, economically, ethically, temporally, spatially and philosophically. Data do not exist independently of the ideas, instruments, practices, contexts and knowledges used to generate, process and analyse them" (Kitchen, 2014a, p. 2)

When a fact is proven false, it stops being accepted as a fact. When data is false, it remains data…

Our beliefs about evidence/data (2)

The relation between data, information, knowledge, evidence and wisdom is much more complex and contested than we may be comfortable with…

Data are political in nature – data are loaded, shaped and limited with the values, interests and assumptions of those who collect, frame and use the data (Selwyn, 2014)

Some provocations (e.g. boyd & Crawford, 2012)

- Data do not speak for itself (as claimed by Mayer-Schönberger & Cukier, 2013)
- It is not enough to know ***that*** people do things without understanding ***why*** they do act in a particular way
- **N ≠ all** (contra to Mayer-Schönberger & Cukier, 2014)
- Data sets represent cultural, moral, and instrumental choices (Brock, 2015)
- More or big(ger) data are not (necessarily) better data (Prinsloo, Archer, Barnes, Chetty & Van Zyl, 2015)
- "The sheer size of analysis does not eschew the limitations of subjectivity" – the "unbearable lightness of information (Papacharissi, 2015, p. 1097)

“what is algorithm but ideology in executable form?” (Nakamura, 2013, par. 3)

"Algorithms do not have agency. People write algorithms. Do not blame the algorithms. Do not blame the drones. The drones are not important. The human operators are important. The human operators of algorithms are not lion tamers. Do not blame the drones for making you depressed. Do not blame the algorithms for blowing up towns. Oceania has not always been at war with Eastasia.”

Source: http://juhavantzelfde.tumblr.com/post/117504109386/algorithms-do-not-have-agency-people-write

Some provocations (cont.)

Objectivity and seeing patterns:

- The claim to 'objectivity' as an "arrogant undercurrent" (boyd & Crawford, 2012, p. 668)
- Mistaking noise for signal (Silver, 2012)
- Apophenia – "seeing patterns where none actually exist, simply because enormous quantities of data can offer connections that radiate in all directions" (boyd & Crawford, 2012, p. 668)
- "Big Data and whole data are not the same. Without taking into account the sample of a data set, the size of the data set is meaningless" (Boyd & Crawford, 2013, p. 669)

Objectivity and seeing patterns (cont.):

- Researchers have to account for – not only the limits of the data set, but also the limits of which questions they can ask of a data set and what interpretations are appropriate (Boyd & Crawford, 2013, p. 670)
- There seems to be a belief that the combination of different data sets increases the potential for understanding a phenomenon, often forgetting that the combination of different data sets raises a number of unique challenges (Bollier, 2010)
- Small data, small patterns matter (Floridi, 2012)
- Deep data (Floridi, 2012)

Objectivity and seeing patterns (cont.)

Looking for the dog that did not bark..
(Sherlock Holmes)

If data are not barking when they
should, something is going on
(Floridi, 2012)

Some provocations (cont.)

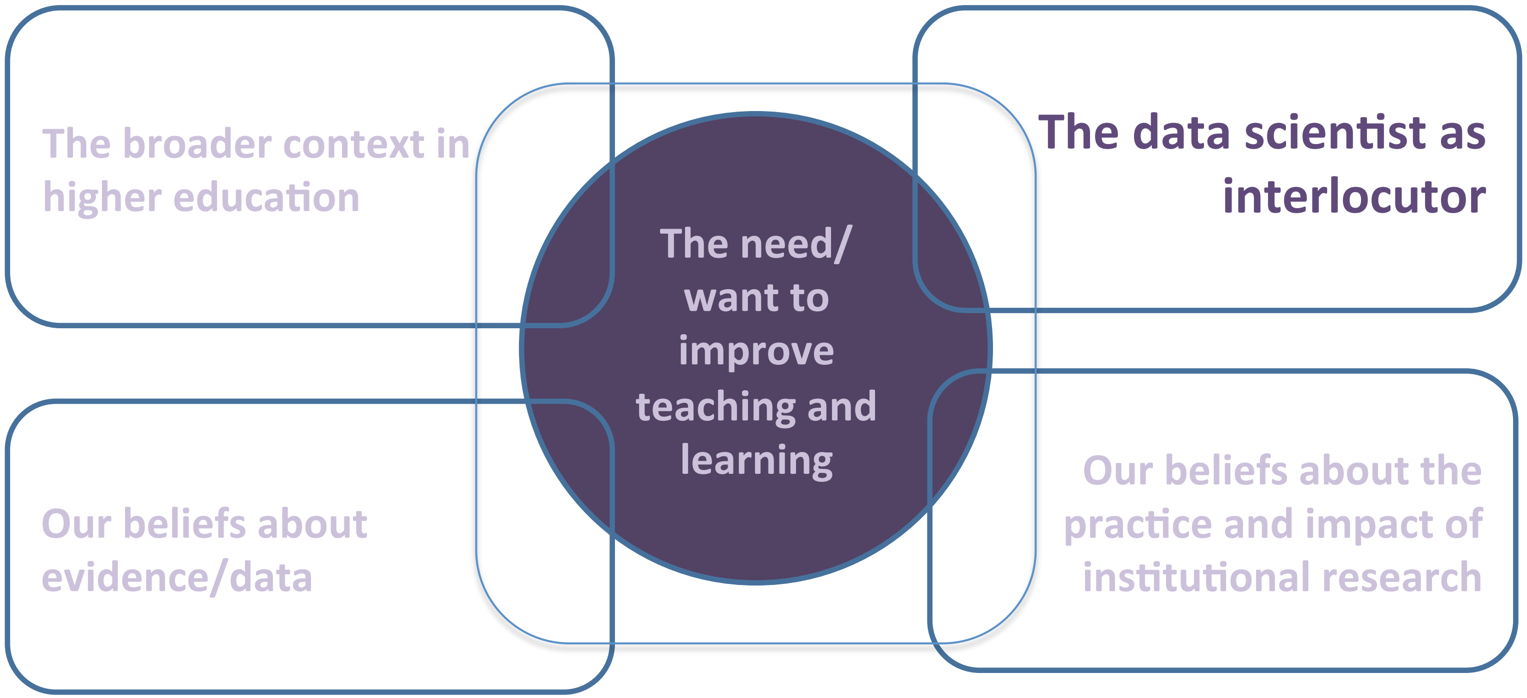
Data, contextual integrity and contextual collapse

- "Not every connection is equivalent to every other connection, and neither does the frequency of contact indicate strength of relationship" (boyd & Crawford, 2013, p. 671)
- What is shared in one context, at a particular time and under perceptions of how the data will be used, necessitates guaranteeing contextual integrity as a relationship (Nissenbaum, 2015)
- Contexts are not stable collection of data points but "relational properties occasioned through activity" (Seaver, 2015, p. 1105)

Some provocations (cont.)

Just because the data are accessible, does not make it ethical

- The increasing reality of re-identification of anonymised data
- No guarantees about downstream use
- Our legal and regulatory frameworks will permanently lag behind (Tene & Polonetsky, 2013)
- Unintended consequences of our analysis and interventions (Henman, 2004; Wigan & Clarke, 2013)
- Algorithmic accountability and transparency (Diakopolous, 2014; also see Kitchen, 2014b; Kraemer, van Overveld & Peterson, 2011)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Gods, rock stars, game changers or …?

The "hottest" job title?

(Chatfield, & Shlemoon & Redublado, 2014, p. 2)

Who are they … really? (Harris, Murphy and Vaisman, 2015) [sample 250]

- **Data developers** (strong on machine learning, programming, good overall)
- **Data researchers** (disproportionally strong in statistics)
- **Data creatives** (all-rounders – statistics, machine learning, programming)
- **Data businesspersons** (disproportionally strong in business, then stats)

Gods, rock stars, game changers or … fallible humans with biases?

"Humans … interpret meaning from data in different ways. Data scientists can be shown the same sets of data and reasonably come to different conclusions. Naked and hidden biases in selecting, collecting, structuring and analysing data present serious risks. How we decide to slice and dice data and what elements to emphasise or ignore influences the types and quality of measurements"

(Walker, 2015, p. 11)

The data scientist/institutional researcher as interlocutor…

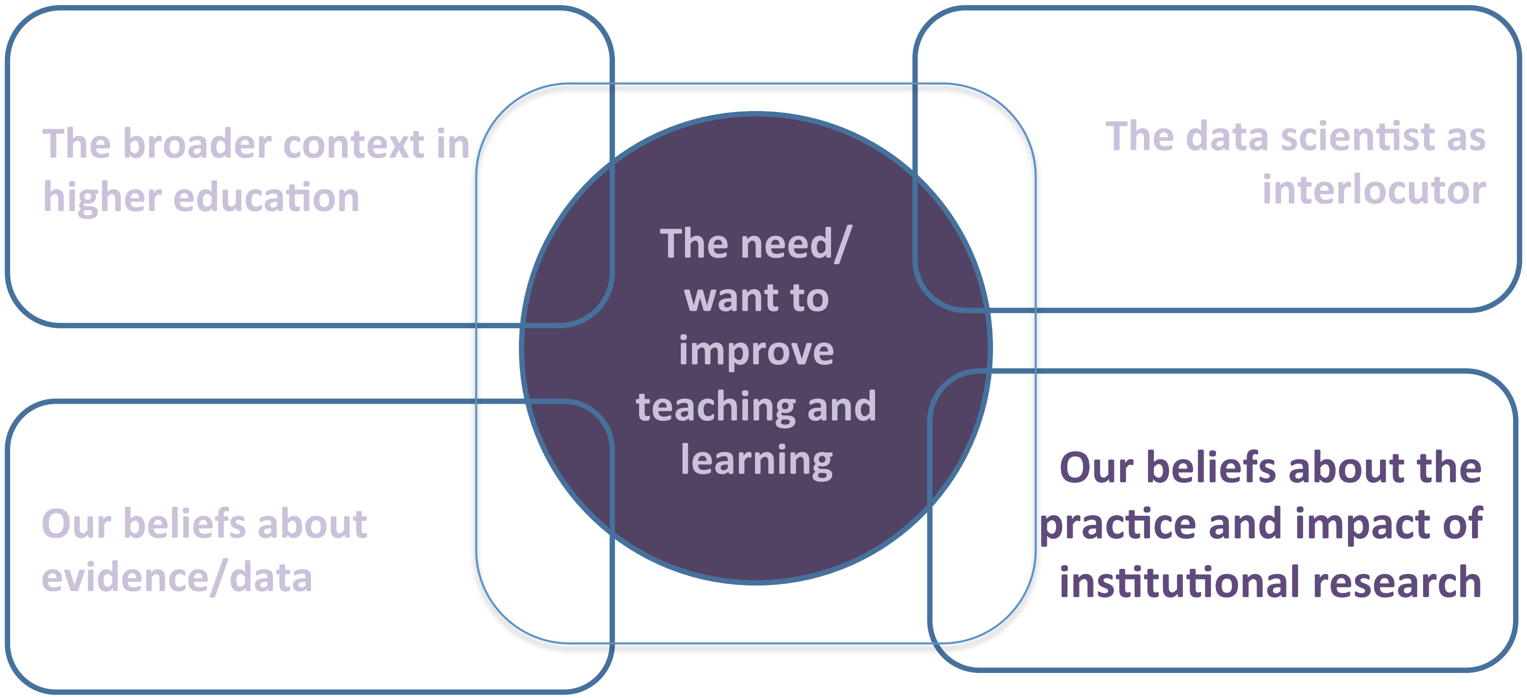
God, rock star, scientist, charlatan, oracle and medium…

Some were believed, were right and became famous

Some were believed, were wrong and were killed

And then there is **Cassandra**, who had the gift of prophecy, predicted among other things the fall of Troy, but who was … not believed

Image credit: https://thecontextofthings.files.wordpress.com/2015/07/cassandra_maa200891_hi.jpg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The role and impact (or lack of) institutional research

The urgent need for evidence/data/information + a medium + a hungry audience ≠ always result in belief…

Governments and higher education management institutions

- Face practical, urgent problems as well as problems-with-reputational-value-if-solved
- Favor positivist and reductionist research modes are preferred rather than critical, interactive and independent modes

Cut out the complexity, turbulence and messiness and give us "simple and elegant solutions" that we can use and control (Kogan and Henkel, 2000, p. 28)

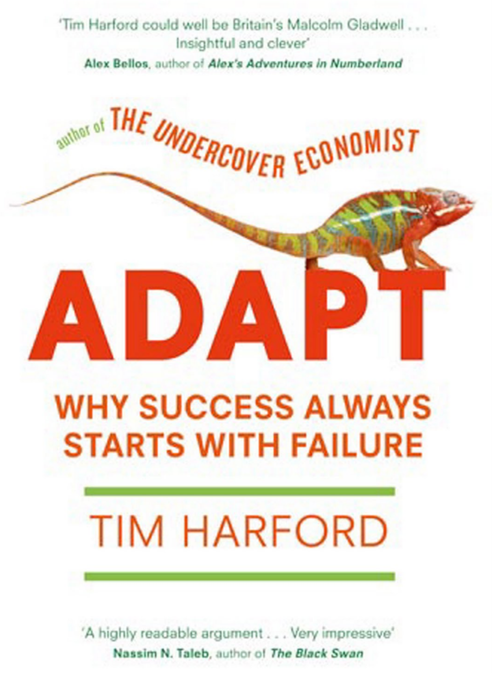
[Also see El-Khawas, 2000]

Sometimes… "actually, we know already…"

"we don't need research to tell us what to do, we know that already" (reference to a recent British minister of higher education in Kogan & Henkel, 2000, p. 32)

And – governments (and higher education institutions) are not, necessarily looking for the content, objectivity or the 'truth' of research – but the **Zeitgeist** – "The 'successful' research well matches the intelligent wisdom of its time. If it is wisdom that accords with the views of those currently in power then it will certainly be listened to" (Kogan & Henkel, 2000, p. 34)

How to be a successful oracle (and live) 101



Problem: Russia 20th century – we need more sustainable water supply

Stalin:

What is the problem? Do research. Propose an evidence-based plan

Palchinsky:

Smaller dams will be more effective

Stalin:

I want to build the world largest hydroelectric dam

Stalin 1, Palchinsky, 0

Outcome:

Disaster

How to be a successful oracle (and live) 101 (cont.)

Problem stream – individuals/stakeholders with information about the actual status and scope of the problem and tacit understanding of what should be done

+

Policy stream – advocates, researchers, and specialists who analyse problems and formulate alternatives

+

Political stream – legislative and elected leaders with reputation, grand ideas, and not much time to make a difference before they move on

(El-Khawas, 2000)

The reality of evidence-based decision making…

Policy reform takes place when these three streams (suggested by Kingdom, 1984, in El-Khawas, 2000) converge:

"when a problem is recognized as serious and requiring a new solution; when the policy community develops a financially and technically workable solution; *and when political leaders find it advantageous to approve it*" (El-Khawas, 2000, p. 50; emphasis added)

Without one of the streams, no effective policy change happens.

Image credit: https://www.flickr.com/photos/mlrs193/6015396482

In order to understand the impact (or lack of impact) of evidence-based research on teaching and learning, we have to consider:

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THANK YOU

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