Learning Informatics
AI • Analytics • Accountability • Agency

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overview

informatics

learning informatics

LA/AIED

4 informatics principles for human-centred LA/AIED

what this looks like in action

We need an overarching lens for designing
effective, usable, ethical learning technology

informatics

You've made a wise choice! ☺

Kristen Nygaard

August 27, 1926 – August 10, 2002

Internationally acknowledged as the co-inventor
with Ole-Johan Dahl of object-oriented programming
and the programming language Simula.

He also was a pioneer of participatory design and the
"Scandinavian school of systems development".

http://kristennygaard.no

"**Informatics** is the science that has as its domain **information processes** and related phenomena in **artifacts, society and nature**".

Nygaard, K. (1986): Program Development as a Social Activity, Invited Lecture, Proceedings of the IFIP 10th World Computer Congress, INFORMATION PROCESSING 86, Dublin. Elsevier Science Publishers, pp. 189-198. Available at: https://ojs.ruc.dk/index.php/pdc/article/view/97/89

No management hand-waving about valuing "user participation"

Let's get specific: who are we talking about?

- Kinds of work tasks carried out.

- Position within the decision system.

- Position within the power system.

Nygaard, K. (1986): Program Development as a Social Activity, Invited Lecture, Proceedings of the IFIP 10th World Computer Congress, INFORMATION PROCESSING 86, Dublin. Elsevier Science Publishers, pp. 189-198. Available at: https://ojs.ruc.dk/index.php/pdc/article/view/97/89

How will such users get to "participate"?

"Collection, storage, processing and use of personal data shall not occur without due cause based on consideration for the operation of the enterprise. The individual enterprise shall clarify the type of personal data which the computer equipment shall collect, store, process and use."

"The enterprise shall keep their employees informed through their shop stewards about conditions which are within the scope of the agreement so that the shop stewards may express their views as early as possible and before the decisions of the enterprise are implemented, ..."
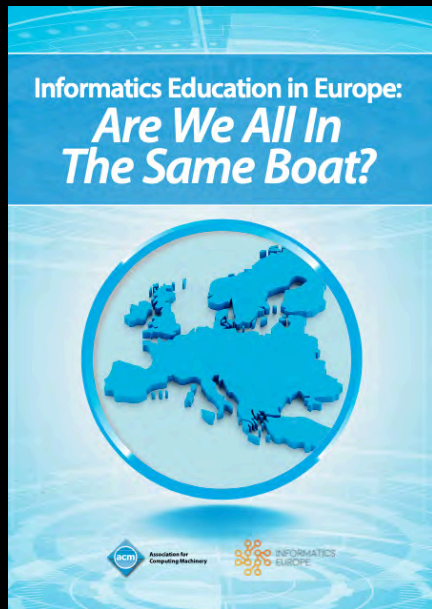
"The information shall be provided in a clear form and in language that can be understood by people without special knowledge of the field."

A group's interests in systems in an enterprise or a public institution may relate to a number of issues:

- What economic benefit will we (the group) get from the system? (As employees, middle or top management, as employers.)

- To what extent may we exercise control (power) over the system?

- How will the system influence the physical and psychological working environment?

- Will the social network in the enterprise be changed to our advantage or disadvantage?

- What is the relationship between the objectives of the system and the objectives we feel should direct our society?

Data shop stewards are elected to represent group interests, and all points listed above may be raised in negotiation within the framework of the data/technology agreements presented later in this paper.

Nygaard, K. (1986): Program Development as a Social Activity, Invited Lecture, Proceedings of the IFIP 10th World Computer Congress, INFORMATION PROCESSING 86, Dublin. Elsevier Science Publishers, pp. 189-198. Available at: https://ojs.ruc.dk/index.php/pdc/article/view/97/89

This laid the foundations for Informatics today…

"Informatics is a distinct scientific discipline, characterised by its own concepts, methods, body of knowledge and open issues.
It covers the foundations of computational structures, processes, artefacts and systems; and their software designs, their applications, and their impact on society"

This laid the foundations for Informatics today…

UCI Department of Informatics
Donald Bren School of Information & Computer Sciences

"Informatics concerns itself with the study of living, working and building in a digital world. Wherever technology touches people, it must be designed with ultimate care. This requires mastery of technological knowhow and a deep appreciation of the social, cultural and organizational forces at work."
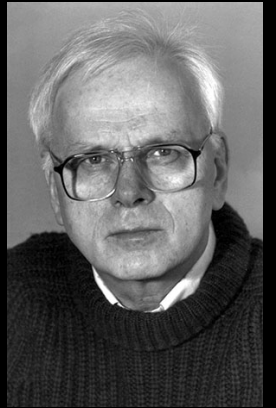
https://www.informatics.uci.edu/explore/chairs-welcome

learning
informatics

Note that the terms Education(al) Informatics have been proposed, and some definitions of this are similar, albeit limited to educational institutions — I prefer a broader focus on lifelong/lifewide learning.

Levy, P., Ford, N., Foster, J., Madden, A., Miller, D., Nunes, M. B., et al. (2003). Educational informatics: An emerging research agenda. *Journal of Information Science,* 29(4), 298-210. [reprint]
Collins, J.W., and Weiner, S.A..(2010). Proposal for the creation of a subdiscipline: Education informatics. *Teachers College Record* 112, no. 10: 2523–2536. [reprint]

learning informatics

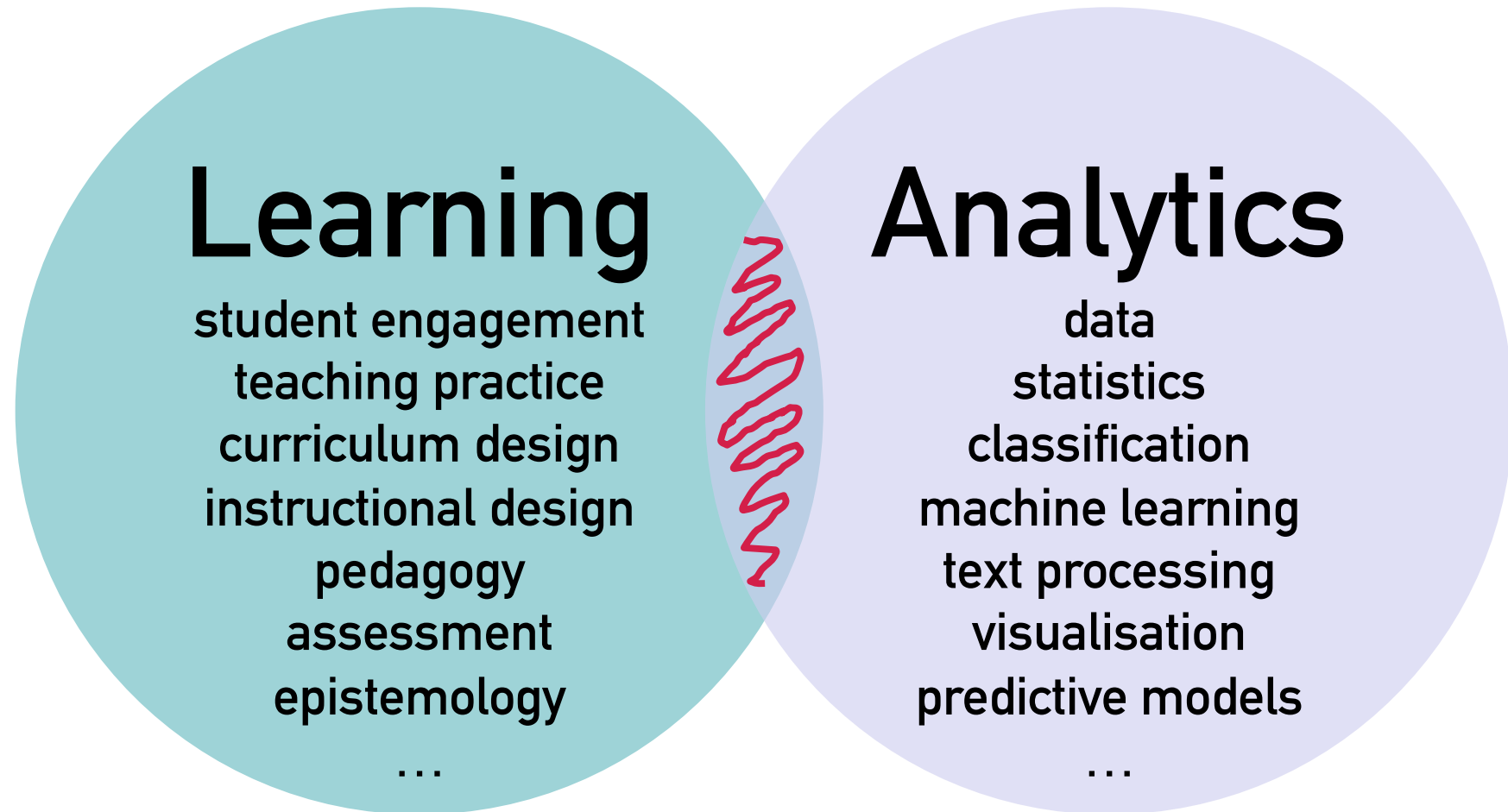How does this lens translate into deploying Analytics/AI for learning?

➡️ Design socio-technical systems

➡️ Design for educator and learner agency

➡️ Design for imperfect computational models

➡️ LA/AIED System Integrity > algorithmic accountability

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Learning Analytics?

AI in Education?

What is Learning Analytics?

Learning

student engagement
teaching practice
curriculum design
instructional design
pedagogy
assessment
epistemology

…

Analytics

data
statistics
classification
machine learning
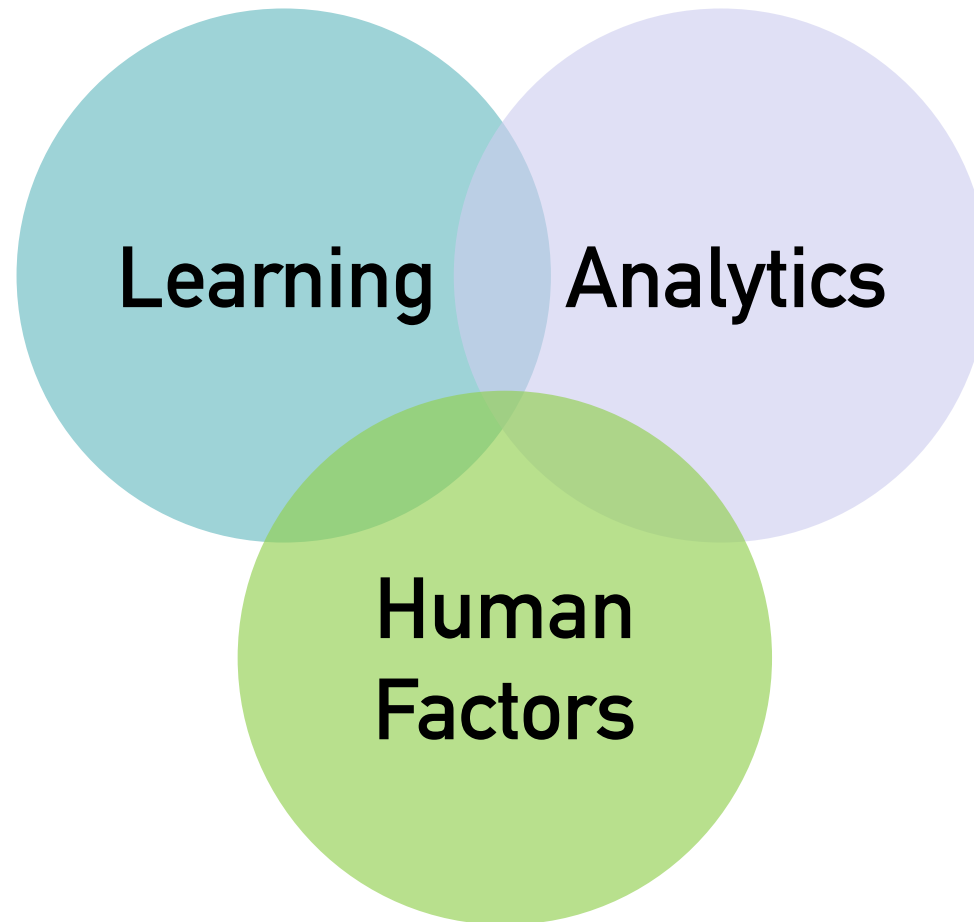text processing
visualisation
predictive models

…

this is not a straightforward dialogue!

A key circle is missing…

Human Factors

stakeholder involvement
participatory design cycles
user interface design
privacy and ethics
end-user evaluation
organisational strategy
staff training

Learning Analytics: A Human-Centred Design Discipline

So where does Artificial Intelligence fit in?

Automated Feedback & Tasks

Learning

Analytics

Sensing beyond the keyboard

Human Factors

18
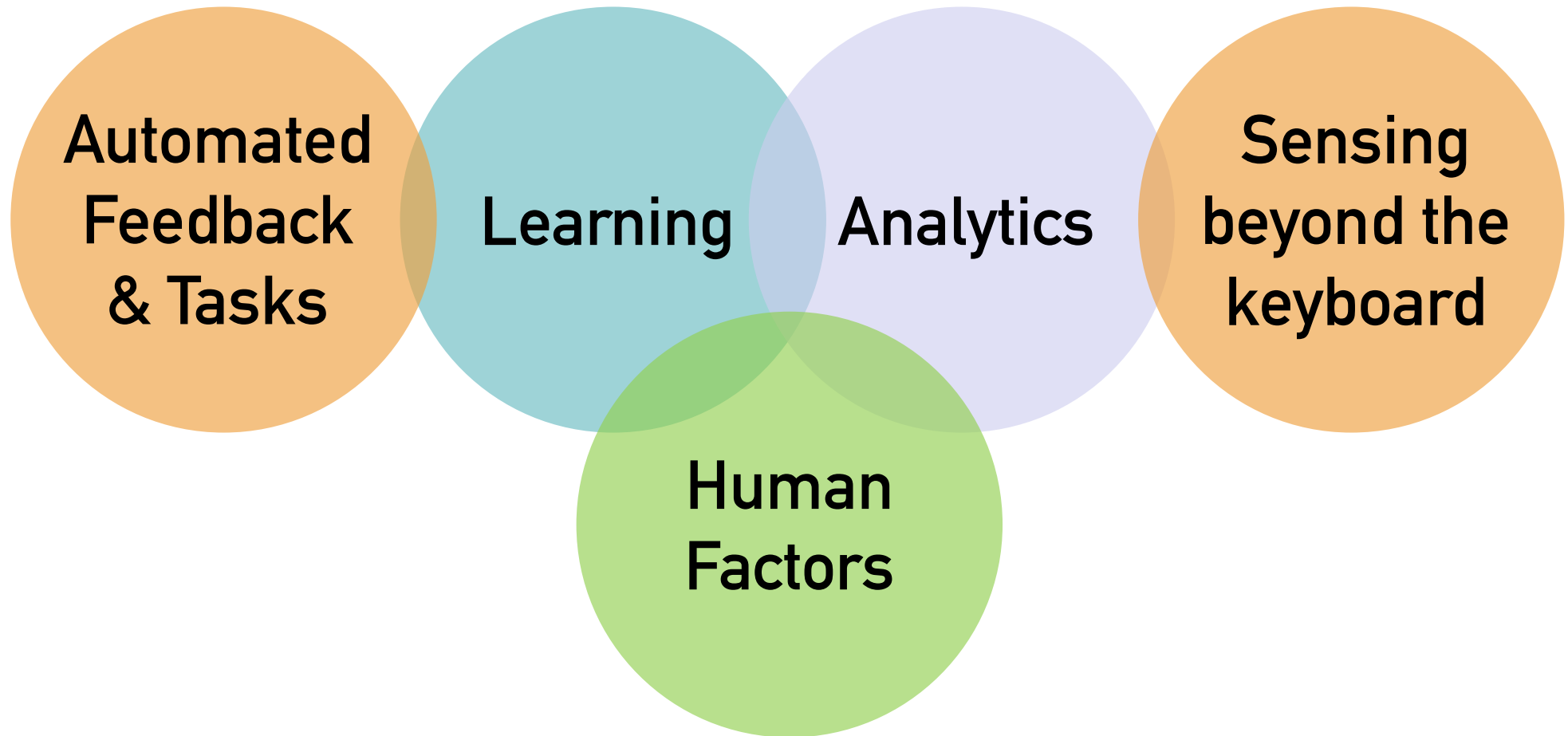
So where does Artificial Intelligence fit in?

AI

now the computer
has greater agency
e.g.
"adaptive learning": tune the task
to each learner's current ability

give personalised feedback based
on the learner's progress

chatbots/avatars

AI

now the computer can
sense more of the human world
e.g.
speech, gestures, posture,
physiology, facial expression…

+ mobile and sensor data:
use of physical tools,
location, other apps…

Human-Centred Analytics/AI in Education

Human-Centred Analytics/AI in Education

By sbs on May 4th, 2019 | Edit

A heads-up that three collections will hit the streets this year focused on how we can design so that human needs and values are well and truly centre-stage in educational tools powered by data, analytics and AI. It will be good to have detailed 'insider accounts' from researcher/developers who are reflecting deeply on how values are baked into their design practices and the infrastructures they are building, and how different stakeholders can engage meaningfully in shaping design. I'm excited about the papers shaping up for these volumes, so watch out for their releases mid- and end-2019...
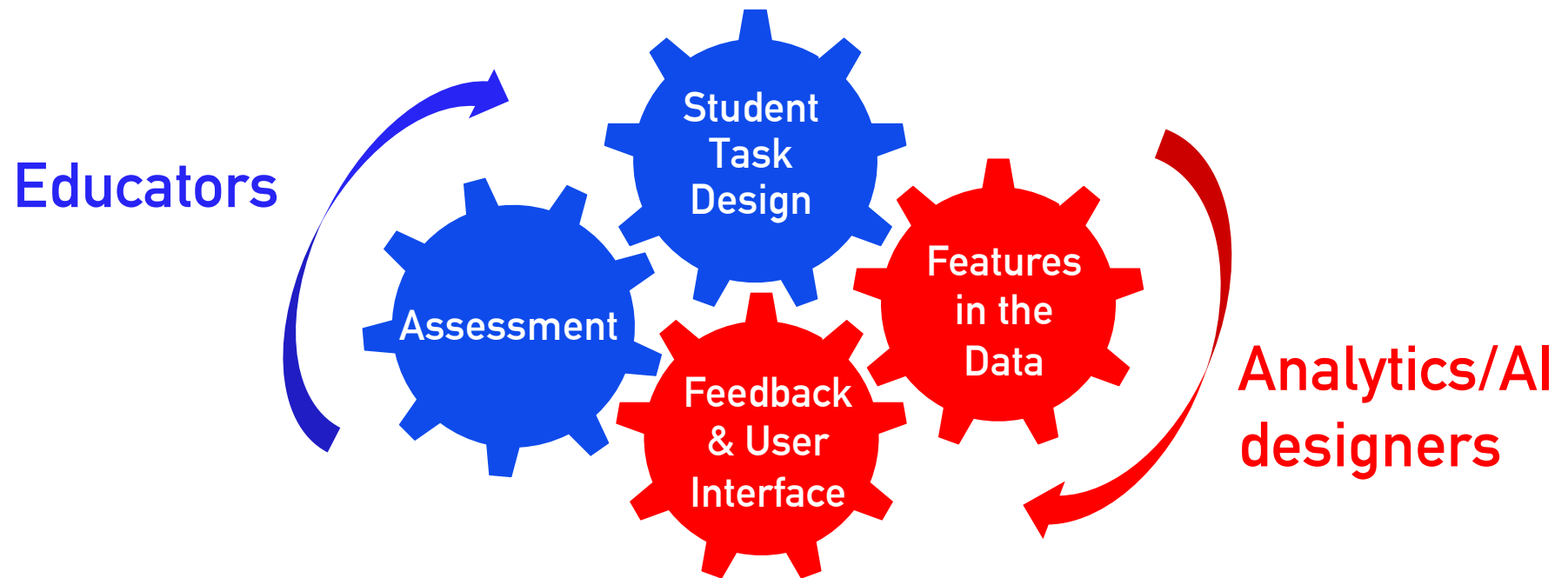
JOURNAL OF LEARNING ANALYTICS

BJET | British Journal of Educational Technology

http://simon.buckinghamshum.net/2019/05/human-centred-analyticsai-in-education

Learning Informatics Principle 1

Design <u>socio</u>-technical systems

Framework @UTS for educators to co-design Analytics/AI → augment teaching practice

PhD by Antonette Shibani: http://simon.buckinghamshum.net/2019/11/congratulations-dr-antonette-shibani
Shibani, A., Knight, S. and Buckingham Shum, S. (2019). Contextualizable Learning Analytics Design: A Generic Model, and Writing Analytics Evaluations. *Proc. 9th International Conference on Learning Analytics & Knowledge (LAK19)*. ACM Press, NY, pp. 210-219. DOI: https://doi.org/10.1145/3303772.3303785. Eprint: https://tinyurl.com/lak19clad

Bundling analytics with educator resources
Integrating Writing Activities with Writing Analytics
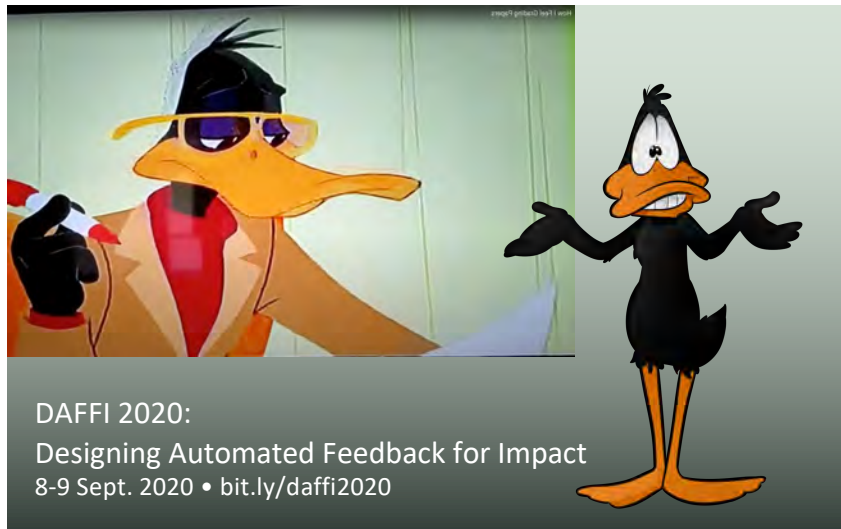
Higher Education Text Analytics
consortium:
http://heta.io/resources

UTS Orientation Portal:
https://uts.edu.au/acawriter

Learning Design

Educator /Student Resources

Evaluation

Analytics Capability
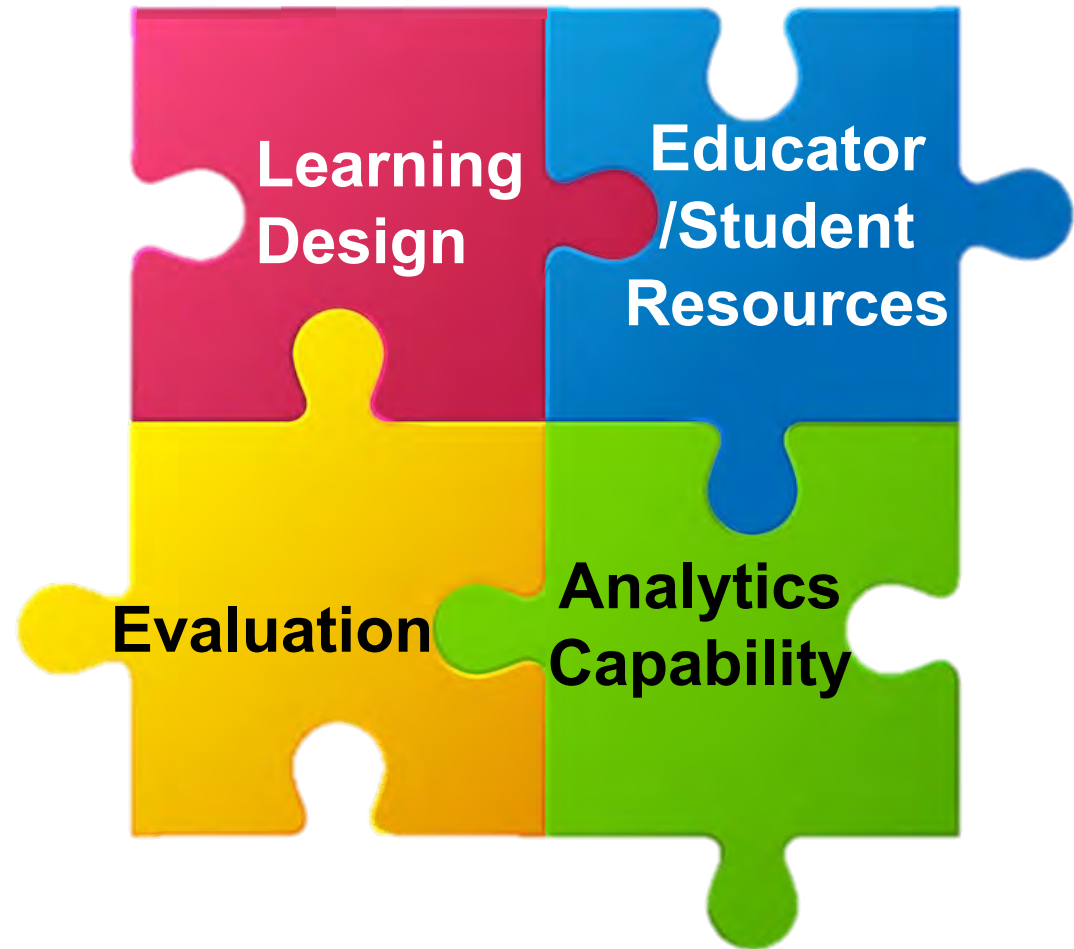
Strong learning design and feedback design practices can compensate for weak machine intelligence

DAFFI 2020:
Designing Automated Feedback for Impact
8-9 Sept. 2020 • bit.ly/daffi2020

http://bit.ly/daffi2020

The role of automated feedback systems in creating feedback-rich environments

Purpose of this symposium

The original concept was to bring the editors and authors from The Impact of Feedback in Higher Education: Improving Assessment Outcomes for Learners (Eds. Henderson, Ajjawi, Boud & Molloy) to the UTS Connected Intelligence Centre, to spend 2 days in a workshop. The pandemic shifted this online, but the goals remain the same and moving online enabled us to more easily bring in additional participants.

> "This book asks how we might conceptualise, design for and evaluate the impact of feedback in higher education. Ultimately, the purpose of feedback is to improve what students can do: therefore, effective feedback must have impact. Students need to be actively engaged in seeking, sense-making and acting upon any information provided to them in order to develop and improve. Feedback can thus be understood as not just the giving of information, but as a complex process integral to teaching and learning in which both teachers and students have an important role to play. The editors challenge us to ask two fundamental questions: when does feedback make a difference, and how can we recognise that impact?"

We call for a deeper dialogue between researchers in the design of assessment and feedback in higher education, and researchers developing automated-feedback tools using Learning Analytics/AI.
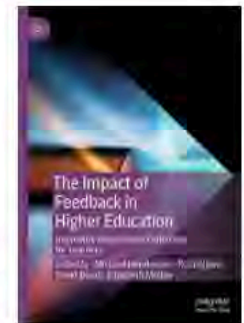
Raising data/learning analytics literacy

(staff and students)

UTS Open: https://open.uts.edu.au

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TASTER COURSE

What Does Facebook Know About You?

Unveil the data that Facebook holds on us and discover how it's shaping the way we consume the news.

($) Free ✕ Self paced ◎ Online

Enrol Now

TASTER COURSE

Journey Through Data

Engage with data systematically and strategically and learn how to tell a data story.

($) Free ✕ Self paced ◎ Online

Enrol Now

TASTER COURSE

Making Decisions in Uncertainty

How do we decide what to do when it's hard to assess all the factors, or be sure of the outcomes?

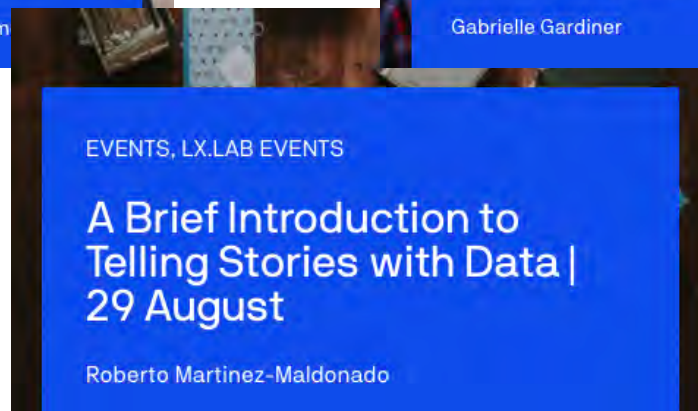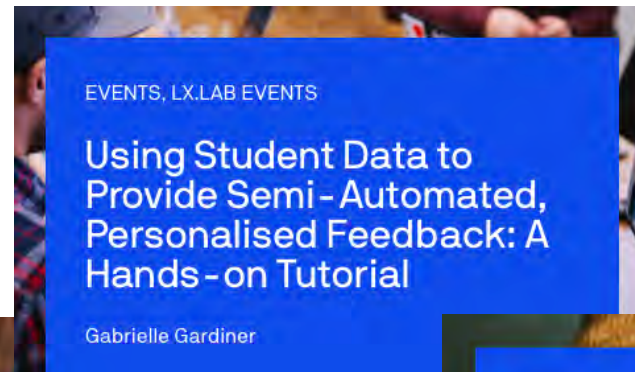($) Free ✕ Self paced ◎ Online

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TASTER COURSE

Writing an Abstract

Want to write an engaging and effective abstract? Learn the hallmark moves in abstracts and how to apply them in your writing.

($) Free ✕ Self paced ◎ Online
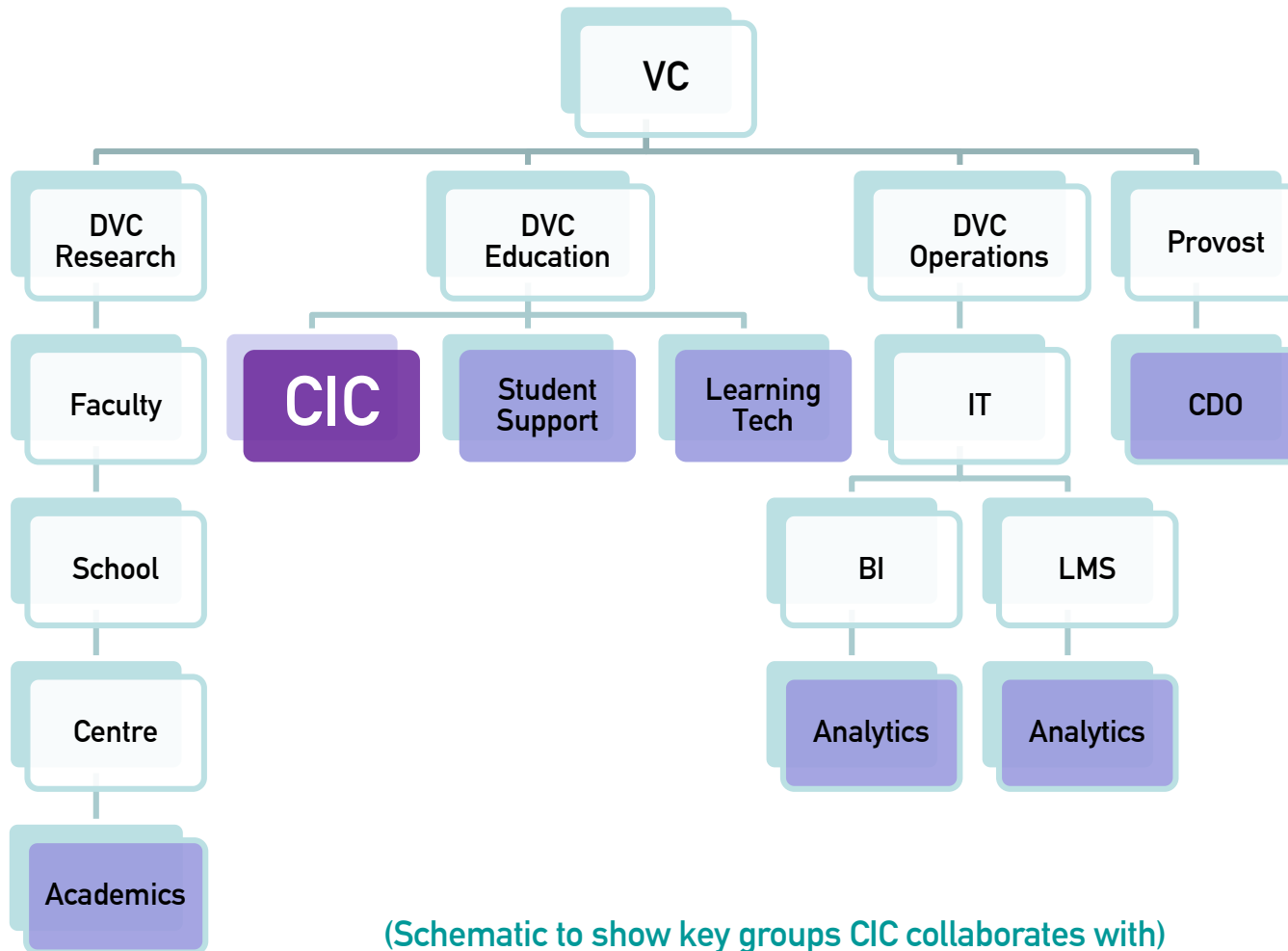
Raising data/learning analytics literacy

Disseminating innovations in Learning Analytics to the UTS community
Briefings • Hands-on Training • Teaching into degree programs

NEWS

Using data in teaching: 4 talks to see at the UTS Teaching and Learning Forum

Allison Glavin | 05 November 2018 | 1 comm

EVENTS, LX.LAB EVENTS

Using Student Data to Provide Semi-Automated, Personalised Feedback: A Hands-on Tutorial

Gabrielle Gardiner

EVENTS, LX.LAB EVENTS

A Brief Introduction to Telling Stories with Data | 29 August

Roberto Martinez-Maldonado

EVENTS

24/7 Instant Feedback on Writing: Integrating AcaWriter into your Teaching | 7 October

Ming Liu

CIC Events archive: https://cic.uts.edu.au/events

CIC's organisational positioning

(Schematic to show key groups CIC collaborates with)

HYBRID INNOVATION/SERVICES CENTRE:

Launched 2014 after 3 years cross-university consultation → Connected Intelligence Strategy

Reporting to DVC (Education & Students)

Analytics R&D in a non-faculty centre: academics, PhDs, full-stack & UX developers, data scientists, professional admin support, interns

Academic and training programs:

- Transdisciplinary Master of Data Science & Innovation (2015-18)

- PhD program in Learning Analytics (2016-)

- Online and blended data literacy (2015-20)

Deploy IT-approved systems UTS-wide

CIC skillset

Interpersonal skills

+

Education, Learning Design, Interface Design, Programming, Web Development, Text Analytics, Machine Learning, Statistics, Visualisation, Decision-Support, Sensemaking, Creativity & Risk, Participatory Design

Board Room
VC/DVCs/Deans/Directors

Common Room
Academic staff

Server Room
IT Division

Organizational architecture for hybrid analytics innovation + service centres

Architecting for Learning Analytics:
Innovating for Sustainable Impact

Simon J. Buckingham Shum and Timothy A. McKay

learning analytics is an academic field that has been taking shape under that banner since around 2010, and it has featured regularly in reports on learning technology futures over the years. It sits at the convergence of learning (learning technology, educational research, learning/assessment sciences), analytics (statistics, visualization, computer/data sciences, artificial intelligence), and human-computer interaction (participatory design, behavioral science, sociotechnical systems design, usability evaluation). In light of the significant investments that some colleges and universities are making in their analytics infrastructures, how can an institution architect itself to innovate at this disciplinary intersection— to innovate pedagogically and analytically in order to tackle substantial, strategically important teaching and learning challenges? In short, how can an institution innovate for sustainable impact?

MARCH/APRIL 2018 EDUCAUSE review 25

A comparison of the drivers behind the creation of 2 university analytics innovation centres, and the org structures that enable impact:

University of Technology Sydney's Connected Intelligence Centre

University of Michigan's Digital Innovation Greenhouse

EDUCAUSE Review
https://er.educause.edu/articles/2018/3/architecting-for-learning-analytics-innovating-for-sustainable-impact

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Design for educator and learner agency
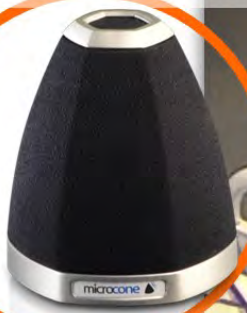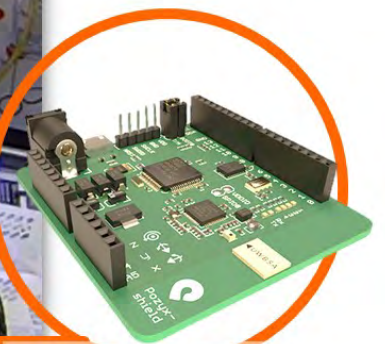
PhDs by Carlos Alvarez-Prieto and Vanessa Echeverria:
http://simon.buckinghamshum.net/2020/09/congratulations-dr-carlos-prieto-alvarez
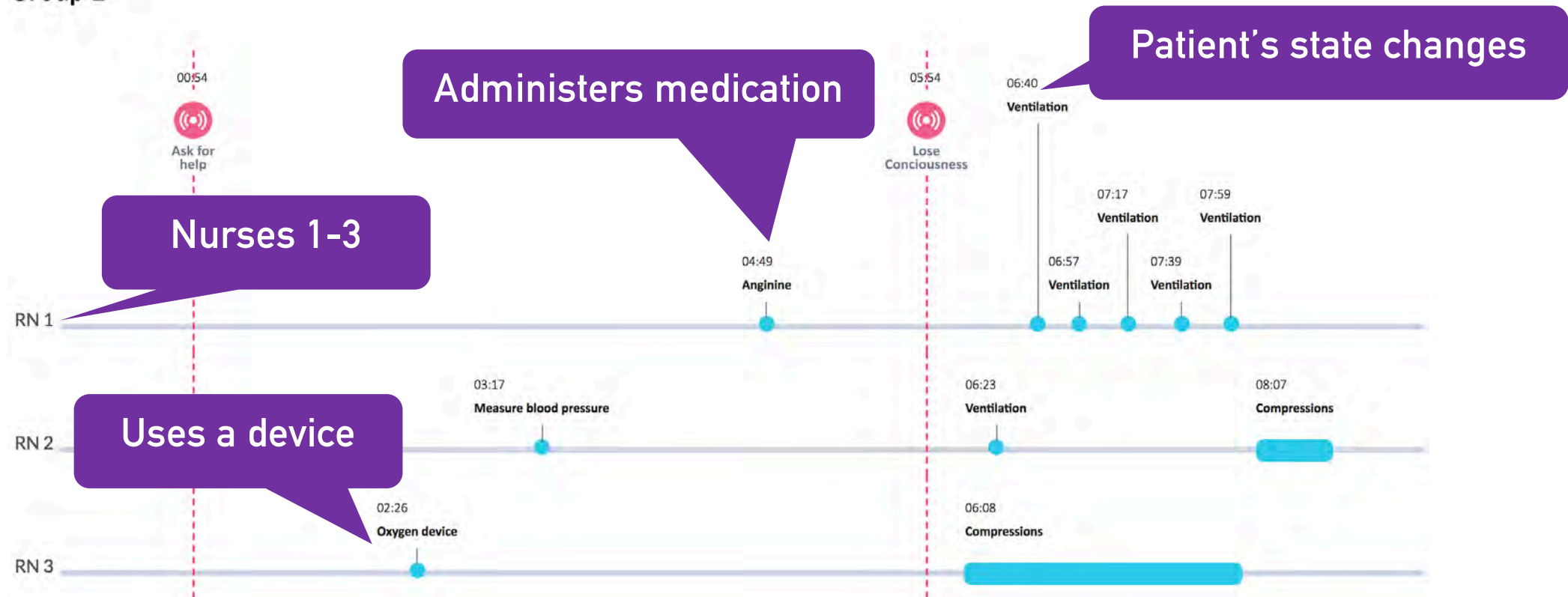http://simon.buckinghamshum.net/2020/05/congratulations-dr-vanessa-echeverria
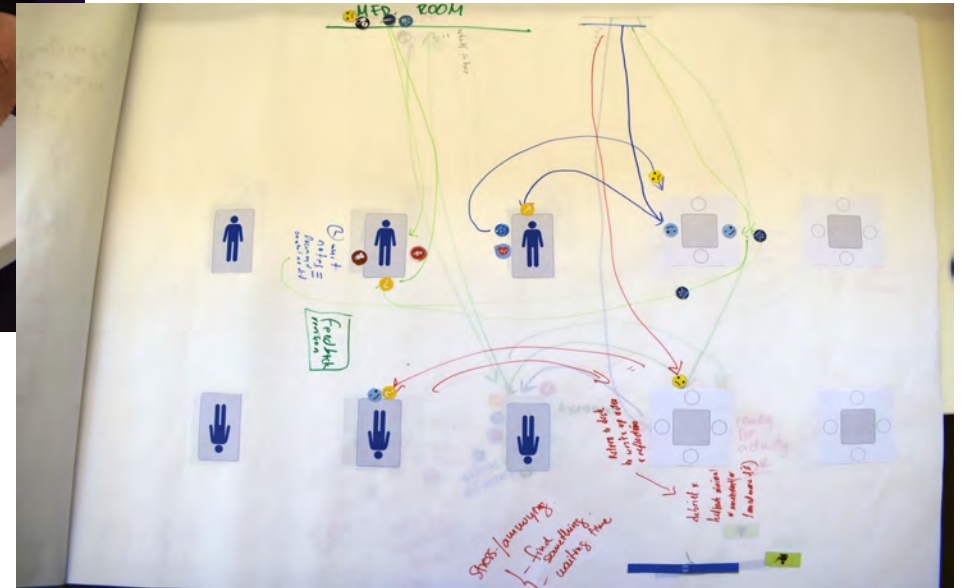
Multimodal student data from simulations

Personalised feedback on high performance teamwork

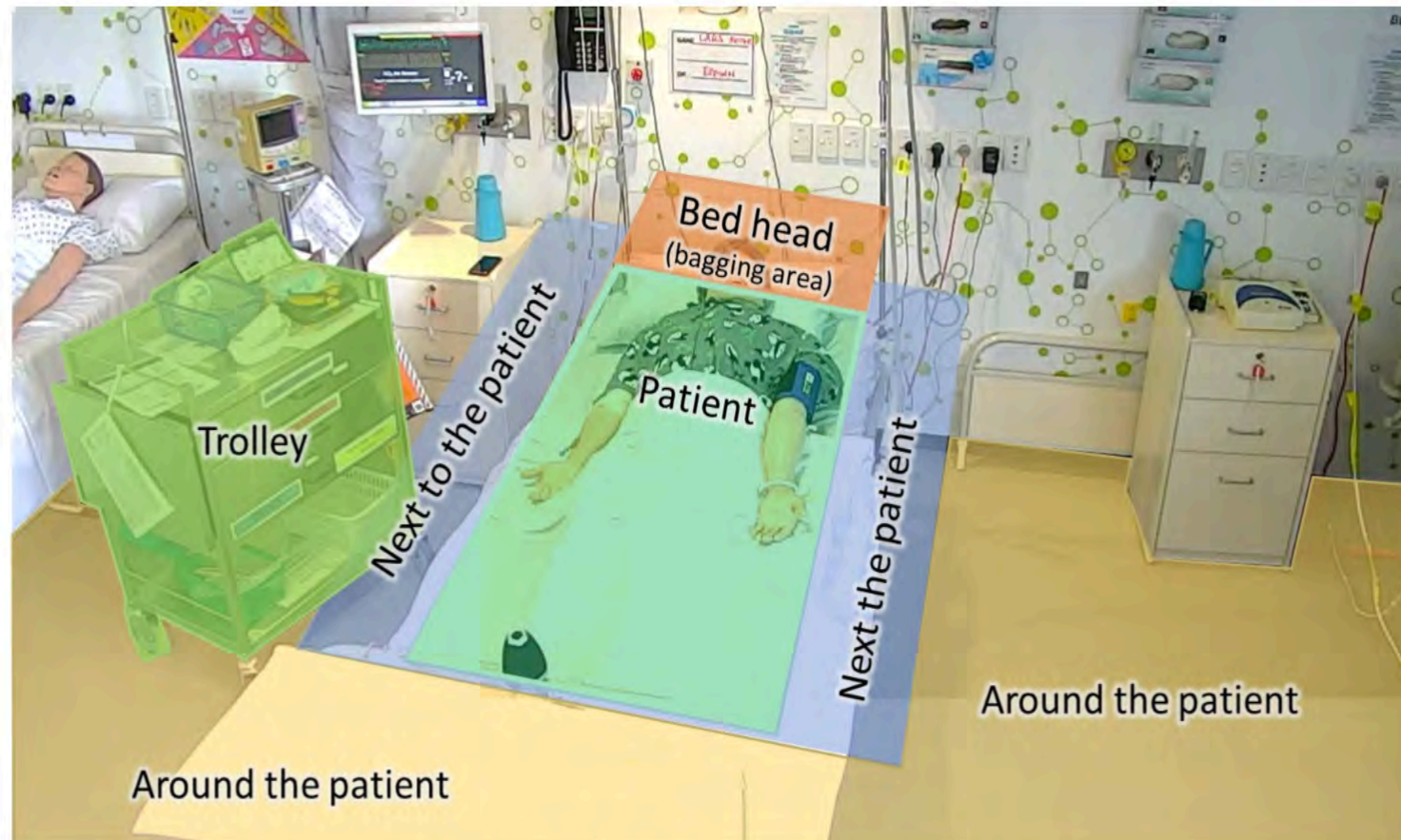## Who did what, when in a nursing simulation? Team Timeline for evidence-based debriefings

Echeverria, V., Martinez-Maldonado, R. and Buckingham Shum, S. (2019). Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In *Proceedings of ACM Conference on Human Factors in Computing (CHI'19)*. ACM: NY. Paper 39, pp. 1-16. https://doi.org/10.1145/3290605.3300269 Open Access Eprint: http://bit.ly/chi19utscic

Co-design techniques to engage students and staff in designing multimodal learning analytics

Prieto-Alvarez, C.G., Martinez-Maldonado, R. and Buckingham Shum, S. (2018). Mapping Learner-Data Journeys: Evolution of a Visual Co-design Tool. *Proceedings of the 30th Australian Conference on Computer-Human Interaction (OzCHI'18)*, Melbourne, Australia, Dec. 2018, ACM, New York, NY, USA, pp. 205–214. DOI: https://doi.org/10.1145/3292147.3292168

MODELLING THE SEMANTICS OF LOCATION

Extensive consultation with educators informed the modelling of 5 key "zones of interest" to help interpret positional data

Echeverria, V., Martinez-Maldonado, R. and Buckingham Shum, S. (2019). Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In *Proceedings CHI 2019*. Paper 39, 1-16. (May 4-9, 2019, Glasgow, UK) https://doi.org/10.1145/3290605.3300269

Making multimodal streams meaningful for nursing student team feedback
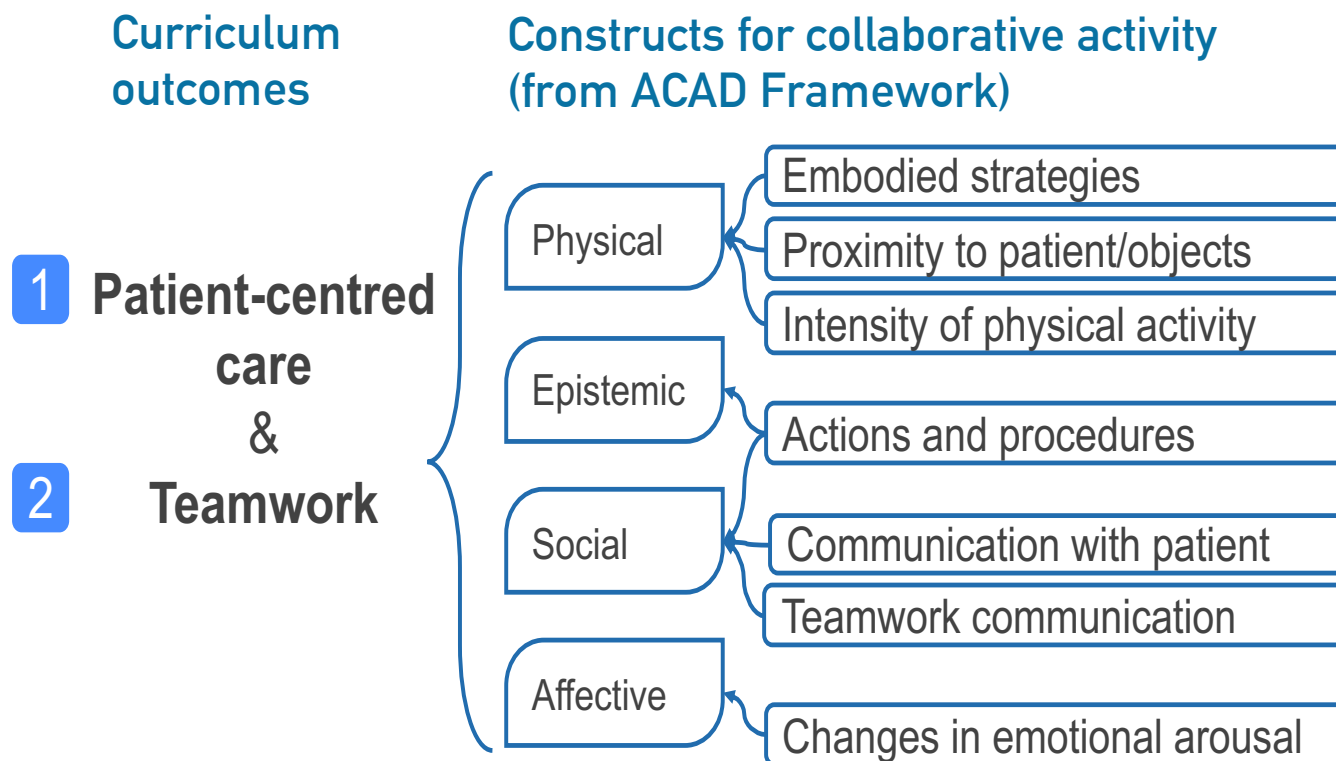
From multimodal logs to curriculum outcomes

Curriculum
outcomes

1 **Patient-centred
care
&**

2 **Teamwork**

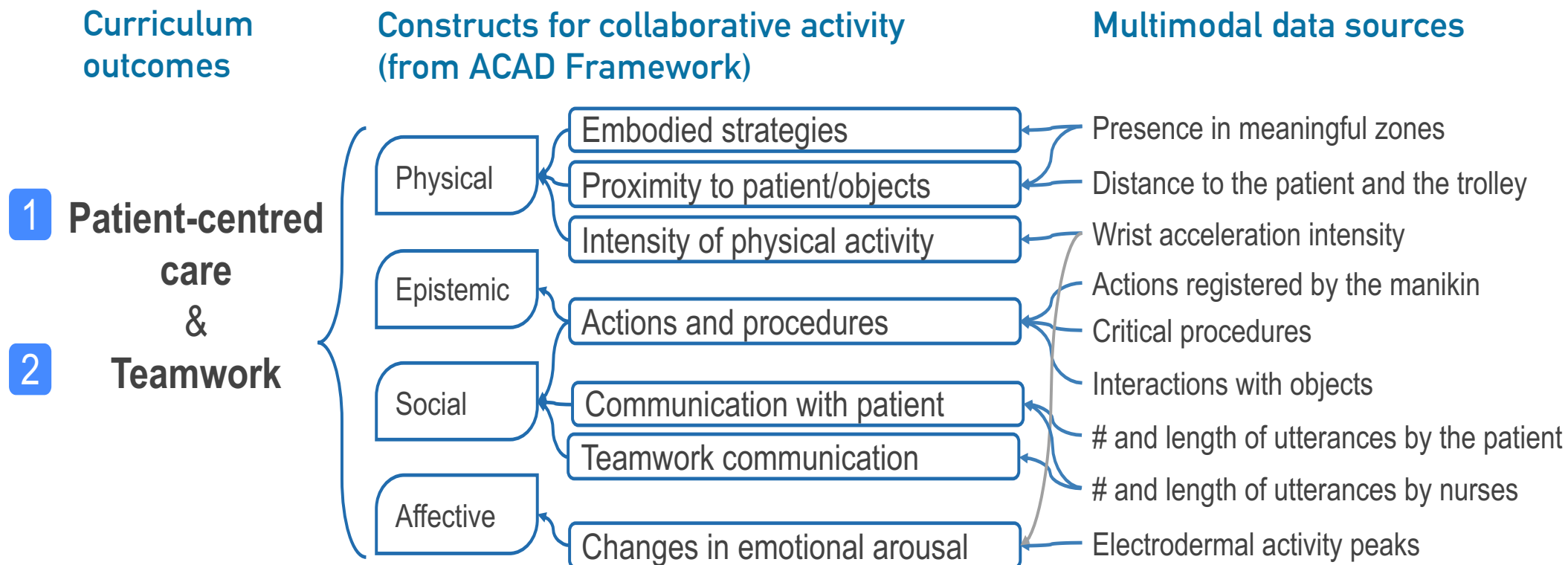# Making multimodal streams meaningful for nursing student team feedback

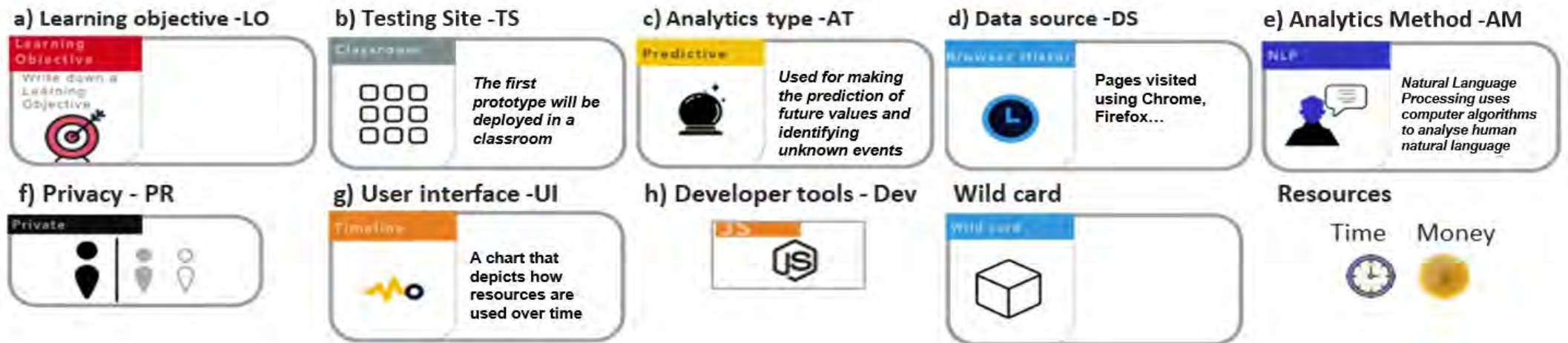## From multimodal logs to curriculum outcomes

Curriculum outcomes

Constructs for collaborative activity (from ACAD Framework)

1 **Patient-centred care**

&

2 **Teamwork**

Physical
- Embodied strategies
- Proximity to patient/objects
- Intensity of physical activity

Epistemic
- Actions and procedures

Social
- Communication with patient
- Teamwork communication

Affective
- Changes in emotional arousal

Making multimodal streams meaningful for nursing student team feedback

From multimodal logs to curriculum outcomes

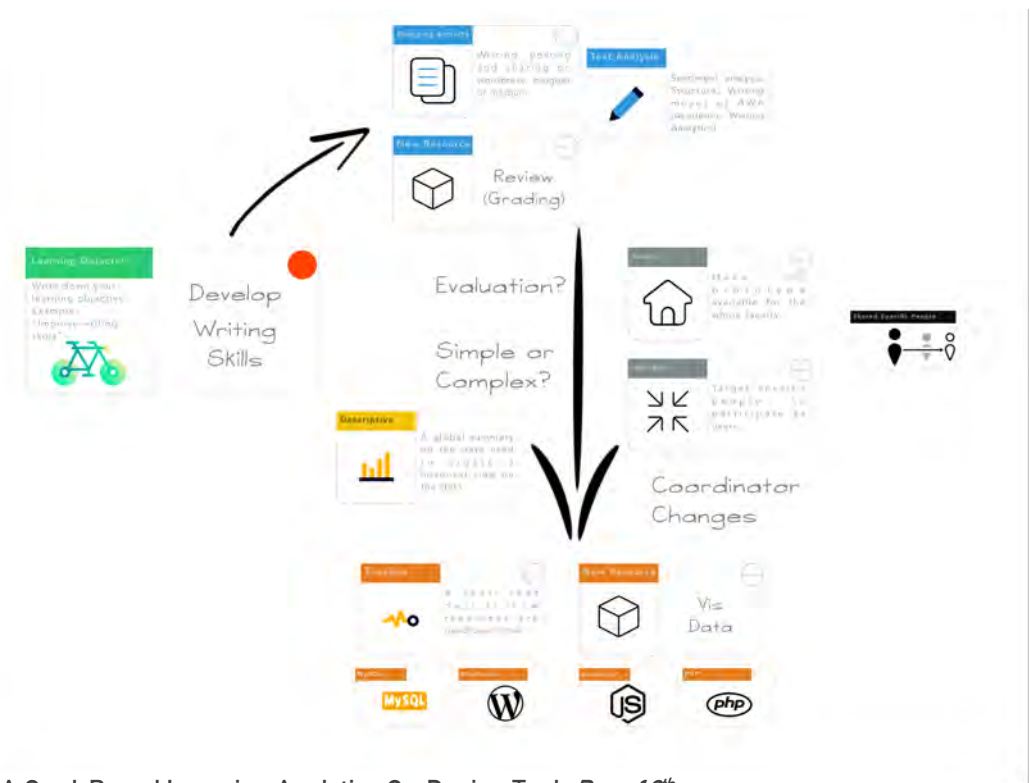Curriculum outcomes | Constructs for collaborative activity (from ACAD Framework) | Multimodal data sources

1 **Patient-centred care** & **2** **Teamwork**

Physical
- Embodied strategies ← Presence in meaningful zones
- Proximity to patient/objects ← Distance to the patient and the trolley
- Intensity of physical activity ← Wrist acceleration intensity

Epistemic
- Actions and procedures ← Actions registered by the manikin
  ← Critical procedures
  ← Interactions with objects

Social
- Communication with patient ← # and length of utterances by the patient
- Teamwork communication ← # and length of utterances by nurses

Affective
- Changes in emotional arousal ← Electrodermal activity peaks

LA-DECK: card-based co-design tool for LA

a) Learning objective -LO
Learning Objective
Write down a Learning Objective

b) Testing Site -TS
Classroom
The first prototype will be deployed in a classroom

c) Analytics type -AT
Predictive
Used for making the prediction of future values and identifying unknown events

d) Data source -DS
Browser History
Pages visited using Chrome, Firefox…

e) Analytics Method -AM
NLP
Natural Language Processing uses computer algorithms to analyse human natural language

f) Privacy - PR
Private

g) User interface -UI
Timeline
A chart that depicts how resources are used over time

h) Developer tools - Dev
JS

Wild card
Wild card

Resources
Time   Money

Toolkit available http://ladeck.utscic.edu.au

Prieto-Alvarez, C.G., Martinez-Maldonado, R. and Buckingham Shum, S. (2020). LA-DECK: A Card-Based Learning Analytics Co-Design Tool. *Proc.10th International Conference on Learning Analytics and Knowledge,* Frankfurt, March 2020, ACM. 10 pages. DOI: https://doi.org/10.1145/3375462.3375476

LA-DECK: card-based co-design tool for LA

Prieto-Alvarez, C.G., Martinez-Maldonado, R. and Buckingham Shum, S. (2020). LA-DECK: A Card-Based Learning Analytics Co-Design Tool. *Proc.10th International Conference on Learning Analytics and Knowledge,* Frankfurt, March 2020, ACM. 10 pages. DOI: https://doi.org/10.1145/3375462.3375476

Automated formative feedback on reflective writing

Knight, S., Shibani, A., Abel, S., Gibson, A., Ryan, P., Sutton, N., Wight, R., Lucas, C., Sándor, Á., Kitto, K., Liu, M., Mogarkar, R. & Buckingham Shum, S. (2020). AcaWriter: A learning analytics tool for formative feedback on academic writing. Journal of Writing Research, 12, (1), 141–186. https://doi.org/10.17239/jowr-2020.12.01.06

Reflective Report	Feedback	Resources

☑ 🟦 Initial thoughts and feelings about a significant experience.

☑ 🟣 The challenge of new surprising or unfamiliar ideas, problems or learning experiences.

☑ **Deeper reflection, personally applied.**

☑ ▶ How new knowledge can lead to a change

☑ Expressions indicating belief, learning, or knowledge.

☑ *Expressions indicating self critique*

☑ *Words associated with strong feelings*

☑ ⚡ Sentence too long, might disengage the reader. Try breaking it into smaller sentences

outcomes for the patient. ▶ **Thus, this experience taught me that in future, *I must* take a patient-centred approach.** 🟦🟣▶ *I must* spend time addressing the patients concerns and demonstrate excellent communication with them so they can fully understand their clinical picture and history. This relates to Domain 2: Communication and Collaboration, Standard 4: Apply Interpersonal Communication Skills to Address Problems, which is a standard in the National Competency Standards Framework for Pharmacists in Australia (2016). The incident has taught me to use a whole range of communication techniques when counselling a patient. It gave me the opportunity to practice this sort of behaviour in my subsequent weeks of clinical placement. 🟣 **It has strongly encouraged me to shift my perspective to one that focuses more on patient-centred care.** 🟦 I personally think that this is crucial in ensuring that a patient's health objectives are met. This standard I have obtained is important for any practising pharmacist.

Participatory prototyping with educators to build trust in the NLP

Learning Analytics researchers work with academics (3 hour workshop)

Goal: calibrate the parser detecting affect in reflective writing, working through sample texts

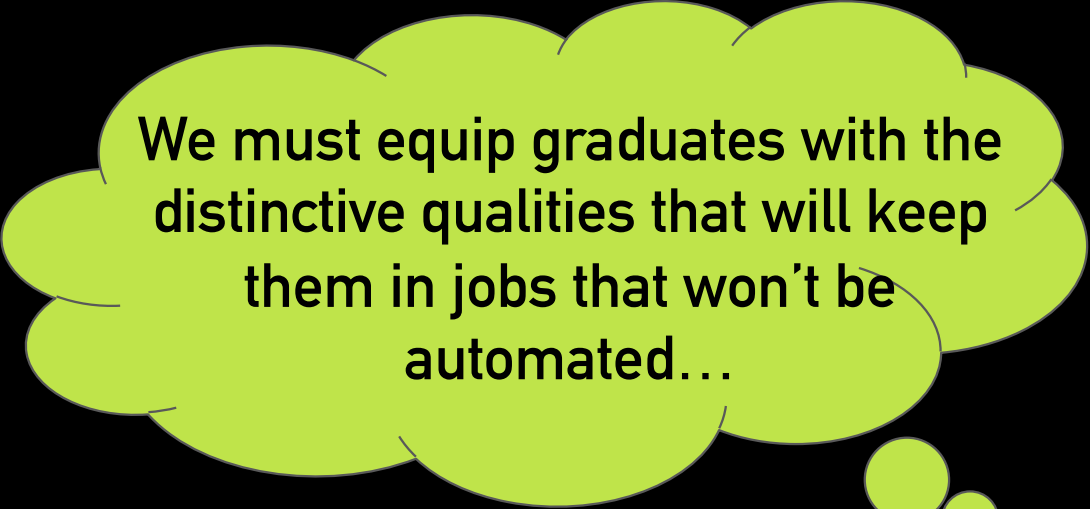Rapid prototyping with a Python notebook, then integrated into full application for further testing

http://heta.io/how-can-writing-analytics-researchers-rapidly-codesign-feedback-with-educators
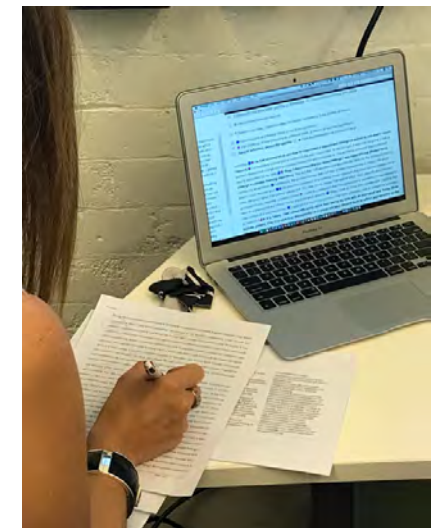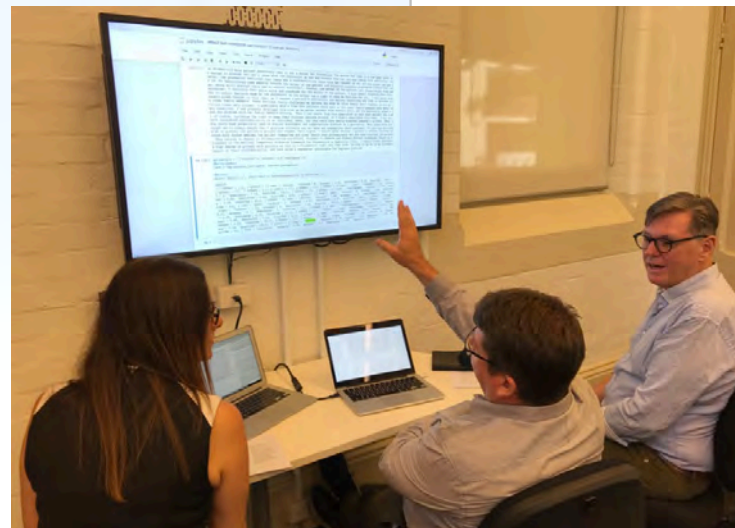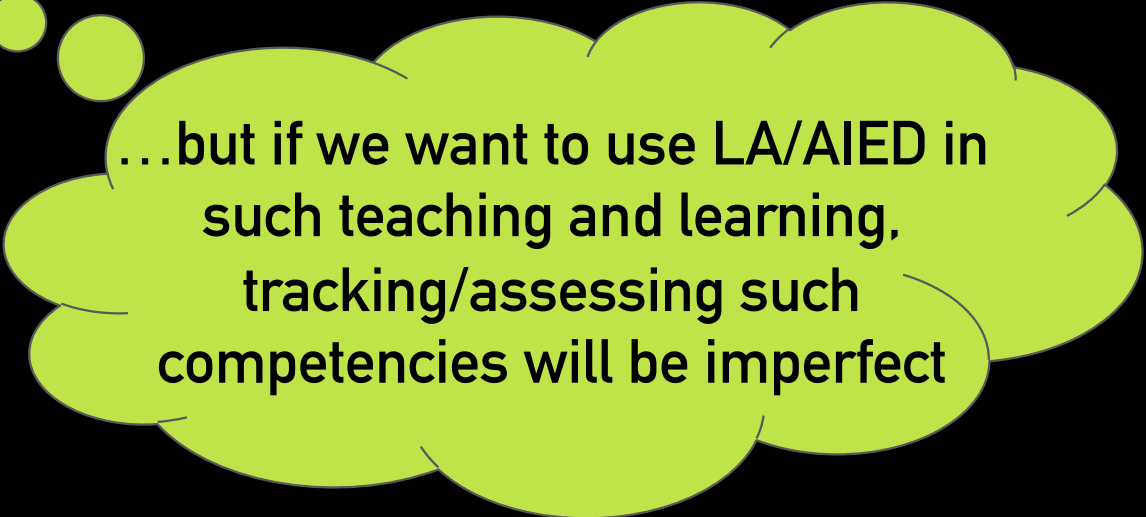
Design for imperfect computational models

Kirsty Kitto, Simon Buckingham Shum, and Andrew Gibson. (2018). Embracing Imperfection in Learning Analytics. In *Proceedings LAK18: International Conference on Learning Analytics and Knowledge*, March 5–9, 2018, Sydney, NSW, Australia, pp.451–460. (ACM, New York, NY, USA). https://doi.org/10.1145/3170358.3170413

The Navajo rug

"In a Navajo rug there is always an imperfection woven into the corner. And interestingly enough, it's where "the Spirit moves in and out of the rug." The pattern is perfect and then there's one part of it that clearly looks like a mistake . . .

Perfection is not the elimination of imperfection.
[...] Perfection, rather, is the ability to incorporate imperfection!
[...] You either incorporate imperfection, or you fall into denial."

Richard Rohr (2011). Breathing Under Water: Spirituality and the Twelve Steps. Cincinnati, OH: Franciscan Media
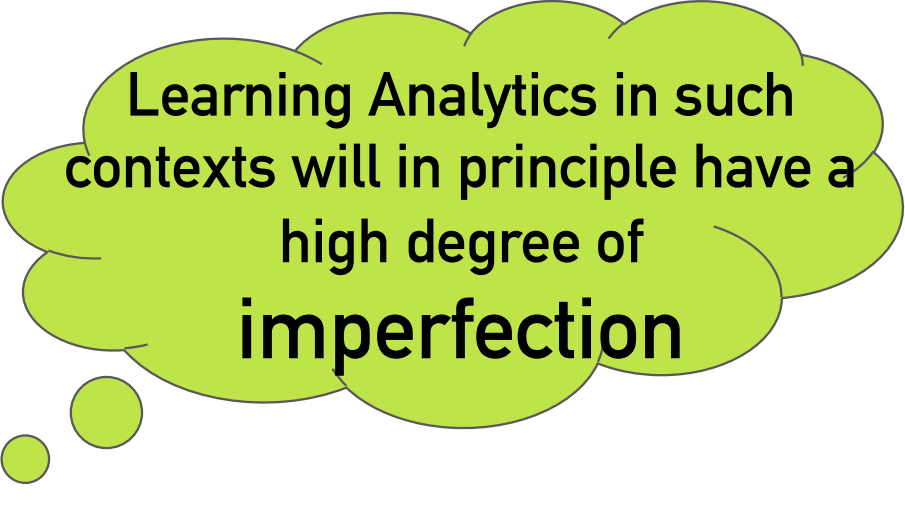See also: https://medium.com/bedolabs/success-through-imperfection-c3ef21cb32ed

http://exhibitions.kelsey.lsa.umich.edu/less-than-perfect/navajo.php

Cultivating the disposition and capacity to "learn how to learn"

Reflection and metacognition are among the highest order outcomes that we aspire to cultivate in learners — the desire and skills to observe one's thoughts, emotions and actions, and glean insights

Reflection on machine intelligence is part of this: critical engagement with AI is now a lifelong learning competency

Tracking such competencies is currently at the edge of A.I.

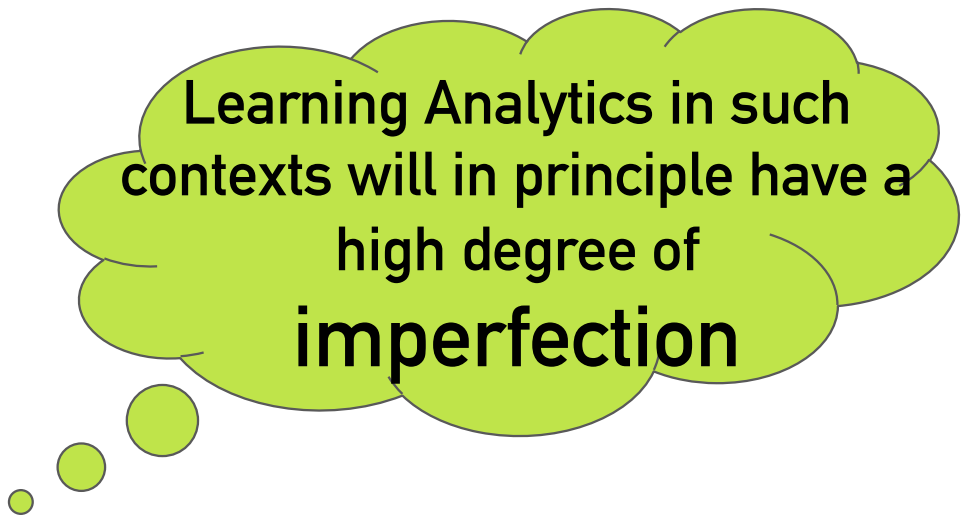Learning Analytics in such contexts will in principle have a high degree of **imperfection**

Authentic learning → C21/LLL competencies

Embodied, skilled performance:

an important part of the learning experience is physically embodied (e.g. inspecting a forest; a social services risk assessment) it's impossible to tightly control what will happen, as well as making outcomes far harder to digitally monitor.

Wicked problems (Horst Rittel):

problems with no correct answer, and no stopping rules — even the definition of the <u>problem</u> is contested
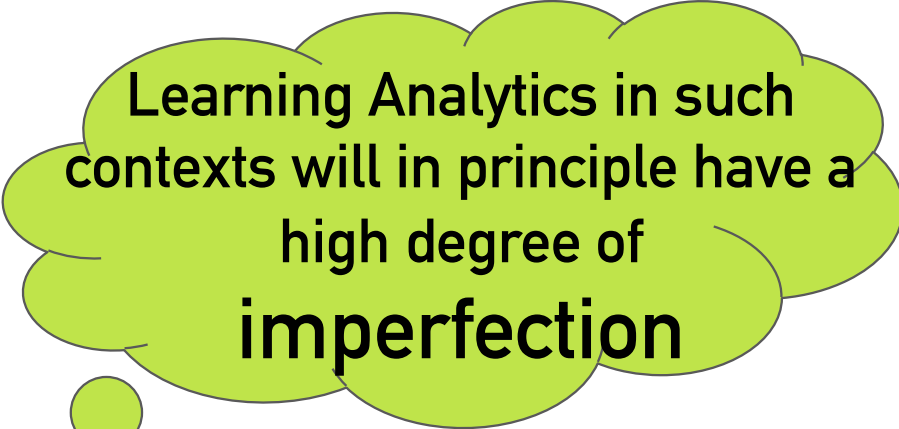
Learning Analytics in such contexts will in principle have a high degree of **imperfection**

Authentic learning → C21/LLL competencies

Socially and psychologically complex performance: scenarios where the outcome is emergent in nature, a function of many drivers that result in unpredictable and/or unique outcomes (e.g. a social worker client interview; conflict resolution)

Deep reflection: the sense that a learner makes of their experience, or a shift in worldview, which by definition is not accessible to the machine, but to which a machine might have partial access

Learning Analytics in such contexts will in principle have a high degree of **imperfection**

Can we **design** for this?

cognitive dissonance
provides a teachable moment…

Imperfect Learning Analytics → cognitive dissonance

"…as D'Mello and Graesser [15] demonstrate, it is when the student experiences dissonance because the analytics fail to match their expectations that they are likely to reflect on why they think the machine is wrong. We believe that this form of critical questioning is more likely to happen if the student has been given an underlying reason to be a little distrustful of the classifier."

Kirsty Kitto, Simon Buckingham Shum, and Andrew Gibson. (2018). Embracing Imperfection in Learning Analytics. In *Proceedings LAK18: International Conference on Learning Analytics and Knowledge*, March 5–9, 2018, Sydney, NSW, Australia, pp.451–460. (ACM, New York, NY, USA). https://doi.org/10.1145/3170358.3170413

Learners' engagement with intelligent technology should not be <u>mindless</u>.

On the contrary we should design for…

"nonautomatic, effortful and thus metacognitively guided processes"

Gavriel Salomon, David Perkins and Tamar Globerson (1991). Partners in cognition: extending human intelligence with intelligent technologies. Educational Researcher 20, 3 (1991), 2–9.

"Embracing Imperfection in Learning Analytics"

1. Robust learning design ensures that the activity involving automated feedback is meaningful whether or not the technology always works

2. Explicit encouragement — in student briefings, and in the user interface — to push back if they disagree with the feedback

| Analytical Report	Feedback	Resources

Thank you for submitting your draft to AcaWriter. Quality writing comes from revision. Research shows that writing drafts and revising your text helps improve the quality of your writing.

Remember AcaWriter is a machine — so it may not highlight all your moves correctly and could give you incorrect feedback. So, don't be afraid to disagree with the feedback, if you believe you have included all three moves in the correct order.

ⓘ It seems you have explained how your research fills the gap or solves the research problem [Move 3 – Occupying the niche (S or N sentences)] before you have indicated the gap or explained your research problem [Move 2 Establishing a niche (C or Q sentences)]. It is more effective to indicate the gap and explain the research problem before you state your solution and aim of your study. Go back and revise

Cultivating "automated feedback literacy"

"Feedback literacy" (Boud)
feedback ≠ transmitting information:
systemic implications for learning
design and assessment

As analytics/AI enable increasing
amounts of automated feedback,
learners must now develop a new
literacy: knowing how much to trust the
machine's judgement, and being able to
push back when they disagree

DAFFI 2020:
Designing Automated Feedback for Impact
8-9 Sept. 2020 • bit.ly/daffi2020

http://bit.ly.daffi2020
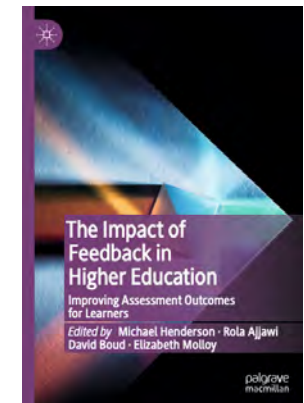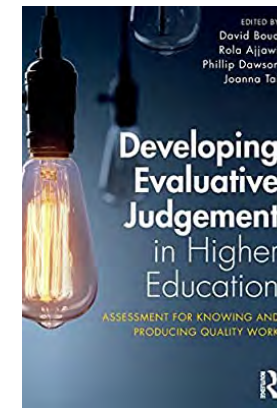
LA/AIED System Integrity
> "algorithmic accountability"
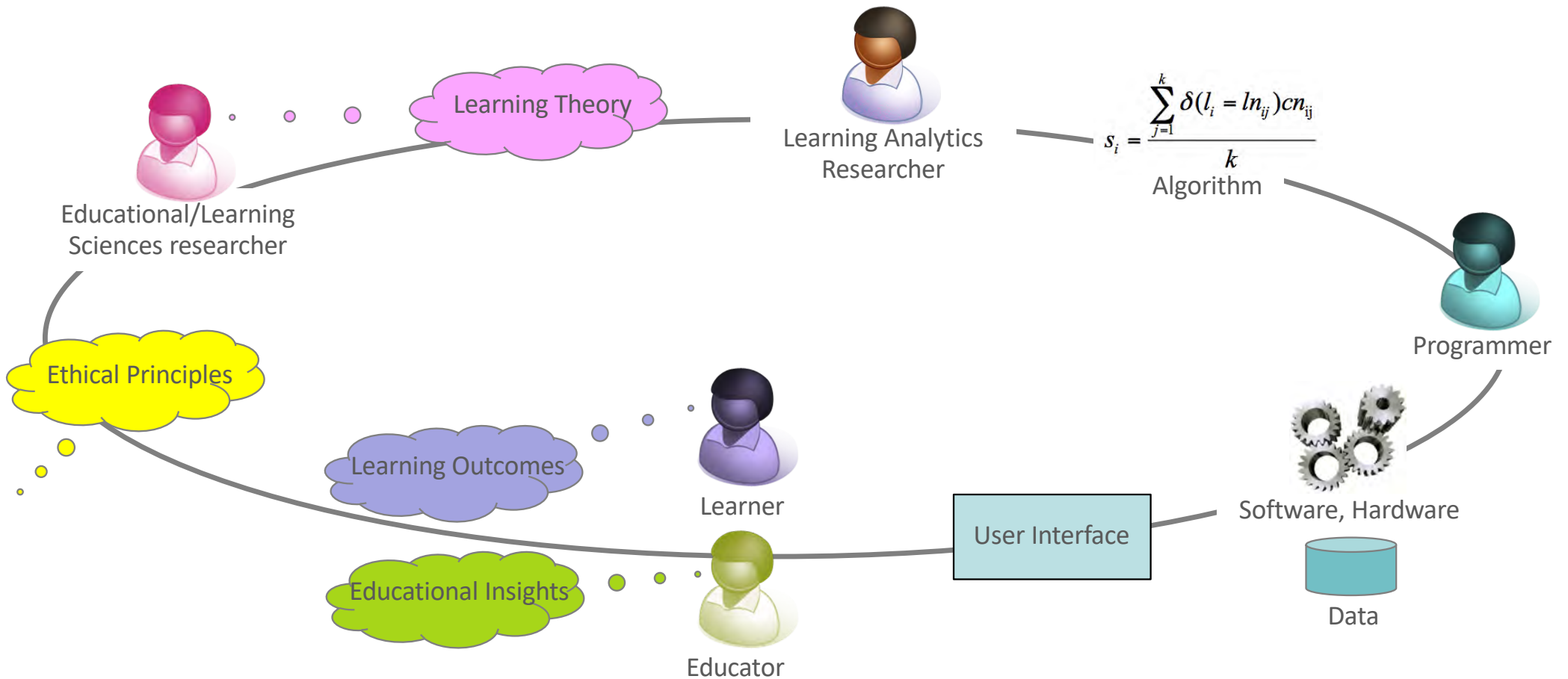
Remind me, why should I trust this system?

Growing public literacy around algorithmic bias and the need for accountability is to be welcomed
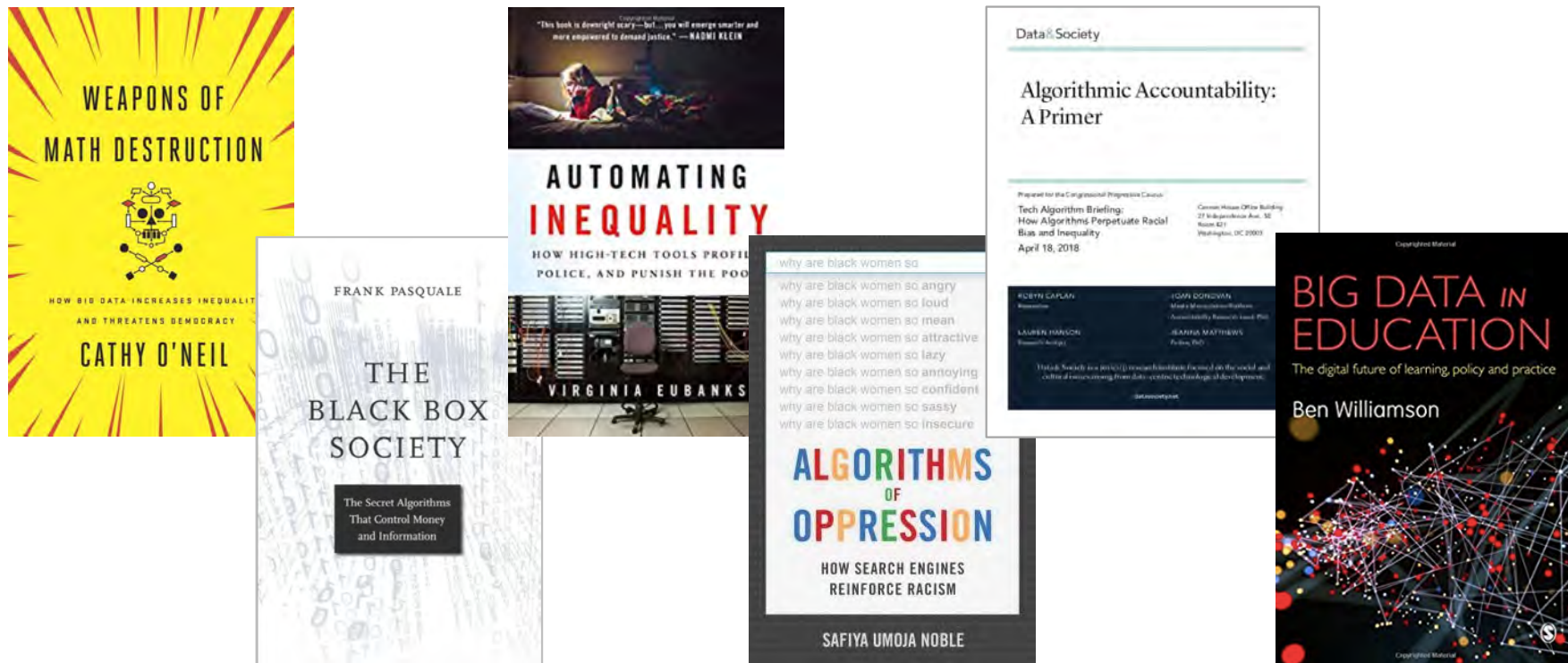
…but is there anything distinctive about algorithms for teaching and learning that shapes how we frame "accountability"?

Stakeholders and key transitions in designing a Learning Analytics system

Learning Theory

Learning Analytics Researcher

$$s_i = \frac{\sum_{j=1}^{k} \delta(l_i = ln_{ij})cn_{ij}}{k}$$

Algorithm

Educational/Learning Sciences researcher

Ethical Principles

Programmer

Learning Outcomes

Learner

User Interface

Software, Hardware

Educational Insights

Educator

Data

So the algorithm is just one ingredient. A better name might be

LA/AIED System Integrity
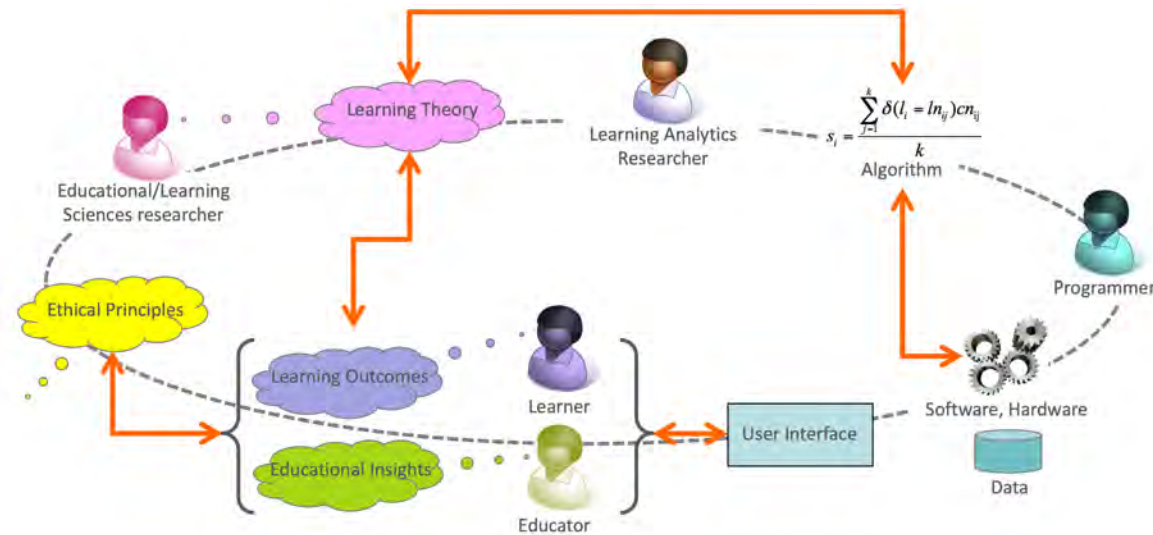
Remind me, why should I trust this system?
Because… <argument>

Accountability in terms of: Computer Science

Learning Theory

Educational/Learning Sciences researcher

Learning Analytics Researcher

$$s_i = \frac{\sum_{j=1}^{k} \delta(l_i = ln_{ij})cn_{ij}}{k}$$

Algorithm

Programmer

Ethical Principles

Learning Outcomes

Learner

Educational Insights

Educator

User Interface

Software, Hardware
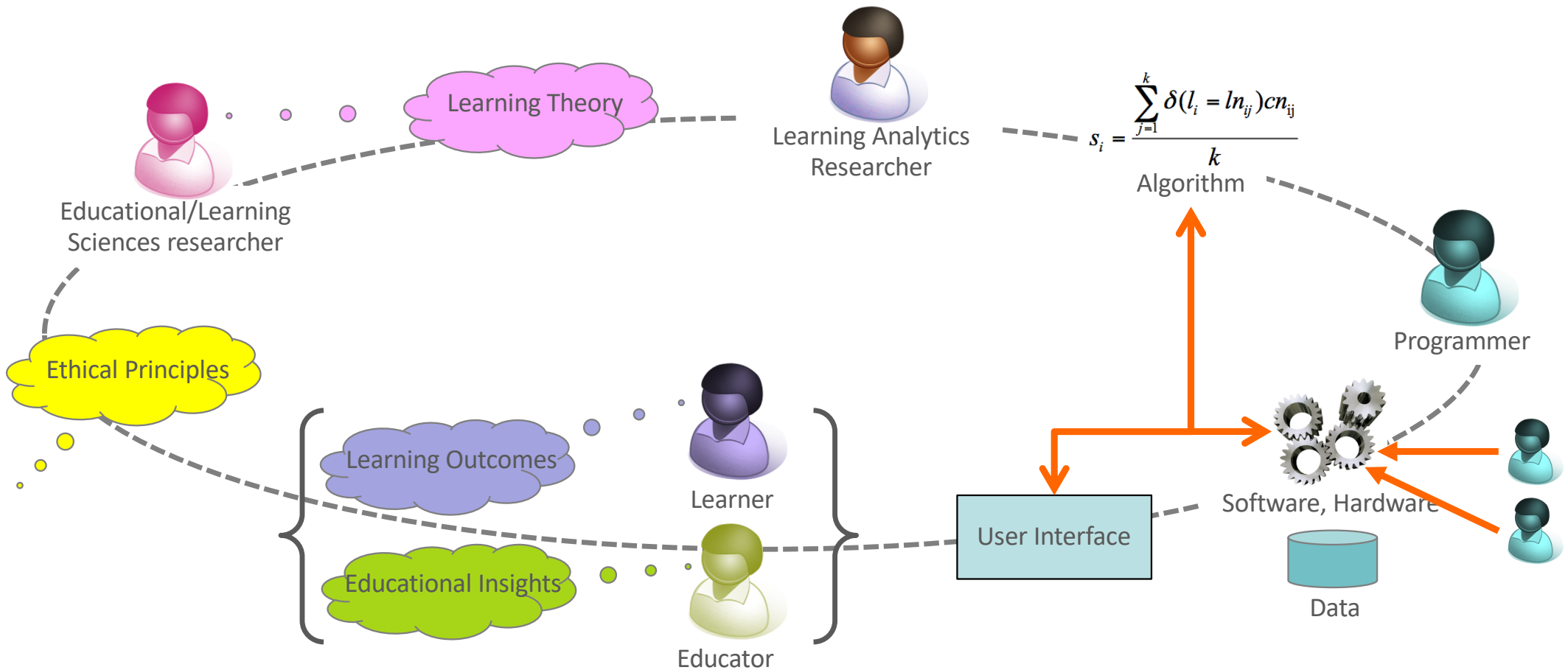
Data

Accountability in terms of: Data Science

Learning Theory

Educational/Learning Sciences researcher

Learning Analytics Researcher

$$s_i = \frac{\sum_{j=1}^{k} \delta(l_i = ln_{ij})cn_{ij}}{k}$$

Algorithm

Programmer

Ethical Principles

Learning Outcomes

Educational Insights

Learner

Educator

User Interface

Software, Hardware

Data

Training Data
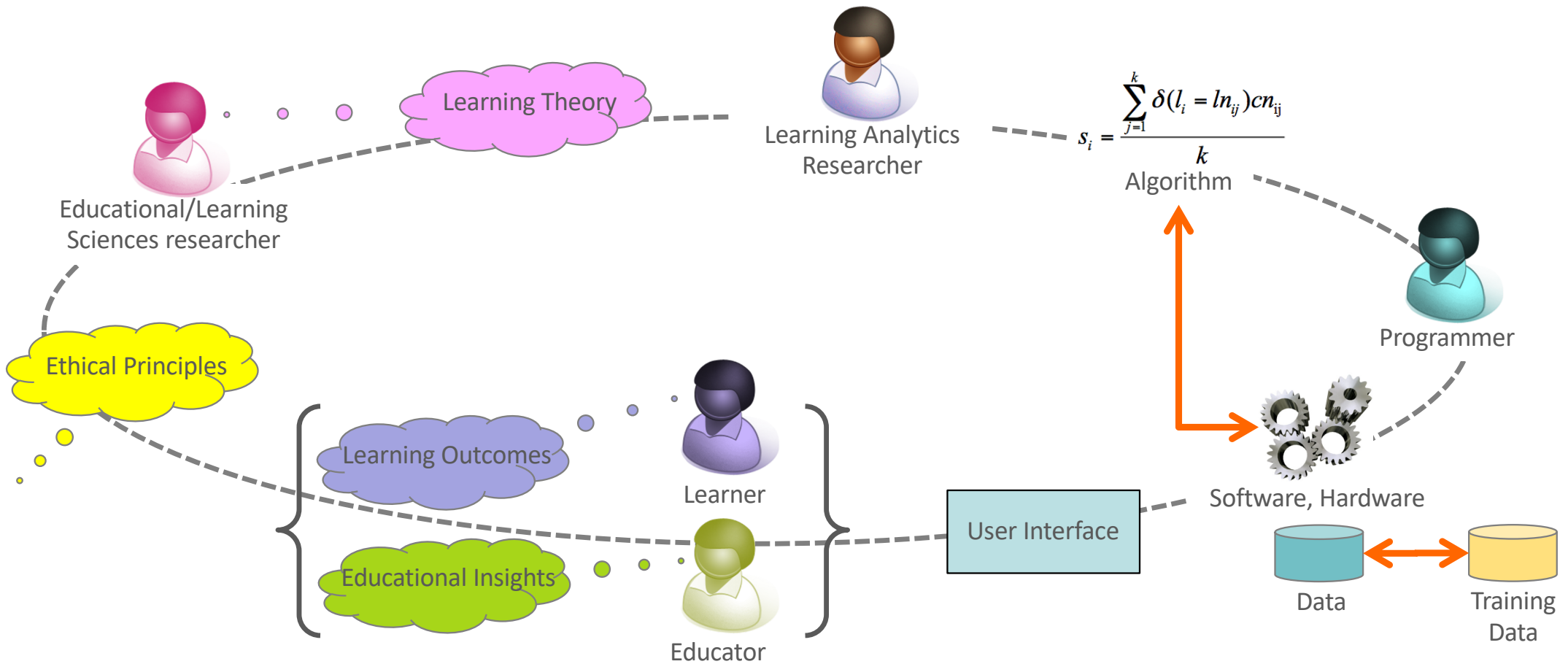
Accountability in terms of: User-Centred Design

Learning Theory

Learning Analytics Researcher

$$s_i = \frac{\sum_{j=1}^{k} \delta(l_i = ln_{ij})cn_{ij}}{k}$$

Algorithm

Educational/Learning Sciences researcher

Design Process

Programmer

Ethical Principles

Learning Outcomes

Educational Insights

Learner

Educator

User Interface

Software, Hardware

Data
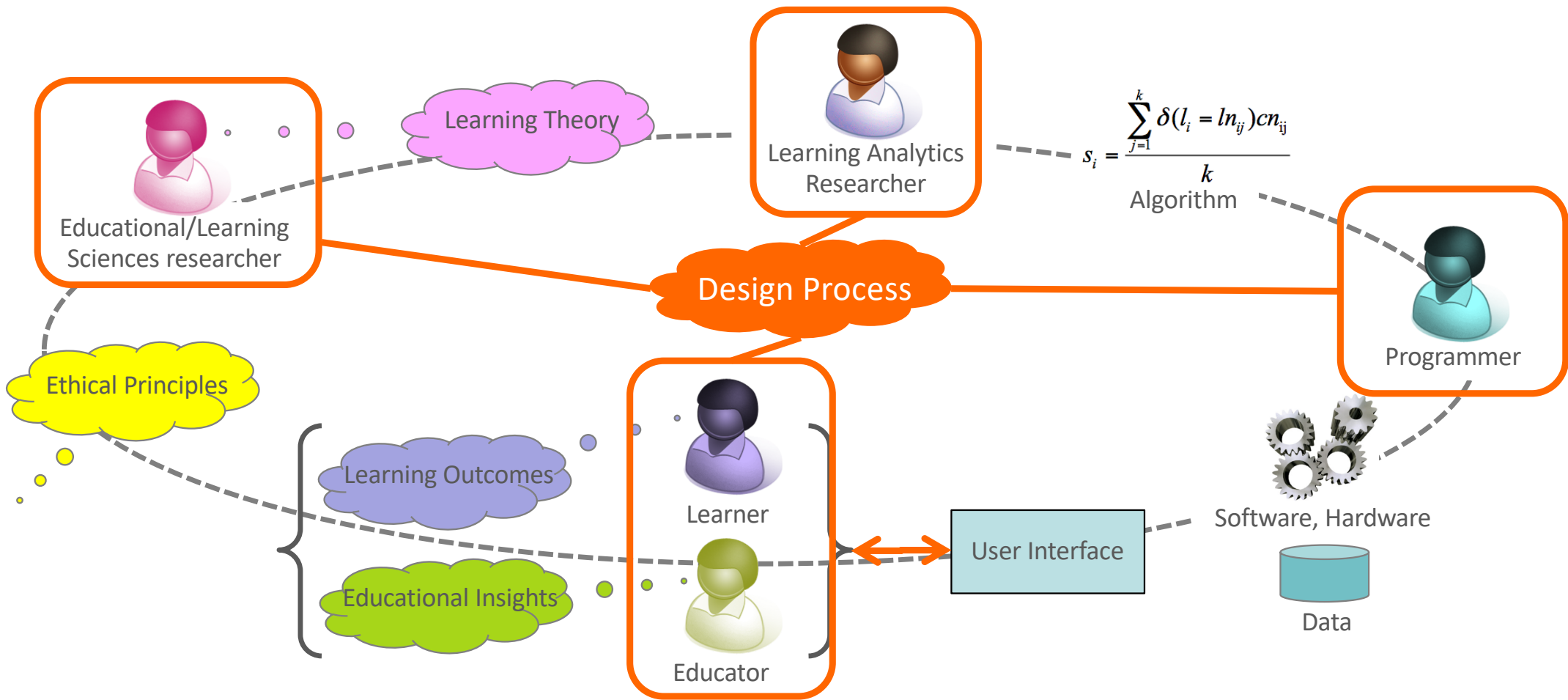
Accountability in terms of:
Learning Sciences & Educational Technology

Learning Theory

Learning Analytics Researcher

$$s_i = \frac{\sum_{j=1}^{k} \delta(l_i = ln_{ij})cn_{ij}}{k}$$

Algorithm

Educational/Learning Sciences researcher

Programmer

Ethical Principles

Learning Outcomes

Learner

User Interface

Software, Hardware

Educational Insights

Educator

Data
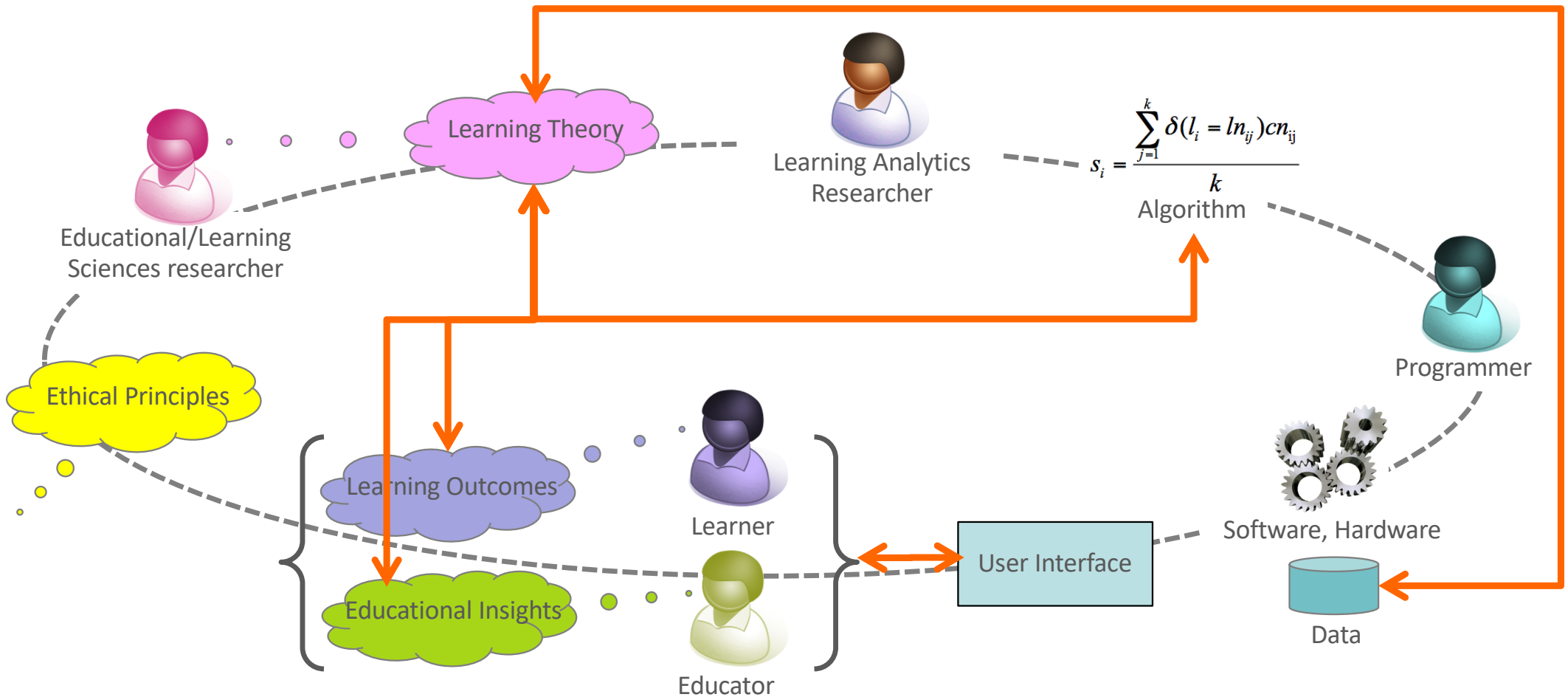
More detailed version…

LASI tutorial: http://simon.buckinghamshum.net/2019/11/black-box-learning-analytics

Elsewhere I have argued that this constitutes
a transition in education's knowledge infrastructure
and discuss different theory → analytics mappings

Simon Buckingham Shum

Professor of Learning Informatics, and
Director of Connected Intelligence Centre (CIC)
University of Technology, Sydney

ICLS Keynote

As part of the London Festival of Learning
27 June 2018, UCL Institute of Education

ICLS 2018 keynote: http://simon.buckinghamshum.net/2018/06/icls2018-keynote

Towards "data agreements" and "data shop stewards" with students and academics

Draft for consultation

UTS Learning Analytics Principles

Introduction: why we need this

Learning Analytics

Firstly, what do we mean by "Learning Analytics" at UTS?

Learning Analytics refers to the use of **data science and analytics** tools to analyse and improve education. However, the creation of productive, usable tools requires integrated expertise from other fields including **education, usability, instructional design and ethics**, with **input from the people expected to use the tools**, such as students and educators.

Learning Analytics may take into account **background data** about students and educators (e.g. nationality, educational history, gender, age), and **engagement data** (with the resources and tools on different websites at UTS).

Learning Analytics can be experienced **inside an existing UTS website** (e.g. Canvas) or as a **specialised website** (e.g. AcaWriter).

Learning Analytics can be used to support both **face-to-face and online** teaching and learning.

Data provides incomplete impressions of people, so important decisions aren't automated

People are complex, and live complex lives. Data gathered using Learning Analytics never provides the whole picture about someone's capability. In fact, we want students and teachers to demonstrate *creativity* — which may well not fit what an algorithm 'expects' to see based on what most people do. So data never "speaks for itself" (a common assumption) but requires interpretation in context. Humans will therefore always be involved in making significant decisions about individuals.

Data is historical, so we are alert to bias

Since data is always a picture of the past, data about people can reflect historic injustices (such as systemic inequalities in the kinds of people who have studied or taught at UTS). Knowing this, we ensure that Learning Analytics do not accidentally perpetuate those injustices: there should be no assumption that past demographics/behaviours determine how we interpret current data.

We equip our target audiences to make effective use of Learning Analytics

While many digital tools are meant to be usable without any training (e.g. retail websites and mobile phone apps), more complex tools do require training. The introduction of Learning Analytics tools will be supported by relevant development activities/resources, so that users are equipped to interpret the information displayed in order to take appropriate actions.

to conclude…

learning informatics

How does this lens translate into deploying Analytics/AI for learning?
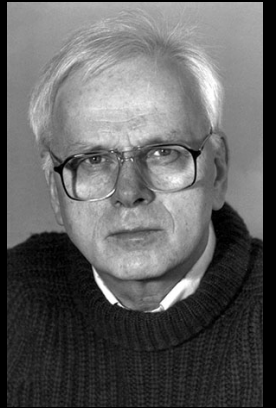
➡️ Design <u>socio</u>-technical systems

➡️ Design for educator and learner agency

➡️ Design for imperfect computational models

➡️ LA/AIED System Integrity > algorithmic accountability

Balancing and aligning the elements

T — Stakeholder Agency

R — Learning Design

U — User Experience

S — Organisational Strategy

T

Photo by Sean Stratton on Unsplash https://unsplash.com/photos/ObpCE_X3j6U