Learning analytics essentials

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MONASH University

COLAM
Centre for Learning Analytics Monash

Learner Analytics: Getting Back to Basics - SAAIR
25 April, 2022

What is learning analytics?

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1. What is your experience with learning analytics?
2. Could you use one word to describe learning analytics?

To participate, go to

flux.qa/L8HTFG

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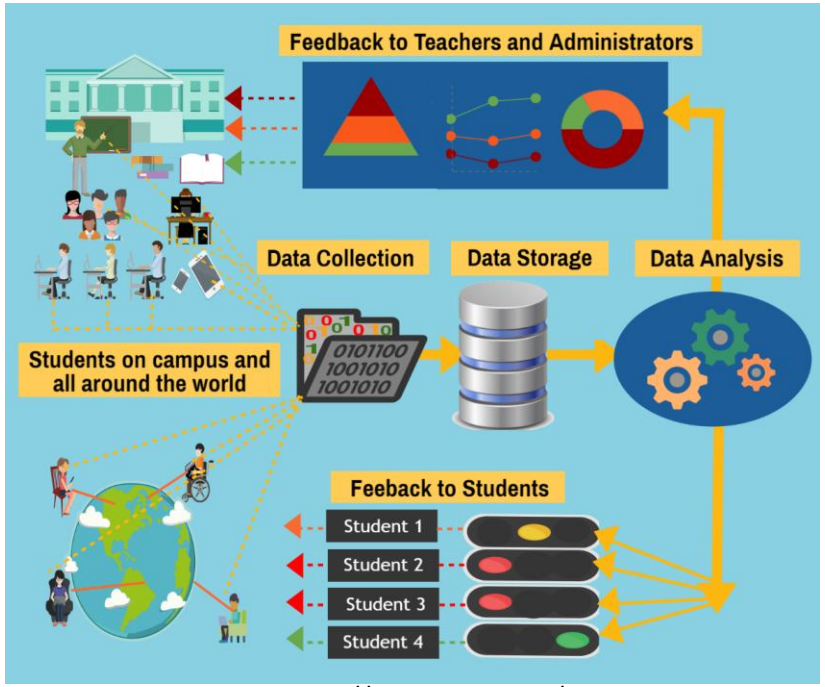
Learning analytics (LA) is…

"the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Long et al., 2011).



https://sheilaproject.eu/

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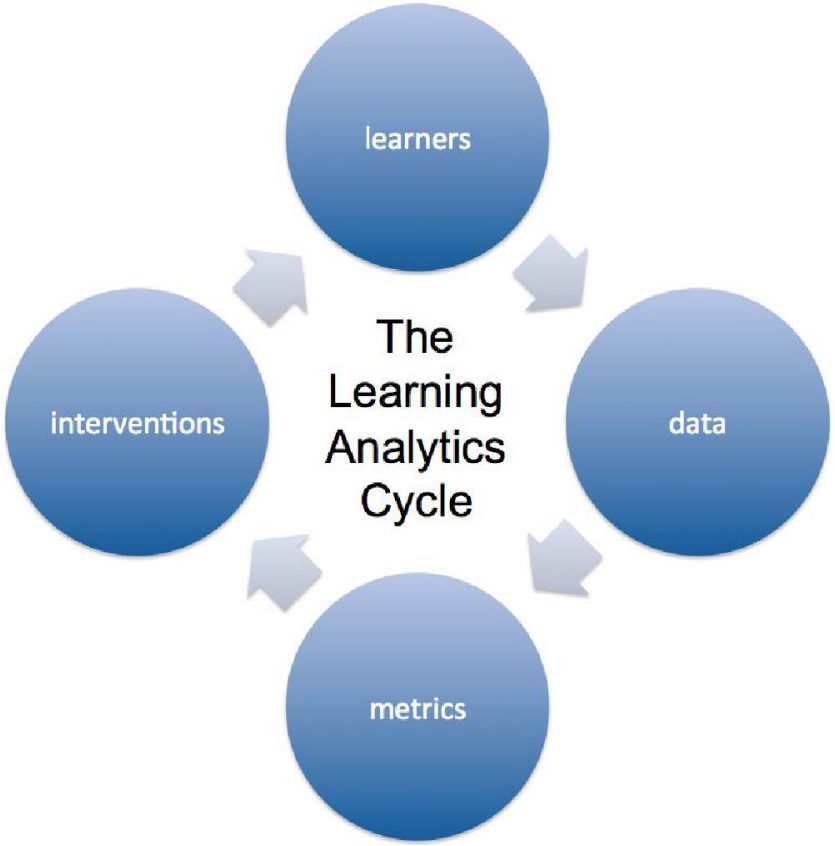
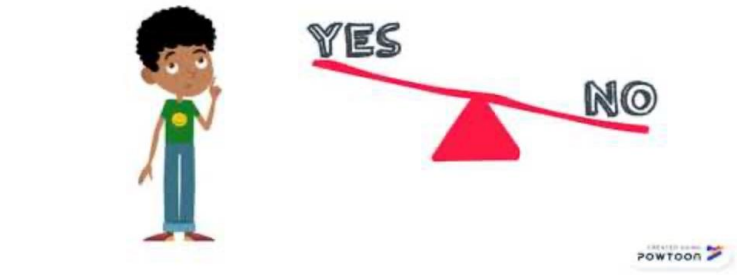
Long, P. D., Siemens, G., Conole, G., & Gašević, D. (Eds.). (2011). In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge (LAK'11)*. Banff, AB, Canada: ACM.

A learning analytics cycle

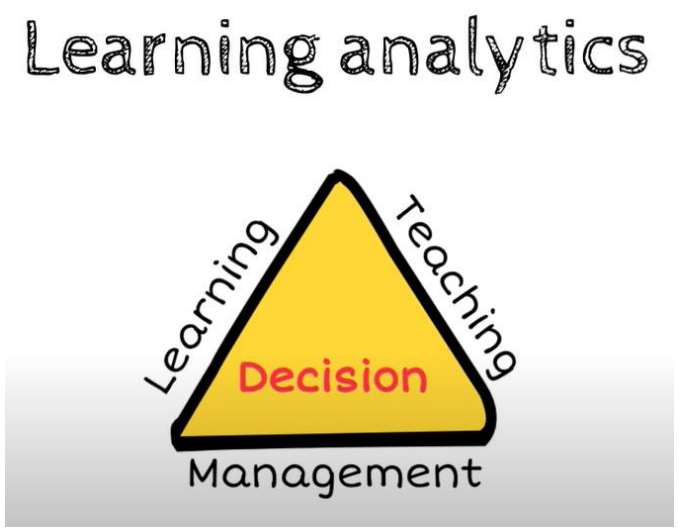


Clow, D. (2012, April). The learning analytics cycle: closing the loop effectively. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 134-138).



Learning analytics in a nutshell

http://bit.ly/la_intro



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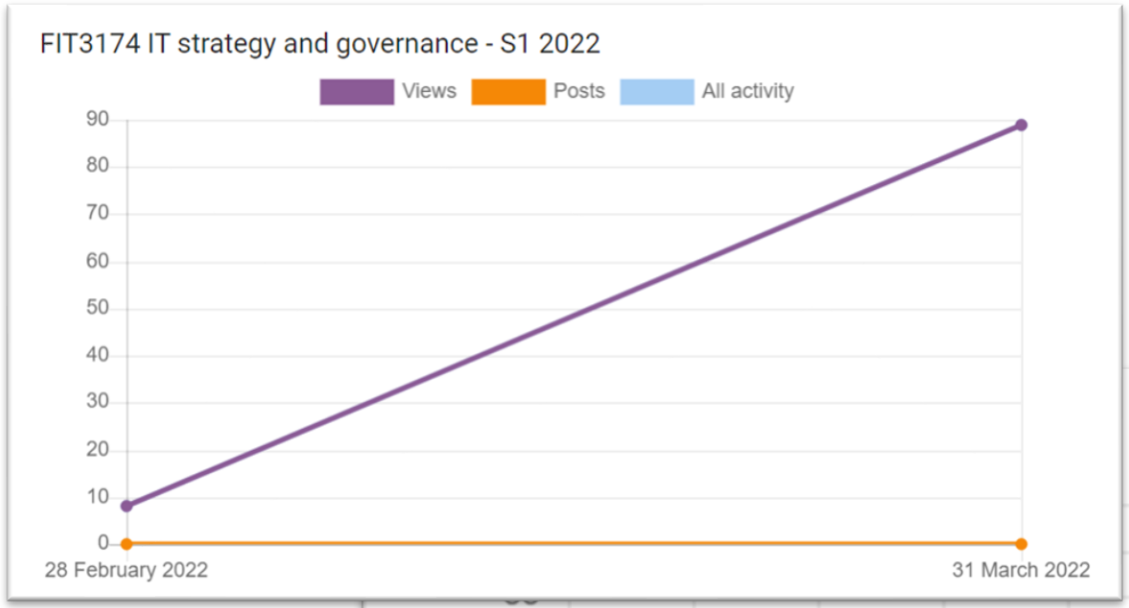
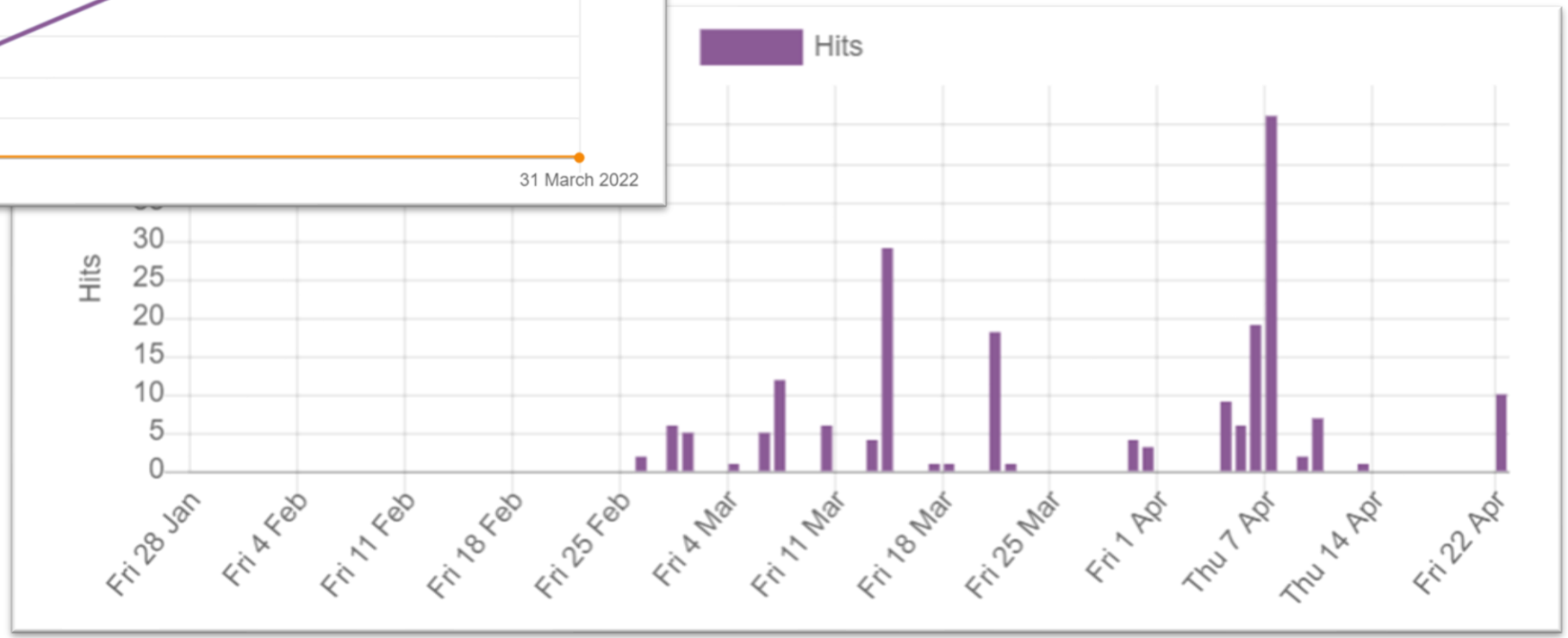
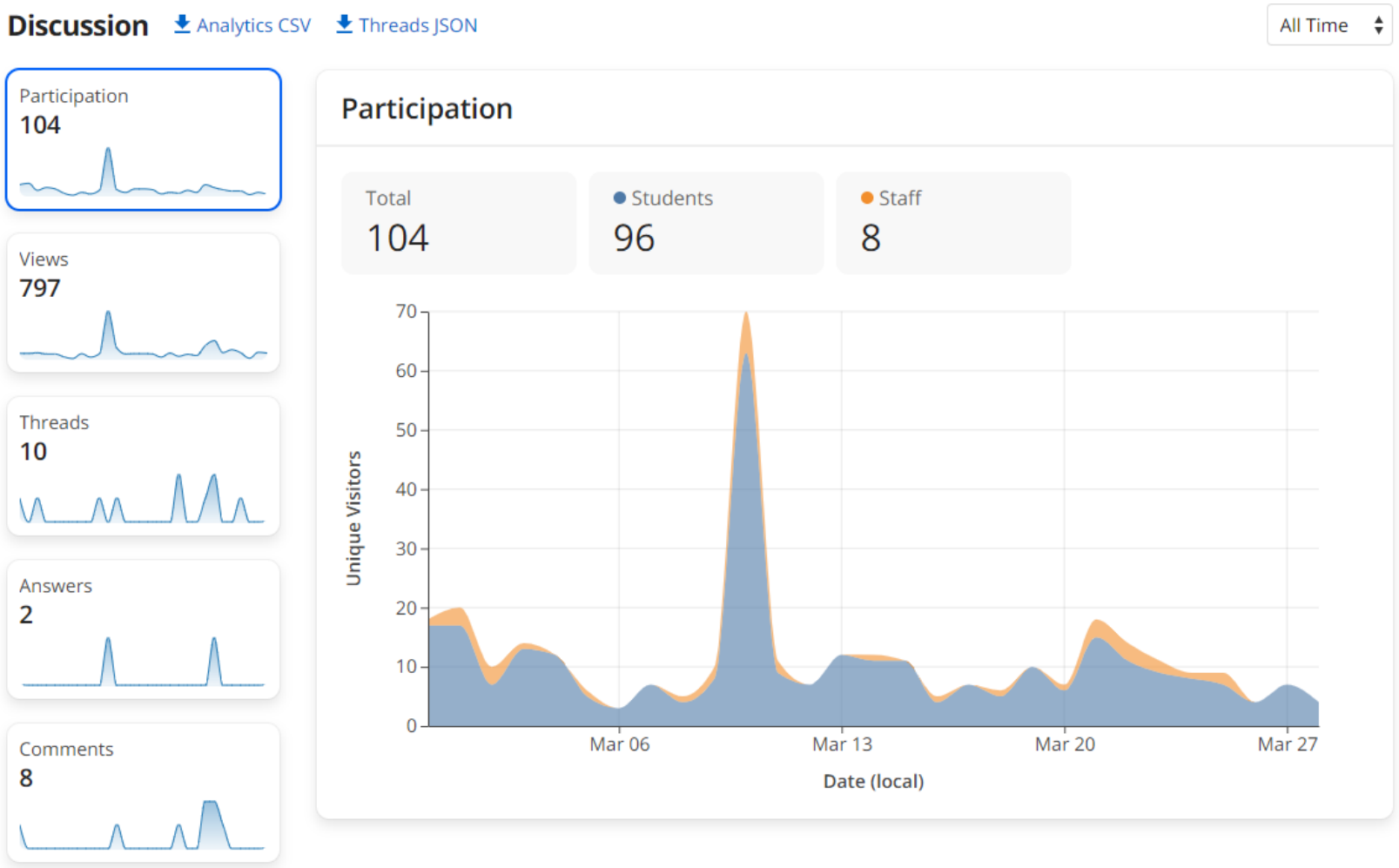
Moodle reports

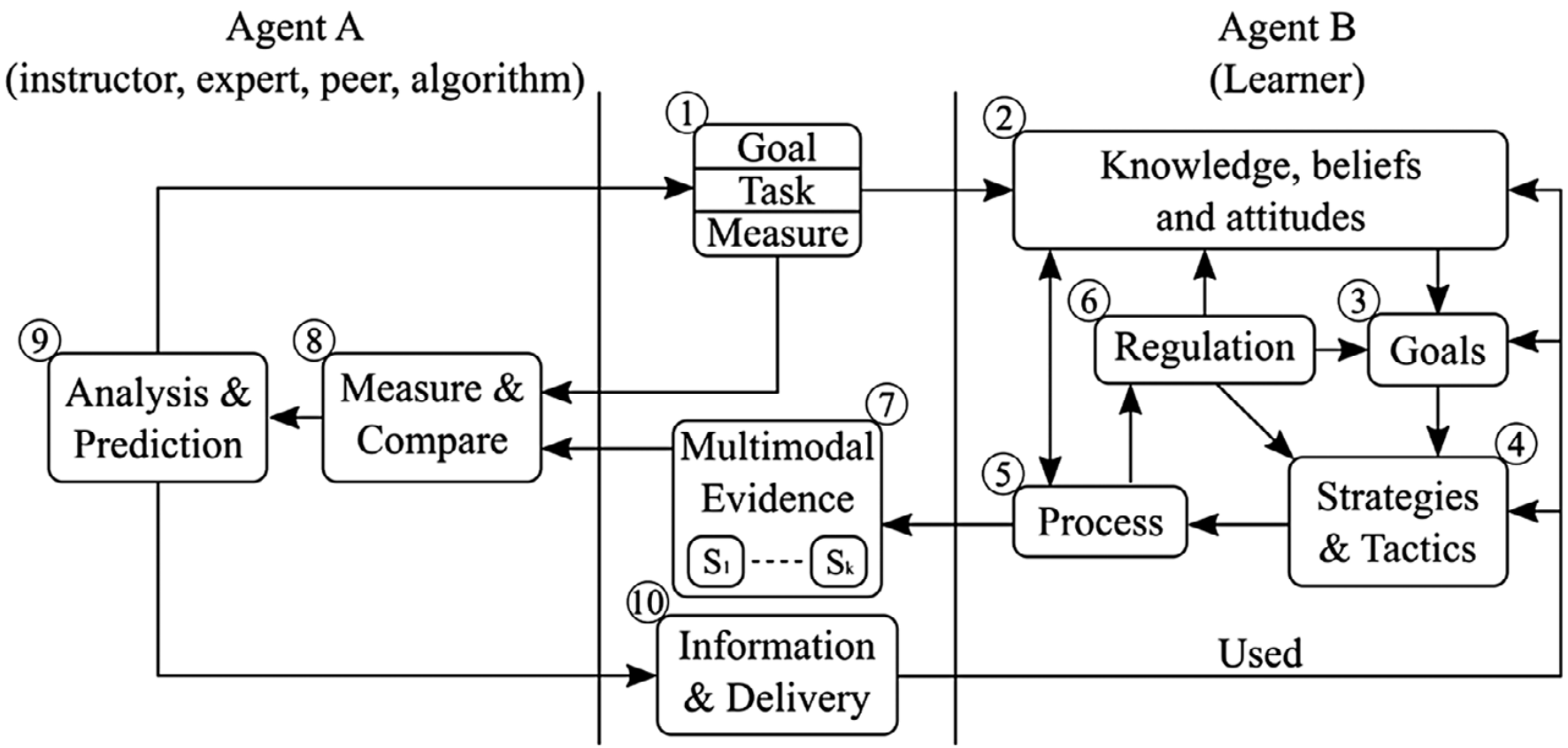




Ed Forum stats

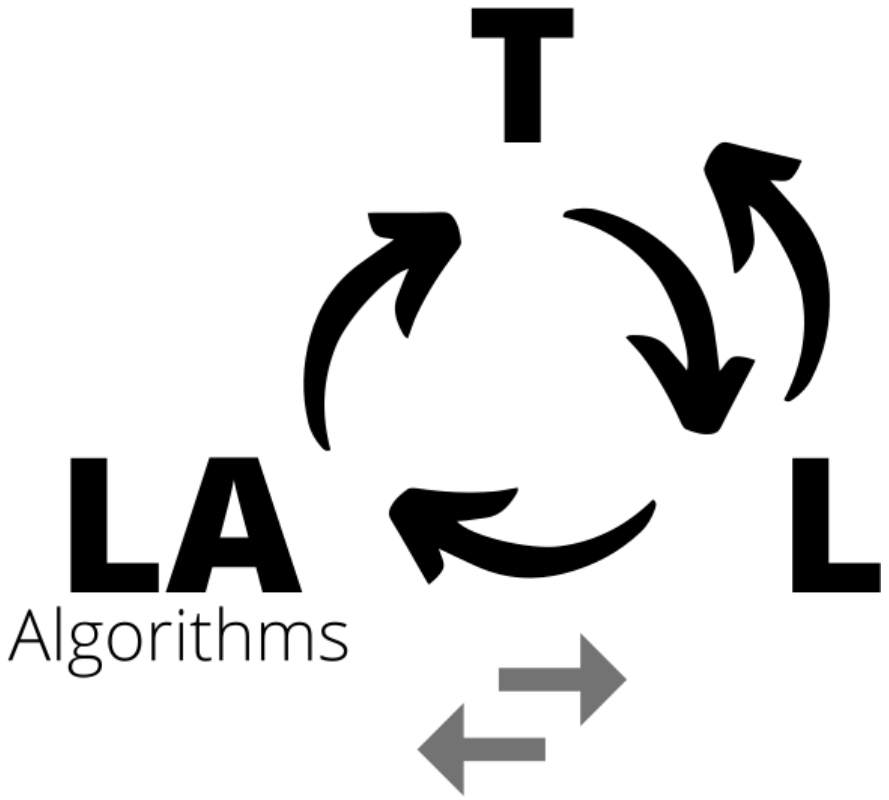


Learning analytics as feedback



Pardo, A. (2018). A feedback model for data-rich learning experiences. *Assessment & Evaluation in Higher Education*, *43*(3), 428-438.

Two types of feedback loops

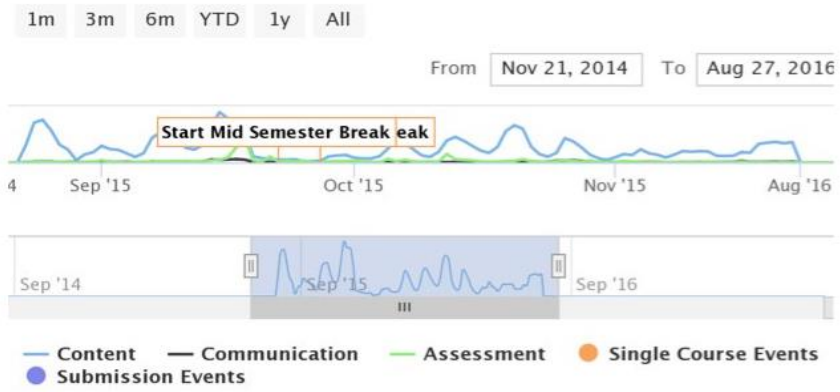


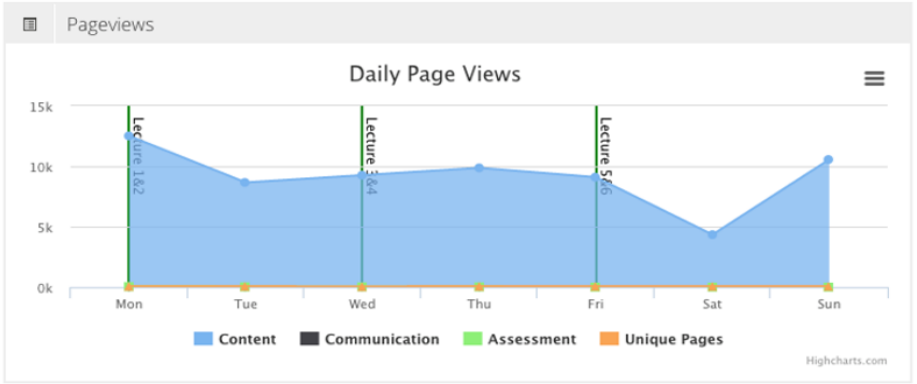
Tsai, Y. S. *(in press*). Why Feedback Literacy Matters for Learning Analytics. In *the 16th International Conference of the Learning Sciences (ICLS)*

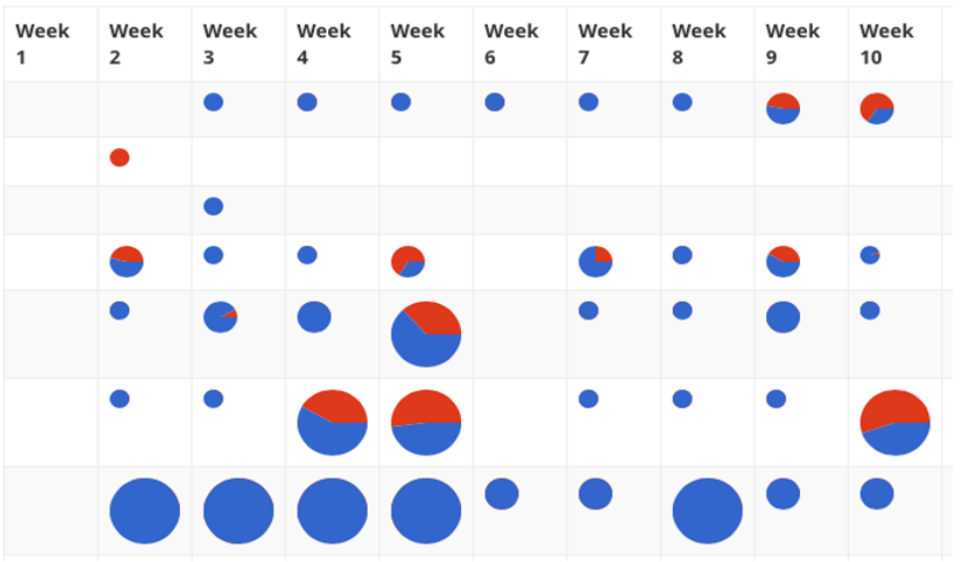
Examples of LA tools
- Feedback for teachers

Feedback for teachers - Loop

https://bit.ly/3qIr7TA



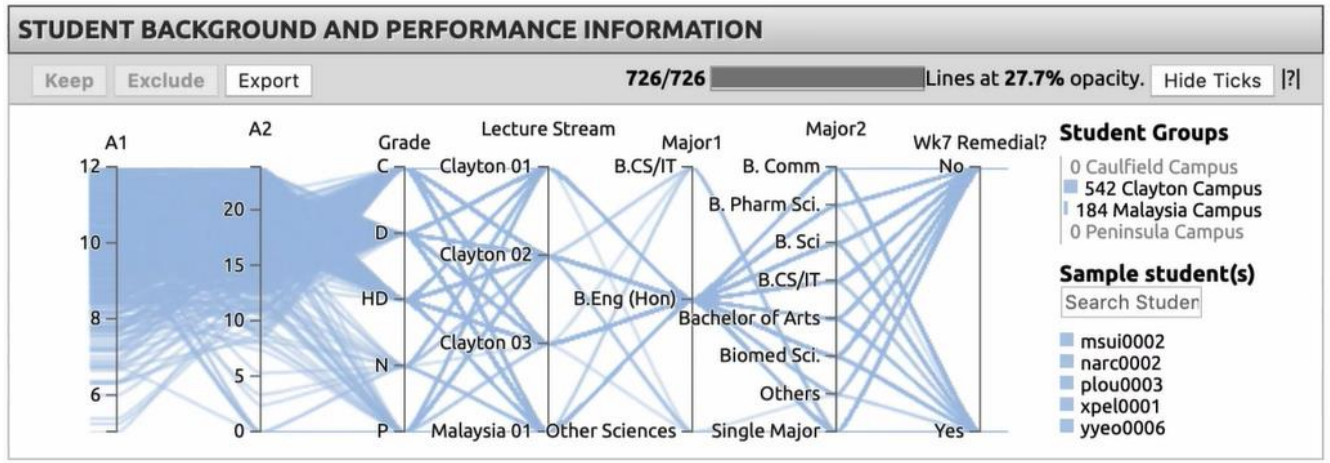


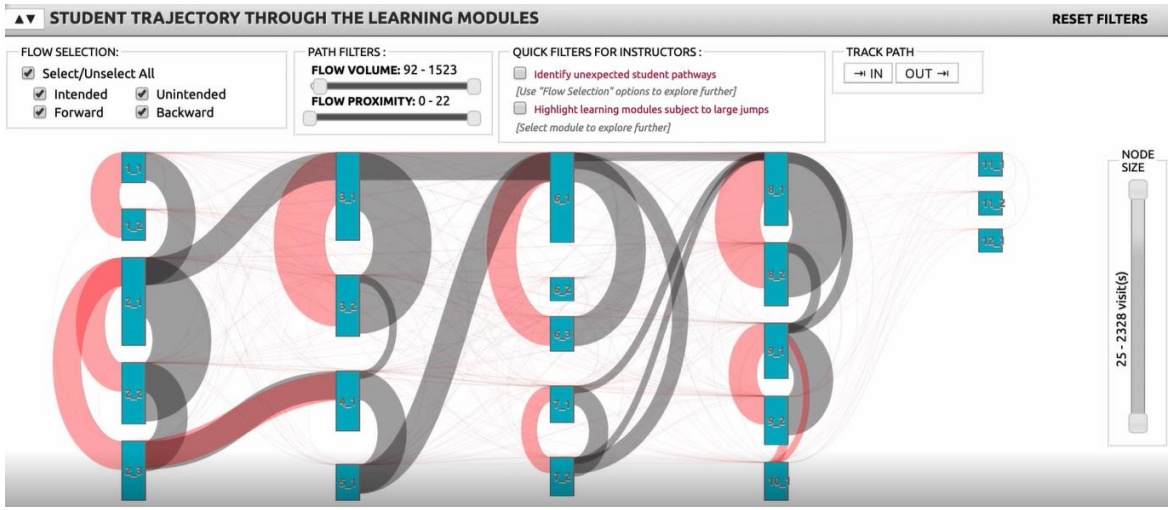


Corrin, L., Kennedy, G., de Barba, P., Bakharia, A., Lockyer, L., Gasevic, D., Williams, D., Dawson, S., & Copeland, S. (2015). *Loop: A learning analytics tool to provide teachers with useful data visualisations.* In T. Reiners, B.R. von Konsky, D. Gibson, V. Chang, L. Irving, & K. Clarke (Eds.), Globally connected, digitally enabled. Proceedings ascilite in Perth 2015 (pp. 409-413).

Feedback for teachers - UserFlow

https://vis.shaveensingh.com/userflow/





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Singh, S., Meyer, B., & Wybrow, M. (2020, June). UserFlow: A Tool for Visualizing Fine-grained Contextual Analytics in Teaching Documents. In *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education* (pp. 384-390).

Feedback for teachers - UserFlow

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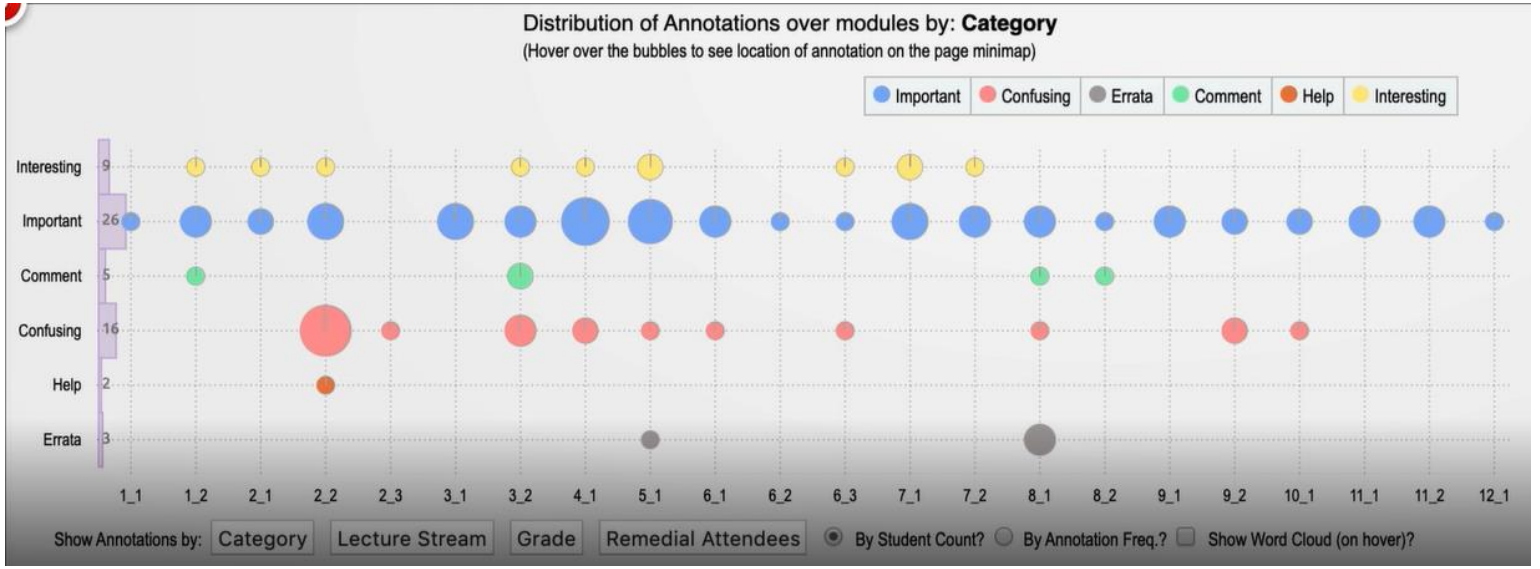

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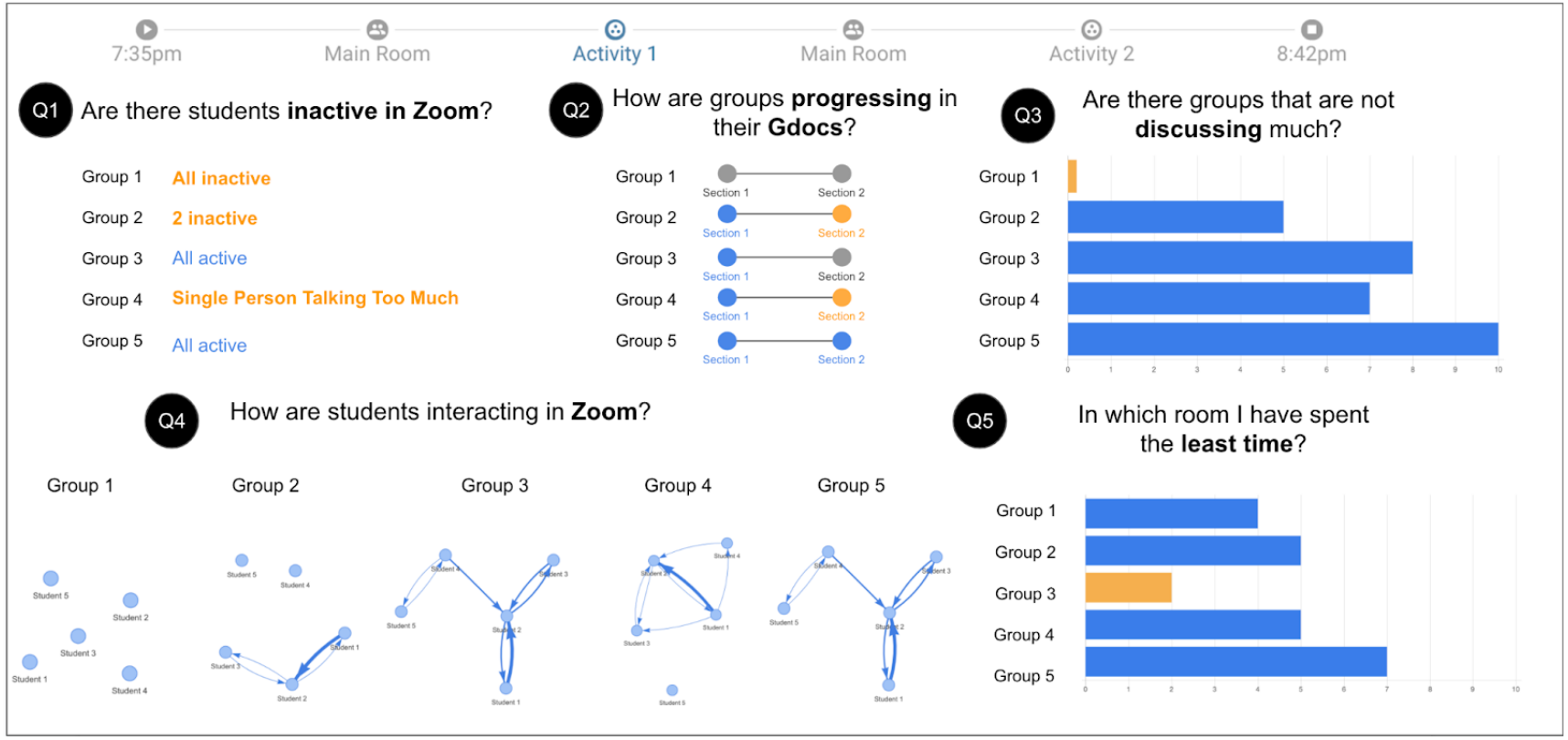
Singh, S., Meyer, B., & Wybrow, M. (2020, June). UserFlow: A Tool for Visualizing Fine-grained Contextual Analytics in Teaching Documents. In *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education* (pp. 384-390).

Feedback for teachers - ZoomSense

https://zoomsense.io/



Pozdniakov, S., Martinez-Maldonado, R., Tsai, Y. S., Cukurova, M., Bartindale, T., Chen, P., ... & Gasevic, D. (2022, March). The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry?. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (pp. 175-185).

Feedback for teachers – Course Signals

Goal: address retention

Predictive algorithm:

-Performance

-Effort

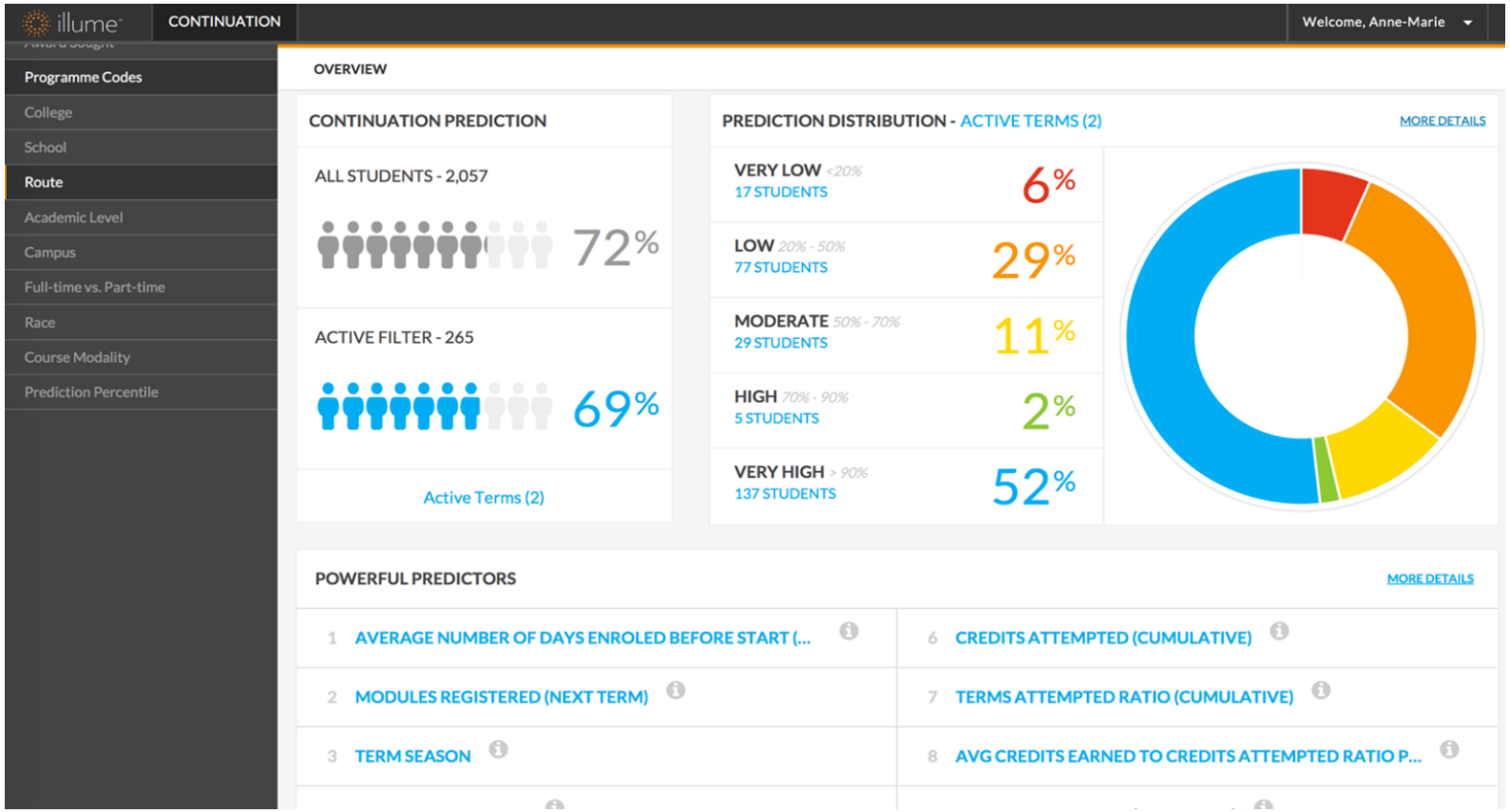
-Prior academic history

-Student characteristics

Arnold, K. E., & Pistilli, M. D. (2012, April). Course Signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267-270).

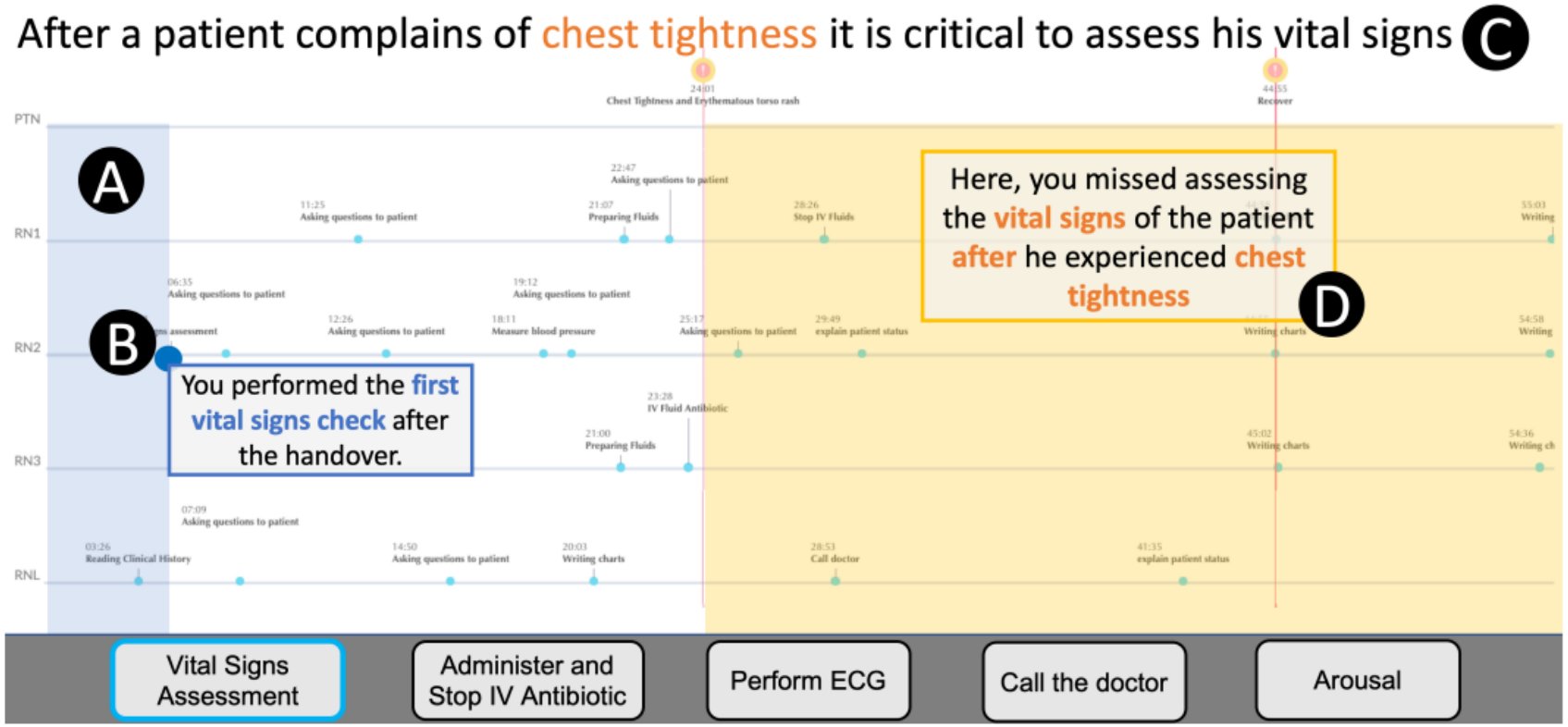
Feedback for teachers – Civitas

https://www.civitaslearning.com/



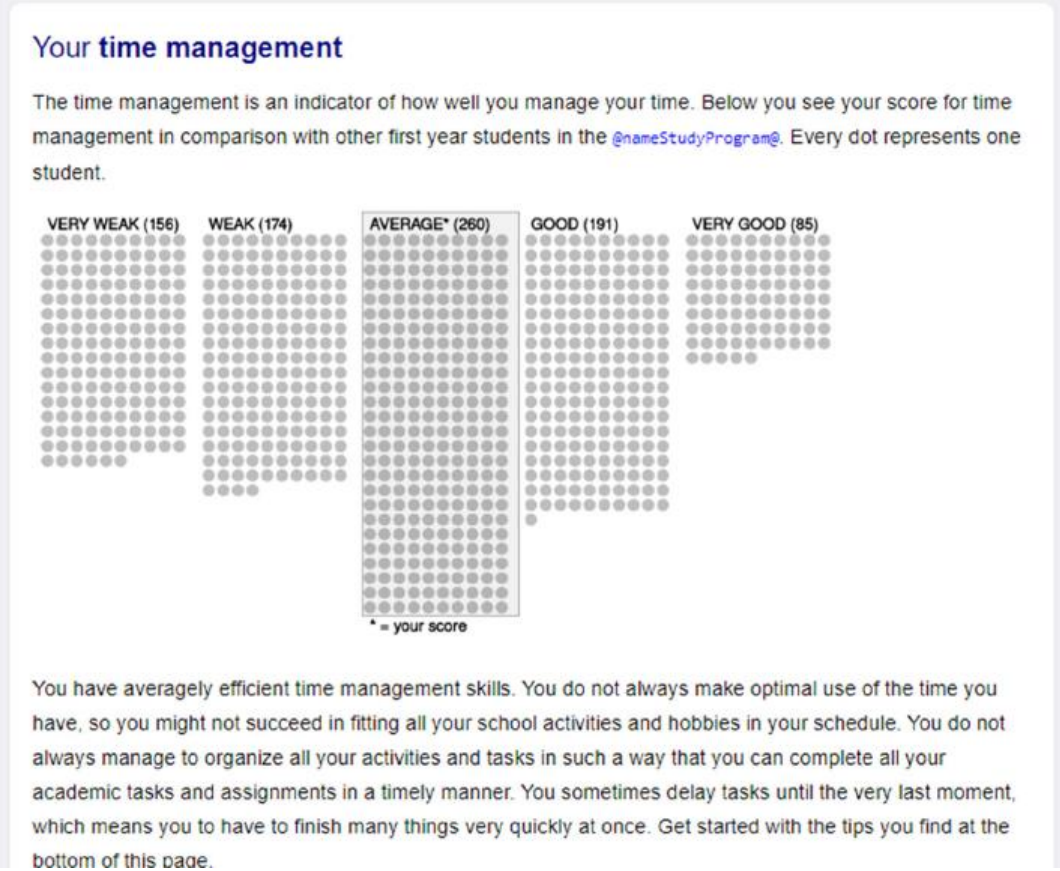
Examples of LA tools
- Feedback for students

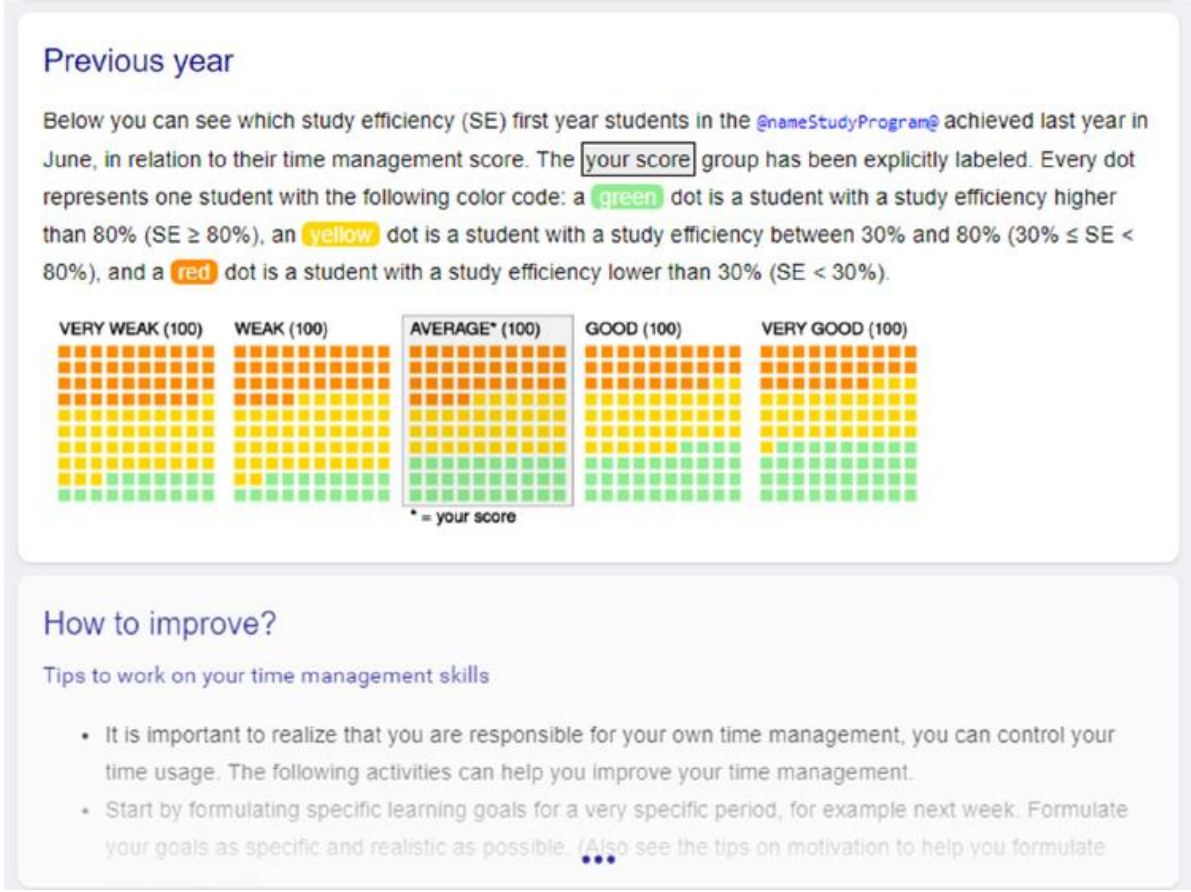
Feedback for teachers – Teamwork Analytics in Healthcare



Fernandez Nieto, G. M., Kitto, K., Buckingham Shum, S., & Martinez-Maldonado, R. (2022, March). Beyond the Learning Analytics Dashboard: Alternative Ways to Communicate Student Data Insights Combining Visualisation, Narrative and Storytelling. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (pp. 219-229).

Feedback for students – LASSI





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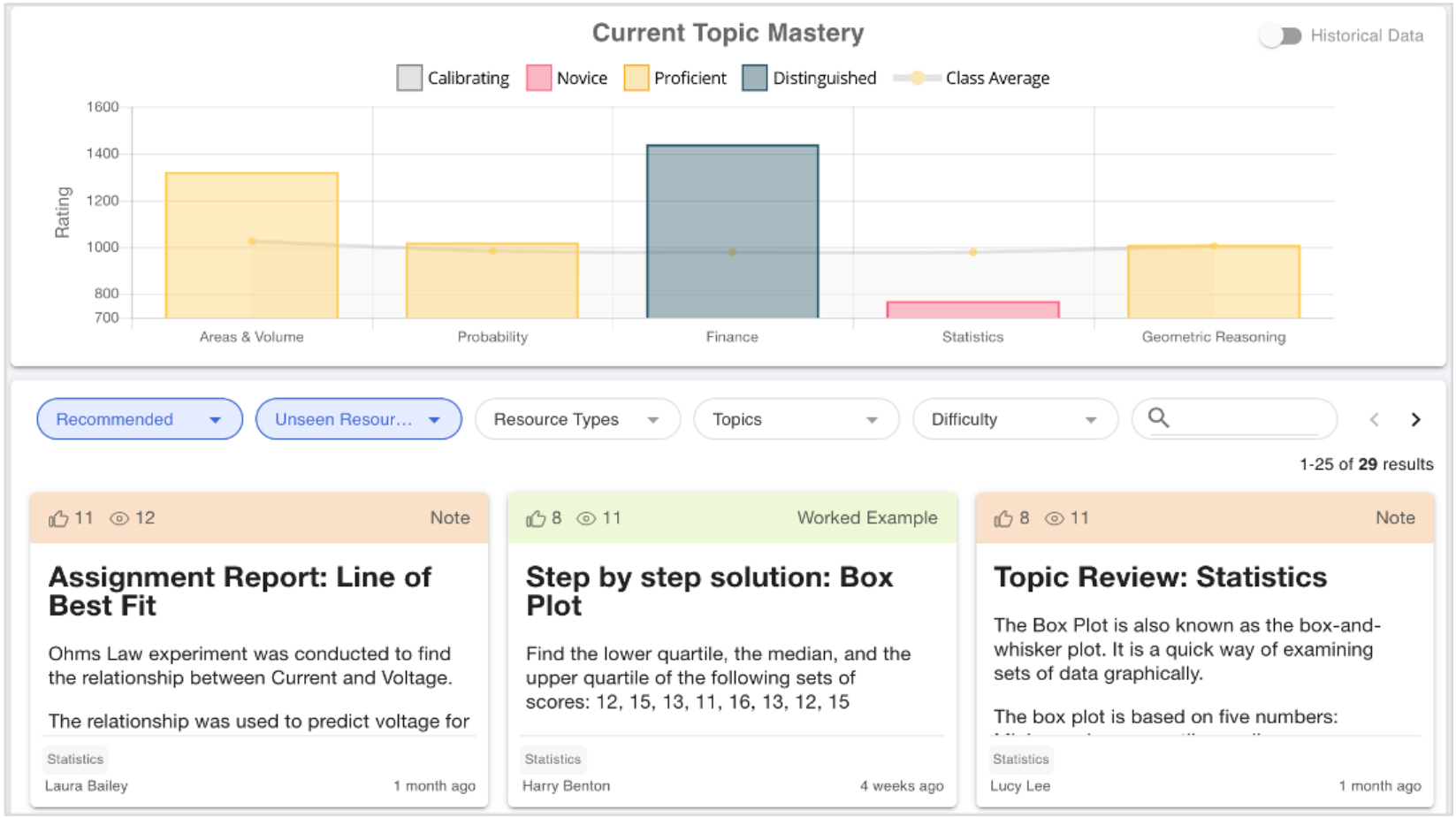
Broos, T., Pinxten, M., Delporte, M., Verbert, K., & De Laet, T. (2020). Learning dashboards at scale: early warning and overall first year experience. *Assessment & Evaluation in Higher Education*, *45*(6), 855-874.

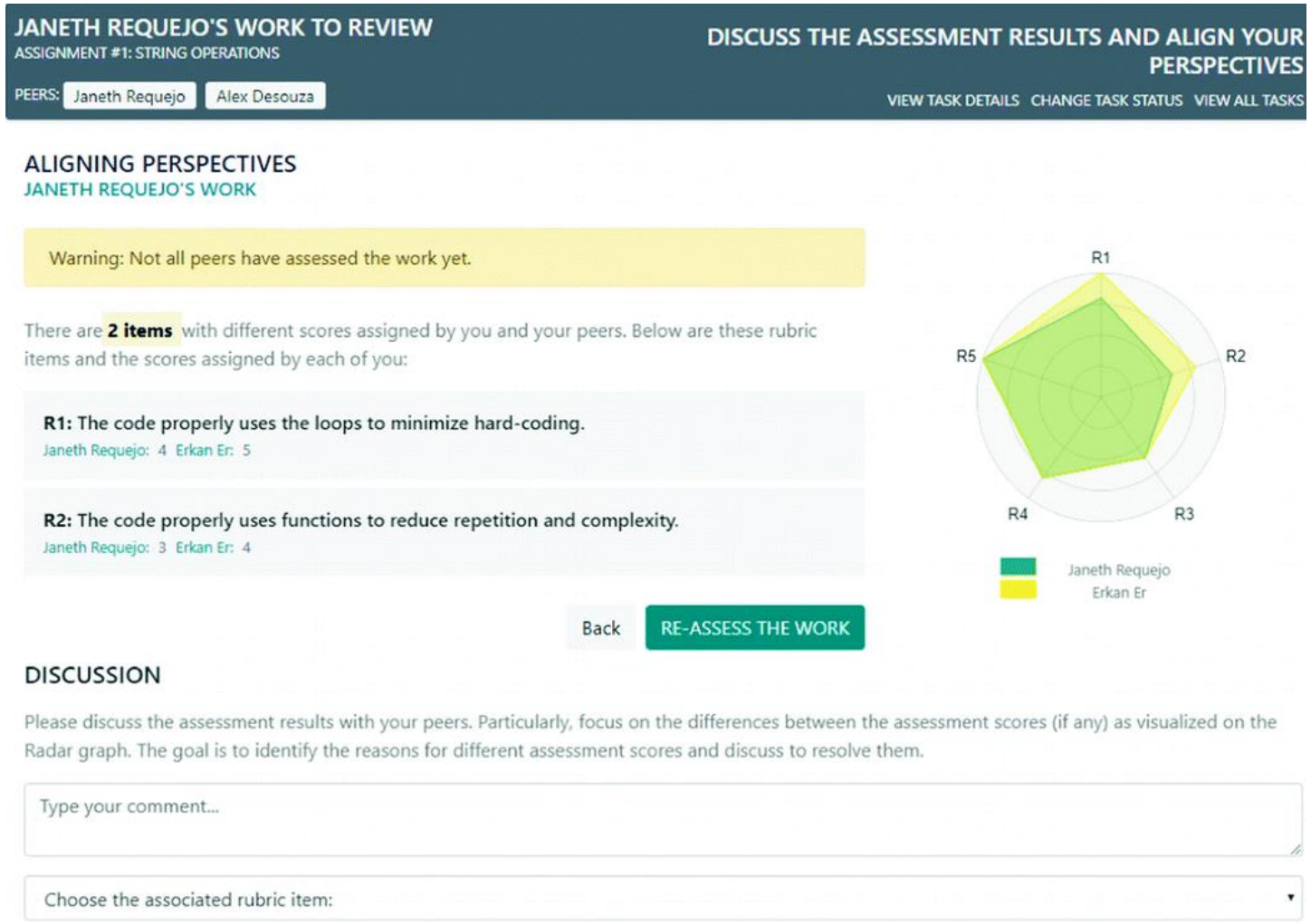
Feedback for students – RiPPLE

https://itali.uq.edu.au/digital-learning/learning-analytics/ripple



Khosravi, Hassan, Kitto, Kirsty and Williams, Joseph Jay (2019) RiPPLE: a crowdsourced adaptive platform for recommendation of learning activities. *Journal of Learning Analytics*, *6* 3: 91-105. https://doi.org/10.18608/jla.2019.63.12

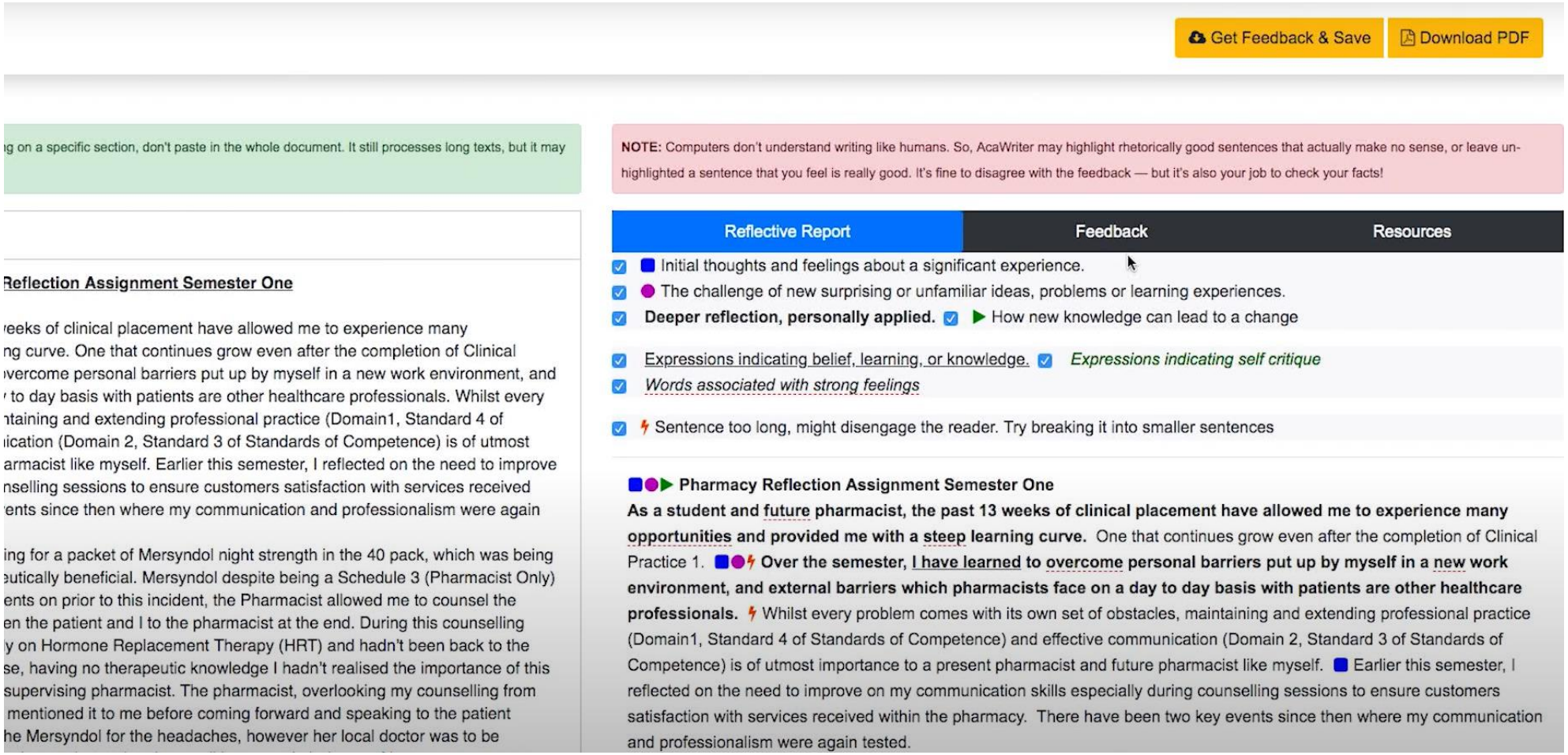
Feedback for students – Synergy

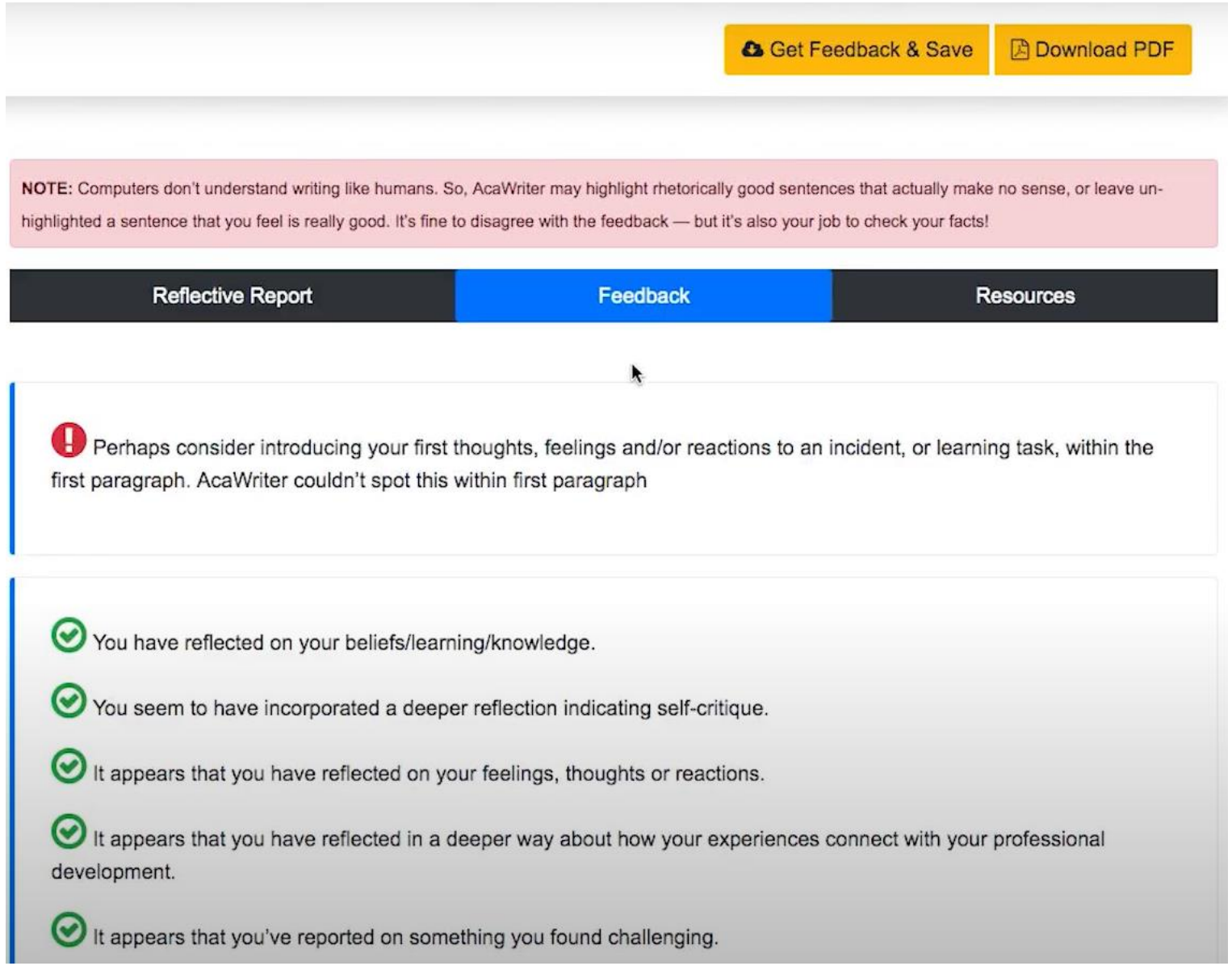


Er, E., Dimitriadis, Y., & Gašević, D. (2019, September). Synergy: A Web-Based Tool to Facilitate Dialogic Peer Feedback. In *European Conference on Technology Enhanced Learning* (pp. 709-713). Springer, Cham.

Feedback for students – AcaWriter

https://www.uts.edu.au/research-and-teaching/teaching-and-research-integration/acawriter




Get Feedback & Save
Download PDF
NOTE: Computers don't understand writing like humans. So, AcaWriter may highlight rhetorically good sentences that actually make no sense, or leave un-highlighted a sentence that you feel is really good. It's fine to disagree with the feedback — but it's also your job to check your facts!
Reflective Report
Feedback
Resources
Perhaps consider introducing your first thoughts, feelings and/or reactions to an incident, or learning task, within the first paragraph. AcaWriter couldn't spot this within first paragraph
You have reflected on your beliefs/learning/knowledge.
You seem to have incorporated a deeper reflection indicating self-critique.
It appears that you have reflected on your feelings, thoughts or reactions.
It appears that you have reflected in a deeper way about how your experiences connect with your professional development.
It appears that you've reported on something you found challenging.

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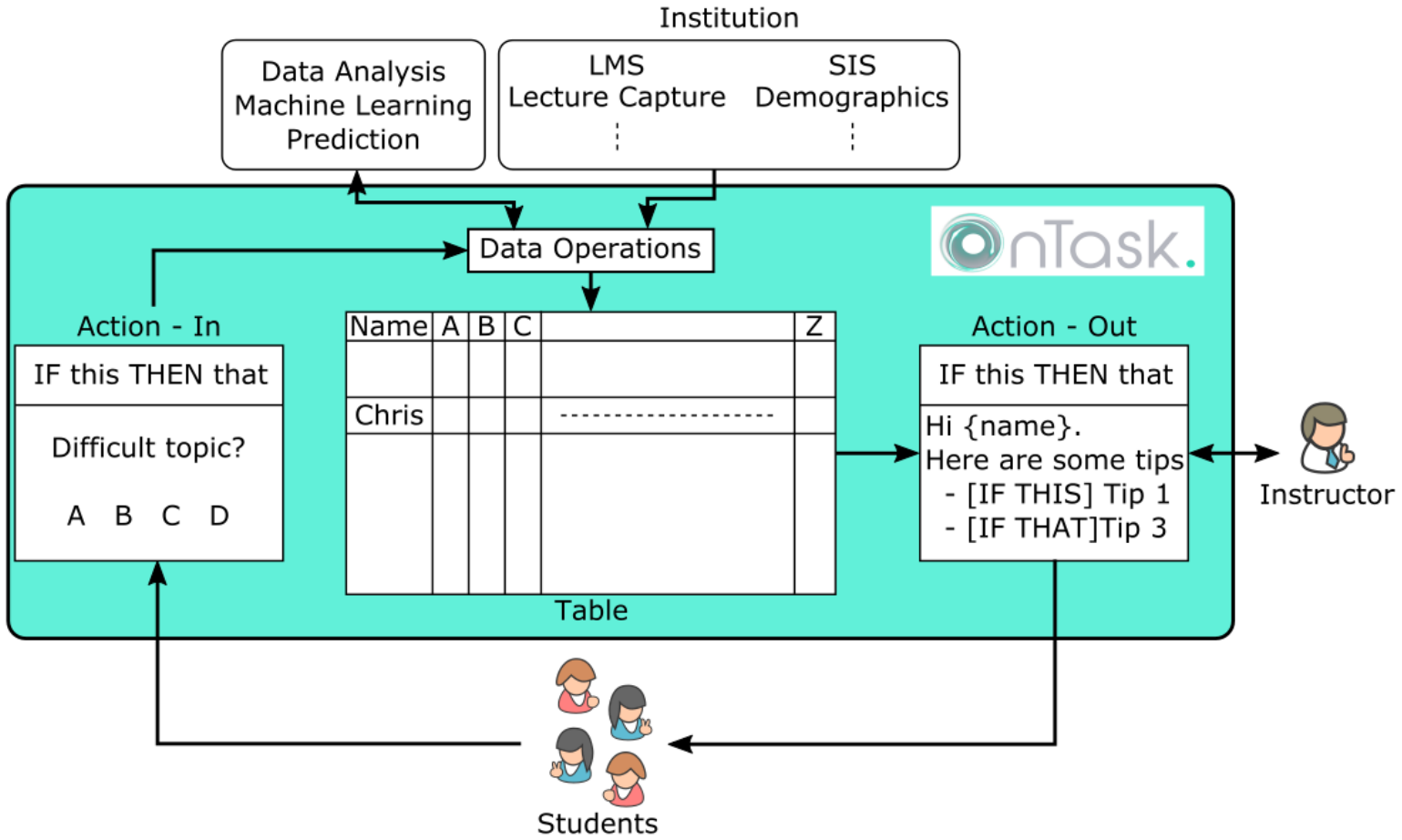
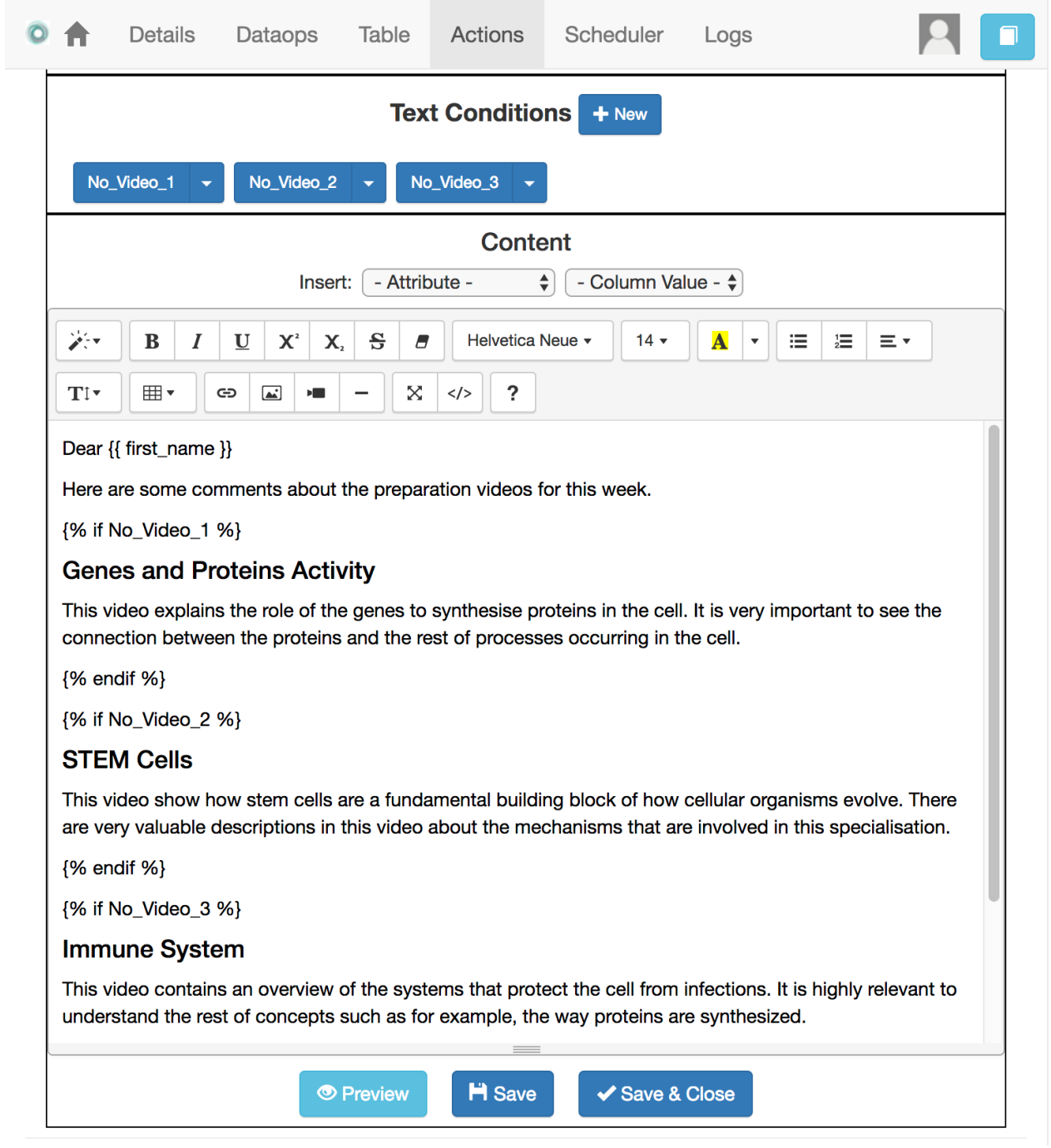
Feedback for students – OnTask

https://www.ontasklearning.org/



Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., & Mirriahi, N. (2019). Using Learning Analytics to Scale the Provision of Personalised Feedback. *British Journal of Educational Technology*, *50*(1), 128–138. https://doi.org/10.1111/bjet.12592


Details
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Text Conditions
+ New
No_Video_1
No_Video_2
No_Video_3
Content
Insert:
- Attribute -
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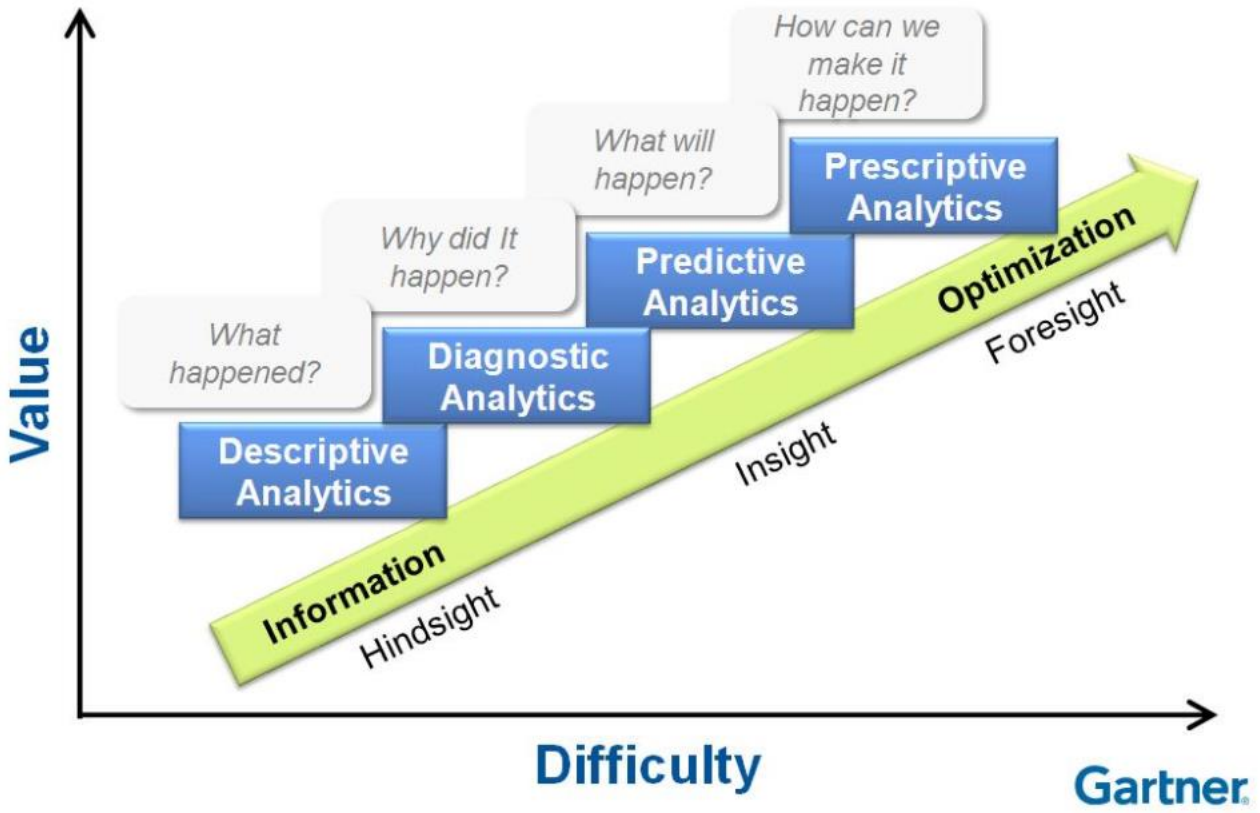
Helvetica Neue
14
Dear {{ first_name }}
Here are some comments about the preparation videos for this week.
{% if No_Video_1 %}
Genes and Proteins Activity
This video explains the role of the genes to synthesise proteins in the cell. It is very important to see the connection between the proteins and the rest of processes occurring in the cell.
{% endif %}
{% if No_Video_2 %}
STEM Cells
This video show how stem cells are a fundamental building block of how cellular organisms evolve. There are very valuable descriptions in this video about the mechanisms that are involved in this specialisation.
{% endif %}
{% if No_Video_3 %}
Immune System
This video contains an overview of the systems that protect the cell from infections. It is highly relevant to understand the rest of concepts such as for example, the way proteins are synthesized.
Preview
Save
Save & Close

Learning analytics methodologies



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https://blogs.gartner.com/matthew-davis/top-10-moments-from-gartners-supply-chain-executive-conference/

Why type of learning analytics is the most useful to you?

To participate, go to

flux.qa/L8HTFG

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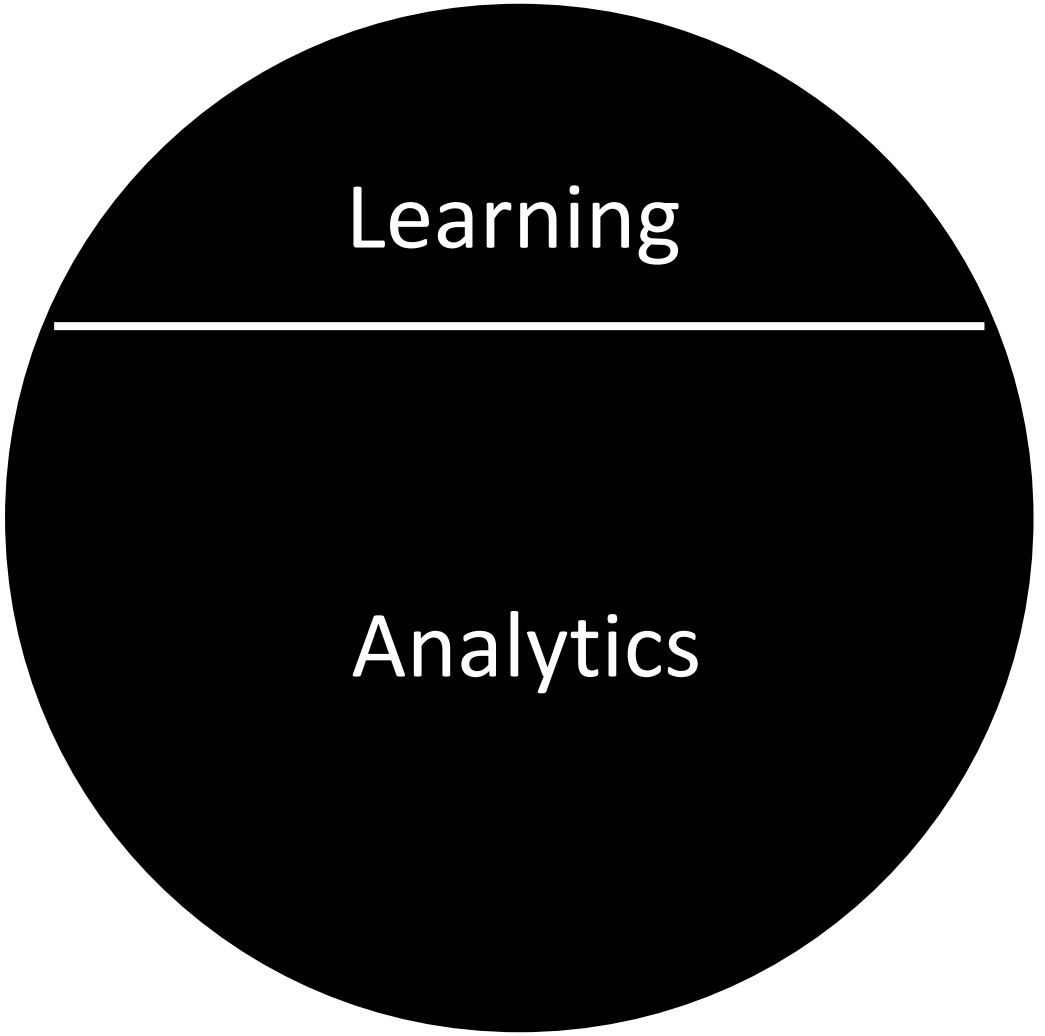
Challenges & Responses



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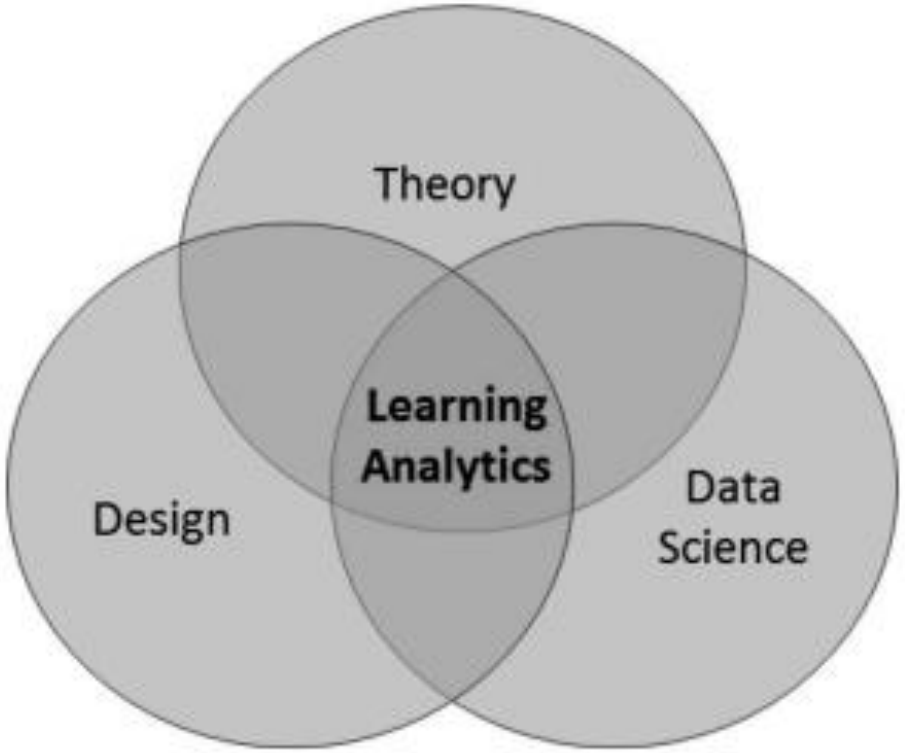
Learning analytics is interdisciplinary



Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: A consolidated model of a field of research and practice. *Learning: Research and Practice*, *3*(1), 63-78.

Let's not forget: Learning analytics are about learning

By Dragan Gašević, University of Edinburgh, Shane Dawson, University of South Australia, George Siemens, University of Texas at Arlington

©Association for Educational Communications and Technology 2015

Abstract

The analysis of data collected from the interaction of users with educational and information technology has attracted much attention as a promising approach for advancing our understanding of the learning process. This promise motivated the emergence of the new research field, learning analytics, and its closely related discipline, educational data mining. This paper first introduces the field of learning analytics and outlines the lessons learned from well-known case studies in the research literature. The paper then identifies the critical topics that require immediate research attention for learning analytics to make a sustainable impact on the research and practice of learning and teaching. The paper concludes by discussing a growing set of issues that if unaddressed, could impede the future maturation of the field. The paper stresses that learning analytics are about learning. As such, the computational aspects of learning analytics must be well integrated within the existing educational research.

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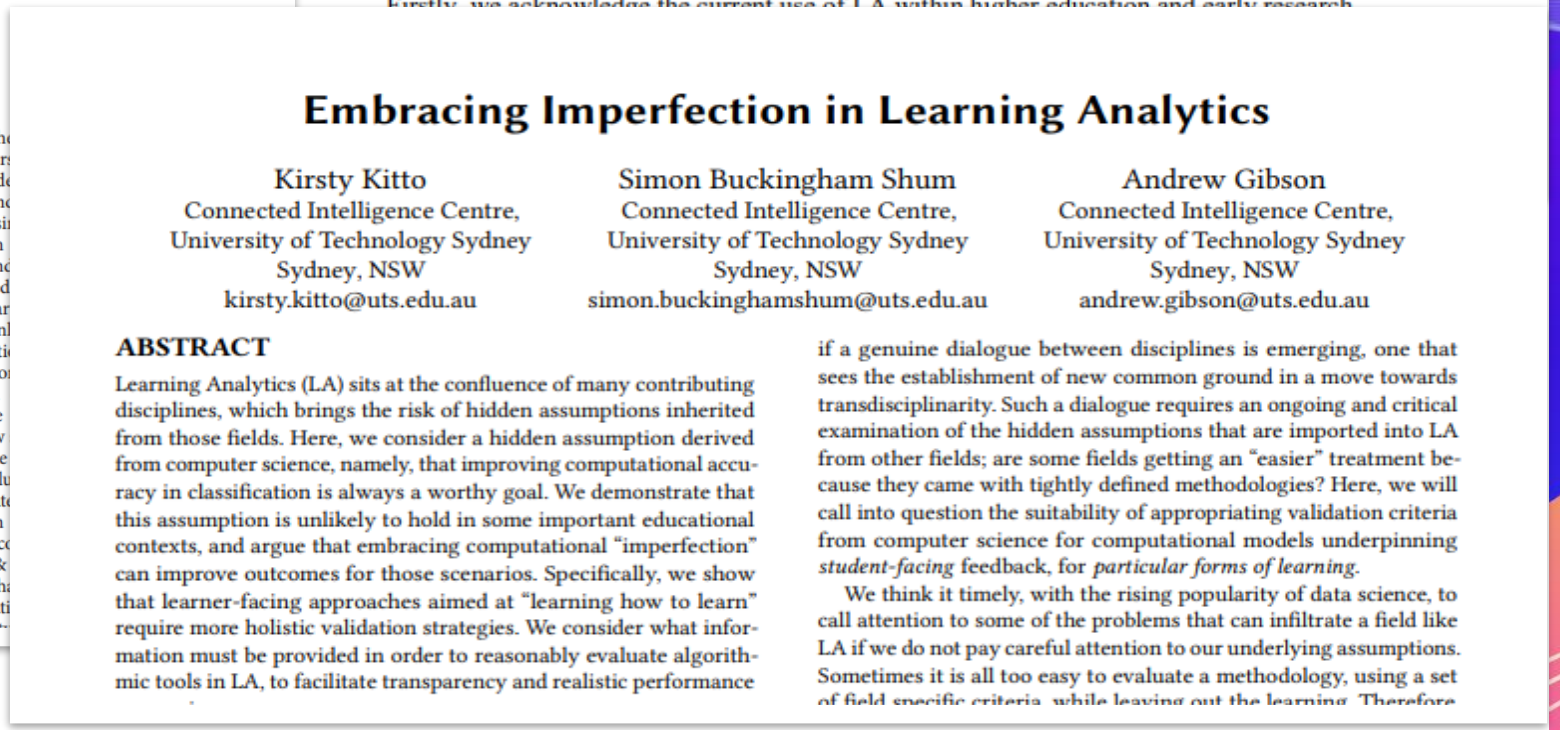
Pigeon pecks and mouse clicks: Putting the learning back into learning analytics

Jason Lodge
Griffith University

Melinda Lewis
The University of Sydney

Learning in higher education can be described as a series of complex tasks and stages of development requiring a range of multifaceted behaviours and ways-of-being. Understanding what contributes to teaching for quality learning and achieving quality learning outcomes in higher education has been the topic of much debate over many decades. The current paper intends to situate and contextualise learning analytics (LA) within a broader debate on quality and student experience, outlining the affordances and constraints of this data-driven approach to quality.



Embracing Imperfection in Learning Analytics

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ABSTRACT

Learning Analytics (LA) sits at the confluence of many contributing disciplines, which brings the risk of hidden assumptions inherited from those fields. Here, we consider a hidden assumption derived from computer science, namely, that improving computational accuracy in classification is always a worthy goal. We demonstrate that this assumption is unlikely to hold in some important educational contexts, and argue that embracing computational "imperfection" can improve outcomes for those scenarios. Specifically, we show that learner-facing approaches aimed at "learning how to learn" require more holistic validation strategies. We consider what information must be provided in order to reasonably evaluate algorithmic tools in LA, to facilitate transparency and realistic performance

if a genuine dialogue between disciplines is emerging, one that sees the establishment of new common ground in a move towards transdisciplinarity. Such a dialogue requires an ongoing and critical examination of the hidden assumptions that are imported into LA from other fields; are some fields getting an "easier" treatment because they came with tightly defined methodologies? Here, we will call into question the suitability of appropriating validation criteria from computer science for computational models underpinning *student-facing* feedback, for *particular forms of learning*.

We think it timely, with the rising popularity of data science, to call attention to some of the problems that can infiltrate a field like LA if we do not pay careful attention to our underlying assumptions. Sometimes it is all too easy to evaluate a methodology, using a set

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64-71.

Lodge, J., & Lewis, M. (2012). Pigeon pecks and mouse clicks: Putting the learning back into learning analytics.

Kitto, K., Shum, S. B., & Gibson, A. (2018, March). Embracing imperfection in learning analytics. In Proceedings of the 8th International Conference on Learning Analytics and Knowledge (pp. 451-460).

Learning Context matters

Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success

Dragan Gašević [a,b,*], Shane Dawson [b], Tim Rogers [b], Danijela Gasevic [c]

[a] Moray House School of Education and School of Informatics, University of Edinburgh, United Kingdom
[b] Teaching Innovation Unit, University of South Australia, Australia
[c] Usher Institute of Population Health Sciences and Informatics, University of Edinburgh, United Kingdom

ABSTRACT

This study examined the extent to which instructional conditions influence the prediction of academic success in nine undergraduate courses offered in a blended learning model (n = 4134). The study illustrates the differences in predictive power and significant predictors between course-specific models and generalized predictive models. The results suggest that it is imperative for learning analytics research to account for the diverse ways technology is adopted and applied in course-specific contexts. The differences in technology use, especially those related to whether and how learners use the learning management system, require consideration before the log-data can be merged to create a generalized model for predicting academic success. A lack of attention to instructional conditions can lead to an over or under estimation of the effects of LMS features on students' academic success. These findings have broader implications for institutions seeking generalized and portable models for identifying students at risk of academic failure.

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Towards the implementation of a countrywide K-12 learning analytics initiative in Uruguay

Luiz Antonio Macarini [a], Henrique Lemos dos Santos [b], Cristian Cechinel [a], Xavier Ochoa [c], Virgínia Rodés [d], Alén Pérez Casas [d], Pedro Pablo Lucas [e], Ricardo Maya [e], Guillermo Ettlin Alonso [f], and Patricia Díaz [f]

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ABSTRACT

The present work describes the challenges faced during the development of a countrywide Learning Analytics study and tool focused on tracking and understanding the trajectories of Uruguayan students during their first three years of secondary education. Due to the large scale of the project, which covers an entire national educational system, several challenges and constraints were faced during its conception and development. Examples of key challenges were: to understand the different nuances of the educational system, to satisfy ethical and legal requirements without narrowing down the scope and potential novelty of the initiative and to deal with integration and inconsistencies in the databases. This paper presents the design decisions and solutions found to address or mitigate the problems found as a contribution to facilitate similar large-scale projects. Three main experiments using data mining were conducted and their results are also described, pointing out the feasibility of finding meaningful patterns that can be used by educational authorities to improve their decision making and foster public educational policies. Finally, the paper describes the use of the data and the findings of the study to create an interactive visual tool to explore the relationship between student variables, performance and persistence in the system.

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Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68-84.

Macarini, L. A., Lemos dos Santos, H., Cechinel, C., Ochoa, X., Rodés, V., Pérez Casas, A., ... & Díaz, P. (2020). Towards the implementation of a countrywide K-12 learning analytics initiative in Uruguay. *Interactive Learning Environments*, *28*(2), 166-190.

Learning Context matters

Charting Design Needs and Strategic Approaches for Academic Analytics Systems through Co-Design

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ABSTRACT

Academic analytics focuses on collecting, analysing and visualising educational data to generate institutional insights and improve decision-making for academic purposes. However, challenges that arise from navigating a complex organisational structure when introducing analytics systems have called for the need to engage key stakeholders widely to cultivate a shared vision and ensure that implemented systems create desired value. This paper presents a study that takes co-design steps to identify design needs and strategic approaches for the adoption of academic analytics, which serves the purpose of enhancing the measurement of educational quality utilising institutional data. Through semi-structured interviews with 54 educational stakeholders at a large research university, we identified particular interest in measuring student engagement and the performance of courses and programmes. Based on the observed perceptions and concerns regarding data use to measure or evaluate these areas, implications for adoption strategy of academic analytics, such as leadership involvement, communication, and training, are discussed.

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1 INTRODUCTION

The extensive amount of student data generated at higher educational institutions have opened up opportunities for educational stakeholders at different administrative levels (e.g., institutional leaders and academic leads) to gain insights into student experience and the effectiveness of teaching [50]. This, in turn, can inform future decision-making processes related to the overall design of academic curricula and educational environment, thereby enhancing student success and experience [2, 19]. The process of collecting, analysing and visualising educational data to generate institutional insights for the purpose of improving institutional decisions in academic matters is generally understood as academic analytics [30], which is inseparable from learning analytics, a field that leverages data generated by learners in a learning context (e.g., patterns of access to learning materials) to understand and optimise learning processes [43].

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Tsai, Y. S., Singh, S., Rakovic, M., Lim, L. A., Roychoudhury, A., & Gasevic, D. (2022, March). Charting Design Needs and Strategic Approaches for Academic Analytics Systems through Co-Design. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (pp. 381-391).

"Often there's all this focus on providing information without any sense of understanding whether this is impactful or enabling action. Okay, so **impactful would be.... the data that you provide is directly aligned with the questions that the people are wanting to ask**. Not, obviously, superimposing questions." – P1F2-R4

Institutional processes	Faculty N = 9	Reference N = 128
Data availability	9	25
Data integration	9	22
Indicators of educational quality	7	36
Data presentation	7	18
Precision & Accuracy	5	10
Ethics & Privacy	2	6
Timing	2	5
Communication	3	5
Funding	1	1

(a) Challenges related to institutional processes

stakeholders	Faculty N = 9	Reference N = 47
Workload	8	15
Awareness & Capability	5	22
Distrust	5	9
Autonomy	1	1

(b) Challenges related to stakeholders

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"Fetishizing of data is not healthy. I know university higher-up bureaucrats love it, you know, they've got numbers, but **numbers are flawed, it depends on what you're measuring**.... And some of that require professional and expert understanding of the communities that your faculty serve.... University generated data has no relevance to that, really." – P1F5-R1

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(b) Challenges related to stakeholders

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People matter

Privacy and Analytics – it's a DELICATE Issue
A Checklist for Trusted Learning Analytics

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ABSTRACT

The widespread adoption of Learning Analytics (LA) and Educational Data Mining (EDM) has somewhat stagnated recently, and in some prominent cases even been reversed following concerns by governments, stakeholders and civil rights groups about privacy and ethics applied to the handling of personal data. In this ongoing discussion, fears and realities are often indistinguishably mixed up, leading to an atmosphere of uncertainty among potential beneficiaries of Learning Analytics, as well as hesitations among institutional managers who aim to innovate their institution's learning support by implementing data and analytics with a view on improving student success. In this paper, we try to get to the heart of the matter, by analysing the most common views and the propositions made by the LA community to solve them. We conclude the paper with an eight-point checklist named DELICATE that can be applied by researchers, policy makers and institutional managers to facilitate a trusted implementation of Learning Analytics.

address issues of ethics and privacy in relation to Learning Analytics. At LAK15, the first workshop on "Ethics and Privacy in Learning Analytics" (EP4LA) has been organised jointly by the EU FP7 project Learning Analytics Community Exchange[1] and the SURF SIG Learning Analytics[2], who also organised similar events at other conferences in the Netherlands (Utrecht), US, (Washingto

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More Than Figures on Your Laptop: (Dis)trustful Implementation of Learning Analytics

Yi-Shan Tsai[1], Alexander Whitelock-Wainwright[2], Dragan Gašević[3]

Abstract

The adoption of learning analytics (LA) in complex educational systems is woven into sociocultural and technical challenges that have induced distrust in data and difficulties in scaling LA. This paper presents a study that investigated areas of distrust and threats to trustworthy LA through a series of consultations with teaching staff and students at a large UK university. Surveys and focus groups were conducted to explore participant expectations of LA. The observed distrust is broadly attributed to three areas: the subjective nature of numbers, the fear of power diminution, and approaches to design and implementation of LA. The paper highlights areas to maintain existing trust with policy procedures and areas to cultivate trust by engaging with tensions arising from the social process of LA.

Drachsler, H., & Greller, W. (2016). Privacy and Analytics: It's a DELICATE Issue a Checklist for Trusted Learning Analytics. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, 89–98.

Tsai, Y. S., Whitelock-Wainwright, A., & Gašević, D. (2021). More Than Figures on Your Laptop:(Dis) trustful Implementation of Learning Analytics. *Journal of Learning Analytics*, 1-20.

Socio-cultural systems matter

Complexity leadership in learning analytics: Drivers, challenges and opportunities

Yi-Shan Tsai, Oleksandra Poquet, Dragan Gašević, Shane Dawson and Abelardo Pardo

Abstract

Learning analytics (LA) has demonstrated great potential in improving teaching quality, learning experience and administrative efficiency. However, the adoption of LA in higher education is often beset by challenges in areas such as resources, stakeholder buy-in, ethics and privacy. Addressing these challenges in a complex system requires agile leadership that is responsive to pressures in the environment and capable of managing conflicts. This paper examines LA adoption processes among 21 UK higher education institutions using complexity leadership theory as a framework. The data were collected from 23 interviews with institutional leaders and subsequently analysed using a thematic coding scheme. The results showed a number of prominent challenges associated with LA deployment, which lie in the inherent tensions between innovation and operation. These challenges require a new form of leadership to create and nurture an adaptive space in which innovations are supported and ultimately transformed into the mainstream operation of an institution. This paper argues that a complexity leadership model enables higher education to shift towards more fluid and dynamic approaches for LA adoption, thus ensuring its scalability and sustainability.

Towards learning analytics adoption: A mixed methods study of data-related practices and policies in Latin American universities

Isabel Hilliger, Margarita Ortiz-Rojas, Paola Pesántez-Cabrera, Eliana Scheihing, Yi-Shan Tsai, Pedro J. Muñoz-Merino, Tom Broos, Alexander Whitelock-Wainwright, Dragan Gašević and Mar Pérez-Sanagustín

Abstract

In Latin American universities, Learning Analytics (LA) has been perceived as a promising opportunity to leverage data to meet the needs of a diverse student cohort. Although universities have been collecting educational data for years, the adoption of LA in this region is still limited due to the lack of expertise and policies for processing and using educational data. In order to get a better picture of how existing data-related practices and policies might affect the incorporation of LA in Latin American institutions, we conducted a mixed methods study in four Latin American universities (two Chilean and two Ecuadorian). In this paper, the qualitative data were based on 37 interviews with managers and 16 focus groups with 51 teaching staff and 45 students; the quantitative data were collected through two surveys answered by 1884 students and 368 teachers, respectively. The findings reveal opportunities to incorporate LA services into existing data practices in the four case studies. However, the lack of reliable information systems and policies to regulate the use of data imposes challenges that need to be overcome for future LA adoption.

CoLAM

Tsai, Y. S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *50*(6), 2839-2854.

Hilliger, I., Ortiz-Rojas, M., Pesántez-Cabrera, P., Scheihing, E., Tsai, Y. S., Muñoz-Merino, P. J., ... & Pérez-Sanagustín, M. (2020). Towards learning analytics adoption: A mixed methods study of data-related practices and policies in Latin American universities. *British Journal of Educational Technology*, *51*(4), 915-937.

Human-Centred Learning Analytics

Simon Buckingham Shum[1], Rebecca Ferguson[2], Roberto Martinez-Maldonado[3]

Abstract

The design of effective learning analytics (LA) extends beyond sound tech
analytics are to be adopted and used successfully to support learning and tea
take into account a range of human factors, including why and how they will b
principles of human-centred design developed in other, related fields that car
the development of human-centred learning analytics (HCLA). We draw or
together with the wider literature, to define human-centred design in the field
challenges that this approach offers. We conclude by suggesting that HCLA
more impact, more quickly, with tools that are fit for the purpose and a pleasu

Learning analytics in higher education – Stakeholders, strategy and scale

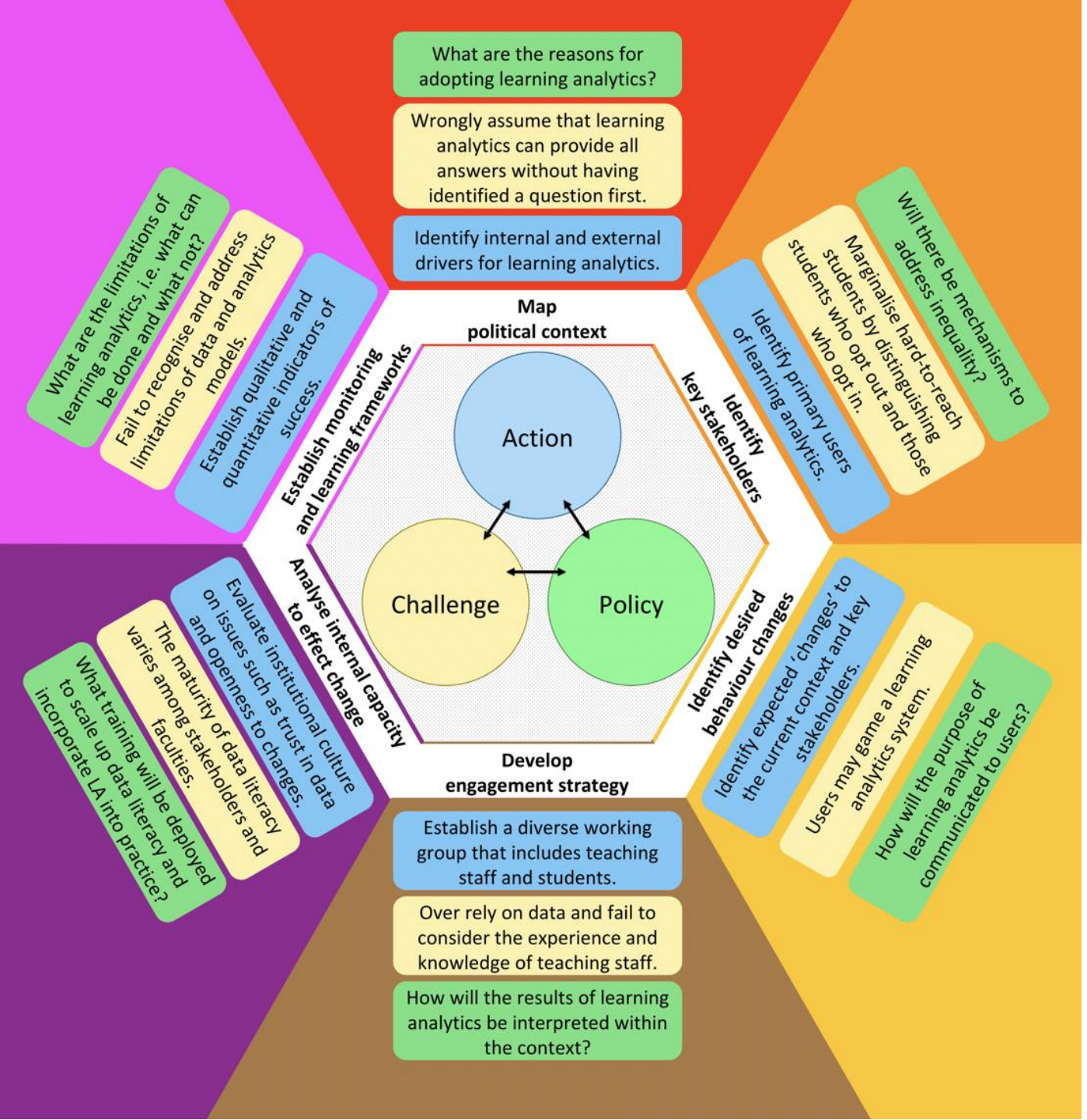
Dragan Gašević [a], Yi-Shan Tsai [a], Hendrik Drachsler [b]

1. Introduction

The growing prominence of digital technologies in higher education creates a futile ground for collection, analysis, and use of digital data. Higher education institutions are increasingly developing strategies for digital learning which rely on the extensive use of digital technology to transform or "flip" pedagogical practices towards more active and flexible learning. Digital technologies in education have receive much attention on different policy levels, change experience for learners, and present a rapidly growing market segment, more so than ever since the global COVID-19 crisis forced educational providers to move teaching online rapidly at scale. The evolution of education in recent years has prompted us to ask, what role does learning analytics have to play as a field that aims to harness unprecedented

Buckingham Shum, Simon; Ferguson, Rebecca and Martinez-Maldonado, Roberto (2019). Human-Centred Learning Analytics. Journal of Learning Analytics, 6(2) pp. 1–9.

Gašević, D., Tsai, Y. S., & Drachsler, H. (2021). Editorial learning analytics in higher education–Stakeholders, strategy and scale. *Internet and Higher Education.*



The SHEILA framework

https://sheilaproject.eu/sheila-framework/

- 89 institutions across 26 European countries
- Multi-stakeholder views
- 49 key action points for institutional adoption
- 69 prominent challenges to address
- 63 questions to answer in policy and strategy formation

SHEILA

Learning Analytics Principles and Purposes—The University of Edinburgh

https://www.ed.ac.uk/academic-services/policies-regulations/learning-and-assessment/learning-analytics

- As an institution we understand that data never provides the whole picture about students' capacities or likelihood of success….
- We recognise that data and algorithms can contain and perpetuate bias….
- Data generated from learning analytics will not be used to monitor staff performance…

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Looking forward

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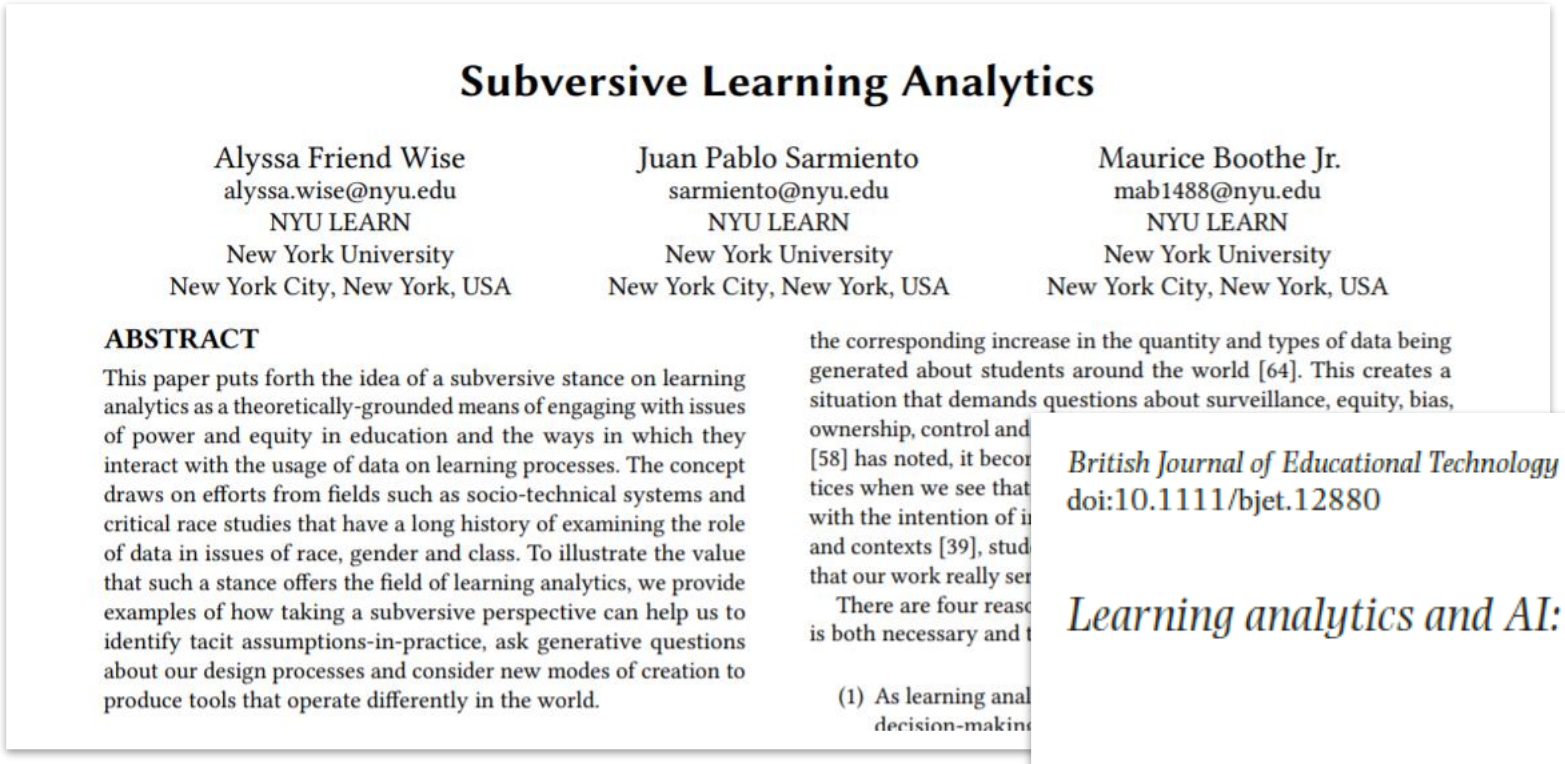

Subversive Learning Analytics

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ABSTRACT

This paper puts forth the idea of a subversive stance on learning analytics as a theoretically-grounded means of engaging with issues of power and equity in education and the ways in which they interact with the usage of data on learning processes. The concept draws on efforts from fields such as socio-technical systems and critical race studies that have a long history of examining the role of data in issues of race, gender and class. To illustrate the value that such a stance offers the field of learning analytics, we provide examples of how taking a subversive perspective can help us to identify tacit assumptions-in-practice, ask generative questions about our design processes and consider new modes of creation to produce tools that operate differently in the world.

the corresponding increase in the quantity and types of data being generated about students around the world [64]. This creates a situation that demands questions about surveillance, equity, bias, ownership, control and
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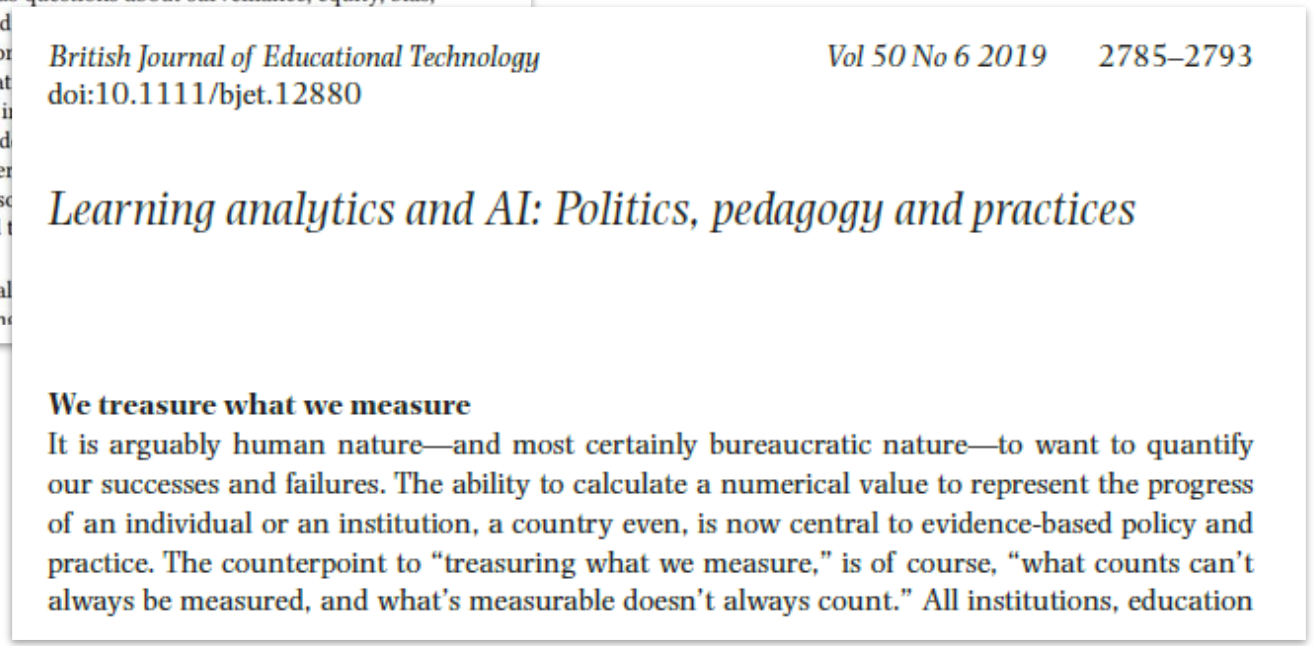

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doi:10.1111/bjet.12880

Learning analytics and AI: Politics, pedagogy and practices

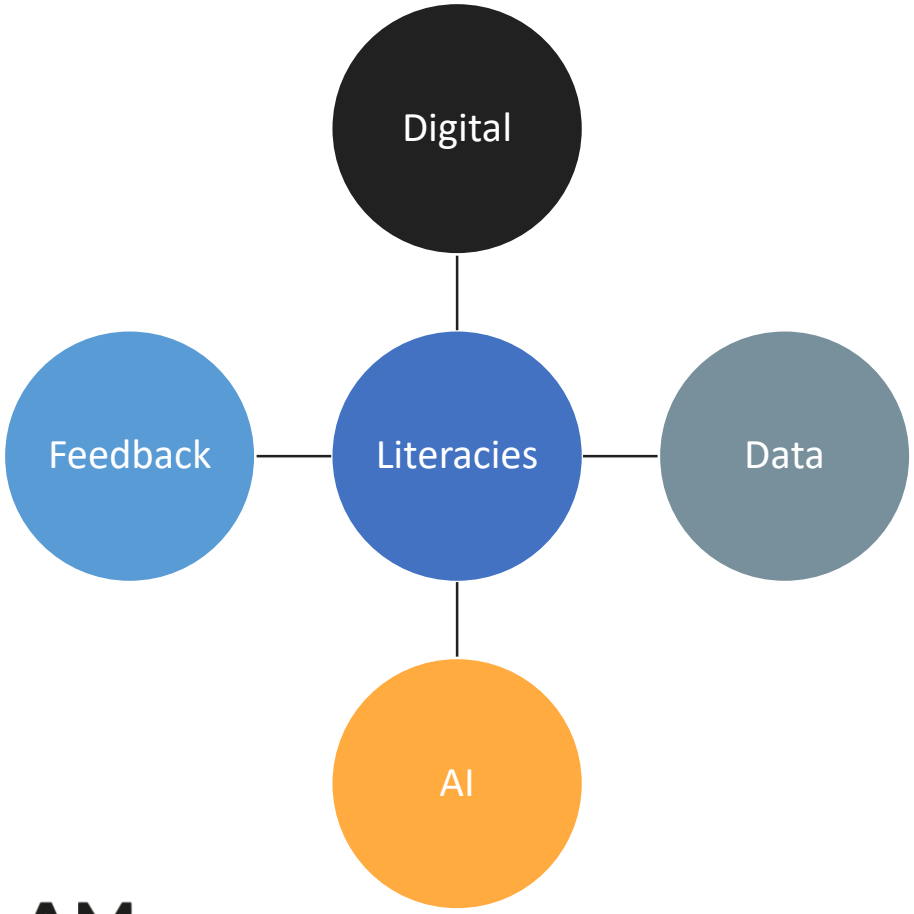
We treasure what we measure

It is arguably human nature—and most certainly bureaucratic nature—to want to quantify our successes and failures. The ability to calculate a numerical value to represent the progress of an individual or an institution, a country even, is now central to evidence-based policy and practice. The counterpoint to "treasuring what we measure," is of course, "what counts can't always be measured, and what's measurable doesn't always count." All institutions, education

Wise, A. F., Sarmiento, J. P., & Boothe Jr, M. (2021, April). Subversive learning analytics. In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 639-645).

Shum, S. J. B., & Luckin, R. (2019). Learning analytics and AI: Politics, pedagogy and practices. *British journal of educational technology*, *50*(6), 2785-2793.

Literacy literacy literacy…



- Appreciating LA-based feedback with critical awareness of its value and limitations
- Translating the computational representation of learning to psychological self or others and enacting the derived meanings
- Managing affect and negotiating power in the feedback loop

Tsai, Y. S. *(in press)*. Why Feedback Literacy Matters for Learning Analytics. In *the 16th International Conference of the Learning Sciences (ICLS)*
Tsai, Y. S. & Martinez-Maldonado, R. (2022). Human-centered Approaches to Data-informed Feedback. *Handbook of learning analytics*, 213-222.

Supporting student engagement and success with learning analytics…

Important questions to ask:

- What does engagement mean to you and to students?
- What does success mean to you and to students?
- What is the input of learning analytics? What is the output? What happens in between?
- What can the collected data tell? What can it not tell?
- Can we and should we explore new sources of data?
- Who's interest is being served?
- What is your role in a learning analytics cycle?

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