Embedding Responsible Al in Learning Analytics: From Ethical Principles to Institutional Practice

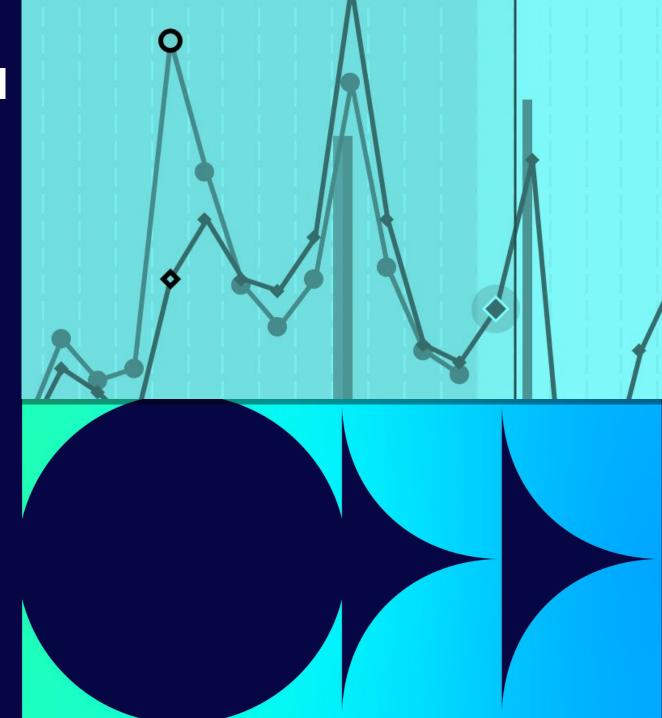
Fairness Innovation Challenge: Promoting Equity in HE

Knowledge Media institute, The Open University **26th November 2024, HESPA Virtual Conference**









Engagement with the Community

Exploring Responsible Al principles within Learning Analytics solutions Context

- Aim: gather information about
 - the current status of the adoption and implementation of Learning Analytics systems in UK Higher Education Institutions and,
 - the adoption of Responsible Tech/AI principles
- The data collected will help us understand
 - challenges institutions face
 - o principles of interest for HEI when adopting Responsible Tech
 - inform and feedback the creation of a Responsible AI
 Framework for Learning Analytics in Higher Education

- HESPA153 HE UK Institutions
- 10 min questionnaire



Questionnaire about the use of Responsible AI principles within LA solutions

Survey Results:

28 participants





3 nations represented: England, Wales, Scotland



Roles represented*:

Strategy and planning			
Technology design and implementation	5		
Data analytics	3		
Teaching and student success	3		
Other	1		



Definitions

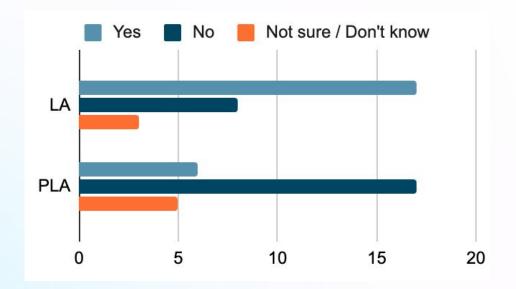
Learning Analytics (LA) [1]:

The measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the environments in which it occurs.

Predictive Learning Analytics (PLA):

A branch of Learning Analytics that aims to forecast what might happen in a learning context.

Does your organisation use of any type of LA or PLA solutions?



- 61% use LA or PLA solutions
- 39% do not use any LA or PLA solution



What type of LA/PLA solutions?

Third party tools, for example:

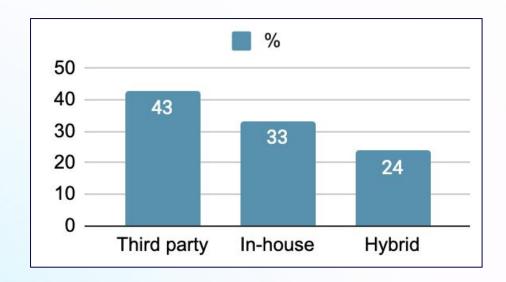
- Blackboard Analytics
- Civitas Learning
- IntelliBoard
- JISC Learning Analytics
- SEAtS One
- Stream

Hybrid, for example:

- Power BI customisation
- AWS tools customisation

In-house

- Python scripts
- Dashboards



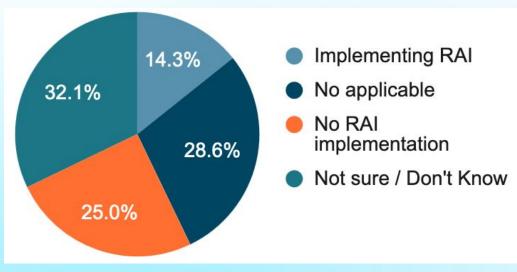


R-AI implementation

Does your organisation implement or consider Responsible AI principles within your LA and PLA solutions?

Responsible principles:

fairness & bias, transparency, security, privacy, safety, accountability, explainability







No R-AI implementation feedback:

"Early implementation of LA, not considered at this stage

"In consideration, but not formalised yet"

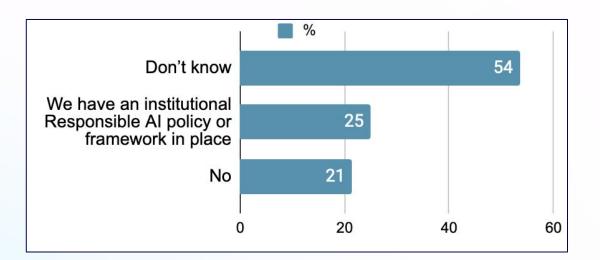
Third party tools seen as "Black-boxes" and difficult to understand

"Lack of policy"

"Need of right infrastructure/tools"

R-Al policy or framework

Does your organisation have an institutional Responsible AI policy or framework, external or internal?



Aspects considered in the Responsible Al policy/framework

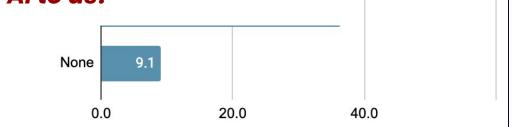
 Social aspects: in aligning with stake the broader socie technology

Social aspects: in Open Question:

Would you recommend any example, tool, policy of Responsible AI to us?

Technical aspect:
 and mitigating algorithms blases, ensuring robust security measures, and safeguarding data integrity





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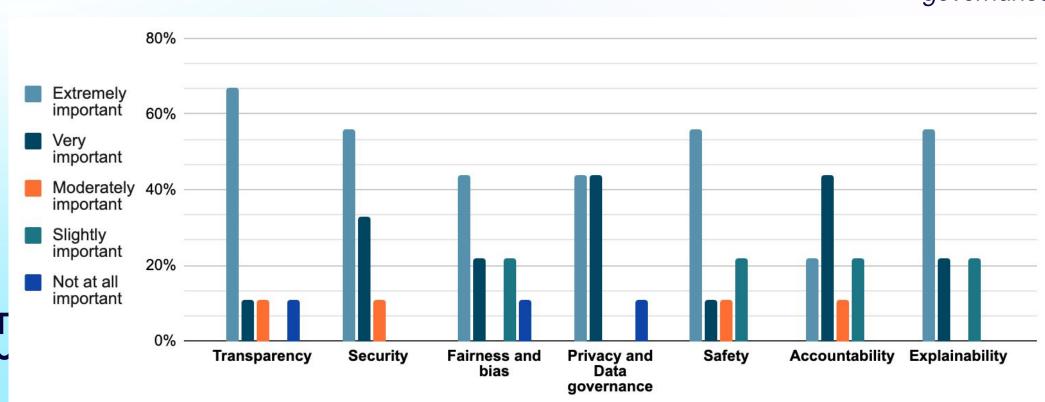
Principles

How important are these principles/factors of Responsible AI within the LA and PLA solutions of your organisation?

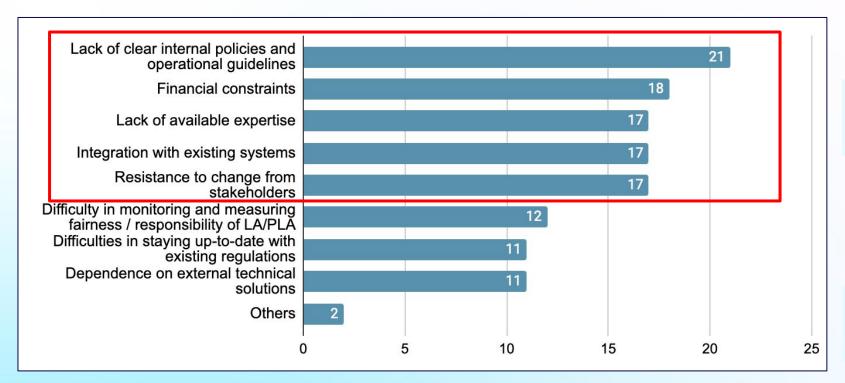
Responsible principles:

- Fairness & bias
- Transparency
- Security

- Safety
- Accountability
- Explainability
- Privacy & data governance



What are the key challenges your organisation faces when implementing Responsible Al principles for LA/PLA solutions?





Others:

"...reliability, accuracy and usefulness have not been proven.."

"Concerns over the metrics used to generate insights..."

"...lack of clarity over when and how much is weighted to predictors."



Open Question:

What do you think are the main challenges Higher Education Institutions in the UK face when implementing Responsible Tech principles?

Promoting Equity in HE

A specific focus on addressing bias and discrimination in Al-driven learning analytics systems.

Our project seeks to establish a framework of best practices, risks, and compliance with UK regulations.

The primary aim of this framework is to provide higher education institutions with actionable guidance on how to incorporate responsible AI principles effectively into their LA initiatives.

Latest publication

https://fairai4edtech.kmi.open.ac.uk/outcomes/

Towards an Operational Responsible Al Framework for Learning Analytics in Higher Education

ALBA MORALES TIRADO, PAUL MULHOLLAND, and MIRIAM FERNANDEZ, Knowledge Media Institute, The Open University, United Kingdom

Universities are increasingly adopting data-driven strategies to enhance student success, with AI applications like Learning Analytics (LA) and Predictive Learning Analytics (PLA) playing a key role in identifying at-risk students, personalising learning, supporting teachers, and guiding educational decision-making. However, concerns are rising about potential harms these systems may pose, such as algorithmic biases leading to unequal support for minority students. While many have explored the need for Responsible AI in LA existing works often lack practical guidance for how institutions can operationalise these principles. In this paper, we propose a novel Responsible AI framework tailored specifically to LA in Higher Education (HE). We started by mapping 11 established Responsible AI frameworks, including those by leading tech companies, to the context of LA in HE. This led to the identification of seven key principles such as transparency, fairness, and accountability. We then conducted a systematic review of the literature to understand how these principles have been applied in practice. Drawing from these findings, we present a novel framework that offers practical guidance to HE institutions and is designed to evolve with community input, ensuring its relevance as LA systems continue to develop

CCS Concepts: \bullet Applied computing \rightarrow Learning management systems.

Additional Key Words and Phrases: Responsible Artificial Intelligence, Learning Analytics, Higher Education



Responsible Al Framework For learning analytics in Higher Education Institutions

Framework development

- Built based on an exhaustive analysis of established Responsible AI frameworks (including leading technology companies) and mapped to the context of LA in HE
- Identified seven common principles including: fairness and bias, transparency, privacy, accountability, explainability, safety and security
- Conducted research to review how studies addressed these principles in practice within the LA domain
- Collected the solutions, challenges, and lessons learned from these studies
- Finally, we propose a framework aimed at guiding HE institutions in the responsible implementation of LA systems.



Responsible Al principles

- <u>Fairness and bias:</u> Ensuring that LA systems are free from biases that could disadvantage certain student groups.
- Accountability: Establishing clear lines of responsibility for the design, deployment, and outcomes of LA systems.
- **Transparency:** Providing clear and accessible information to all stakeholders.
- <u>Explainability</u>: Ensuring that predictions and decisions made can be understood by non-expert users
- The Open University

- Security: implementing robust technical safeguards to protect the integrity, confidentiality, and availability of data.
 Secure predictive models from manipulation or misuse.
- Privacy: Protecting the personal data of students and staff, ensuring that LA systems comply with legal and ethical standards around data privacy.
- Safety: Ensuring that LA systems are designed to minimise harm to staff and students

Responsible Al Framework For learning analytics in Higher Education Institutions

Structure

Recognising that institutions are at various stages of their LA adoption, we have structured the framework to follow the stages of the software development lifecycle





Framework proposal V0.1

RESPONSIBLE AI FRAMEWORK							
Principles/ Stages	Requirements & Data Collection		Design	Development	Testing	Release & Monitoring	
Accountability							
Explainability							
Fairness & bias							
Safety	Actionable guidance						
Security							
Transparency							
Privacy							

Responsible Al Framework For learning analytics in Higher Education Institutions



Fairness & Bias

Tools & examples

AI FAIRNESS-> https://github.com/Trusted-AI/AIF360

 Al Fairness 360 - Python: AlF360 is an extensible open-source library containing techniques developed by the research community to help detect and mitigate bias in machine learning models throughout the Al application lifecycle. This document will provide an overview of its features and conventions for users of the toolkit.

Fairlearn (python) -> https://fairlearn.org/

 Fairlearn is an open-source, community-driven project to help data scientists improve fairness of AI systems.

WhatIfTool -> https://pair-code.github.io/what-if-tool/

 Using WIT, you can test performance in hypothetical situations, analyze the importance of different data features, and visualize model behavior across multiple models and subsets of input data, and for different ML fairness metrics.

Using Al Fairness360 & Fairlearn

 Deng, W. H., Nagireddy, M., Lee, M. S. A., Singh, J., Wu, Z. S., Holstein, K. and Zhu, H. (2022) 'Exploring How Machine Learning Practitioners (Try To) Use Fairness Toolkits', 2022 ACM Conference on Fairness, Accountability, and Transparency. DOI: 10.1145/3531146.3533113.

Common accuracy metrics

- false positive rate (FPR), false negative rate (FNR), true positive rate (TPR), true negative rate (TNR), Positive predictive value (PPV)
 - Examples and definitions: Agarwal, S. and Mishra, S. (2021) Responsible Al: Implementing Ethical and Unbiased Algorithms. DOI: 10.1007/978-3-030-76860-7

Fairness metrics

- Equal Opportunity, Predictive Equality, Equalized Odds, Predictive Parity, Demographic Parity, Average Odds Difference
 - Examples and definitions: Agarwal, S. and Mishra, S. (2021) Responsible Al: Implementing Ethical and Unbiased Algorithms. DOI: 10.1007/978-3-030-76860-7

Bias audit toolkit

 AEQUITAS. University of Chicago's open source bias audit toolkit for machine learning developers. https://www.datasciencepublicpolicy.org/our-work/tools-guides/aequitas/

Software for detecting algorithmic discrimination

Repositories: https://github.com/megantosh/fairness_measures_code/

Ethics

An ethics checklist for data scientists. https://deon.drivendata.org/



Responsible Al Framework

Open conversation

While many works have explored the need for Responsible AI principles in LA, existing works often lack practical guidance for how institutions can operationalise these principles

- 1. What are the **barriers** to moving from guidance to practical implementation?
- 2. What **best practices** exist for implementing these principles?
- 3. Which <u>new types of support or guidance</u> do organisations need for implementation?
- 4. What are the **implications in terms of policy** and **regulations**?



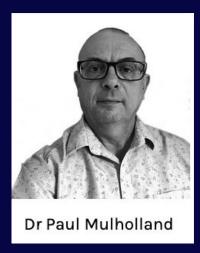
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Meet the speakers:









Thank you!

For more information visit:

https://fairai4edtech.kmi.open.ac.uk









