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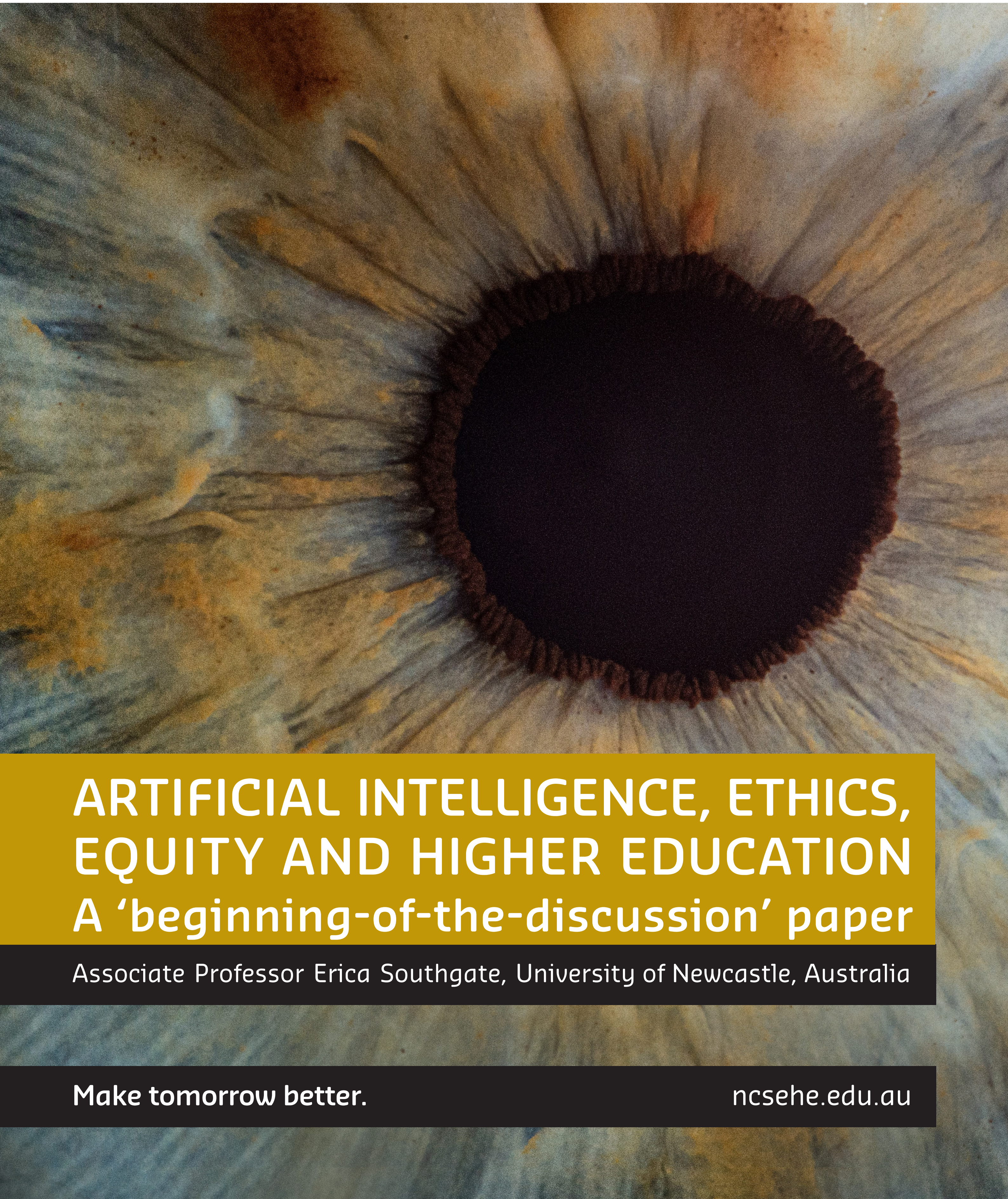

ARTIFICIAL INTELLIGENCE, ETHICS, EQUITY AND HIGHER EDUCATION

A 'beginning-of-the-discussion' paper

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Artificial intelligence, ethics, equity and higher education:

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Artificial intelligence will shape our future more powerfully than any other innovation this century. Anyone who does not understand it will soon find themselves feeling left behind, waking up in a world full of technology that feels more and more like magic (*Maini and Sabri, 2017, p.3*).

What is the purpose of this paper?

Artificial intelligence (AI) can been defined as:

> *a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy (OECD, 2019).*

AI is all around us, infused in everyday computing applications and the automation of organisational processes and systems. From search engines, to smartphone assistants, to systems that evaluate job and loan applications, online product recommendations, and the use of biometric facial recognition technology in social media and security applications, AI increasingly and invisibly powers our digital interactions and influences what we can do, know and, some would argue, who we can be.

The purpose of this discussion paper is three-fold:

1. As AI-powered applications become more ubiquitous it is incumbent upon educators, administrators and leaders in universities to **develop a foundational understanding** of what the technology is and how it works so that we can ask critical questions about its design, implementation and implications for humans in educational systems. As the opening quote suggests, we do not want to be working and learning in institutions where decisions about processes involving, and interactions with, AI feels like magic.
2. Having a foundational understanding should **prompt informed dialogue and democratic decision making about the ethical design, implementation and governance of AI in higher education**. This includes leveraging existing legal and regulatory mechanisms and developing new robust governance frameworks to ensure fairness, transparency and accountability.
3. It is important to **raise awareness of the unique challenges that AI poses to equity in education and to commonly held views on discrimination.**

No document can cover all the issues related to the fast-evolving landscape of AI; hence, the reason this is called a ‘beginning-of-the-discussion’ paper. However, it is my intention to equip stakeholders with talking points to prompt informed and sustained dialogue on how AI might be used for good, and for what it’s good for, and importantly, to consider where it should not be used at all.

What are some of the assumptions that underpin this paper?

In this paper the idea of equity is underpinned by Fraser’s (2009) concept of social justice that evokes the connected areas of: the fair redistribution of resources so that people facing disadvantage and marginalisation can reap material benefits and opportunities; recognition of difference on its own terms which entails respecting non-dominant cultural ways of knowing, doing and being; and representation which involves the right to participate and have a valued voice in decision-making processes where diverse perspectives are possible.

At a pragmatic level, equity is also used to denote fair and affordable access to, and support for, success in education including across university and degree types (something I have written extensively about) (Southgate, 2017). In the Australian context, ‘equity groups’ refers to cohorts that have traditionally been underrepresented in higher education (students from rural, remote or regional, low socioeconomic and Indigenous backgrounds, and those with a disability) and in course types (women in non-traditional areas such as computer science or engineering).

This paper is based on a key assumption that education is an intrinsically human endeavour that must be grounded in equitable and ethical principles and practice related to human flourishing for individual and social good, and for the benefit of the planet. At its very heart, education is about explaining things, not just in terms of content but also in relation to practice. Explainability is the capacity of, and commitment by, educators and those operating and leading educational institutions to explain — with proficiency, clarity and transparency — pedagogical and administrative processes and decisions and be held responsible for the impact of these.

There is a very important literature which addresses how automation may create grave inequality and under/unemployment (see Gulson and colleagues [2018] for an overview). This is an important topic that higher education is exploring in the 'future of work' domain. It is not a topic covered in this paper as I am specifically examining the integration of AI into universities' systems and processes for business intelligence, administration, student services, and teaching and learning.

Finally, this discussion paper is a piece of translational research written for those interested in educational equity policy, practice and research. It aims to provide a plain English, evidence-informed overview of AI and its myriad implications for equity in higher education. It is a springboard for discussion and debate and not the final word.

What is artificial intelligence (AI)?

The CSIRO state that:

> *Artificial Intelligence (AI) is a broad term used to describe a collection of technologies able to solve problems and perform tasks without explicit human guidance. Some of these include: machine learning, computer vision, natural language processing, robotics and deep learning. A general-purpose technology, AI uses data-driven algorithms to autonomously solve problems and perform tasks without human guidance. The algorithms that underpin artificial intelligence have existed for quite some time, however exponentially growing volumes of data and the widespread availability of affordable computation mean that Australia, and the world, can operate this revolutionary technology at a scale and speed never seen before (CSIRO, n.d.).*

As a field of computing, AI has been around since the 1950s. From the beginning of the 2000s several advances have facilitated rapid innovation in the AI-related areas of computer vision, graphics processing and speech recognition technology (Mitchell and Brynjolfsson, 2017). These include increased data storage especially cloud computing with its ability to house and manage large amounts of 'big data' required for machine learning (ML) which is an important subfield of AI (and a topic covered in the next section). Big data refers to the growth, availability and use of information from a variety of sources such as the internet, sensors, and geolocation signals from devices, and is characterised by its volume, variety and velocity (or how fast it is being added to, harvested and used in real time) (Michalik, Štofa, and Zolotova, 2014).

AI can be embodied in robots (although not all robots have AI) and disembodied in computing programs. Children and adults often overestimate the intelligence of AI and are prone to anthropomorphising it (giving it human qualities) in both its embodied robot and disembodied computer program forms (Faggella, 2018).

Although science fiction depicts AIs as equally or more intelligent than humans, it is important to know that at present we are in an era of narrow AI. Narrow AI are only able to do the single or focused task they were designed to do and do not exhibit the full range of intelligent and emotional characteristics associated with humans. Sometimes their efficiency or effectiveness at focused tasks can outperform humans; for example, AI-powered search engines can locate and organise vast amounts of information on the internet faster than a human could. While the quest to develop General AI is underway (that is, AIs which have a 'theory of mind' or self-awareness of the mental states of themselves and others just as humans do), there is no guarantee this will be achieved. Hence, we should concentrate on understanding how current AI works and its benefits and risks.

What is machine learning (ML)?

Today, discussion about AI is invariably linked to ML. Put simply, ML is:

> *the science of getting computers to learn and act like humans do, and improve their learning over time in autonomous fashion, by feeding them data and information in the form of observations and real-world interactions (Faggella, 2018).*

ML is all about developing algorithms that can learn through experience (an algorithm is instructions that tell the computer or machine how to achieve a task or operation). The system learns as it receives data but does not need to be specifically programmed to do this. Specifically, ML is:

> *(A) subfield of artificial intelligence. Its goal is to enable computers to learn on their own. A machine's learning algorithm enables it to identify patterns in observed data, build models that explain the world, and predict things without having explicit pre-programmed rules and models (Maini and Sabri, 2017, p.9).*

It is important to grapple with the basics of ML because there are a range of ethical issues and real-world examples of both benefits and harm associated with it. Briefly, some of the different types of ML are:

- Supervised learning: Qualified people label or classify initial input data to train an algorithmic model to identify patterns and make predications when new data is given to it. The algorithm learns from experience that is guided by a human labelling the data.
- Unsupervised learning: In this type of ML, algorithms create their own structure (features) that can be used to detect patterns and classifications in unlabelled data. Unsupervised learning is used to explore and detect patterns when an outcome is unknown or not predetermined. It is possible that with large enough data sets, unsupervised learning algorithms would identify patterns in behaviour or other phenomena that were previously unknown.
- Reinforcement learning: This has an algorithm interacting with a specific environment to find the best outcome through trial and error without training: 'The machine is trained to make specific decisions. … (It) learns from past experience and tries to capture the best possible knowledge to make accurate … decisions' (Ramzai, 2020).
- Deep learning: Associated with artificial neural networks (ANN) this type of ML is inspired by the way neurons connect in the human brain. It has numerous layers of algorithms that interact to model data and make inferences. There are multiple ANNs at lower levels of abstraction to effectively solve chunks of a problem and provide these partial solutions to ANNs at higher levels to derive a larger solution (LeCun, Bengio and Hinton, 2015). ANNs are 'organized into layers of nodes, and they're 'feed-forward," meaning that data moves through them in only one direction (so that an) individual node might be connected to several nodes in the layer beneath it, from which it receives data, and several nodes in the layer above it, to which it sends data' (Hardesty, 2017). Deep learning is being used to understand complex data such as natural language processing which involves complicated vocabularies or machine vision processing that has intricate pixel information (Maini and Sabri, 2017).

If people who are not technologists can develop some knowledge of how ML works through algorithmic mathematical models then we may be better able to identify when AI is present and intervening in our lives through automated 'nudging' based on machine predictions and classifications. This will allow us to proactively ask critical questions about the predictions and classifications generated by machines. For example, AI is known to have issues with classification bias and errors as the following example illustrates:

> *(AI) trained to detect rude, disrespectful, or unreasonable comments may be more likely to flag the sentence "I am gay" than "I am straight" (and) face classification models may not perform as well for women of colour, (and) speech transcription may have higher error rates for African Americans than White Americans even if sensitive variables such as gender, race, or sexual orientation are removed (Packer, Halpern, Guajardo-Céspedes, and Mitchell, 2018).*

In fact, the history of AI using ML algorithms is punctuated with problems of bias and error:

> *Amazon stopped using a hiring algorithm after finding it favoured applicants based on words like "executed" or "captured" that were more commonly found on men's resumes. … Another source of bias is flawed data sampling, in which groups are over- or underrepresented in the training data. For example, Joy Buolamwini at MIT working with Timnit Gebru found that facial analysis technologies had higher error rates for minorities and particularly minority women, potentially due to unrepresentative training data (Manyika, Silberg and Presten, 2019].*

A key problem is the often 'black box' components of ML. This means that the algorithmic 'decision making' processes between inputs and outputs is not transparent either because the algorithms are proprietary (the property of companies and governments who will not open these for independent review) or so complex in their operation, like ANNs, that the machine's decision-making processes are not wholly explainable even to the scientists who develop the systems (Campolo, Sanfilippo, Whittaker and Crawford, 2017). 'Black box' AI which has limited transparency (and therefore limited contestability under current regulatory frameworks) can materially affect life opportunities — it can determine if someone gets a job interview or a loan, which welfare recipients gets a debtor's notice, which learners gets categorised as 'at risk' of attrition or failure, or who has access to a particular curriculum pathway in an intelligent tutoring system. Many ethical and governance issues arise with the use of AI and the types of ML it utilises and these will be discussed later in the section on ethics.

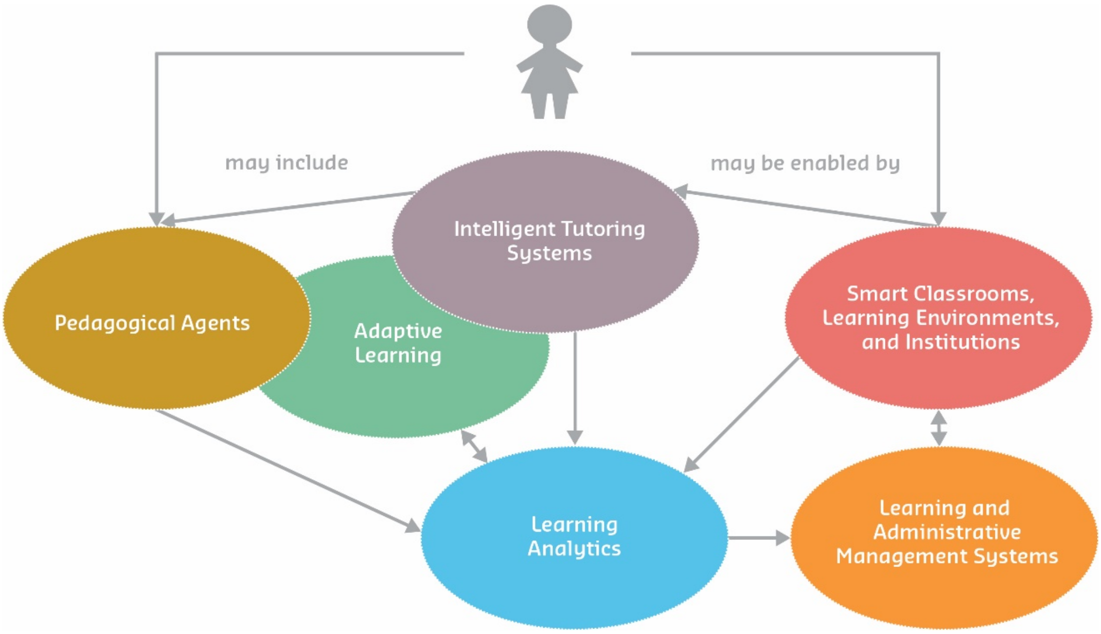
How is AI used in education?

The specialist field of AI in Education (AIED) has been around since the 1970s and is concerned with developing computer programs to enable more personalised, flexible and engaging learning and to automate routine teaching tasks including automated assessment and feedback (Luckin, Holmes, Griffiths, and Forcier, 2016). Figure 1 gives an overview of educational application that may include or be enabled by AI.

Intelligent Tutoring Systems (ITSs) simulate human tutoring (Luckin et al, 2016). ITs can be adaptive in their responses to individual students with research showing that ITSs had similar positive effects on learning as human tutors; however, this was less pronounced for college students (Steenbergen-Hu and Cooper, 2014). Pedagogical agents (PAs) are digital or virtual characters in learning technologies that can be used to provide information, model learning, coach, guide, motivate or scaffold and assess learners. Most PAs are used for low-level functions such as providing information (Schroeder and Gotch, 2015). Evidence regarding the effectiveness of PAs for learning is mixed (Schroeder and Gotch, 2015); however, interest remains in developing digital learning companions. The development of informational and learning bots to assist students attests to this.

While ITSs and PAs provide a user interface for AIED, there is often use of AI in adaptive systems that are running in the background and these have algorithms that determine how and when to customise learning environments and/or tasks for students. Computer based learning environments can capture, in an ongoing manner, significant amounts of data about academic performance and engagement such as numeric information, text, images, and video. Combined, these constitute the type of big data used for today's ML. The domain of learning analytics, with AI used to power analysis, is usually combined with human judgement to interpret and act on analytics in teaching contexts. Similarly, educational data mining seeks to provide insights into learning and engagement but with an emphasis on automated analysis.

Figure 1. Overview of typical AIED applications and their relationship to each other (adapted from Southgate et al., 2019).



The other way to think about AI in education is the myriad ways the technology can be infused into the business intelligence, learning and administrative systems of higher education. For example, students using photoshop for learning are using an AI-powered application and plagiarism checking software is powered by ML. Increasingly university administrators are looking to applications that use student smartphone geolocation data (to ascertain attendance for example) and biometrics applications which aim to verify the identity of students undertaking assessment online. This links to a future vision of educational institutions as integrating the Internet of Things (IoT). The IoT concentrates on developing the capability of objects and devices to digitally connect and interact with each other through constant data collection which feeds big data for ML. This is associated with the idea of 'smart' classrooms where institutional systems and student devices connect and sensor technology automates functions such as climate control and security. This vision includes the collection of many different types of information including geolocation and biometric data.

The area of biometrics warrants special attention. Biometrics is the automated collection of bodily information that is often analysed using ML, often but not solely for verification purposes. It includes biological data for facial and voice recognition, fingerprints, iris patterns, heart rate, body temperature or perspiration, and behavioural information such as vocal patterns, eye tracking/gaze attention, finger and gait tracking and typing recognition (Royakkers, Timmer, Kool and van Est, 2018). Biometric data is not just information about a person — for example, the type of information someone shares so that they can set up an online account — but information directly of the person's body. Biometrics raises questions about privacy and consent, ownership and security of data, the human right to bodily integrity (Southgate, 2018), and function creep which refers to the expansion of a data collection system where data is collected for one purpose and then applied to another (for example, surveillance). The issue of function creep also applies to other types of data collection including geolocation information. It is worth noting that in the United States the use of facial recognition technology for university security purposes has caused a backlash with opponents objecting to invasion of privacy and false image matching errors particularly for people of colour [1]. Biometric capture is currently being integrated in a range of platforms and applications including augmented and virtual reality with the tracking of legs, arms, and finger movement, and eye gaze and pupil dilation (the latter supposedly used as proxies for engagement), and in the experimental realm of brain-computer interaction. As we move into an era of the 'internet of bodies' understanding the processes, and ethical and legal implications of biometric data capture will be vital for all citizens.

Higher education is the main driver of AIED. While we are still in a relatively early phase of widespread use of the technology, especially for front-line teaching and learning, it is worth considering the findings of a recent systematic review of four key areas of AIED: profiling and prediction; assessment and evaluation; adaptive systems and personalisation; and intelligent tutoring systems (Zawacki-Richter, Marín, Bond and Gouverneur, 2019). The review found that there was inadequate theoretical connection to pedagogical theory and perspectives, limited critical reflection of challenges and risks of AIED, and a need for more research on the ethical implications of using the technology in education.

How can we think ethically and equitably about AI and education?

AI ethicists have designated education as a 'high stakes domain' (Campolo et al., 2017, p.1) that requires urgent, ongoing scrutiny and a coordinated response to ensure that the technology is used for the benefit of students, educators, communities and society more broadly. There has been national (Dawson et al, 2019) and international (IEEE, 2019; European Parliament, 2019) activity on documenting and framing an applied ethics for the general design, implementation and governance of AI. The stakes are high for individuals, groups and institutions:

> *What does it mean for an AI system to make a decision? What are the moral, societal and legal consequences of their actions and decisions? Can an AI system be held accountable for its actions? ... (H)ow should their use and development be regulated? (Dignum, 2018, p.1).*

I have previously developed al framework (Figure 2) on how we can think ethically about AI in educational systems. While the framework was initially developed with reference to schooling, it is equally applicable to higher education where any engagement with the technology should reflect broader human rights and be underpinned by a set of ethical pillars (for a full explanation see Southgate et al., 2018).

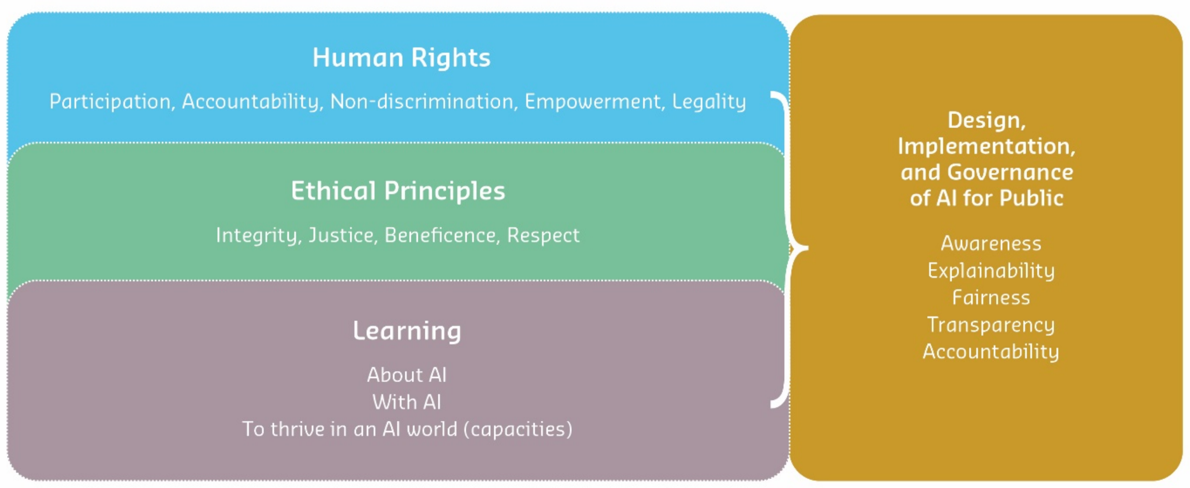
Human rights

In this document, human rights refers to principles established in 1948 by the United Nations (http://www.un.org/en/universal-declaration-human-rights/) and subsequently synthesised by the Australian Human Rights Commission into common principles under the acronym 'PANEL' (paraphrased below):

1 For example, see https://www.insidehighered.com/news/2020/02/21/ucla-drops-plan-use-facial-recognition-security-surveillance-other-colleges-may-be and https://www.thejustice.org/article/2020/03/brandeis-university-professor-signs-letter-opposing-facial-recognition-technology-on-college-campuses-joining-brandeis-and-other-institutions-in-this-effort

- **<u>P</u>articipation** is the right of humans to participate in decisions which affect them. It must be active, free and meaningful, and give attention to issues of accessibility, including access to information in a form and a language which can be understood.
- **<u>A</u>ccountability** requires effective monitoring of compliance with human rights standards and achievement of goals and appropriate remedies for breaches. Accountability must include appropriate laws, policies, institutions, administrative procedures and mechanisms of redress.
- **<u>N</u>on-discrimination and equality**: In the realisation of rights all forms of discrimination must be prohibited, prevented and eliminated. Priority should be given to people in the most marginalised or vulnerable situations who face the biggest barriers to realising their rights.
- **<u>E</u>mpowerment**: Everyone is entitled to claim and exercise their rights and freedoms. Individuals and communities need to be able to understand their rights and fully participate in the development of policy and practices which affect their lives.
- **<u>L</u>egality**: The law should be consistent with human rights principles and recognise these as legally enforceable entitlements. (https://humanrights.gov.au/our-work/rights-and-freedoms/human-rights-based-approaches).

Figure 2. The Education, Ethics and AI (EEAI) framework from Southgate et al. (2018).



Human rights have been regularly applied to ethico-legal aspects of AI (there are alternative traditions in social and cultural knowledges that can also be used). A human rights approach prompts us to have broader public and community-based dialogue about whether the use of automated and intelligent systems have violated, or are likely to violate, rights and freedoms, and continue to prompt concern about accountability both in terms of designing and implementing the technology. Specifically, humans have the right to live free of discrimination, with their privacy and bodily integrity protected. AI can pose significant risks to these human rights. It is not enough for universities to review legal requirements related to using AI-powered systems; they must proactively evaluate the potential impact of automated and intelligent systems on the human rights of students and staff. To comprehensively respond to this, I propose five ethical pillars to underpin higher education’s approach to the technology. We now turn to these pillars and some of their implications for equity.

Five pillars of AI ethics and some of their equity implications

The five ethical pillars are premised on higher education institutions committing to public, democratic dialogue and decision making regarding the design, implementation and governance of AI. The pillars uphold the human rights of students and staff and the communities that universities serve. The ethical pillars are:

1. Awareness: The pillar of awareness reflects a human rights approach to participation, empowerment and legality. It involves developing the awareness of individuals and groups so that they can take informed action and decisions related to the technology. Universities should proactively develop foundational knowledge about AI so that all stakeholders can understand what AI is, what it can and can't do, and where it is present in applications and systems especially when it operates in invisible ways. Education for awareness will need to be refreshed because AI is an evolving field and digital products and systems are incorporating it at a rapid rate. Importantly, many people 'are not aware of the multiplicity of agents and algorithms currently gathering and storing their data for future use' (boyd and Crawford, 2012, p.673). All members of the university community should be made fully aware of AI data harvesting, storage and third party and other sharing arrangements with strong informed opt-in consent obtained. The IEEE (2019), the global peak industry body for electrical and software engineers, recommends AI ethics certification for institutions which includes training on informed consent and implementation of strong informed consent processes.

Actively and continually promoting awareness of AI with informed consent will provide some protection from deception and allow all stakeholders an opportunity to be involved in deciding the role and parameters of the technology in education. Universities must consider how they will develop an ongoing education program to raise awareness of AI and its implications for human rights and what approach they will take to ensure strong informed consent, especially from students who may have lower literacy and digital literacy skills.

2. Explainability: The pillar of explainability reflects a human rights approach to participation, empowerment and accountability. Explainability has two foci. The first is a pedagogical project that involves the sustained development of approaches to explain AI more generally and its function in specific systems or applications in an accessible manner (this is part of raising awareness). This pedagogical project seeks to provide all stakeholders with genuine, consultative and public opportunities to ask questions about applications of technology in a university and have these questions responded to in an honest, intelligible (plain English) and timely way. The second focus involves the responsibility of manufacturers, vendors and procurers of AI technology to clearly elucidate:

- what the technology should do, can and can't do
- the educational and societal values and norms on which it was/is trained and acts
- the learning and pedagogical theory and domain knowledge on which it is based
- evidence of its efficacy for learning for diverse groups of students
- arrangements for data collection, deidentification, storage and use including third party or other sharing agreements, and those for sensitive information such as biometrics or measures embedded in affective computing applications
- if 'nudging' is part of the system, how it complies with ethical principles
- how the application upholds human rights
- full, timely disclosure of potential or actual benefits and risks, and any harm that may result from a system (this relates to the pillars on Transparency and Accountability).

Universities should be able to clearly explain why they are using an AI-powered system, what it is intended to do and actually does (including if unintended consequences related to discrimination and bias emerge), how the system makes its decisions, and its benefits and risks. When harm is caused by AI systems those in educational governance positions must publicly explain how this occurred and how they will respond, not only to the incident but for future use (or not) of the technology.

3. Fairness: The pillar of fairness reflects a human rights approach to non-discrimination, accountability and legality. Fairness is used in several ways in AI ethics. The first relates to the potential social inequality that AI is forecast to generate over the coming decades with structural economic shifts due to automation. The second relates to the potential benefits of interacting with AI being fairly distributed and the burdens of experimental use being minimised. The other area, and one that has garnered a lot of public interest, involves AI bias. There are many publicised cases of AI bias with sexism, racism and other forms of discrimination occurring. Campolo et al. (2017, p.14) explain that:

> *biased AI can result from a number of factors, alone or in combination, such as who develops systems, what goals system developers have in mind during development, what training data they use, and whether the systems work well for different parts of the population.*

When AI-powered systems predict outcomes for or categorise individuals or groups, they influence, subtly and overtly, how we understand those people, and sometimes this leads to discrimination and stigma even when humans are in an automated decision-making loop. Campolo et al. (2017) recommend standards be established to track the provenance, development, and use of training datasets throughout their lifecycle in order to better understand, monitor and respond to issues of bias and representational skews.

4. Transparency: The pillar of transparency reflects a human rights approach to accountability, non-discrimination, empowerment and legality. It is an area that has received considerable interdisciplinary attention: An 'important underlying principle is that it should always be possible to find out why an autonomous system made a particular decision (most especially if that decision has caused harm)' (Winfield and Jirotka, 2017, p.5). AI is often described as an opaque technology. It is commonly invisibly infused into computing systems in ways that can influence our interactions, decisions, moods and sense of self without us being aware of this (Cowrie, 2015). Furthermore, the often proprietary status of the data sets used to train AI and its algorithms hinder scrutiny from independent experts. Customers must rely on industry assurances that adequate checks have been carried out regarding privacy implications for the type of personal data being harvested and shared, and that the potential risks of algorithmic bias have been addressed. Relatedly, industry can have a legal obligation to protect data, making full disclosure problematic if bias or other harm does occur (boyd, 2016). Another reason AI can be considered opaque relates to the 'black box' nature of some types of ML particularly deep learning. Some researchers suggest that black box ML should not be used in 'safety critical systems' where classification, predictions and decisions made by AIs can have serious consequences to human safety or wellbeing (Winfield and Jirotka, 2018), and this includes the realm of education. The dynamic, changeable decision-making logic of some AI systems presents ethical issues that have not been resolved either through technical or ethical processes:

> *Software developers regularly use "black-box" components in their software, the functioning of which they often do not fully understand. "Deep" machine learning processes, which are driving many advancements in autonomous systems, are a growing source of 'black-box' software. At least for the foreseeable future, AI developers will likely be unable to build systems that are guaranteed to operate exactly as intended (IEEE, 2019, p.136).*

Technologists have described four technical ways in which AI systems can be made transparent, especially in relation to how a system interprets and implements norms that influence decisions made by the machine. These are:

- **Traceability** which refers to technical inspection of which norms have been implanted, for which contexts, and how norm conflicts are resolved by system. This can reveal biases which may have been built into a system.

- **Verifiability** through formal mathematical techniques including a log of ethical reasoning that should be available for inspection.
- **Non-deception and honesty** where systems are designed to accurately represent what the system is capable of doing to the person using it.
- **Intelligibility** which entails a clear requirement for a system to be able to explain its own reasoning to a user, at a level commensurate with human reasoning, when it suspects user confusion (IEEE, 2019).

5. Accountability: The pillar of accountability reflects a human rights approach to accountability and legality. Governance of AI will entail new ways of thinking about the interconnections and tensions between proprietary interests, (public and transparent) algorithmic auditability, regulatory standards, policy and risk assessment, legal obligations, and broader social, cultural and economic responsibilities. Accountability in an AI world is complex and an ongoing area of development:

> *the complexity of (autonomous and intelligent) technology and the non-intuitive way in which it may operate will make it difficult for users of those systems to understand the actions of the (system) that they use, or with which they interact. This opacity, combined with the often distributed manner in which the (automated and intelligent systems) are developed, will complicate efforts to determine and allocate responsibility when something goes wrong. Thus, lack of transparency increases the risk and magnitude of harm when users do not understand the systems they are using, or there is a failure to fix faults and improve systems following accidents. Lack of transparency also increases the difficulty of ensuring accountability. (IEEE, 2019, p.27).*

Regulation and standards that clearly identify the types of operations and decisions that should *not* be delegated to autonomous and intelligent systems are slowly being formulated with some of these approaches outlined later in this paper. Both manufacturers of, and those procuring, AI systems need to have policies that address algorithmic maintenance, pre-conditions for effective use, and supply training for those implementing the systems. The IEEE (2019) suggest that algorithmic maintenance needs due diligence and enough investment in relation to monitoring outcomes, complaints, inspection and replacement of harmful algorithms, and that delegating responsibility to end-users for this is not appropriate.

Gulson and colleagues (2018) provide a sensible set of recommendations in relation to AI governance and education. These include developing procurement guidelines that encourage ethical, transparent design of AI; reviewing international data protection legislation to develop a suitable approach for Australian education; and establishing official guidelines for adaptive and personalised learning systems that ensure learning efficacy and equity.

Governance structures must have accessible contestability mechanisms for students and staff that include access to independent expert technical and ethical advice so that potential bias and other harms might be identified earlier rather than later. There are distinct and unique informational and power asymmetries evident in universities regarding the introduction of new technologies for business intelligence, administration, student services and learning purposes. With a field as ethically and technically complex as AI, it is imperative that accountability mechanisms be accompanied by resourced empowerment strategies. This is very important for staff and students who have a right to ask questions about the data universities collect from, and on, them; how that data is used, stored or combined internally and shared with third parties; and how it may affect their human rights.

Issues of surveillance, algorithmic bias and discrimination, privacy and consent, the growth of integrated biometric and geolocation harvesting through administrative and learning applications, function creep, and the security of personal data and its potential for reidentification, all raise very serious ethical issues that the higher education sector needs to address in a more systematic, transparent and accountable way. It is difficult enough for staff (with some status and basic technical knowledge) to ask ethical questions about these aspects of the digital domain of the university, let alone students. Documented, transparent, ethical decision making and avenues for communication and dialogue about 'datafication' and/or automation are often not well developed, encouraged or well known within universities. This can more profoundly impact students from less economically privileged backgrounds because they may not have the literacy and digital literacy skills (or access to those that do) required to navigate university systems and ask questions about data policies. This also applies to first year students and those from culturally and linguistically diverse backgrounds who may be more affected by information and power asymmetries.

There has been some excellent work undertaken on the ethics of learning analytics which includes scoping of key issues related to data privacy (and to a lesser extent, equity), and which provide case studies on analytics governance in the Australian context (Corrine et al., 2019; Jones, 2016; Roberts, Chang and Gibson, 2017). Insights from this research can be leveraged to develop robust governance and accountability structures and mechanisms for the use of AI in higher education, and the ongoing harvesting of big data from diverse sources inclusive of university-managed and university-mandated applications on personal devices.

The learning analytics literature provides a good window into the scope and types of data that are being harvested and that can be combined to create big data for ML in higher education. These include (a) provided data which is intentionally given by individuals, for example, when they fill out a form; (b) observed data recorded automatically, for example, via online cookies or sensors for biometric (for example, facial recognition); (c) derived data produced from other data based on simple calculations that may provide proxy insights; and (d) inferred data produced by using analytic methods to find correlations between datasets used to categorise or profile people (Abrams, 2014). Not all uses of big data or ML have the same ethical implications. However, as we negotiate our way through this era of machine classification, prediction, profiling and decision making, it is worth considering who will be classified or profiled based on what data and with what consent, and what the implications of this are for real humans within universities. Education has a distinguished history of investigating the negative effects of labelling on humans. This critical stance must be maintained during the new machine age.

What about AI and accessibility?

A recent article by Morris (2020) provides a topical overview of the implication of AI for people living with disability. She suggests that AI offers a range of possibilities, from computer vision assisting people who are blind to better navigate the world, to speech recognition technologies offering real-time captioning and translation for people who have hearing loss. She also highlights a range of technical, practical and ethical issues paraphrased below:

- **Inclusivity and data:** The data sets used to train AI typically do not include samples from populations of people living with disability. For example, speech recognition, such as those used for virtual assistants, do not work well for people with speech disabilities. This means that people with disability may be prevented from interacting with the next generation of computing technologies. In addition, the need to create more inclusive data sets have led to the simulation of data which can involve digitally modifying or generating data. However, simulated data used to train machines may not accurately reflect the capabilities of people with disabilities, leading to erroneous outputs.
- **Bias and privacy:** AI have been shown to infer people's status from data traces, including disability status, and this represents a challenge to privacy and autonomy. The author cites research on how AI inferred whether a person was blind by analysing their Twitter profile and activity, or whether a person had Parkinson's

disease from their mouse movements while on a search engine homepage. Disability (and other statuses) can be implicitly revealed through the data collected about, and of people (biometrics), and this raises issues of both algorithms and people treating others differently or in a biased manner because of computational inferences. Relatedly, research conducted with my colleagues (Grimes et al., 2017) indicated that there is a substantial hidden population of university students living with a disability. These students have a right to non-disclosure of their disability status: The potential for AI to 'out' these students and others with statuses they would prefer kept private is very real.

- **Error:** Many people with disabilities need to trust that outputs from AI systems are accurate and safe but may have limited capability to verify this. For example, a study found that people who were blind were over-trusting of an AI image captioning system, even if the output made limited sense. This adds an extra level of vulnerability that requires attention if AI-powered applications are to be introduced.

What else is there to consider about AI, bias and discrimination?

In a ground-breaking paper, Wachter, Mittelstadt and Russell (2020) explore the idea that fairness cannot be automated and that current laws may not be adequate to the challenges of AI bias and discrimination. AI bias is often detected after harm has occurred. This can happen because people from groups that have historically been discriminated against identify the bias and use well documented definitions and understandings of discrimination to highlight harm (a good example of this is Buolamwini and Gebru's[2] highly significant research on racial and gendered bias in AI and how the decision-making of technologists regarding AI algorithms and models can amplify bias). Wachter and colleagues argue that the automation of fairness through algorithms may not always be possible because decisions about discrimination are contextualised and open to judicial interpretation made on a case-by-case basis. They further elaborate on the challenges AI presents in terms of new forms of discrimination:

> *Compared to human decision-making, algorithms are not similarly intuitive; they operate at speeds, scale and levels of complexity that defy human understanding, group and act upon classes of people that need not resemble historically protected groups, and do so without potential victims ever being aware of the scope and effects of automated decision-making. As a result, individuals may never be aware they have been disadvantaged and thus lack a starting point to raise a claim under non-discrimination law (Wachter et al., 2020, p.6).*

It is vital that we understand that AI systems may discriminate in ways that are without precedent and that there are currently few means of detecting or investigating this to prevent discrimination. Furthermore, Wachter and colleagues argue that this can hinder the collection of evidence to mount a *prima facie* case for new forms of discrimination (for example, that automated discrimination may only be observable at a statistical level and this may be inaccessible to technical people and non-technical people alike given the proprietary and often opaque nature of AI algorithms and/or the need for highly specialised mathematical knowledge).

Put simply, discrimination produced by machines may not be the same sort of discrimination historically enacted by humans and evidencing algorithmic discrimination may be particularly difficult as it won't necessarily be 'felt' in a manner comparable to human discrimination as we now know it (Wachter et al., 2020).

2 See https://www.media.mit.edu/people/joyab/updates/ and Buolamwini & Gebru (2018).

Are there regulations and guidelines on AI?

It is fair to say that, across the globe, the speed of AI innovation has largely outstripped legislation, regulation and the traditional policy levers commonly used to ensure public good. Some suggest that it may be difficult for governments to regulate the technology in traditional ways (Guihot, Matthew and Suzor, 2017). There are substantial technical and information asymmetries between wealthy and influential multinational technology companies who primarily develop AI and those in governance and procurement positions in educational insitutions. Universities with internal expertise in computer science and information systems are in a better position to ask critical technical and privacy questions about proprietary AI products. They will, however, need to draw on a combination of deep technical *and* ethical expertise to adequately assess — in an initial and ongoing way — the impacts of intelligent and automated systems on students and staff, especially from an equity perspective. Without this, there is increased potential for regulatory capture which refers to those in governance positions becoming dependent on potentially conflicted commercial advice on safety and ethical issues. It is therefore incumbent on those of us in higher education with a commitment to equity to educate ourselves on the technical and ethico-legal aspects of AI so that we can play an expert role in guiding its implementation and governance in universities. We might also advocate for an active role in its design.

To this end, I point the reader to some key resources and organisations that can assist in building knowledge about legal, regulatory and procedural approaches to ensuring that AI does not infringe on human rights. While there are numerous international organisations working in this area[3] and I strongly recommend familiarising yourself with their work, the brevity of a discussion paper entails a more Australian-focused approached to recommended reading. The following represent a few good national starting points:

- The Australian Human Rights Commission (AHRC) has produced a relevant discussion paper as part of a consultation process — https://humanrights.gov.au/our-work/rights-and-freedoms/publications/artificial-intelligence-governance-and-leadership
- The Law Council of Australia has put in a submission to the AHRC inquiry — https://www.lawcouncil.asn.au/resources/submissions/human-rights-and-technology
- The Office of the Australian Information Commissioner has resources on information privacy and a link to the Privacy Act — https://www.oaic.gov.au/ and an excellent privacy impact assessment training — https://www.oaic.gov.au/privacy/guidance-and-advice/guide-to-undertaking-privacy-impact-assessments/
- The Commonwealth Ombudsman has a must-read better practice guide to automated decision-making which covers areas around assessing the suitability of automated systems, legal compliance, privacy and governance, and ensuring transparency and accountability — https://www.ombudsman.gov.au/better-practice-guides#:~:text=Automated%20decision%2Dmaking%20better%20practice,rights%20and%20privacy%20of%20individuals.

3 From an international perspective arguably the strongest legal and regulatory framework is the European Union's General Data Protection Regulation which includes biometrics (https://gdpr.eu/). Also see the EU Independent High-Level Expert Group on Artificial Intelligence (https://ai.bsa.org/wp-content/uploads/2019/09/AIHLEG_EthicsGuidelinesforTrustworthyAI-ENpdf.pdf) and the European Data Protection Supervisor https://edps.europa.eu/data-protection/our-work/subjects/artificial-intelligence_en; for some of the most influential research on the social impacts of AI see the AI Now Institute (https://ainowinstitute.org/) and the Algorithmic Justice League (https://www.ajlunited.org/). Try this excellent free tutorial from Gebru and Denton on AI Bias and accountability (https://sites.google.com/view/fatecv-tutorial/schedule). Other sites of interest include: Algorithm Watch (https://algorithmwatch.org/en/); Data Ethics (https://dataethics.eu/); Data and Society (https://datasociety.net/); The Electronic Frontier Foundation for civil liberties, privacy and technology (https://www.eff.org/issues/privacy); and the social and ethical component of The Human Brain project (https://www.humanbrainproject.eu/en/social-ethical-reflective/); and AI Regulation (https://ai-regulation.com/).

- The NSW information and Privacy Commission has a good guide to Privacy by Design — https://www.ipc.nsw.gov.au/fact-sheet-privacy-design

Understandably, much of the emphasis and many of the useful resources are on privacy, particularly on engineered and design solutions, and legal compliance through privacy impact assessment. While very important, privacy is not the only issue that needs to be addressed. We need to significantly broaden the conversation in order to grapple with, and respond to, the myriad ethical concerns AI raises for the field of education.

What can we do now?

As I finish writing this discussion paper, in the midst of the June global protests for the Black Lives Matter movement, news has arrived that a number of technology companies have announced moratoriums or partial bans on supplying facial recognition technology to police agencies (Guariglia, 2020). This action comes after prolonged global activism from people of colour and significant research highlighting racial bias and error related to AI. In the field of AI technology (and technology policy in general) there are two tropes that get deployed with regularity: the need to build trust in technology and the need to consider trade-offs.

Not all AI-powered applications and systems represent the same level of threat to human rights as, say, the use of facial recognition for policing and surveillance or automated decision making in welfare or criminal justice systems. Nevertheless, it is important that we as educators and equity champions engage with the technical and ethical complexity of the technology in order to be able to evaluate and have informed dialogue about its use in universities no matter where it can be found — in business intelligence, administration or student service operations, or teaching and learning. Predictive classifying technologies that can automate decision making or influence human decision making need to be critically engaged with because they are not neutral or unbiased in either design or material effects. Too often there is too much trust in technology with critical engagement prompted only after significant harm has occurred. Building trust in AI means: consciously, carefully and transparently developing open, democratic avenues for education about what the technology is, where it is used, and what it can and can't do; promoting opportunities to be involved in its design and genuine, honest consultation about its procurement and implementation; and creating clear public contestability and accountability policies and mechanisms.

Talk of efficiency, safety or privacy 'trade-offs' with the use of AI should not come at the cost of the human rights of students or staff. If this occurs, it is not a trade-off but a rip-off. There are international efforts underway to create design and engineered solutions to maintaining privacy, addressing bias and error, and detailing when humans should be engaged in the decision-making loop with automated systems. There are also efforts in developing AI literacy curricula (Long and Magerko, 2020) and public education and community dialogue about the technology. There is a growing literature on governance and accountability of AI and some useful guidelines and resources to assist with aspects of this. These are the areas we need to actively participate in. With automated and intelligent systems, there is more than compliance at stake. As, Wachter and colleagues (2020) point out, we are now entering a world where machines may discriminate in ways that are different to humans, with harm not always discernible in ways humans can conventionally comprehend or that may not be apparent until well after harm has occurred. AI may very well reshape discrimination as we now understand it. It is time to move swiftly and proactively to ensure that equity and human rights are considered above matters of efficiency and the optics of innovation in the AI and higher education space.

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