AI IN STUDENT RECRUITMENT AND SELECTION

ARTIFICIAL INTELLIGENCE AND THE NEED FOR AUTHENTICITY AND INTEGRITY

Divya Singh and Avani Singh

Introduction

There is no gainsaying the changes wrought by technology to regular human engagement.[292] Technology enables connection across geographic borders as well as social and economic boundaries, creating new and still unchartered opportunities for learning and self-development. These changes, with their inherent potential for innovation and development, are recognised in the objectives of the National Qualifications Framework (NQF). Sections 5(1)(b) and (d) of the NQF Act 67 of 2008 are of specific relevance, providing that:

> The objectives of the NQF are … (b) to facilitate access to, and mobility and progression within education, training and career paths; … (d) accelerate the redress of past unfair discrimination in education, training and employment opportunities.

This paper focusses on the critical issue of access to higher education through recruitment and selection processes. The discussions consider the efficacy of technology-enabled selection and recruitment practices in

[292] This article was originally published in the *South African Qualifications Authority Bulletin*, 20:1 September 2021, and is republished here with permission.

higher education institutions, and the likelihood of technology optimising the NQF agenda. As institutions become increasingly responsive to the possibilities proffered by the Fourth Industrial Revolution, artificial intelligence (AI) - with its yet unharnessed capabilities - will become more salient over the next decades. Emphasising this reality, the World Economic Forum (WEF) points to the impressive progress made in AI in recent years, driven by exponential increases in computing power and the availability of vast amounts of data.[293] Further explaining why today's technological transformations represent more than merely a prolongation of the Third Industrial Revolution and rather the arrival of a fourth and distinct one, the WEF highlights the critical factors of velocity, scope, and systems impact.[294]

Business and organisations are increasingly confronted with artificial intelligence that promises opportunities to streamline complicated, cumbersome, time-consuming, and resource-intensive processes through automation, and universities have not been exempt. While alluring and significant in any decision-making process, this is never the full consideration. As a rule of general application, decisions to adopt artificial intelligence should integrate two further key vectors, namely, the legal and ethical deliberations of the decisions taken. In this context, the reminder from Hanson is apposite: "In higher education … we face a decade in which institutional integrity and legitimacy is under fire."[295] As higher education institutions prepare for the deluge of technology in

---

[293] World Economic Forum (WEF). Fourth Industrial Revolution: What it Means, How to Respond, 2016, no page, https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

[294] WEF, 2016, op. cit.

[295] Hanson, W.R. *Ethical leadership in higher education: Evolution of institutional ethics logic.* Dissertation Graduate School of Clemson University, 2009, 1. https://tigerprints.clemson.edu/all_dissertations/377/

the Fourth Industrial Revolution, the duality of the relationship between ethics and technology must be an integral aspect of adoption, and the promise of technology should consciously align with the broader higher education commitment to academic authenticity and integrity.

AI for Recruitment and Selection

There is no gainsaying that the state's financial contribution to higher education has not kept up with the number of learners with access to university study. According to the Institute for Security Studies, government funding *per capita* has been consistently declining since 1994. In 2016, spending on higher education was 0.76% of gross domestic product (GDP) – lower than both the African (0.78%) and international (0.84%) averages.[296] With the limited budgets and institutional rivalries built on reputation, institutional rankings and competition linked to success and throughput, universities are keen to ensure that students enrolled are both most likely to be retained and will succeed to graduation. While not restricted by enrolment caps and state subsidies, private higher education institutions are equally committed to demonstrating graduate success and throughput.

As emphasised by Chen and Do the accurate prediction of students' academic performance is one of the critical factors considered by institutions these days when making admission decisions.[297] Supporting this imperative, AI and machine learning - specifically predictive

---

[296] Reva, D. No Date. Getting to the heart of South Africa's higher education crisis. *ISS Today.* Pretoria, South Africa: Institute for Security Studies, n.p. https://issafrica.org/amp/iss-today/getting-to-the-heart-of-sas-higher-education-crisis

[297] Chen, J.F. and Do, Q.H. "Training neural networks to predict student academic performance. A comparison of cuckoo search and gravitational search algorithms". *International Journal of Computational Intelligence and Applications.* 13(1), 2014, 18, https://doi.org/10.1142/S1469026814500059

analytics for recruitment and selection - has already become an intrinsic aspect of the institutional admissions management plans of many universities in the USA.[298] These universities have been increasingly applying machine learning for purposes of new student profiling and prediction of success, as well as to promote institutional efficiency during the enrolment processes.

With the focus on widening access and the massification of higher education, universities in South Africa receive thousands more

---

[298] The literature provides various definitions and descriptions of AI. One of the less complex definitions is provided by Kukulska-Hulme *et al*. (2020), who explain it as "computer systems that interact with people and with the world in ways that imitate human capabilities and behaviours." A more comprehensive definition is provided by the Independent High-Level Expert Group on Artificial Intelligence, set up by the European Commission, as follows:

"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions. As a scientific discipline, AI includes several approaches and techniques, such as machine learning,… machine reasoning,… and robotics." (European Commission 2019: 6)

As noted above, machine learning – underpinned by algorithms – is a sub-field of AI which involves "software able to recognise patterns, make predictions, and apply newly discovered patterns to situations that were not included or covered by their initial design" (Popenici and Kerr, 2017, op. cit., 2). Detailed references are: Kukulska-Hulme, A., Beirne, E., Conole, G., *et al*. *Innovating Pedagogy 2020. Open University Innovation Report 8.* United Kingdom: Institute of Educational Technology, Milton Keynes: The Open University, 2020, http://www.open.ac.uk/blogs/innovating/; European Commission. 2019. A definition of AI: Main capabilities and solutions. April, 8. Brussels: European Commission www.aepd.es/sites/default/files/2019-12/ai-definition.pdf applications for places than they can accommodate. While many universities depend solely on quantitative data, globally, universities are also recognising that the "inclusion of qualitative components in applications can provide a more comprehensive representation of each applicant's potential than quantitative measures could do on their own."[299] However, qualitative applications are significantly more resource-intensive process as each one requires individual consideration. Furthermore, the method introduces different apprehensions, such as the potential for human bias and subjectivity.

That said, with the advances in machine learning and the AI capabilities to 'read' text statistically, this could be an attractive solution to the resource burden and subjectivity constraints confronting institutions.[300] It also has the potential to provide for better customer service and quick turnaround times to ensure that students can receive feedback much sooner. Reflecting on the promise of machine learning, Klutka, Ackerly and Magda describe forms of AI currently available in marketing automation and predictive analytics "that plug into customer databases and 'learn' what the ideal customer is that has purchased a product."[301] Describing the success of Harley Davidson sales in the New York City market, they note that how a person behaves in the buying process, and what the person responds to, are all possible of being diagnosed by the system. "This AI can then find individuals that match

---

[299] Alvero, A.J., Arthurs, N., Antonio, A.L., Domingue, B.W., Gebre-Medhin, B., Giebel, S, and Stevens, M.L. "AI and holistic review: Informing human reading in college admissions." *2020 AAAI/ACM Conference on AI, Ethics, and Society (AIES '20), February 7-8, 2020, New York, NY, USA.* ACM, New York, NY, USA, 2020, 7p. https://doi.org/ 10.1145/3375627.3375871, section 2.1

[300] Alvero et al, 2020, section 2.3.

[301] No Date: 9

these traits and show them ads for the product."[302] In higher education admission processes, such technology will enable much more focused student recruitment, thereby allowing universities to "narrowly define the 'ideal' student and use AI to select the best candidates."[303] The university can thus single out the best students for individualised engagement about the university, and why it is best suited for them.

Against this backdrop, the remaining issue then appears to be that of cost – yet this is not so. The most crucial consideration is whether the AI system will be a responsible solution. Considering the possibilities of AI for university selection and recruitment practices, the test stands on three pillars: (i) is the machine thinking rationally; (ii) is the machine making the right decision; and (iii) will the machine behave ethically. Triangulating the responses will aid in assuring a functionality that subscribes to the values of higher education and the priorities of the NQF.

Bearing in mind the objectives of the NQF, examples of how universities have applied AI in recruitment and selection are analysed to identify the risks and opportunities. Some cases specific to the university sector include the work of Andris, Cowen and Wittenbach who used machine learning to find spatial patterns that might favour prospective college students from specific geographic areas in the USA.[304] The university was then able to establish 'loyalty ZIP codes' and hone into particular areas and target those students most likely to apply, enrol and succeed.[305] This approach was undoubtedly more efficient as compared

---

[302] Klutka, J., Ackerly, N. and Magda, A.J. *Artificial Intelligence in Higher Education. Current Uses and Future Applications*. Learning House, No Date, 10, www.201811-AI-in-Higher-Education-TLH.pdf

[303] Klutka, Ackerly and Magda, ND, 20.

[304] Andris, C., Cowen, D., and Wittenbach, J. "Support vector machine for spatial variation." *Transactions in GIS*, 17(1), 2013, 41-61. https://doi.org/10.1111/j.1467-9671.2012.01354.x.

[305] Andris, Cowen and Wittenbach, 2013, 58.

with the traditional, often superficial, broad-brush method commonly employed by universities due to limited funding.

Other universities use a combination of historical and current enrolment data, learning analytics and academic performance data of past and current students to develop predictive models for 'recommender systems'. The system then guides the students' enrolment to specific programmes and majors in which the system calculates they will be most likely to succeed.[306] While optimised student success is an unambiguous objective of every higher education institution, this limited and shoehorned strategy to access must beg the following questions: what about the student's acquisition of new knowledge in an area outside of his/her comfort zone?; what about extending the neural pathways of the student to explore something different?; while prioritising student success, what happens to the student's overall development and focus on issues such as social consciousness and civic engagement?; and what about learning for enjoyment? It would be naïve to suggest that university education is not about discipline-specific learning. However, there is a concurrent groundswell of research emphasising the need for higher education to focus on holistic student development. Another important consideration for universities using predictive analytics to guide students towards specific learning paths is the acknowledgement that the best grade is not necessarily what will gear a student to be successful in the current world-of-work and life. (Stelnicki and Nordstokke 2015). There is also no consensus on the existence of a linear correlation between academic grade excellence in

---

[306] Ekowo, M. and Palmer, I. The promise and peril of predictive analytics in higher education. 7, 9 October 2016, https://www.luminafoundation.org/resource/the-promise-and-peril-of-predictive-analytics-in-higher-education/

high school, university success and achievement in the world of work. (Muller 2013; Wolmarans, Smit, Collier-Reed, and Leather 2010).[307]

Further interrogations on the use of algorithms for selection and recruitment highlight apprehensions about producing student archetypes. If properly founded, this question raises a more profound concern about whether such an outcome is not inherently counterintuitive to the fundamental principles of diversity and democratisation of access to higher education and learning. A further challenge with the process of universities shoehorning students based on algorithmic factors of success arises when the information is used by enrolment officers to *exclude* students from an institution even before they start the learning journey because they are considered a success risk.[308] There is no

---

[307] Stelnicki, A.M. and Nordstokke, D.W. "Who is the successful university student? An analysis of personal resources." 45(2), 2015, *Canadian Journal of Higher Education.* 214-228. www.184491-ArticleText-198393-1-10-20150822 (1).pdf.; Muller, A. The predictive value of Grade 12 and university access tests results for success in higher education. March 2013. Masters Dissertation in Education, Stellenbosch University, www.scholar.sun.ac.za/handle/muller _predictive_2013.pdf; Wolmarans, N., Smit, R., Collier-Reed, B. and Leather, H. 2010. "Addressing concerns with the NSC: An analysis of first-year student performance in mathematics and physics". Paper presented at the 18th Conference of the Southern African Association for Research in Mathematics, Science and Technology Education, KwaZulu-Natal, 274-284. https://www.researchgate.net/publication/236934790_Addressing_concerns_ with_the_NSC_An_analysis_of_first-year_student_performance_in_ Mathematics_and_Physics.

[308] At Mount St Mary's University, the institution used to survey to identify students likely to drop-out. The idea was that the students would be "encouraged to leave before they were included in the retention data" collated for purposes of government reporting and national rankings. A fundamental ethical concern with this approach is that students were neither informed of the purpose of the survey, nor were they aware that some students may, as a result of the findings, be "pressured to leave" (Ekowo and Palmer 2016, op. cit. 2). In defence of the university, the president explained that unsuccessful students would be refunded

gainsaying the material costs linked to marketing and student recruitment and universities – with all their current cost containment imperatives – need to be as strategic as possible with their limited resources. However, while the positive potential of machine learning for recruitment and selection processes engenders excitement, there is a definite alternate reality.

Discussion: Ethical and Legal Decision-Making

The advent of artificial intelligence and other similar technologies gives rise to critical and thorny legal and ethical questions, including questions about safety, security, the prevention of harm and the mitigation of risks; about human moral responsibility; about governance, regulation, design, development, inspection, monitoring, testing and certification; about democratic decision-making; and the explainability and transparency of AI and 'autonomous' systems.[309] To protect society against the abuse of AI and new technologies, it proposes nine ethical principles and democratic prerequisites when contemplating a new system: human dignity; autonomy; responsibility; justice, equality and solidarity; democracy; the rule of law and accountability; security, safety and bodily and mental integrity; data protection and privacy; and sustainability. These ethical considerations constitute the yardstick for the design and implementation of any AI system in a higher education institution.

---

their study fees and advised to enroll elsewhere where they had a better opportunity for success. According to the university, it was in fact "helping [students] avoid accumulating debt for a degree they might not have any chance of earning." (ibid.)

[309] European Group on Ethics in Science and New Technologies, 2018. *Statement on Artificial Intelligence, Robotics and 'Autonomous' Systems*, http://ec.europa.eu/research/ege/pdf/ege_ai_statement_2018.pdf

AI bias in selection and recruitment

As stressed by Remian:

> "Authenticating the knowledge and predictions of AI becomes more important when AI is used for education since the further spread of inaccurate or outdated content could defy educational goals and further reinforce false information."[310]

One of the gravest concerns with artificial intelligence and especially machine learning is that bias in the system may be unconscious or more critically, not programmed at all but, as seen in the examples below, learned by the machines acting on their own. In addition to bias, two other elements, namely transparency and accountability, must be considered when adopting machine learning. Only when all three aspects are successfully in place will an institution be able to claim the authenticity and integrity of the system.

While machine learning in higher education, and specifically in the domain of selection and admission (access), has tremendous potential, it also presents an equal danger. Today, there is neither the will nor the proven reason to stop the tsunami of technology. However, one of the most significant risks of the Fourth Industrial Revolution is for persons to become sucked into the hype and excitement and, fearful of being left behind, inadvertently further propagating and entrenching stereotypes and current inequalities. Confirming this challenge, Alvero *et al.* reiterate that:

> "AI is often described as having the ability to rapidly scale discrimination and exacerbate social inequality."[311]

---

[310] Remian, D. Augmenting education: Ethical considerations for incorporating artificial intelligence in education. 24 November 2019, ScholarWorks at UMass Boston, 20. https://scholarworks.umb.edu/cgi/viewcontent.cgi?article=1054and context=instruction_capstone

[311] Alvero, 2020, op. cit. section 2.3.

The South African entrant to higher education over the last 25 years (and perhaps in the next 25 years) presents with a significantly different profile to those who fed the university pipeline in the pre-1994 era and the few years post-democracy. As the numbers of historically disadvantaged students entering university grew, different race and gender demographic representations began to emerge, and the student profile changed from many (if not most) coming from homes where parents were not university graduates. With the introduction of fee-free higher education, the opportunity for students from lower-income families to enter university has increased exponentially. However, the stark reality is that the admission and success track records of the post-apartheid university student continue to be chequered by the apartheid legacy and are still developing. Against this backdrop, the even-handed outcomes of predictive analytics are doubtful, especially taking cognisance of the factors (such as race, ethnicity, high school, anticipated study areas, and family history) included by the data to 'train' the machines for recruitment and selection. For example, at Wichita State University, the student recruitment programme uses the specific factors of gender, race, ethnicity, standardisation test scores and parents' university background. Based on comparative ratings which interpret and indicate the individual's likelihood to attend the institution, the university targets prospective students for recruitment.[312]

Also using machine learning for recruitment, the University of Ithaca extended the list of factors for selection include the number of friends and photographs on social media. The university collected information about its students from their posts on the internal university social media platform, intended for communication between peers *inter se*, and between students and their lecturers. The university then linked the information with the academic performance of the identified students and using machine learning and analytics, compared the student data

[312] Ekowo and Palmer, 2016, op. cit. 11.

with that from applicants to determine prospective students based on their potential for success.[313] The example from the University of Ithaca highlights a material ethical (and legal) concern, namely whether students received advance knowledge about how the institution intended further using their social media information, beyond the academic imperative, and had the opportunity to consent. In a similar vein, Ekowo and Palmer explain that "[c]olleges have long streamlined their recruitment efforts by purchasing student names and their scores for relatively little from third-party organisations."[314] As will be seen later, such practices raise real questions about the integrity of the collection process.

Colleges have also used predictive analytics to assist in identifying the financial need and ability of students.[315] The ethical challenge with this is whether the outcome is to enable the university to better budget to support such students or whether the universities are using the data to eliminate students who may not be able to pay the fees of the institution.

In looking at algorithms and machines to determine recruitment, one may be lulled into a false sense of acceptance that at least the process will be objective. However, the sub-optimal outcome of Amazon's experimental recruitment engine – intended to mechanise the search for *top talent* – dashes the thought. Early in the process, the developers realised that the system displayed a distinct gender bias toward male applicants when it came to recruiting for specific technical positions. Upon further examination, it transpired that the computer models had been trained on résumés submitted to companies in the preceding ten years – a time when the industry was overwhelmingly male-dominated.

---

313 Felton, E. "Colleges shift to using 'big data' – including from social media – in admissions decisions", 21 August 2015. *The Herchinger Report*, https://hechingerreport.org/colleges-shift-to-using-big-data-including-from-social-media-in-admissions-decisions/

314 Ekowo and Palmer, 2016, 11.

315 Ekowo and Palmer, 2016, 6.

Consequently, the machine learned to penalise résumés which included the word “woman”. Amazon eventually disbanded the project, acknowledging that while in this instance the bias was identified and remedied, there was no guarantee that the machines would not themselves devise other secondary or *proxy* attributes that could also prove discriminatory.[316]

The Amazon experience was not an isolated instance of machine learning going rogue.[317] In a different experiment, researchers at Carnegie Mellon University also noticed that men were more likely to be targeted for high paying executive jobs. In this instance, the researchers were not able to identify the cause.[318] In another project, the system was explicitly trained to reject candidates with poor English language skills, and, over time, the algorithm taught itself to equate English sounding names generally with acceptable qualification for the job.[319] Such examples demonstrate the need for absolute assurance that where the human factor is crucial, data that informs the algorithm must be both reliable and valid.

Given the socio-economic factors used to *train* the machines, none of the AI systems indicated above resonates with the NQF objective of widening higher education access to previously disadvantaged individuals. Ekowo and Palmer also stress the potential for predictive models to perpetuate injustice for historically underserved groups because “they include demographic data that can mirror past discrimination included in the historical data.”[320] The majority of South African applicants - for any number of reasons including the reality of being first-generation university entrants - would either have their

---

316 Dastin, 2018, op. cit.; Kim, Soyatu and Behnagh, 2018, op. cit.

317 Popenici and Kerr, 2017, op. cit. 2-3.

318 www.harver.com

319 www.harver.com

320 Ekowo and Palmer, 2016, 14.

applications declined or be steered away from the more intense (and often economically lucrative) programmes on the basis that the system indicates a lack of potential to succeed. Such an approach must be antithetical to the national goals for more black graduates and more women graduates, especially in the discipline fields of science, technology, engineering, and mathematics at a national level. It further points out why in South Africa machines alone will not effective in university recruitment and selection practices.

The research further illuminates the need for universities considering AI systems for admission to understand how and why the machine was trained and who prepared it. Institutions must understand the system and be able to clearly define the value and its synergy with the institutional mission and purpose. In a country of acknowledged social, structural, and economic inequality, the factors applied must not - intentionally or otherwise - reinforce discrimination. Summarising the three fundamental problems that arise with the use of AI, Yu refers to algorithmic deprivation; algorithmic discrimination; and algorithmic distortion.[321] With specific regard to algorithmic discrimination, he notes that the concerns "range from errors to biases and from discrimination to dehumanisation" which tend to be particularly problematic for those on the unfortunate side of the algorithmic divide.[322] In most instances, the worst affected are the poor, the disadvantaged, and the vulnerable.

Confirming the findings in the case studies above, Yu states:

> "While the existence of algorithmic bias alone is bad enough, the problem can be exacerbated by the fact that machines learn themselves by feeding the newly generated data back into the algorithms. Because these data will become the new training and feedback data for machine-learning purposes, algorithms that are improperly designed or that utilise problematic data could

[321] Yu, 2019, op. cit. 19.

[322] Yu 2019, 19.

> amplify real-world biases by creating self-reinforced feedback loops. As time passes, the biases generated through these loops will become much worse than the biases found in the original algorithmic designs or the initial training data."[323]

Further to the above considerations, Alvero *et al*. stress the distinctly different approaches by AI researchers and university selection and enrolment officers to the values of fairness and bias. They note:

> "AI researchers tend to be concerned with fairness and bias at the population level, and worry when patterned evaluative outcomes do not approximate population demographics. By contrast, admission officers tend to emphasise fairness of evaluation for individual applicants."[324]

These divergent ethical priorities must be much more closely aligned before universities begin to consider AI and machine learning for recruitment and selection and the caution by Popenici and Kerr bears notice:

> "With the rise of AI solutions, it is increasingly important for educational institutions to stay alert and see if the power of control over hidden algorithms that run them is not monopolised by the tech-lords. … Those who control algorithms that run AI solutions have now unprecedented influence over people and every sector of a contemporary society."[325]

In private higher education, in the absence of state funding, it is plausible that algorithms used in recruitment management will continue to favour selecting wealthier students over their less affluent peers simply because these are the students always enrolled. Some institutions

---

323 Yu, 2019, 17.

324 Alvero et al., 2020, op. cit. sect. 6.

325 Popenici and Kerr, 2017, 4.

will accept this, satisfied that the commercial enterprise will be protected; however, other institutions may find that this unacceptable and contradictory to their central vision to widen access for *all* South Africans.

The legal parameters and standards

As is often the case, the law tends to lag technological developments. However, in South Africa, the Constitution – and specifically section 9 (which provides for the right to equality) and section 14 (which guarantees the right to privacy of every person) – may provide the necessary guidance that will be especially applicable to AI. As seen from the discussion above, the implementation of AI-based technologies in student recruitment and selection has the potential to violate these rights, and it is therefore imperative that institutions contemplating the use of AI take appropriate measures to safeguard against any rights violations.

The right to equality

The right to equality is given content through the Promotion of Equality and Prevention of Unfair Discrimination Act 4 of 2000 (PEPUDA). Section 1 defines *equality* as including "the full and equal enjoyment of rights and freedoms as contemplated in the Constitution and includes de jure and de facto equality and also equality in terms of outcomes." Section 6 expressly prohibits unfair discrimination based on:

(a) race, gender, sex, pregnancy, marital status, ethnic or social origin, colour, sexual orientation, age, disability, religion, conscience, belief, culture, language and birth; or

(b) any other ground where discrimination based on that other ground –

(i) causes or perpetuates systemic disadvantage;

(ii) undermines human dignity; or

(iii) adversely affects the equal enjoyment of a person's rights and freedoms in a serious manner that is comparable to discrimination on a ground in paragraph (a).

In relying on AI for decision-making, universities must be cognisant not to violate the right to equality or perpetrate an act of discrimination based on any of the prohibited grounds (cf. Wichita State University above). Relying on section 13(1) of PEPUDA, a prospective student alleging that s/he has been the subject of a discriminatory decision by the university need only make out a *prima facie* case of discrimination. Thereafter, the burden shifts to the university to prove either that the discrimination did not take place, or that its conduct was not based on any of the prohibited grounds. To satisfy its onus, the university will firstly, have to justify the basis of its decision; and secondly, show that its decision followed the law.

The right to privacy

In addition to the constitutional and common law right to privacy, higher education institutions must comply with the Protection of Personal Information Act 4 of 2013 (POPIA),[326] which provides a comprehensive legal framework for data protection in South Africa. POPIA requires higher education institutions using AI or machine learning to make decisions about students to ensure that: (i) the affected students are adequately informed of the intention; and (ii) the personal information processed for decision-making purposes complies with the conditions stated in the Act.[327] POPIA further expressly requires that personal data may only be processed if, given its purpose, it is relevant,

[326] All provisions of POPIA came into effect on 1 July 2020.

[327] The eight conditions include the principles of fairness, transparency and accountability, and the rights to be informed, to object, to access, and the rights related to automated decision-making.

not excessive, and there is a valid justification for the processing. Additionally, the collection of personal information must be for a specific, explicitly defined and lawful purpose related to a function or activity of the university and should not be retained for any longer than is necessary to achieve the goal, unless one of the legislated exceptions applies. Importantly, while higher education institutions may seek consent from data subjects for the processing of their personal information, this is not a silver bullet. The burden will remain on the institution to prove that the consent was given in a voluntary, specific, and informed manner (that is, that it was validly obtained). As such, higher education institutions must be open and transparent with students about the purposes for which personal information is being collected and used, as well as the consequences of their compliance or refusal to provide the information as requested.[328]

Restrictions on automated decision-making

Section 71 of POPIA deals specifically with the question of automated decision-making. Sub-section (1) provides that a data subject may not be subject to a decision which results in legal consequences for them or which affects them to a substantial degree, which is based solely on the automated processing of personal information intended to provide a profile of that person. Sub-section (2) sets out certain exceptions to the general prohibition. For instance, if the decision is in connection with the conclusion or execution of a contract, and appropriate measures are in place to protect the data subject's legitimate interests. "Appropriate measures" in this regard require that the data subject has an opportunity to make representations about the decision and provided with sufficient information about the underlying logic of the automated processing of the information to make such representations. The insertion of this provision evinces a clear understanding from the legislators of the

[328] Cf. University of Ithaca.

potential for risk attendant upon automated decision-making, and the broader implications that this may have on affected persons. Universities would be advised, as a rule of general application, to avoid decisions taken by solely automated means unless there is absolute certainty and clarity that the rights and interests of students can be appropriately protected.

The European Parliament report by the Panel for the Future of Science and Technology describes data protection as being at the forefront of the relationship between AI and the law.[329] AI systems need to collect and process data to make intelligent decisions, therefore making access to data fundamentally important.[330] However, appropriate means and mechanisms must be in place to ensure that the personal data in the possession or under the control of the university is not subject to unlawful access or abuse. As noted by the Panel for the Future of Science and Technology:

> "AI enables automated decision-making even in domains that require complex choices, based on multiple factors and non-predefined criteria. In many cases, automated predictions and decisions are not only cheaper, but also more precise and impartial than human ones, as AI systems can avoid the typical fallacies of human psychology and can be subject to rigorous controls. However, algorithmic decisions may also be mistaken or discriminatory, reproducing human biases and introducing new ones. Even when automated assessments of individuals are fair and accurate, they are not unproblematic: they may negatively affect the individuals concerned, who are subject to

---

329 European Parliament report by the Panel for the Future of Science and Technology, 2020, op. cit., 1.

330 WEF, 2019, op. cit., 6.

pervasive surveillance, persistent evaluation, insistent influence, and possible manipulation."[331]

To withstand the legal (and ethical) challenge, universities will, therefore, need to be transparent in setting out their recruitment strategies and the principles that inform their selection processes. Students must know if they are being subject to automated decision-making, as well as provided with the underlying logic of the automated processing, with a reasonable opportunity to make representations on the decision. To the extent that an automated outcome determines a result, universities should consider coupling such automation with human interventions to oversee the process and apply an independent mind to the determinations to preserve the values of a human-centric society.

Conclusion: The Need for AI – Authenticity and Integrity – With Machine Learning

When implementing artificial intelligence, it is vital to ensure that in the final analysis, the ethics, values, rights and standards espoused by the university and the higher education sector are protected and promoted, as well as the principles required by law. Where machine learning is used, this will inevitably include how the predictive models are created and by whom. Given the complexity of the processes and the decision-making involved, universities must develop institutional frameworks (including risk and impact assessments) to guide their approach, implementation, and application of AI within the institution, based on multi-stakeholder collaboration. This is an optimal strategy to promote accountability, transparency, privacy, and impartiality and create trust in what could quickly become a contested activity.[332] As explained by the United Kingdom Information Commissioner's

[331] Panel for the Future of Science and Technology, 2020, i.

[332] WEF 2019, 9&11.

Office (ICO) an approach that favours explaining AI-assisted decisions to affected individuals makes good business sense. It fosters trust, enables one to obtain more credible and reliable information, and gives one an edge over other organisations that are not as progressive and respectful in their interactions (2020: 16). The ICO further points to the risks incumbent in not explaining AI decisions, including the potential for regulatory action, reputational damage, and disengaged public.[333] Crucially, and as a further demonstration of considered and informed decision-making, it is imperative that institutional spokespersons explaining AI-assisted decisions to affected individuals fully understand the models, choices and processes associated with the AI decision-making processes (ICO 2020: 16).

While the increasing use of AI can have revolutionary benefits for higher education institutions, it is only by fostering a culture of authenticity and integrity that it will be possible to truly and meaningfully realise the opportunities that AI can offer. This means adopting an approach that is clear, coherent, transparent, responsible and abides by relevant principles of law and ethics. As students increasingly demand agency over their information and the decisions taken about them, higher education institutions should not risk being on the unfortunate side of the benefits that the technology can create.

---

[333] Expanding on its recommendation for explanation and engagement, the ICO has identified six main types of explanation: rationale explanation; responsibility explanation; data explanation; fairness explanation; safety and performance explanation; and impact explanation (2020: 20).