Chapter 5

Unpacking the Role of Big Data, Artificial Intelligence, and Predictive Analytics in Education: Implications for Educators and Research Ethics Review Committees

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Introduction

Goodbye to ChatGPT (chat generative pre-trained transformer), hello to AI (artificial intelligence) on the moon! AI is daring to have its finger touching the surface of the moon. The CMCSS (Canadian Mission Control Space Services) through budgetary funding of $3.04 million by the Canadian Space Agency made history when it launched the Rashid Rover on 11 December 2023, with the aim of spending one lunar day[1] in space. The mission will see the Rover capturing and identifying geological features through pictures, and it was motivated by CMCSS' urge to be the pioneer in showcasing AI's DL (deep learning) capabilities first in lunar space. DL is a subset of ML (machine learning) and it relies on large and vast volumes of data, based on complex algorithms to train the model (Rane, Kaya, Mallick, & Rane 2024:218).

The enormous datasets, whether structured or unstructured, are where big data and PA (predictive analytics) traverse. Using data points and the precision of analysis are just a drop in an ocean in terms of capabilities and insights that can

1 One lunar day is equivalent to 29 Earth days.

be drawn from this interaction. The data gigantic is known as 'big data,' a term which, according to O'Leary (2013:96), has experienced exponential growth and has to date accumulated many definitions. Goh, Cheong, Tan, and Sharma (2023:16) allude that voluminous amounts of data that are being produced across various platforms, flourish exponentially. The authors go further to predict that this growth is expected to double every two years, and with such massive datasets, human-geared analysis is almost impractical, hence the need for sophisticated computational analysis (Emanuel & Wachter 2019:2281). To demonstrate the surge in data on the internet, Solarwinds Pingdom (2013) breaks down various types of datasets globally available on the web. For example, in 2012, there were approximately 2.2 billion e-mail users, 144 billion e-mail traffic per day, half a billion websites, 2.4 billion internet users, and over 100 million blogs. This constitutes data in unstructured form such as pictures, audio, text, and videos. As of 2023, there were over 5.3 billion internet users translating into almost 67% of the global population. In terms of the social media, there were about 4.95 billion users coupled with over 600 million blogs (Petrosyan 2023). These data statistics, according to Chu, Kim, Lin, Yu, Bradski, Ng, & Olukotun (2006:1 of 8) reflect data evolution through the 'internet of people and things' and the 'internet of everything.'

The introduction of personal computers almost five decades ago (Flamm 1988:6), the prevalence of supercomputers and their interaction with human beings (Chen, Chen, & Lin 2020:75265), as well as the use of mobile technology (Alexandru, Alexandru, Coardos, & Tudora 2016:123) and social media have enabled the generation and availability of data in excessive forms (Luan, Geczy, Lai, Gobert, Yang, Ogata, Baltes, Guerra, Li, & Tsai 2020:2 of 11), which consequently paved way, and to some extent enabled these developments. According to Grand View Research (2023), the proliferating utilisation of mobile devices and their applications have transmogrified modern life in various ways, and this has caused a paradigm shift away from brick-and-mortar operations to digital and recently to cloud-based operations. Similarly, still on digital and technological transformation, Nam and Pardo (2011:185) highlight a number of evolutions in applications, ML techniques, DM (data mining), ICT (information and communication technology), as well as data fusion and pattern-recognition techniques as instrumental to the industrial revolution, with smart cities of the future being one part of it.

Big data as O'Leary (2013:97) puts it, were originally brought to the fore by Cox and Ellsworth in their 1997 work which reflected on how big data can be managed in the era of scientific visualisation (Cox & Ellsworth 1997). In that article, the two authors use the term 'large data.' Big data refers to information that is generated rapidly and in a wide variety from digital sources (Venugopal & Mamatha 2023:1). Conducting a literature review, an analysis of statistical data, mathematical, and statistical problem solving, improved personalised learning is purporting benefits driven by technological advancements in AI, big data, ML, and PA (Venugopal & Mamatha 2023:1). PA and AI rely on massive data warehouses that store both historical and real-time information. The connection between AI and big data can be best explained through a process of symbiosis, in that they are both dependent on one another to deliver above-par insights, where data analytic capabilities become an enabler in the journey for many industries to leverage the gains. For example, it is reported that the fusion of big data and ML tools and techniques such as DL models – CNNs (convolution neural networks) and LSTM (long-short term memory) architectures – enable abilities of metropolitan municipal departments to realise the emergence of smart cities, where they are able to predict region-based traffic flow (Khan, Nazir, García-Magariño, & Hussain 2021). In these models CNNs are applied to classify spatial data whereas LSTM is used for temporal data classification (Khan *et al.* 2021:1-4 of 11). Other industrial areas benefiting from the application of AI, analytics, and big data include but are not limited to predictions of crowd flow (Zhou, Gu, Ling, Li, Zhuang, & Wang 2020:338), traffic flow (Khan, Ali, Ullah, & Bulbul 2018:71; Khan *et al.* 2021:1-2 of 11), water quality (Assem, Ghariba, Makrai, Johnston, Gill, & Pilla 2017:317), and air quality (Xiong, He, Huang, Yu, & Jing 2020:78). Neha and Sidiq (2020:48) allude that within the educational landscape, IHEs (institutions of higher education) are able to predict students' performances and success through additional ML techniques such as CF (cooperative filtering) and recommender systems (RS). DM, regression techniques, classifications, neural networks, and SVMs (support vector machines) are some of the terminologies associated with ML and big data (Neha & Sidiq 2020:49).

No exploration of AI in education would be complete without addressing the challenges that arise in tandem with the integration of big data and PA. Algorithmic bias, ethical concerns, and the potential erosion of privacy are formidable issues that demand attention – hence they are discussed in the chapter. The chapter not only identifies these challenges, but quest also to highlight possible measures and principles aimed at mitigating against these challenges and concomitant risks that are complement to the implementation and integration of AI, big data, and PA education. Peering into the future, the concluding section of the chapter ventures into the implications that big data and AI clench for work and responsibilities of RERCs (research ethics review committees). The key questions worth exploring include the following:

- How will the advancements in big data, AI, and PA reshape the ethical considerations governing educational research and functions or RERCs?
- What novel challenges and opportunities will emerge as we tread further into this technological frontier?

These questions propel us towards an informed reflection on the evolving landscape of research ethics, underscoring the need for adaptable frameworks in the face of accelerating technological progress. This chapter is an exploration and exciting journey beaming through the past, present, and future of AI, big data, and PA integration in education. The threads that weave these technologies into the fabric and the nature of the educational sector are therefore unravelled, contemplating their impact on educators, research ethics review committees, and the very foundations of educational practices. The next section sets the scene for the chapter by delving into the classifications of AI systems.

Classifications of AI Systems

In this era of AI, where its capabilities and prowess are taking the world by storm, ML remains one of the topical issues within academic discussions and conferences (Sen, Hajra, & Ghosh 2020:99). The enhancement, efficiency, and precision of education practices can be attributed to how AI alongside data science and ML algorithms are leveraged. While data science, AI, and ML are closely connected to one another and can be clustered in the same domain, their overlap, specific applications, and meanings are worth being explored. Signifying the importance of ML techniques and their convergence with AI, Salem (2015:201) echoes sentiments in the literature that ML and computational intelligence coupled with DM techniques amplify the wherewithal of e-Iearning systems, thereby enabling them to reveal even more intelligent behaviour beneficial to the educational landscape.

The popularity of ML systems and techniques is credited to the work of Alan Turing, a British scientist who through his seminal work on computing, machines, and intelligence asked what could at the time be a rhetorical question: 'Can a machine think?' (Turing 1950). In his work, Turing hypothesises that it is possible that machines have the ability to think and execute decisions just as humans can. It goes without saying that he was mocked, however, little did they know that almost eight decades later, his thoughts would be poised to be the turning point for the AI of the future. Furthermore, his thoughts would continue to be the centre of debate between machines and human abilities. Muhammad and Yan (2015:946) point at the supernatural abilities of ML as computers are guided how to automatically explore good predictor drawing from previous experience. The authors go on to acclaim that abilities like that depend on how good the classifier is. Machines, referring to computers are extrapolated to be lacking abilities to learn from past experiences, while humans have that attribute (Muhammad & Yan 2015:947). This is an interesting reflection point to witness how far AI and in particular ML has evolved!

ML is built on the principle of incessant learning algorithms that continuously engage in decision-making or the identification of patterns. ML models are trained to utilise preexisting data (this is one of the commonly used forms) or ML is a subset of AI empowered by neural network technology, and it is within the domain of data science. For example, the ChatGPT model by OpenAI is empowered by a transformer architecture that is used to generate text. This is the key strength and capability of generative AI (Gen-AI), and models like these are trained on enormous, large data, mainly testing the equivalent of over eight million documents in excess of 10 billion word characters (ATRIA 2023).

There are three main types of ML, namely supervised, unsupervised, and reinforcement learning. Big data, DM, and training are at the core of ML tools' efficiency (Manne & Kantheti 2021:79), as all of these are using ML algorithms. Figure 5.1 below provides a schematic presentation of various classifications of AI systems. In comprehending the ML capabilities, Muhammad and Yan (2015:946) discern between supervised learning and unsupervised learning and explain that the former demonstrates the ability of machines to learn in a trained form. Supervised learning is one of the broad categories of ML, as it refers to algorithms and models that make predictions about future outcomes (Sen *et al.* 2020:100). These models draw their strengths and efficacy from the training they have been subjected to, which is based on previous data – hence they are referred to as 'supervised' models.

Unsupervised learning models on the other hand, are those models that are able to use machine intelligence to identify patterns and categories in the dataset. What sets them apart from supervised learning models is that they rely on unlabelled data and can independently organise that data to discover insights (Barlow 1989:295; Hastie, Tibshirani, & Friedman 2009:485-486).

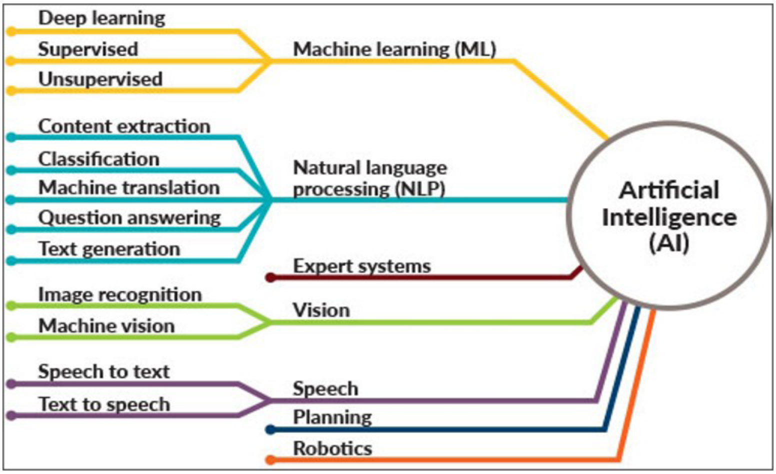

Figure 5.1: Classification of AI systems. (Source: Kumar 2018)

Therefore, the distinguishing feature between supervised and unsupervised learning is the ability to act independently and is underpinned by data preparation and data pre-processing (Kotsiantis, Zaharakis, & Pintelas 2007:249). Lastly, reinforcement learning models are those models that act as intelligent agents and are aimed at taking actions and decisions within a well-defined environment. Each instance of datasets in ML is characterised by similar features, which could be continuous, categorical, or binary (Muhammad & Yan 2015:947). This is where ML and DL intersect and play an influential role. The two concepts are both characterised by a spectrum of approaches such as supervised, unsupervised, and reinforcement learning, neural networks, decision trees, and other forms of learning techniques (Samoili, López Cobo, Gómez, De Prato, Martinez-Plumed, & Delipetrev 2020:4).

NLP (natural language processing) applications and LLMs (large language models) are primarily conversational AI technologies, also known as dialogue or chatbot AI, focused on creating intelligent systems that can engage in natural language conversations with humans. These systems are designed to understand and generate humanlike responses to text or speech inputs. Conversational AI models employ techniques such as

NLU (natural language understanding) to comprehend the user's input, dialogue management to maintain context and flow within the conversation, and NLG (natural language generation) to generate appropriate and coherent responses. Their goal is to create interactive and engaging conversational experiences, whether in text-based chatbots, voice assistants (speech recognition), or other conversational interfaces. The other AI capabilities like expert systems, robotics, planning, and machine vision fall outside the scope of this chapter – however, they are worth exploring.

AI, Big Data, and Predictive Analytics Applications and Capabilities

The decussation of big data and AI is driven by their quest and ability to analyse vast datasets, recognise intricate patterns through classification techniques, and generate insights that are practically beyond the grasp of traditional human-geared abilities. The efficacy of big data and PA depends on the integration of a variety of AI technology tools and ML techniques, such as DM, social network analysis, statistical analysis, text analytics, data visualisation, and signal processing (Sivarajah, Kamal, Irani, & Weerakkody 2017:265). Chen and Zhang (2014:314) share similar sentiments on big data capabilities and suggest that they rely on the ability to conduct social network analysis. Such level of prowess needs access to data, a voluminous one for that matter, as well as ML algorithms. ML is fortified by DL, which is a subset of ML, relying on using large and gigantic volumes of data through complex algorithms to train the model. The enormous datasets, whether structured or unstructured is where big data and data analytics traverse (Janiesch, Zschech, & Heinrich 2021:685). It is from this perspective that PA thrives.

The interrelatedness between AI and associated techniques such as ML algorithms, NLPs, DL, and computer vision capabilities and techniques is depicted in Figure 5.2 below. Researchers are increasingly leveraging on these tools and techniques to accelerate their work (Ekman 2021:25). ChatGPT, Google Bard, and Microsoft Co-Pilot are some of the popular Gen-AI tools that can be clustered within the domain of NLP applications.

They are basically meant for language translation, summarising text, content evaluation, and language generation, all of which play a transformative role of improving efficiency, enhancing communication, task automation, and gathering insights.

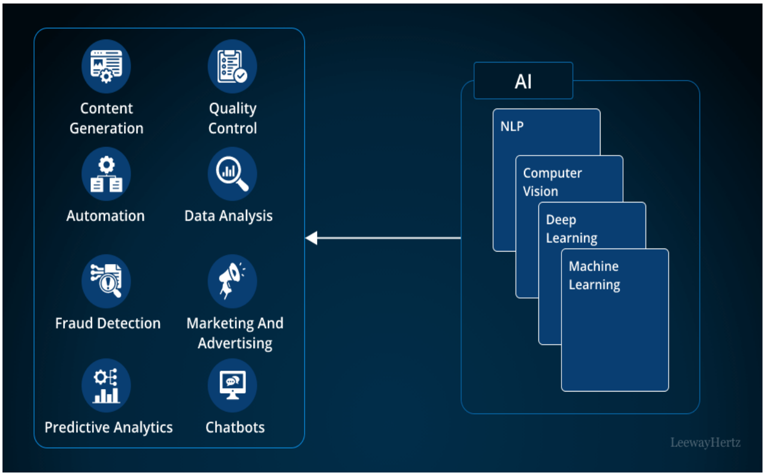

Figure 5.2: Interrelatedness between AI techniques and their selected application in the industry. (Source: Takyar 2022).

This is where Gen-AI and conversational AI through the use of chatbots come into play. Second, automation, fraud detection, data analysis, and predictive analytics are other uses of AI, including its related techniques and algorithms. With automation, monotonous tasks are by nature programmed to improve efficiency and productivity. This function is dependent on AI models, as well as ML and DL algorithms and techniques to use historical data to analyse voluminous amounts of data, to predict and make forecasts for planning and resource optimisation. The engendered output then drives informed decision-making, thus sparking data-driven insights.

The value in the decisions that are made is likely to be manifested in sustainable competitive and superior advantage (Coyne 1986:54). For fraud detection, AI algorithms have an amassed ability to detect the prevalence of any anomalies during transactions, and where necessary point out the existence of patterns. This will enable the provision and detection of early warnings for triggering risk mitigations and the prevention of fraud. The last two uses include quality enhancement and control as well as e-commerce for marketing and the creation of advertisements. With the former, AI systems can be used for the automation of quality control processes, for example, in the automotive industry for ensuring product consistency and reducing defects during the car manufacturing process. Mishra (2019:1025) states that AI systems and big data can be used to improve quality assurance in the administration of quality processes as well as teaching and learning. Likewise, Chassignol, Khoroshavin, Klimova, and Bilyatdinova (2018:17) corroborated by Chen *et al.* (2020:75269) affirm their use towards improving performance and efficiency through the automation of administrative tasks and processes.

The precipitous technological evolution of big data and AI has impacted modern life and humanity, from transforming economies, business, workplace, science, and politics to education (Grand View Research 2023; Luan, Geczy, Lai, Gobert, Yang, Ogata, Baltes, Guerra, Li, & Tsai 2020:1-2 of 11). The common applications of AI, big data, and predictive analytics highlight their versatility and impact across various industries. Some of these advancements have enabled improved service delivery and enhanced customer experiences, leveraging data-driven decision-making, personalised experiences, systems and process automation, and operational efficiencies (Takyar 2022).

The source of big data as identified by Kanika and Khan (2017:193), among others, include wearable and sensor devices, social media sites, and medical data. With each click, as of late, IHEs are also leveraging opportunities brought by AI and big data, for example, ensuring smooth teaching and learning (Khan & Vivek 2022:9), undertaking education research, enhancing assessments, and individualised learning experiences and policy-making (Luan *et al.* 2020:1 of 11), automated audit management and predictive analysis, and modelling student behaviour (Hjuler 2019:2-7).

Characteristics of Big Data

Big data characteristics are displayed in the transformative power of ML and DL algorithms. Drawing from the definition of AI by HLEG (the high-level expert group on artificial intelligence), it is undeniable that data and analysis anchor the AI capabilities across different disciplines, from psychology, political science, and education to the medical industry (Luan *et al.* 2020:2 of 11). The increasing use of social media and smart mobile devices has powered the generation and availability of capacious amounts of data across various platforms (Alexandru *et al.* 2016:123). At the core of big data definitions lies three key traits, namely volume, variety, and velocity, denoted as the 3Vs. The first V refers to the voluminous amount of data generated from various sources; the second V relates to the multiplicity of sources from which these data are generated; while the last V relates to the speed with which these data are generated or become available (O'Leary 2013:96).

As research on big data continues, new traits are added. For example, Amit Sheth in a 2014 conference paper on how big data can be transformed into smart data cited the fourth characteristic, that is veracity (Sheth 2014:2), thus changing the denotation to four Vs. In the same view, Patgiri and Ahmed worked in 2016 on the Vs of the game changer in big data as the authors confidently affirmed that as big data continue to disrupt and blossom across industries across the world, this domination will endure until 2030 (Patgiri & Ahmed 2016:17). Fast forward, the literature on big data is fairly demonstrating what characterises the field has evolved, with more Vs added. Khan *et al.* (2021:2 of 11) mention five Vs, with the addition of value referring to what insights the generated data can produce. Two additional characteristics – variability and visualisation – as identified by Alexandru *et al.* (2016:124) complete the characteristics of big data as illustrated in Figure 5.2. Variability refers to data changes, while visualisation is an extent of data readability. The IoT (internet of things) has enabled developments in big data and generate both structured and unstructured data (Solarwinds Pingdom 2012). Likewise, Wang and Preininger (2019:18) point out that most of the data being generated, especially in the medical sector remain unstructured. Due to unclear, ear-splitting, and incomplete data, a comprehension of the variability of diseases in patients can be a complicated process.

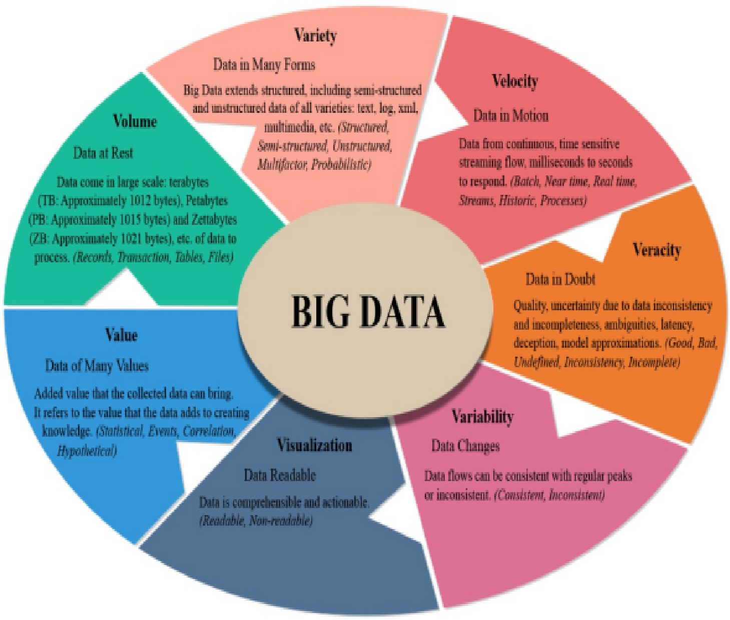

Figure 5.3: The characteristics of big data. (Source: Alexandru *et al.* 2016:124)

A slow adoption of technological advancements and applications in various sectors is another drawback (Manne & Kantheti 2021:87). Nonetheless, the promise of AI in these sectors is not as bleak as it is imagined. The key capability of AI in big data is automation and the enhancement accompanied by the data analysis process. This impact consequently fuels capabilities for PA to be more accurate and scalable. On scalability, O'Leary (2013:98) calls for AI that will be ascendable to the cluster of machines.

Advancements in Big Data, AI, and Predictive Analytics for Education

According to Cheng, Chen, Sun, Zhang, and Tao (2018), the developments and rise in numbers of technological tools propelled by AI has transformed various industries. At the heart of big data and AI capabilities lies the power of algorithms, which are also evident through the field of data science and PA. These sentiments are also shared by Goh *et al.* (2023:2) in a consultation paper prepared by a big data and AI review group on behalf of the bioethics advisory committee of Singapore. The authors put forward that developments in and the increasing use of big data, AT (auto tech) tools, and techniques enable researchers to merge and analyse large amounts of data, from which they are able to identify patterns, trends, and correlations. It is from these analyses that insights and data-driven decisions are drawn. Just as the other sectors or industries are reaping the benefits of AI and big data advancements, so is the education sector also witnessing a variety of benefits. The benefits for the education sector caused that IHEs are able to use PLA (predictive learning analytics) to track students' learning progress, to enhance curriculum planning and development, to measure the efficacy of teaching strategies, and trigger data-driven decision-making and support for an enhanced teaching and learning environment (Zawacki-Richter, Marín, Bond, & Gouverneur 2019:3-4). Additionally, educators are efficient and effective in how they deliver content (Cheng *et al.* 2018).

The integration of AI, ML, and data analytics in education offers many benefits. Johnson (2023) adds that personalised learning strategies such as enabling early and tailored interventions in learning for struggling or at-risk students and promoting an adaptive learning environment to adjust course content to match the teaching styles are possible. The other benefits include stimulating a dynamic learning environment through which students' answers can be assessed with the necessary effective teaching pedagogies (Lin, Huang, & Lu 2023). Naveenkumar (2023) highlights that the ability to adapt the learning process according to the needs and preferences of students makes it possible to provide personalised feedback. Goh *et al.* (2023:21) succinctly put some of these benefits as follows:

- Better prediction abilities and diagnostic functionalities;
- quality improvements and efficiency; and
- advancements in personalised experience.

These advantages affirm the potential power of big data and AI-ML (artificial intelligence and machine learning). It is therefore valid that the why and how questions of big data and AI's applicability in education are explored, with a detailed analysis being provided in the next four subsections.

Algorithms and AI in Education

Salem (2015:201) opines that ML algorithms coupled with data mining techniques, computational intelligence, and electronic Iearning systems, boost additional computing capabilities to display more intelligent behaviour. The application of big data and AI algorithms and systems in education is gradually gaining momentum. Hence, integrating ICT into the classroom has changed the focus of education from the educator to the student, making it possible for students to study whenever and wherever they want, around the clock. AI provides the most efficient means of communication with students and helps businesses to learn about their many talents. Niklas Hjuler in his 2019 work focusing on algorithms and AI in education presents a variety of specialised uses of big data and AI technologies (Hjuler 2019). For example, in a natural language community, neural network models, writing style development, authorship verification, and ghostwriters detection are some of many uses of big data and AI systems as explained below.

On writing style development, Stephan Sloth Lorenzen along with his two colleagues Hjuler and Stephen Alstrup, conducted a large-scale examination of writing-style development among more than 10,000 Danish high school learners in 2019 (Lorenzen, Hjuler, & Alstrup 2019). In that work, they have analysed over 100,000 essays through a Siamese neural network[2] to determine the existence of similarities between two sets of texts. They were able to construct a writing style development profile for

2 It is often referred to as a twin neural network which is a form of an artificial neural network popularly used in biometric identity verification technologies and systems such as handwritten text recognition, fingerprints detection, face detection, and signature verification (cf. also Taigman, Yang, Ranzato, & Wolf 2014; Bromley, Guyon, LeCun, Säckinger, & Shah 1993; Chopra, Hadsell, & LeCun 2005).

the learners in order to distinguish between global development trends and patterns among the learners and identify at-risk learners that may need support and guidance. The study reveals general development trends among the learners, suggesting that their writing styles deviate as they advance through their grades, thus portraying huge differences between when they started and when they left school. In appreciation of the power and abilities of the Siamese neural network, Chicco (2021:73-74) advocates that when confronted with the need to compare to more complex data samples, consisting of features with different dimensionalities and types, compression is needed before processing. Writing style is important for educators to understand behavioural patterns of students, as Lorenzen *et al.* (2019:573) advise that changes in the writing style may be indicative of students attempting to cheat. This insight is vital because such ML and PA detective abilities may not have been possible through a human-driven exercise.

Relating to writing style development detecting abilities, the other feature of DL abilities is that of authorship verification. Authorship verification in the era of AI-powered text generation bots using NLP, plagiarism, and essay mills are on the rise. These potentially compromise academic integrity and ethical principles expected of the authors as explained in the chapter on AI and academic integrity decussation. Work in the area of authorship verification includes Qian, He, and Zhang (2017), Stamatatos (2009), as well as Stavngaard, Sørensen, Lorenzen, Hjuler, and Alstrup (2019), to name a few. The methods and techniques usually used to study authorship verification involve learning a similarity measure for writing style through examination of examples from different sets of authors. With advancements in AI technologies almost on a daily basis, chances of advancement in plagiarism acts are also increasing. That mentioned, it would be ideal that future developments in authorship verification space investigate predictions and changes in writing styles to make provision for early alert systems to identify at-risk or cheating students (Lorenzen *et al.* 2019:573).

With the increase in AI and big data usage in education, a number of articles has examined the rise in mechanisms aimed at detecting ghostwriters in academic writing. The work by Ali and Alhassan (2021) puts to light the increasing concerns around ghostwriting and contract cheating in HE (higher education). In response to these concerns, the literature on ghostwriting and academic writing and integrity suggests that AI and big data techniques can be applied to determine instances where such acts have occurred and proposes guidance and solutions on how such practices can be prevented. Draxler, Werner, Lehmann, Hoppe, Schmidt, Buschek, & Welsch (2023) apply a Siamese neural network to examine the effect of AI-geared ghostwriting by comparing the similarity of texts and constructing a specific profile for students based on writing style development. In these instances, the co-conspirators would normally and deliberately decide not to declare authorship and ownership of AI-generated text. Still on ghostwriting, Zimmerman provides a discourse analysis on the possible prevalence of bias in NLP tools such as ChatGPT in generating pre-print scientific articles and co-write editorials (Zimmerman 2023). To circumvent against such acts and practices, the author proposes using tools such as DetectGPT while Originality.ai can be used to detect AI-written content. Similarly, Turnitin-AI detection software has also been introduced and all in all these measures are aimed at ensuring the fair and transparent use of AI-text generation tools and chatbots. The challenges with these tools are documented in the literature and some of them include the inability to keep up with the speed with which AI-text generation tools are advancing and being developed. Second, given the ability of these AI systems to impersonate human element, it is still difficult to distinguish between human-generated and ML-generated text (De Vries 2022:93). Lastly, Heikkilä (2023) supported by Kirchner, Ahmad, Aaronson, and Leike (2023) put forward that AI-text detection software and systems are still battling the high rates of false negatives and false positives, thereby underscoring the complexity that comes with effective AI-text detection tools and the dire need for investment in an enduring research and development efforts.

Predictive Analytics

Gen-AI and NLP models usually make use of historic data to make predictions and forecasts, aiding industries. Education is no exception as Choi and McClenen (2020:1-2) are of the opinion that through powerful DM and AI capabilities, learning analytics and performance predictions can be executed at ease. Within the context of education, the ability to predict the performance of students remain topical in the era of AI and big data (Bhushan, Shingate, Vyas, Naman, & Shirsath 2023:1-2 of 7). The success of students is an issue of paramount importance for a myriad of stakeholders – the government for funding purposes and assessing value for money, the institution for gauging teaching strategies and efforts of teaching staff, and parents for personal development and progress of their children.

Hlosta, Herodotou, Papathoma, Gillespie, and Bergamin (2022:1 of 12), examining PLA in online education, have revealed that due to a number of unforeseen events such as new family and work commitments, health challenges, and technology infrastructure accessibility issues that can take place during the course of their studies, students' behaviour is thus affecting their performance. Their study therefore recommends new data sources that may possibly be integrated into predictions to abate the impact of some of these events, and these include data on financial assistance. Such data when thoroughly integrated and properly analysed can lead to insights that can highlight the importance of complementing AI-based systems with human intelligence. The information about the academic performance of students is therefore necessary to devise mechanisms aimed at improving the learning outcomes and also reducing dropout among students (Neha & Sidiq 2020:48; Zawacki-Richter *et al.* 2019:3). This information can particularly be useful to both students and educators to leverage the pros of technology-enhanced learning. This approach goes beyond what a good AI system and DM can offer.

The selected associated DM techniques and their uses among others include classification technology, being illustrated in Table 1. To realise these benefits, automation of processes, ML, and AI technologies and techniques such as expert systems, DL, ANNs (artificial neural networks), and CNNs are crucial to being able to predict student success. The result of predictions will help to anticipate students' actions and behaviour, improving the instructional style of educators, and devising necessary support measures to aid learning. When classifying learning behaviours, unsupervised learning methodologies and clustering algorithms tend to be applied in the absence of true and reliable data to train the model (Lin *et al*. 2023:5 of 22). Muhammad and Yan (2015:946) define classification as 'the process of using a model to predict unknown values (output variables), using a number of known values (input variables).' PA relies on DM and SVMs to classify and regress massive amounts of data to be able to predict or make forecasts. This ability is one of the ML algorithms and it can best be applied in text recognition, which is within the ambit of Gen-AI (Neha & Sidiq 2020).

Table 5.1: Application, uses, and classification accuracy of selected ML DM techniques

ML DM Techniques	Application and Uses	Classification Accuracy Range
Decision trees	Predict students' enrolment and identify dropout cases (Baradwaj & Pal 2012).	Up to 98.90%
Feature selection algorithms	Predict students' failures (Jantawan & Tsai 2013:2; Karabulut, Özel, & Ibrikci 2012:323).	Up to 99.30%
Bayesian and ensemble methods, as well as multilayer perceptions and sequential minimal optimisation techniques	Predict postgraduate students' employability chances (Mishra, Kumar, & Gupta 2016:2275).	Up to 97.45%
Neuro-fuzzy techniques	Pace and assess mathematics students in early stages of their academic year (bin Mat & Buniyamin 2017:685).	90.03%

ML DM Techniques	Application and Uses	Classification Accuracy Range
Clustering techniques	Analyse students' causes of failure, utilising association rule mining to analyse students' performances (Deperlioglu & Birtil 2016:505; Kumar 2016:24).	99.81%
CNNs	Extract features from images usually used for handwriting recognition (Lin, Kuo, & Chiang 2021; Remaida, Moumen, El Bouzekri El Idrissi, & Abdellaoui 2021:71) and to assess students' emotional understanding (Hung 2021:715; Sharma & Mansotra 2019:4692; Zhang, Jiang, Zhang, Wang, Zhao, & Wang 2022:2)	99-100%
SVMs	Research for the classification of educational resources and regression analysis from biology, financial analysis, the medical industry, etc. (Ma & Guo 2014:2; Murty & Raghava 2016:41; Quan & Pu 2023:8097)	93.90%

The added benefit of most of these techniques and methods is that their level of accuracy ranges between 93 and 100%. Muhammad and Yan (2015:947) acknowledge that the number of methods and techniques aimed at measuring prediction accuracy is many and varies depending on how the training data set is split. Cross validation and rotation estimation methods are but a few examples of those measurements. In their study, they measure accuracy as a function of the number of correct classifications divided by the total number of test cases. The lowest performance on accuracy prediction as shown in the table is SVMs, with decision trees and Bayesian methods performing in the median range. CNNs on the other hand are topping the list with a 100% accuracy.

Intelligent Educational and Tutoring Systems

Nowadays, robots in education can perform a wide range of activities. Salem (2015:196) identifies IESs (intelligent educational systems), cognitive science, knowledge structure, intelligence authoring shells and interfaces, teaching and learning aspects, as seven areas in which AI can be applied in education. According to Salem, ITSs (intelligent tutoring systems), educational robotics, and multimedia systems are the key systems of IES. IES can be categorised into two broad groups of AI integration. In this section, the role of AI and ML integration, predictive data analytics and big data technologies in advancing the capabilities of ITSs is explored.

ITSs refer to computer-based learning systems which utilise AI capabilities to deliver students' personalised and adaptive learning instructions (Lin *et al.* 2023:2). The origin of the concept, according to Carbonell (1970:190), can be drawn back as far as the 1970s. Most ITSs are empowered by AI technology such as NLPs through which chatbots are used as an interactive platform to provide feedback and necessary insights pertaining to learning (Liddy 2001:12) through flipped learning environments (Lin & Mubarok 2021:16). AI-driven ITSs are knowledge-based systems acting as intelligent tutors and can be used in real teaching, learning, and training environments to provide for personalised guidance and support to students. These systems analyse student performance data and adapt the learning content and assessments to cater to individual strengths and weaknesses. Among many benefits, these technologies boost the advantages of personalising students' learning experiences for them.

Through PA, ITSs foster a student-centric approach (Bhushan *et al.* 2023) and allow for student learning to be personalised through an analysis of student datasets, highlighting the areas of improvement (gaps) as far as learning is concerned. Through the identified gaps, ITSs are able to tailor the instructional design preferences accordingly and stimulate learning engagement and emotions of students, improving their academic performance (Lin *et al.* 2023:2 of 22). The other associated benefits of ITSs are geared towards researchers who are interesting in devising adaptive learning environments which, according to Papamitsiou and Economides (2014:42), can potentially promote individualised tutoring pedagogies through one-on-one support and guidance. Furthermore, Zawacki-Richter *et al.* (2019:3) in highlighting the importance of adaptive learning suggest that it gears its advantage towards adjusting learning content pace and difficulty in real-time dependence on student's preferences and unique learning styles, level of comprehension, and previous performance. The other multifaceted benefits of ITSs as identified by Salem (2015:197) are depicted in Figure 5.4 below.

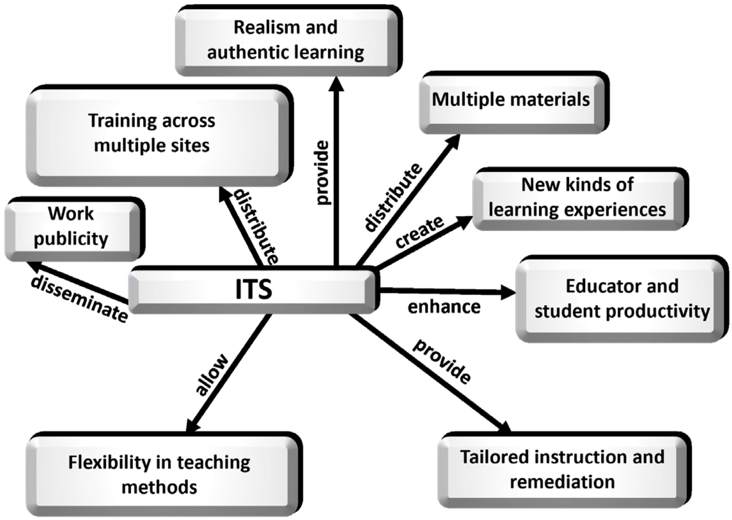

Figure 5.4: The multifaceted role of ITSs in education. (Source: Adapted from Salem 2015:197)

These range from enabling the possibility of employing flexible and tailored teaching methods and support measures, enhancing students' learning experiences, creating and facilitating new kinds of learning experiences, as well as the distribution of training and learning materials for students, enabling authentic learning environments and collaboration.

Automated Grading Systems

Adopting automated grading systems remains a watershed moment in education. Like other teaching-enhanced systems and techniques, automated grading systems are significantly benefiting from big data and the AI-ML integration. The systems thrive on the availability of large volumes of data which are collected and draw a variety of insight from these data. It is on this purported insight that PA play a crucial role by revealing students' behavioural patterns and predicting their academic performances. The content vector analysis technique (Chauhan, Saharan, Singh, & Sharma 2020:4 of 7) digs deep into students' responses such as texts, essays, numeric answers, and in some cases images. Therefore, through ML and DL algorithm capabilities, Lin *et al.* (2023:3 of 22) signify that grading is automated, thus providing an added benefit of reducing routine tasks for teachers and markers of grading assessments. For students, they leverage timeous and personalised feedback. For academic staff, integrating automated grading means that inefficiencies inherent in manual grading systems are eliminated, the grading process is streamlined, and errors are minimised (Zhu, Lin, Jain, & Zhou 2023:13344).

Notwithstanding the benefits of ITSs, its development is definitely evolving with technological advancement. Therefore, this journey is not without shortcomings or implications, one of which includes accessibility and inclusivity. Therefore, more research is necessary to understand the implications and benefits of ITSs, especially when taking into cognisance students and staff from the marginalised and disadvantaged groups, especially those with learning difficulties and other forms of disabilities. Some of the associated challenges and ethical implications are explored next.

Challenges and Ethical Implications of Using Big Data, AI, and Predictive Analytics Techniques

Big data and AI technologies offer an advantage of allowing users the ability to accumulate, process, and integrate vast amounts of data from a variety of sources in no time. This capability has yielded a number of benefits as discussed in the previous section. Through data analytics tools, researchers are now more than ever before able to access, integrate, and leverage expertise and knowledge across various disciplines – from physics, science, and computing, to mathematics, biology, and statistics. Within bio-medicine and the health fraternity, medical diagnosis and clinical solutions are also pointing to the success of AI and big data in the field of health (Madani, Arnaout, Mofrad, & Arnaout 2018:1 of 8).

Despite the reported benefits, ethical dilemmas exist, and it is therefore important as Ben-Porath and Ben Shahar (2017:245) note that the implementing of big data and AI in education needs to be complemented by vigorous ethical frameworks and considerations to ensure a fair and transparent education process where equity is practised.

With ghost detection technologies, the downside here could be associated with false positives and false negatives. In the former, systems could fail to detect when the ghostwriter has indeed been utilised, whereas with the latter there could be false accusations of one purported to have used a ghostwriter when that was not the case. Lines (2016:889) warns that with an increasing and continuously evolving technology in the education space, digital plagiarism is on the rise, and subsequently ghostwriting services are proving and boost the potential of producing high quality services, thus making it difficult to detect. This is akin to essay mills and contract cheating as identified by Medway, Roper, and Gillooly (2018) in the work they did on covert investigation within the HE sector of the UK (United Kingdom). Sharing her findings, Lines is alarmed that the majority of these essay mills could have been easily submitted for assessment without any act of plagiarism being detected (Lines 2016:889). For the purpose of the current chapter, fairness and bias in algorithmic systems and decision-making, student privacy, and governance issues are ethical challenges that are in detail explored alongside their mitigating strategies in the next three sections.

Algorithmic Fairness and Bias in Academic Decision-Making

It is undeniable that AI algorithms such as ML, DL, neural networks, and expert systems anchor and continue to transform educational processes and settings through NLPs (Hjuler 2019:4). The by-product of these algorithms which eventually becomes a critical ethical consideration is to ensure that academic decision-making is fair and free from bias. Algorithms used in assessment tools, grading systems, and even admission processes may inadvertently perpetuate biases present in historical data. For instance, if training data used to develop an AI system reflects historical disparities, the algorithm might inadvertently reinforce existing inequalities. This may well lead to a IHE's practices being questioned under suspicion of stereotyping, which is purported to be an act of practising unfairness and discrimination. Therefore, the disadvantaged individuals from certain demographics of the population who may feel that they are being discriminated against may accuse the institution, thereby bringing its name into disrepute. This will then tarnish its image and integrity, and consequently making associates and alumni of the institution to suffer from reputational damage.

The implications are what may well be thought to be revolutionising processes, practices, and procedures though AI may inadvertently raise concerns about an institution's fairness, equity, and the likelihood that certain demographics may be disadvantaged. IHEs therefore need to be proactive in devising measures that are aimed at addressing potential algorithmic bias and unfairness. Their AI systems and processes need to be regularly audited and refined in line with the best practices. Furthermore, these systems should abide with compliance requirements of the regulatory bodies such as the government, local authorities, and accreditation institutions (Mishra 2019:1025). Lastly, diversity forms an integral part of an inclusive environment where diverse perspectives should be incorporated into AI development and auditing. This will help to ensure that unintended consequences are mitigated and an equal and fair representation for both students and academic communities is achieved.

Preservation of Student Privacy in the Era of AI

Data-driven insights and decision-making are the cornerstones of AI advancement and big data (Hjuler 2019:66-67). In the era of AI, crucial issues in the application of AI in education centre around data. Integrating AI in the education space habitually and inevitably often encompasses processes by which students' data are collected and analysed. These are usually voluminous amounts of data, and in some cases, students are oblivious of this practice. Leslie (2019:5) talks of the invasion of privacy as one of the potential harms posed by AI systems owing to their design, development, and deployment procedures. For example, during the deployment of AI systems, data subjects can be targeted, nudged, and profiled obliviously of their knowledge or consent. This may lead to violations of data privacy and data breach.

While student data can be invaluable for personalising learning experiences, it also raises ethical concerns related to privacy. Two elements worth mentioning here are mechanisms and practices of ensuring that the collected data are protected, and privacy is assured. Striking a delicate balance between leveraging the AI-geared insights and benefits is thus required of IHEs to guard against the misuse and unscrupulous handling of student data and the undue invasion of their privacy. This, therefore, calls for an honest and responsible use and preservation of student data whilst protecting their rights at the same time. The aim is to allow IHEs to leverage insights from data centralisation without student privacy being compromised. As an attempt to circumvent against unethical practices possibly compromising privacy, Akgun and Greenhow (2022:431) as well as Samad, Arshad, and Siraj (2021:17) through their PPDM (privacy preserving data mining) model recommend the following measures to preserve student privacy:

- Ensuring compliance-friendly data collection processes and practices.
- Implementing and practising robust and secure measures towards protecting data, such as authorised access, anonymity, and informed consent.
- Employing data privacy-preserving AI techniques, such as federated learning.

Practising AI Governance in Education and Safeguarding Academic Integrity: A Lens of Generative AI, Responsible AI, and Explainable AI

Stephen Hawking was quoted as follows in Akgun and Greenhow (2022:431): 'Success in creating AI would be the biggest event in human history. Unfortunately, it might also be the last, unless we learn how to avoid the risks.' It cannot be denied that as AI is evolving, so is the proliferation of related tools. This evolution presents an abundance of opportunities in various sectors, and education is one of them. The emergence of and AI's ascendancy in the education landscape has ushered in new transformative opportunities and challenges. The associated benefits range from data-driven insights, enhanced support for students and educators, improved and automated assessment methods, and personalised learning experiences (Akgun & Greenhow 2022:431; Remian 2019:4).

Striking the right balance is one step towards distinguishing between responsible and ethical use of AI in education. Transparency and explainability fall within the domain of responsible AI and XAI (explainable artificial intelligence) (OECD 2023). Lin *et al.* (2023:2 of 22) expound that as much as XAI is gradually gaining attention within the realm pf computer science, its popularity within the education space is still in the introductory stages. The outlined principles of XAI as Faggella (2018) elucidates, strive to ensure that with AI integration, inclusive growth and sustainable development should be prioritised. As far as a people-centric view is concerned, the adoption of AI should be centred on humane values and fairness. XAI refers to a set of processes and methods that allow human users to comprehend and trust the ML algorithm's outputs. Additionally, explainability can increase accountability and governance as practising trust in AI will potentially guarantee human value (Chamola, Hassija, Sulthana, Ghosh, Dhingra, & Sikdar 2023:78998).

To keep up with the continuous demand of more accurate AI models, hard-to-explain (black-box) models are used. Not being able to explain these models makes it difficult to achieve user trust and to pinpoint challenges (bias, parameters, etc.), which can result in unreliable models that are difficult to scale. Due to these concerns, the practice of XAI is fast gaining momentum. Samoili *et al*. (2020:6) bring to the fore the issue of *black-box AI*, which is described as scenarios where the ability to track AI reasoning for certain decisions is marred with impossibilities. Such scenarios require XAI principles to provide some form of explanations for AI actions and decisions.

Arrieta, Díaz-Rodríguez, Del Ser, Bennetot, Tabik, Barbado, García, Gil-López, Molina, Benjamins, and Chatila (2020:83-

84) caution that XAI is often confused with interpretability. The authors go further to explain that challenges impeding the development of shared understandings and meaning revolve around the interchangeable misapplication of the terms ‘interpretability’ and ‘explainability’ in scholarly works. These concepts exhibit distinct differences. Initially, interpretability pertains to the inherent trait of a model, signifying the extent to which the model is comprehensible for a human observer. This attribute is alternatively described as transparency. In contrast, explainability represents an active aspect of a model, encompassing any action or procedure undertaken by the model to elucidate or delineate its internal operations. Key stakeholders – students, educators, and policy makers – require a clear and shared understanding of how AI systems influence educational processes.

Transparency and Accountability

In the era of Gen-AI, transparency and accountability are cornerstones of ethical practice. Along the same lines, the OECD. AI Policy Observatory (OECD 2024) by the OECD (Organisation for Economic Cooperation and Development) goes further to identify value-based principles and associated recommendations for policy makers as depicted in Figure 5.5.

These principles can be enabled by XAI and responsible AI. Both transparency and accountability are the anchors of the corporate governance fraternity and have for the longest time been reference points for governance-friendly institutions (Tjano 2021:175). The King IV version of corporate governance by the IoDSA (Institute of Directors South Africa’s) has also put an emphasis on these principles. With these principles in mind, the OECD’s position is promoting AI that instils innovation and trust, but most importantly ensures that human rights and democratic values are respected unconditionally (Perset 2024). Equal to the task of ensuring that the use of AI in education is free from bias and is fair, data are protected from misuse, and entrenching responsible AI, the other two governance principles worth practising are transparency and accountability. Responsible AI is underpinned on the principle that development, deployment, and the usage of AI systems are guided by ethical and responsible conduct. The ultimate end is striking a balance between AI benefits and risks' reduction. This will provide an assurance that AI systems conform to social norms and human values, thus embraced with concerns. Furthermore, this will also dilute the debate between AI and human intelligence.

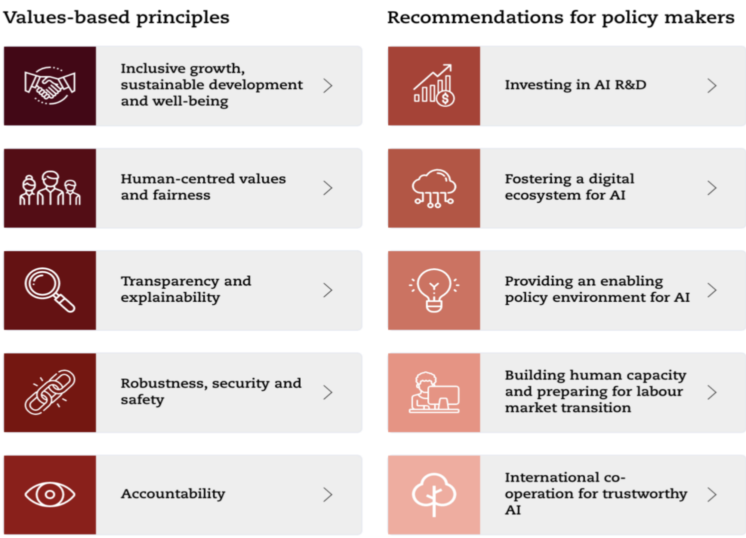

Figure 5.5: OECD AI principles. (Source: OECD 2024)

The OECD recommended that institutions should gear trustworthy efforts towards the international cooperation for AI. Without exercising accountability, trust will be difficult to attain. A high-level expert group in Arrieta *et al.* (2020:105) highlights the auditability of AI algorithms, data, and the design process, redressing unjust practices, minimising, and reporting negative impacts of AI systems as the key attributes towards attaining accountability in the use of AI. In line with these principles and recommendations for policy makers, IHEs should equally be put to task to ensure that the adherence of AI governance is beyond reproach. The following recommendations are provided:

- There is a need to proactively communicate how AI is utilised in various aspects of education, from automated grading systems to adaptive learning platforms.
- Transparent policies regarding the use of AI in assessment should be established, addressing concerns related to bias, data privacy, and the overall impact on academic integrity.
- Mechanisms for accountability, such as regular audits and external reviews, should be in place to ensure that AI systems align with ethical standards and educational goals.

Ownership of Content

Another element of the negative consequences of AI authoring tools is that of co-authoring which, according to Biermann (2022:22-23), puts a threat on the control, autonomy, and ownership at the expense of the author. As to who owns the content that comes from LLMs remains a debatable issue. The threat on ownership is exactly what the Australian writers' guild was against as AI was understood to be threatening ownership of authors and their compensation. As previously stated, LLMs are part of supervised ML trained on massive amounts of data. The downside of this could have unintended biases and inaccuracies as outcomes. This point is affirmed by Poola (2023:16) who points out difficulties with LLMs and associated hallucinations. Poola adds that ChatGPT for example, has computational shortcomings, which could lead to misconceptions, errors of judgements, or incorrect interpretations (Poola 2023:16). The outcome of this may well be generated text that is misleading or harmful.

Fact-Checking

The superlative capability of LLMs lies in their ability to produce impressive fluent output, which research has indicated that humans are struggling to detect and distinguish it from human-generated texts (Wahle, Ruas, Kirstein, & Gipp 2022:1-2). Notwithstanding this unique and outstanding aura of performance, most of the models have limitations that cannot be overlooked. LLMs have been reported to hallucinate (Poola 2023:16), lacking semantic coherency, having less diverse lexical ability (Gehrmann, Dai, Elder, & Rush 2018:2), limited to recent events and data (Perkins 2023:7). Nonetheless, researchers are hard at work trying to find solutions to overcome these issues and enhance the model's accuracy and dependability (Poola 2023:16).

With these developments, generative performance transformers are being trained to stipulate their confidence level when generating output, whether it is factually incorrect or misinterpreted (Lin *et al.* 2023:3 of 22). Likewise, if one is using ChatGPT and is not satisfied with the output it generates, one can challenge it through correct and accurate facts. What the model does in these instances is to adjust its responses accordingly whilst learning at the same time. Therefore, given ethical implications, these models have on academic integrity and it is important that the output generated by these models is fact-checked for accuracy and correctness (Perkins 2023:7 of 24).

Ethical Utilisation of AI (AI Ethics)

Both XAI and responsible AI are influencing ethics with reference to the use of AI. Due to the reported range of harms, misuses, and abuses at individual and societal levels, the field of AI ethics emerged. The following are six forms of potential harms that can be caused by AI systems as identified by Leslie (2019:4-5):

- Bias and discrimination.
- Denial of individual autonomy, recourse, and rights.
- Non-transparent, unexplainable, or unjustifiable outcomes.
- Invasions of privacy.
- Isolation and disintegration of social connection.
- Unreliable, unsafe, or poor-quality outcomes.

The fourth strand of value-based principles as described by the OECD include robust, secure, and safe measures which were covered in the previous section. Assuring honesty and ethical considerations in the use of data is of paramount important. Once transparency is lacking, trust is by extension eroded, thus enabling an environment where ethical concerns fester. This closely connects with the fifth strand of the OECD's principles on AI, which is accountability. Vigorous governance frameworks and mechanisms are necessary to ensure accountability in developing, deploying, and using AI. This includes defining roles and responsibilities, adhering to legal and ethical standards, and implementing processes for monitoring, auditing, and addressing any issues or risks that arise.

In addition to the above-discussed challenges, Johnson (2023) identifies more and more reliance on technology, a limitation in the amount of data for training AI algorithms, a lack of capacity development for users (for example, students, administrators, and educators), and high costs of AI-powered tools and techniques as among some of the challenges that may hinder IHEs' quest to adopt these techniques. With these challenges in mind, this may affect inclusivity and access, which need keen consideration for all stakeholders involved. Luan *et al.* (2020:6-7 of 11) raise the issue of costs through the commercialisation of intelligent educational tools and systems and accede that novel features can be priced to also expand a revenue stream for developers. However, there must be a balance and mutually exclusive beneficiation between academics and the developers of these tools in the industry.

AI technologies and big data techniques can to an extent do good to governments, thus improving their efficiency and decision-making (Eggers, Schatsky, & Viechnicki 2017:2; Martinho-Truswell 2018). Mehr (2017) observes that governments are yet to fittingly embrace the adoption just as much as the private sector did. This should be concerning considering the role played by governments in their developmental agenda and upliftment of the societies they serve. Therefore, these advancements have the potential to influence the public's interaction with the government and public policy goals and development (Wirtz, Weyerer, & Geyer 2018:596). For example, Martinho-Truswell (2018) states that traffic departments can use AI for assessing exam papers. This function could be in instances of government-run tests such as psychometric tests for employment, driving permits, and licenses. In some countries, governments use virtual assistants or chatbots to serve the public: According to the Institute of Public Administration Australia, their government relies on AI systems to predict crime, traffic congestions, and road maintenance needs, and then dispatch the necessary assistance. Mehr (2017) adds that the Australian government utilises chatbots to help citizens complete forms, schedule appointments, and search civil documents. Likewise in Estonia, the government uses AI systems through automated push services to interact with the public *via* chatbots to register new births and bereavements and provide updates on statistics such as unemployment (Moltzau 2020). In the next section, the future implications of AI and big data integration on the role of RERCs is explored.

The Future Implications of AI and Big Data on Research Ethics Review Committees

It is inevitable that industries are witnessing the increasing use of big data. However, just as this irresistible adoption is on the back of reported various benefits, there are equally associated implications. Luan *et al*. (2020:7 of 11) identify a number of major challenges and propose solutions in the area of research, policy-making, and industry. From a research perspective, the authors highlight that 1) the mode of teaching and learning is persistently transitioning to personalised and adaptive learning environments; 2) there is a single domain for educational AI research that is pro intelligent computing; and 3) machine-generated data need careful consideration redesign. For policy-making, the paradigm shift from traditional teaching methods and techniques to the digital world implies a shift in policies and guidelines, therefore there is a dire need for data privacy and the protection of personal information against unauthorised access and undue commercial exploitation. From an industrial perspective, commercialisation and high costs of intelligent tools remain a big challenge as these affect inclusivity and access.

Kanika and Khan (2017:195) cite security issues and warn that these issues may potentially invade one's privacy – be it an individual or institution. Taking cognisance that these issues may well transcend into the HE landscape, it is important that a risk-oriented mindset and ethical lens in harnessing the potential of use of AI in the big data space is adopted. This position is premised on the potential impact of AI and big data on the work of RERCs.

The work of Ferretti, Ienca, Velarde, Hurst, and Vayena (2021b:138) sheds a light on challenges posed by big data research on the functions of RERCs, citing the magnitude of big data research projects. The authors argue that typical of these projects, they tend to have a scope that broadly requires a unique expertise, comprising new actors and making use of exceptional methodological approaches (Ferretti, Ienca, Sheehan, Blasimme, Dove, Farsides, Friesen, Kahn, Karlen, Kleist, & Liao 2021a:4 of 13). With this peculiarity, RERCs are typically constituted of skills and expertise from a variety of backgrounds (Nichols 2016:351), thus enabling the infusion of cross discipline (Garrard & Dawson 2005:419). Reviewers are grouped and get allocated content that match their strengths and expertise.

The aim of the ethical review process is to ensure that ethical guidelines during the research process are adhered to by researchers, to guard against unethical or illegal acts (Dove 2020:4). All in all, the end goal is to validate ethical procedures of the research being undertaken (Biagetti, Gedutis, & Ma 2020:1-2) to mitigate risks (Ferretti *et al.* 2021:8 of 13) and to reassure public and data subjects that the research process can be trusted (Resnik 2018:87).

In the era of AI and big data, it is important that the expertise of RERC members is assessed to ensure that review processes are not compromised. Once the process is compromised, trust and the validity of the research results and adopted methodologies are questioned. Ferretti *et al.* (2021a:8 of 13) identify persistent and novel weaknesses pertaining to failures of RERCs. Three weaknesses are identified, namely functional, purview, and persistent weaknesses, which are depicted in Figure 5.6. The functional and purview weaknesses are identified by the authors as novel, which implies that they are linked with traditional research ethics and are specific to the nature of big data projects (Ferretti *et al.* 2021a:3-4 of 13). The functional weaknesses stem from RERCs' inabilities and inadequacies to review big data research projects. The purview weaknesses on the other hand relate to big data projects that may likely skew the horizon of RERCs.

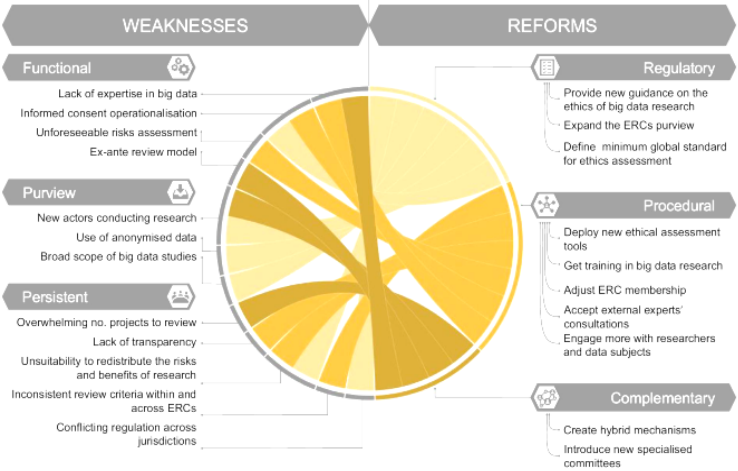

Figure 5.6: Weaknesses and reforms pertaining to the impact of AI and big data on the work of RERCs. (Source: Ferretti *et al.* 2021a:8 of 13)

The persistent weaknesses include a lack of transparency in the review process, capacity, a load to review projects, inconsistent review criteria, conflicting regulatory frameworks across jurisdictions, and a lack of an unsuitable environment to redistribute research risks and associated benefits. The proposed reforms to mitigate against these weaknesses are also indicated in the figure above, and these include regulatory, procedural, and complementary reforms (Ferretti *et al.* 2021a:8 of 13). Having discussed the implications brought by big data research and AI on the functions of RERCs, the conclusion focuses on the future trends that can be expected from the evolution of AI and related challenges.

Conclusion

The ascendancy and transformative power of big data, AI, and PA in the field of education has caused the ethics of research, teaching, and related procedures to be undoubtedly reshaped. The chapter delved in on the symbiotic relation between algorithms and education, exploring the nuances of their implementation.

These include writing style development detecting abilities, authorship verification, ghostwriter detection tools in academic writing, and AI-text generation tools. The chapter has dissected the intricate balance between algorithms and educational outcomes, which has shed a light on the implications and challenges associated with their integration into pedagogical practices. PA tools and their uses were discussed, including IESs, ITSs, and automated grading systems. From the perspective of research, responsive strategies on account of protecting and enhancing research and academic integrity were enacted. Through this lens, potential benefits, challenges, and possible governance measures of adopting and integrating big data, AI, and PA in education were discussed. These strategies are underpinned by the governance of AI, where protocols, guidelines and policy framework aimed at managing unethical conduct and malpractices in research were developed. This aligns with principles of responsible and ethical deployment, development, and application of AI tools. The work of RERCs was also not spared from this disruption. Various committees had to intensify issues relating to ethical consideration in line with their respective institutions' research ethics policies and guidelines. That said, this necessitated a need to focus on operational informed consent in the era of AI, big data, and PA. Other related principles such as confidentiality, prevention of harm, data privacy, addressing bias and discrimination in algorithms, transparency, and accountability also had to be re-examined. This journey of reform meant that power dynamics in the field of ethics review processes and research governance has to adjust with the time. In essence, these advancements necessitated the need for stronger and robust ethical frameworks to empower RERCs to minimise and mitigate ethical blurred lines.

As far as challenges are concerned, ethical concerns dominate the discourse in the literature. For this chapter, I draw on weaknesses categorised as functional, purview, and persistent being documented by Ferretti *et al.* (2021a). The functional weaknesses relate to among others, a lack of proper expertise in regulating and reviewing research projects within the big data and PA space. These challenges are trailed by difficulties in operationalising the informed consent, following ex-ante review models and inability to comprehend unforeseeable risk assessments. On the purview category, challenges relate to difficulties of dealing with new actors conducting research, how to anonymise data and the broad scope of big data-related studies. The last category deals with persistency and challenges such as lack of transparency, conflicting regulations across various jurisdictions, and inconsistent review practices and criteria within and across various RERCs.

With these challenges, there are associated opportunities that arise. These may manifest themselves through reforms that may need to be instituted to mitigate risks and ethical concerns. These reforms can be categorised as regulatory, procedural, and complementary. The regulatory opportunities imply that there is a need to provide a new guidance on the practice of ethics in this new era. Furthermore, the purview of RERCs need to be expanded to bring new expertise. Given that AI transcends beyond borders, there is also a need to specify foundational global standards for the assessment of ethics. Global bodies like the OECD, European Commission on AI, and UNESCO (United Nations Educational, Scientific, and Cultural Organisation) have already started in this regard.

From a procedural perspective, there is a need to introduce new ethical assessment tools and systems to guide the behaviour of various role players such as researchers, ethics managers, and review members. This may also mean that the membership of the RERCs need re-examination and adjustment to ensure that there is a diversity of skills in the board, preferably the presence of external experts. From a complementary viewpoint, creating hybrid mechanisms for the review process will assist in mitigating the risks that come with the new era. This can be augmented by introducing new specialised committees to ensure that unfamiliar or too technical research projects related to AI and big data are properly assessed for ethical compliance. In parting shots, the multifaceted roles and capabilities of AI, big data, and PA in shaping the landscape have brought about challenges and opportunities. These changes mean that educators, research review committees, and educational institutions have to relook their governance processes, protocols, and policy frameworks.

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