The Basis for Splitting Assessment from Education; utilising the power of AI.

A Presentation of the Research

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A note on the aim and presentation of this report

This report presents the findings from research addressing the issues and opportunities facing contemporary education, assessment and business arising from the rapid growth of AI technologies. It is the second report produced to inform a discussion document that presents a vision for the future.

This report is, hopefully, written clearly, but has not been refined into a succinct argument. The research was conducted and this report written to inform the writing of a report presenting a vision for education and assessment supported by AI. The subsequent report, Assessment, Education; a new paradigm facilitated by Artificial Intelligence, is available at https://aithefutureofeducation.com/

This report and both the previous report and the subsequent report, are the culmination of three years of research, consideration, correspondence and debate with friends, associates and experts.

The intention of publishing the subsequent report is to draw attention to the need for revolution rather than evolution of our education system. That report proposes a vision of the system we believe is essential if we are to adequately prepare our nation for the challenges of the foreseeable future. Indeed the authors believe that the vision described is inevitable though there may be some adjustments as AI becomes better understood.

A note on the authors

This report was written by Niall Dolan and Andrew Paterson. Research was conducted by Niall Dolan, Andrew Paterson, and Rachel Cairns.

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Writing the report has been an enjoyable and illuminating experience for the authors.

The Argument for Splitting Assessment From Education

"*Everybody is a genius. But if you judge a fish on it's ability to climb a tree it will live its whole life believing it is stupid*" Albert Einstein.

Section 1:

Advances in Artificial Intelligence

1.0:

An introduction to artificial and human intelligence

There are no universally accepted definitions for the term 'artificial intelligence’ or ‘AI’. As noted by Parnas, the catch-all term ‘AI’ obscures numerous and disparate technologies that are used to affect AI (2017). This report defines AI as:

The domain of computer systems capable of actions and behaviours that require intelligence when done by humans (Copeland, 2000).

AI is currently limited to domain-specific artificial intelligence; meaning that the extent of the AI’s capabilities are limited to a specific and bounded domain, such as playing a game of chess or driving a car. Max Tegmark, in his influential book, *Life 3.0: Being human in the age of artificial intelligence* (2017), describes domain-specific AI as being only narrowly intelligent. Domain-specific artificial intelligence may be contrasted with artificial general intelligence (AGI), defined as an AI capable of outperforming humans at most economically valuable work; including re-designing or improving itself or of designing AI more advanced than itself (OpenAI, 2022). The point at which AGI is achieved has been termed ‘*The Singularity*’. Renowned futurologist and Google’s Director of Engineering, Ray Kurzweil, puts the date of the singularity at 2045 (Reedy, 2017; see also Kurzweil, 2005). CEO of Japanese telecommunications multinational, Softbank, Masayoshi Son, puts the date at 2047 (Galeon, 2017). However, as Luckin (2018) is keen to stress, we are not at the singularity yet: AI systems remain extremely constrained both to the specific task for which they have been trained and to the potential problems to which they can currently be applied.

Whilst AI systems may be considered exceptionally efficient and reliable information processing machines within bounded domains, human intelligence may be considered an interwoven and complementary set of different intelligences. Luckin (2018) argues that the intelligence that AI demonstrates is such a diminished form of intelligence when compared to human intelligence, that AI should not be conflated with human intelligence (HI).

AI is in its infancy but is developing at breakneck speed. Competition between nation states means that the development of AI is inevitable (Gawdat, 2021). The UK is currently ranked third in terms of its investment, innovation, and implementation of AI, in a global index by the journalistic media company Tortoise; only the US and China are ahead (2022).. In its 2017 national AI strategy, The Chinese Government outlined $22.4 billion of funding over the next 13 years. The US, in contrast, earmarked $2 billion over 5 years; the same as Russia and slightly more than the UK (Mousavizadeh et al, 2019).

The entrepreneur and industrialist, Elon Musk, has warned that AI presents a greater existential risk than nuclear weapons and called for global regulation: "*It's capable of vastly more than almost anyone knows and the rate of improvement is exponential.*". Google CEO, Sundar Pichai, has hinted at the good AI could bring to humanity: "*It holds the potential for some of the biggest advances we are going to see*" (Mousavizadeh et al, 2019). AI is neither good nor bad; like any other technology, it is and will be what we make of it.

This report will examine the nature of the interrelationship between AI and HI and what it means for the future of work, education, assessment, and hiring. AI and related technologies have ushered in the fourth industrial revolution. The implications of the revolution for the labour force and for society must not be underestimated.

1.1

A General Review of Advances in AI Technologies

1.1.0 Terminology of AI

Data (singular and plural) is/are deliberate measurements about a particular variable. In modern computer science, data is information that has been converted into a digital form to enable its transmission and processing.

[and…]

Algorithms are sequences of finite instructions used in mathematics and computer science to solve a particular type of problem or perform a particular computation.

[are used in…]

Artificial intelligence is the domain of computer systems capable of actions and behaviours that require intelligence when done by humans (Copeland, 2000). – things like driving a car, or reading an MRI scan.

[which spawned…]

Machine learning is a branch of artificial intelligence and computer science which combines data and algorithms to enable the move from programming machines, to training them. Machine learning systems gradually improve their accuracy and performance, just as human learners do.

[and then…]

Deep learning is a type of machine learning that uses algorithms and artificial neural networks to mimic the way the human brain learns by learning by example. For example, if you have ever been asked to identify road signs within multiple photos before proceeding to a webpage, you are doing the work of tagging photos which deep learning systems use to learn what a road sign looks like.

[which utilises…]

Neural networks are formations of artificial nodes in computer systems based on simplified models of neural networks and signalling within biological brains.

1.1.1 Technologies underlying AI

The core technology behind most AI is machine learning, especially deep learning and reinforcement learning, powered by large data sets and computational power. In the past ten years, machine-learning technologies have moved from research labs into the real world (Littman et al, 2021).

1.1.2 Robotics

Highly agile and dynamic robotics systems are being used in industry and the home. Boston Dynamic's state-of-the-art humanoid robot, Atlas, has demonstrated the ability to jump, run, backflip, and manoeuvre uneven terrain. Another Boston Dynamic robot is being used on construction sites for monitoring and mapping (Littman et al, 2021).

Whilst we have seen robots doing repetitive, simple movements for the past decade, the more complex task of packing or unpacking random objects has hitherto had to be done by nimble human hands. The combination of deep learning, advanced computer vision, and robotic grippers with agile robotics is opening up new opportunities in industrial robotics. The ability to pick up and put down diverse objects is a key competence in a variety of human work from tidying homes to packing products to harvesting crops (Littman et al, 2021). The technology was brought to market in 2019 and is being used by shipping and distribution companies such as Amazon and DHL. The demand for nimble industrial robots in the shipping and distribution industries was accelerated by the Covid pandemic as e-commerce skyrocketed and labour shortages intensified (Hao, 2021).

1.1.3 Games and simulations

Developing AI algorithms within the adversarial conditions of games and simulations has long been a fertile ground and showcase for the advancement of AI technologies (Littman et al, 2021). AI first appeared in a digital game in 1979, when the developers of Pac-Man used it to control whether or not a ghost moved towards or away from the player (Luckin et al, 2016). AI achieved superiority over humanity's best player in chess in 1997 (Tran, 2021); the ancient Chinese game of 'go' in 2016 (Zastro, 2016); heads-up, no limit Texas hold'em poker in 2017 (Brown and Sandholm, 2018); StarCraft II, a multiplayer strategy game, in 2019 (Vinyals, 2019); Quake III Arena, a multiplayer first-person shooter, in 2019 (Jaderberg, 2019); 6-player Texas hold'em poker in 2019 (Brown and Sandholm, 2019); Alpha Dogfight, a US Defence Department-sponsored jet fighter simulation in 2020 (Pressman, 2020); and Gran Turismo, a car racing game, in 2022 (Sample, 2022). The algorithm that first beat the world champion of 'go', AlphaGo, was subsequently developed into an improved AI system called AlphaZero. Presented only the rules of 'go' as human inputs, it took AlphaZero just three days of playing against itself to beat its predecessor, Alpha Go, 100 - 0 (Silver et al, 2018). The implications of these wins go far beyond the games themselves because the algorithms used by the winning AI systems are often not specific to the games; they take as inputs the rules of the game and output strategy. Many of the algorithms initially applied to games are being developed for commercial applications.

1.1.4 Self-driving vehicles

The AI technology behind self-driving cars is not yet sufficiently agile and reliable to accommodate the diverse challenges human drivers contend with every day. The need for exceptional levels of safety in complex physical environments makes the problem more challenging and expensive to solve than had been anticipated (Littman et al, 2021). Chris Urmson, of self-driving technology company, Aurora, describes the mainstream adoption of autonomous cars as "*a transformation that is going to happen over 30 years and possibly longer*" (Metx, 2021). Nevertheless, Waymo, the self-driving vehicle technology unit of Google parent, Alphabet Inc., launched the world's first fully autonomous taxi service within a 50 square mile area of Phoenix, Arizona in 2020 (White, 2020), whilst the Chinese technology company, Baidu, launched the first fully autonomous taxi service in the suburbs of Beijing in 2021 (The Independent, 2021).

1.1.5 Natural language processing

Developments in natural language processing technology, powered by increasing data and computational power, have led to the creation of network architectures with enhanced capability to learn from complex and context-sensitive data. Neural network language models learn about how words are used in context by sifting through naturally occurring text. Processing unprecedented quantities of data (over one trillion words in some cases) and utilising billions of adjustable parameters, the technology can string together likely sequences of words and generate passages that are often indistinguishable from human-generated text, including poems, fiction, and computer code (Littman et al, 2021).

Natural language processing models are already supporting applications such as machine translation, text classification, speech recognition, writing aids, and chatbots. Current challenges include obtaining quality data sets for minority languages and detecting and removing biases in their behaviour. Notably, the technology does not yet exhibit a deep understanding of the texts they produce (Littman et al, 2021).

Conversational interfaces, such as Google's *Siri*, Amazon's *Alexa*, and Microsoft's *Cortana* have benefited from advances in AI natural language processing and have experienced tremendous growth in their use and integration into products (Littman et al, 2021).

1.1.6 Computer vision and image processing

Computer vision and image-processing technology is now widespread, finding uses from video-conference backgrounds, to deep fake photographs, to directing driverless cars (Littman et al, 2021). Deep learning techniques have been applied to the field and training times have been substantially reduced; in some cases work is done 100 times faster than just three years ago (Zhang et al, 2021).

It is now possible to generate images and videos that are, to an untrained eye, indistinguishable from 'real' images and videos; in some cases seamlessly replacing existing components of images or videos with new ones, so that it appears as if the new image was in the scene all along. Whilst deep fake images and videos could be created by skilled artists in the past, this new technology has substantially lowered the barriers to producing credible output (Littman et al, 2021).

Real-time object-detection systems such as YOLO (you only look once) and improved facial recognition software are used to detect specific faces in crowds and control access to smartphones and buildings. China, for example, holds records of all of its citizens' faces; and the FBI has photos of half the adult population of the USA (Seldon and Abidoye, 2018). In the UK, five police forces have aquired live facial recognition technology (Milmo, 2022). Whilst the technology can be a powerful tool to improve efficiency and safety, it has raised concerns about bias, privacy, and human rights (Amnesty International et al, 2021) and its military applications (Dua, 2021; Redman, 2020).

1.1.7 Healthcare

Current penetration of AI technologies into healthcare is relatively low compared to other sectors but that seems likely to change in the near future as already-mature AI technologies are transferred from other sectors (Littman et al, 2021). AI is currently fulfilling roles in diagnosis, drug discovery, clinical decision making, risk management, medical education, personalised medicine, robotic prostheses, physical task support systems, and mobile manipulators assisting in the delivery of telemedicine. An AI system has recently been developed that is as accurate as trained dogs at correctly identifying cases of prostate cancer from urine samples (Guest et al, 2021). Ethical challenges in the development of AI systems in healthcare include overcoming biases inherent in the training data (Nagendran et al, 2020; Rigby, 2019), maintaining confidentiality, and building systems that are able to explain the decisions they have made (Pawar et al, 2020).

1.1.8 Finance

AI has been thoroughly adopted into finance. Deep learning models now partially automate lending decisions for several highstreet lenders (Littman et al, 2021). Credit scoring has been transformed through the use of previously unavailable customer data and is being used both to offer credit to new groups of people (Littman et al, 2021) and to coerce others, as in the case of the Chinese government (Heberer, 2020). So called 'robo-advisors', automated financial advisors, planners, and managers, are becoming mainstream in personal finance. In financial institutions, AI is detecting fraud and money laundering and automating legal and compliance documentation and is driving predictive analytics which utilise existing data to identify trends and risks and reduce labour costs (Cutbill, 2021).

1.1.9 Recommender systems

Machine learning models, known as recommender systems, have become ubiquitous; they automatically recommend and prioritise what we see online and so shape user preferences and guide choices, both individually and socially. They have become ever-more-sophisticated in their methods; one shift in the past five years has been the near-universal incorporation of deep neural networks into recommender systems to better predict user responses to recommendations. There has also been increased use of sophisticated methods to analyse the content of recommendations so that machine learning systems better understand why a specific item might be a good recommendation for a particular person or query (Littman et al, 2021). The increasingly ubiquitous nature of recommender systems within modern life has raised significant issues around fairness, diversity, the cultural appropriateness of recommendations, privacy, autonomy, personal identity, opacity, polarisation, and the emergence of echo chambers and accompanying social effects (Milano et al, 2020).

1.2

A Review of Advances in AI in Educational Assessment

1.2.1 Computerised Adaptive Tests

Computerised adaptive tests (CATs) are a core form of machine learned assessment, typically used in high stakes summative assessment contexts, such as entry exams for elite schools or employers (Gardner et al, 2021). Many MBA courses, the big four accounting companies, and the UK Civil Service employ CATs. The two most successful CATs used in education are the Graduate Management Admissions Council's *GMAT* and ETS's *GRE General examinations*. ETS charges a $205 entry fee and in 2020 had 286,461 candidates in the USA and approximately 100,000 more across the globe (ETS, 2020). These two systems follow similar design criteria and have relatively simple operational models (Davey, 2011). The systems offer the examinee a sequence of questions,each selected on the basis of two associated measures; the examinee's ability (estimated from previous performance) and question characteristics (predetermined by developers and continually augmented with user analytics). In contrast to traditional exams which administer a fixed set of questions, CATs are item-level tests that dynamically adjust to the examinee's responses to individual items. CAT proponents claim that they are much less vulnerable to the security issues encountered in fixed tests; have lower invigilation demands; more efficiently arrive at an acceptable assessment of the examinee's ability; and offer a more replicable assessment (Gardner et al 2021).

CATs work best when assessing a relatively well-defined knowledge domain with dichotomous answers, i.e. correct/incorrect or multiple choice; they work less well with polytomous or partially correct answers, ie, a score of 0-100 for an essay. Moneta-Koehler et al (2017) and Hall et al (2017) note that CATs are poor at predicting candidate success in later life. Miller and Stassun (2014) contend that ETS's GRE, which is an admissions requirement for most US graduate schools, does a poor job of selecting the most capable students because like most standardised tests, it reflects certain demographic characteristics of test-takers — such as family socioeconomic status — that are unrelated to their intellectual capacity or academic preparation. The result, they claim, is that the GRE severely restricts the flow of women and minorities into the sciences: '*the GRE is a better indicator of sex and skin colour than of ability and ultimate success*'. Instead, they argue, the GRE test should be augmented with measures of other attributes — such as drive, diligence and the willingness to take scientific risks. The change would make for a more diverse learning cohort and better completion rates (2014).

1.2.2 Automated Writing Evaluation

Automated writing evaluation (AWE) or automatic essay scoring (AES) systems use natural language processing and other AI techniques to automatically assess and provide feedback on student essays.
These systems can accurately and efficiently evaluate students' composition, including structure, grammar and overall score (Huang, 2021). They have been primarily designed for the efficient, consistent and low-cost assessment of writing tasks, especially in large-scale testing contexts such as MOOCs (Miao, et al, 2021). AWE are applied to formative and summative assessment in many educational and commercial settings with systems such as *WriteTo Learn* by Pearson from the UK; *e-Rater* by Educational Testing Service from the USA; *Turnitin* by Turnitin from the USA, and *Grammarly* by Grammarly from the Ukraine and USA.

Using appropriate weightings, AWE systems have been seen to have agreement levels of up to 80% with the assessments of human judges. Gardiner et al (2021) argue that many of these claims may be attributed to the typical scoring scales of 1-4, 5, or 6. In such a scoring system, brilliant and terrible essays may reasonably be expected to display respectively more or less of the proxy indicators. However, variance between AI and human judges occurs where higher order aspects of writing such as creativity, analysis argument, synthesis, are privileged in the scoring system, largely because these aspects are as of yet much more difficult for a AWE to detect (Gardner et al, 2021). Feathers (2019) notes that summative AWE systems have been controversial ever since they were introduced. By giving students credit for surface features such as sentence length, they can be 'fooled by gibberish'; many AWE algorithms display bias against groups who use different vocabulary and sentence structure from that exhibited in the data used to train the AWE algorithm; AWE systems do not detect 'deep fake' essays that have been written by AI systems. Lastly, AWE systems deprive the teacher of the opportunity to mark essays, an often tedious and time-consuming but nonetheless valuable opportunity to understand students' competencies. It seems likely that AWE technology will advance in accordance with its ability to mimic nuanced aspects of human judgement.

1.2.3 Intelligent Tutoring Systems

Intelligent tutoring systems (ITS), of all educational AI applications, have been researched for the longest period of time (over 40 years), experienced by the largest number of students (millions), and attracted the highest level of investment. The system lays out a structured body of knowledge and takes the student through individualised, step-by-step tutorials. Intelligent tutoring systems combine realtime user data, expert knowledge of the content, cognitive science, knowledge tracing, and machine learning, to determine the student's optimal pathway through a set of learning material (Miao et al, 2021). There are more than 60 commercially available ITS across the globe today including: *Alef Platform* by Alef Education from the UAE*;* *ALEKS* by McGraw Hill's from the USA; *Byju's* by Byju's from India; *Knewton Alta* by Wiley from the USA; *Mathia* by Carnegie Learning from the USA; *Qubena* by Compass from Japan; *RiiidTUTOR* by Riiid from South Korea; and *Squirrel AI Learning* by Yixue Group from China.

As with AWE, the efficacy of ITS is contested. It has been suggested that ITS replicate the legacy education system's instructionist approach to imparting knowledge; students are led through predefined curricula with little to no opportunity for students to proactively direct or adapt the content or manner of their learning. When applied within physical classrooms, ITS tend to increase the time that a teacher spends at their desk due to the necessity to monitor students on a computer dashboard, instead of walking around the room. Whilst ITS have been adopted by educational providers around the world, there is little robust evidence that the systems are as effective as their developers claim (Holmes, 2018).

Nonetheless, ITS look set to make a significant impact on the global educational sector. Byju's was established in Bangalore in 2011; by 2021, the company was valued at $18 billion making it the world's highest valued ed-tech start-up (Singh, 2021). Since the pandemic, the start-up has added an additional six million paying users, with a 85% renewal rate (Inamdar, 2021). In a country where rote learning has been the predominant approach to education and many schools are under-resourced, Byju's Learning App, has introduced constructivist teaching and learning methods (Palliyalil and Mukherjee, 2020) and has increased access to engaging learning content (Casanova, 2018). However, the BBC reports that the company's rapid growth, supported by a high-profile marketing campaign featuring Bollywood superstar, Shah Rukh Khan, has been accompanied by reports of aggressive sales techniques and anecdotal reports of low customer satisfaction (Inamdar, 2021). The global market for successful ITS is massive and potentially lucrative. Regulation appears to be imminent in India (Inamdar, 2021).

1.2.4 AI-supported reading and language learning

Reading and language learning tools are increasingly utilising AI. Many use ITS-style personalised pathways through a curriculum with AI-driven speech recognition and semantic analysis. The system provides automatic feedback on students' pronunciation (Miao, 2021). Reading and language learning AI applications include *AI Teacher* by TAL from China which delivers Mandarin language teaching in remote areas of China (TAL, 2021); *Babbel* by Lesson Nine GmbH from Germany which is a subscription-based app and e-learning platform providing teaching in 14 major languages (Babbel, 2021), and *Duolingo* by Duolingo from the USA. *Duolingo* is a website, mobile app, and a digital language proficiency assessment exam. Offering courses in 40 languages, including Hawaiian, Navajo and Scottish Gaelic, *Duolingo* is the world's most-downloaded language learning app, amassing over 500 million downloads to date. Duolingo is currently valued at $6.5 billion (Wang and Nishant, 2021).

1.2.5 Dialogue-based tutoring systems

Dialogue-based tutoring systems use natural language processing and other AI techniques to simulate a conversation between a human student and one or several virtual agents, typically represented on screen by an animated avatar. Voice assistants such as Google's *Siri*, Amazon's *Alexa*, and Microsoft's *Cortana* use similar technology. The avatars in dialogue-based tutoring systems take students through a step-by-step curriculum or interact in a less structured, more open domain. Dialogue-based tutoring systems are predicated upon a socratic and social approach to learning. Knowledge and confidence is co-created through dialogue (Miao, 2021). There are relatively few dialogue-based tutoring systems in commercial use; Alelo's software (Alelo, 2021) and IBM and Pearson Education's, *IBM Watson Tutor* are two examples.

1.2.6 Self-regulated learning

The overwhelming majority of investment and research into AI in education has been directed at solving existing challenges or problems within the legacy education system. However, fierce international competition and game theory imply that the continued development of AI technology is inevitable (Gawdat, 2021). Within the context of vastly improved AI capabilities, it is likely that education will undergo major transformation (Seldon and Abidoye, 2018).

The FLoRA project is an international research collaboration involving institutions from the UK, Germany, the Netherlands, and Australia. In response to perceived future needs, the project seeks to better understand meta-cognitive learning, or 'learning about learning'. Research shows that self-regulated learning leads to better learning outcomes; however, it is difficult for learners to adequately self-regulate. The project will apply learning analytics and machine learning to better measure and understand self-regulated learning processes during learning and so generate insights on the process (FLoRA Project, 2021).

1.2.7 Applying neural feedback in education

Preliminary results of brain science suggest that it will be possible to conduct realtime, objective evaluations of brain functions which will facilitate the development of systems designed to evaluate learning ability, measuring attributes such as attention, cognition and self-control. Such systems could help learners understand how the state of their brains affects the state of their learning and so help them to adjust their mental states and learning strategies accordingly (Yu and Lu, 2021).

Section 2

Work, Education, and the Transition to the Fourth Industrial Revolution

2.1

Past and future changes in the job market

2.1.1 Glossary

- **Aptitude** is synonymous with talent and an innate or acquired capacity to do something.
- **Character** is the combination of mental and ethical qualities or traits that are distinctive to an individual.
- **Knowledge** is gained by assimilating information and experience into a mental framework. Knowledge affords humans the ability to act and think in consciously informed ways.
- **Skills** are synonymous with expertise and the ability to do a defined action well.
- **The Industrial Age** is a historical period that started in the mid 18th century and continued into the mid 19th century. It is characterised by an economy based upon industrial machines powered by water and coal. The age is associated with mass manufacturing, rapid urbanisation and population growth, and a relative explosion in annual growth rate of national economies, from an average of under 0.1% in the preceding 10,000 years covering the agricultural and scientific ages, to an average of 2% (Wiblin, 2021).
- **The Information Age** (also known as the **Computer**, **Digital**, **or Electronic Age**) is a historical period that began in the mid 20th century and is characterised by an economy based primarily on information technologies such as computers, televisions, telephones. The age is associated with the mass utilisation of electricity and combustion engines and modern globalisation.

2.1.2: How technology has affected the job market

The third industrial revolution, or digital revolution, began in the late 1900’s and was initiated by the introduction of electronics and computers. Computers, in contrast to AI, are fundamentally bound to follow procedures that are meticulously laid out by human programmers, to simulate work processes that would otherwise have been done by a human. The *principle* of computers simulating workplace tasks has remained unchanged since the dawn of computing whilst the *cost* of computing has plummeted (David, 2015). The cost of performing a standardised set of computations has fallen by a factor between 1.7 trillion and 76 trillion since the manual computing era, with most of that decline occurring since 1980 (Nordhaus, 2007). It was the precipitous drop in the price of computing that precipitated the mass adoption of computers in the workplace.

Computers and robots began entering the workplace and substituting for human labour in the 1980’s. Automation in the 1980’s was focused on manufacturing, middle-management, clerical, and sales occupations (Acemoglu and Autor, 2010; Brynjolfsson and McAfee, 2011) because the majority of tasks in these occupations were well defined, and thus lended themselves to automation by computers and robots. As computers replaced humans in manual and repetitive tasks, large sections of the labour supply shifted to low-income service occupations, in which the high degree of manual dexterity, flexibility, and adaptability precluded automation (Autor et al, 2003; Autor and Dorn, 2013; Goos and Manning, 2003). In the same period, the demand for higher-order cognitive and problem solving skills rose in proportion with the complexity of the economy (Frey and Osborne, 2017). Those who had access to higher education and training took advantage of the new technologies and they increased their earnings in line with the new found productivity that the new technologies afford them (David, 2015).

Despite conspicuous job losses, ‘computerisation’ of the workplace appears to have created more new jobs than it displaced (David, 2015; Manyika et al, 2017). Between 1980 and 2015, computers displaced bookkeepers and auditing clerks, secretaries, and typists; but created previously unheard of jobs in industries ranging from computer hardware to enterprise software, online retail, marketing, and data analysis to name but a few. The McKinsey Global Institute calculated the net gain in employment in the United States during the same period to be 15.7 million jobs- or almost 1 in 5 jobs (Manyika, 2018).

The history of technological developments in the workplace suggests that technological transformations affect workers in unequal ways and over long time periods. For example, as technological innovations swept through Britain in the first industrial revolution, the wages of the lower classes stagnated for almost half a century despite a strong surge in productivity- a phenomenon first identified by the philosopher Friedrich Engels and subsequently known as ‘Engel’s Pause’. At the same time, the incomes of the upper classes and the emergent middle classes soared as the returns on capital outpaced the returns on land and labour. This inequality led to increased savings rates which in turn created more investors and the capital to sustain the industrial revolution. Lower class wages began to rise with productivity only once capital accumulation had caught up with capital investments in the technologies sweeping the workplace (Allen, 2007). The third industrial revolution has arguably led to a similar situation. Median hourly compensation in the USA rose only 11% from 1973 to 2016, even as hourly labour productivity grew by 75% (Manyika, 2018).

2.1.3: The future job market: the fourth industrial revolution

Where the second industrial revolution was characterised by standardisation and mass production, and the third by information technologies, the fourth is characterised by AI technologies. There appears to be a consensus in the literature that the technologies of the fourth industrial revolution will eventually affect most workers, and that the accelerating speed of the transition will present a challenge to society. The fourth industrial revolution is not happening in isolation: other contemporary and interrelated macro trends such as environmental sustainability, urbanisation, rising inequality, globalisation, demographics, technology change, and political instability (Bakhshi et al, 2017) are intersecting and compounding the scale of the challenges humanity faces.

As with previous industrial revolutions, the fourth industrial revolution will usher in a new wave of automation. The result will likely be an increase in productivity at the cost of many workers being forced to adapt quickly and/or change jobs. Manyika et al calculate that 60% of occupations across developed economies have at least 30% of their constituent tasks exposed to potential automation (2017). Many workers will end up working alongside rapidly evolving machines. Developments in AI could automate tedious subtasks, improve production quality, and increase productivity. These changes may help individuals become more agile, curious and nimble; enhance human collaboration; and promote cognitive diversity, but they will require workers to adapt.

Workers will have to begin habits of lifelong learning, and become more adaptable and flexible. Training and education programs will have to focus on the aptitudes that humans perform better than AI. These aptitudes such as creativity, curiosity, imagination, empathy, human communication, and innovation. Focusing human efforts on these aptitudes is a strategic decision that allows human workers to add most value in the workplace and ensure that we work productively alongside advanced machines, rather than being replaced by them (Tata Communications, 2019).

Increased investmentment in education and in-work training will be necessary to support workers to adapt to workplaces newly augmented with AI and related technologies. However, across the OECD, an international group of rich countries, spending on worker education, training, and transition and dislocation assistance, has been in decline over the last two decades. It seems inevitable that if the historic underspending continues it will compromise the adaptability of the workforce, making the transition to the fourth industrial revolution more difficult (Manyika and Sneader, 2018). This observation seems particularly salient given that the histories of previous industrial revolutions highlight the critical role of education in enabling workers to benefit from the new technologies, as opposed to being harmed by them.

According to an estimate by Frey and Osborne (2017), 47 percent of total US employment is in occupational categories with a high risk of being automated over a period speculated to cover the first to second decades of the fourth industrial revolution. These occupations include physical activities in highly predictable and structured environments such as transportation, logistics, office administration, sales, and manufacturing (Frey and Osborne, 2017). More developed economies are likely to experience more displacement than less developed ones due to higher wages in the former and thus a greater economic incentive to automate. Between 2016 and 2030, demand for physical and manual skills is predicted to fall by 16% overall in Western Europe but will nonetheless continue to be the single largest category of skills (measured by time spent) at 25% of the total workforce in 2030 (Bughin, 2018). The jobs that are most resistant to automation include managing others, innovating, complex problem solving, enabling interoperability between systems, interfacing with stakeholders, and social- and emotional literacy.

Based upon previous industrial revolutions, it seems likely that the fourth industrial revolution will create more jobs than it destroys. The dynamics driving demand for work and workers may include: technological innovation driving productivity growth; rising incomes leading to increased consumption; ageing populations leading to increased healthcare requirements; and investments in new infrastructure (Mayika and Sneader, 2018). Future scenarios envisioned by Manyika and Sneader suggest a range of additional labour demand of between 21% to 33% of the global workforce (555 million and 890 million jobs) by 2030 with jobs that we currently haven't been imagined accounting for as much as 10% of the new jobs (2018).

The number of high-wage jobs, particularly in high-skill, medical, technological, and other professions, is likely to grow significantly in the coming decades. Demand for higher cognitive skills, such as creativity, critical thinking, decision making, complex information processing, and social and emotional skills, will grow through 2030, by 14% in Europe, from sizable bases today (Bughin, 2018). Relatively low-paid jobs, particularly in the caring and education sectors, are also likely to grow in number too. In other words, the wage polarisation that occurred within the labour markets of the first industrial revolution may be repeated in the fourth, deepening entrenched income inequality (Berkhout et al, 2021) and stoking social and political tensions.

2.1.4: 'The future is going to happen a lot quicker than the past did'

It is important to note that the studies reviewed in this report predict areas of work in which some impact from AI and automation is expected. The studies do not specifically predict whether or how AI will substitute for existing work, complement it, or create entirely new work. The interplay between AI and automation, other key macro trends, and local concerns will ultimately shape the future job market.

A major dynamic that makes predicting the future of the job market difficult is the exponential rate of technological development. Gordon Moore (1975) observed that computing power (defined by the number of transistors per integrated circuit) was doubling approximately every two years, a pattern that remains consistent to this day. This exponential dynamic is expressed in the ‘law of accelerating returns’ which predicts that key milestones in technological innovation will happen increasingly frequently as the power of technology increases exponentially (Kurzweil, 1998). The dynamic underlying the law of accelerating returns is exponential growth, which human minds are notoriously poor at conceptualising because our brains are evolutionarily adapted to thinking linearly (Wagenarr and Sagaria, 1975). How tall would a sheet of paper be if you were to fold it on itself 50 times? The answer is that it would reach past the moon; yet having been told this and calculated it for one’s self, the answer still seems to evade our ‘sense of correctness’. In a presentation on future technology trends, Ray Kurzweil retold the following story.

In 1995 it was announced that it would take 15 years to sequence the human genome. Seven years into the project, only 1% had been sequenced. Mainstream critics, including a Nobel Prize winner, concluded that the project would never be completed on time. Yet Kurzweil concluded that the project was half way there on the basis that the rate of sequencing would double every year. Low and behold, within 7 years the project was complete (WOBI, 2016).

The difficulty that most humans experience when conceptualising exponential growth is one reason why we have consistently underestimated the rate at which technology will develop in the future (Booth, 2020; Gawdat, 2021). Knowing this dynamic should give us pause for thought when thinking about the potential impact of the fourth industrial revolution on our lives and work. It also implies that the problems caused by new technologies entering the workplace will become exponentially larger in proportion to the duration of our procrastination.

2.1.5: Transitioning into the fourth industrial revolution

Addressing the critical teaching and training requirements precipitated by the advancement and growth of AI is now *the* major task of transitioning into the fourth industrial revolution (Luckin, 2018). A well trained workforce with the skills to take full advantage of AI and related technologies will ensure that our economies enjoy strengthened productivity growth and that humanity is afforded the power to solve some of our most complicated and challenging problems. Failure to support the workforce to adapt and reskill will likely result in rising skill-and-wage bifurcation, political and social unrest, and a prolonging of the period it will take to realise the gains of the new technology (Bughin et al, 2018).

Skills, character, and aptitudes appropriate for the twenty-first century will have to be taught in education and work. Companies will have to create new cultures of continuous learning, provide financial and other support to employees undergoing major shifts in their roles, and accept a higher degree of movement of staff between employers as workers find new roles. Educational institutions, which are largely still teaching skills, character, and aptitudes appropriate for the twentieth century, will need to overhaul their internal structuring and credentialing systems to suitably prepare learners for life and work in the future (Manyika, 2018).

2.2:

AI is changing which skills have value and so what education must teach

2.2.1: AI and and related technologies are transforming the value of human skill sets in the workplace

In their new book, *The Age of AI*, former US Secretary of State, Henry Kissinger; former executive chairman of Google, Eric Schmidt; and Dean of the MIT Schwarzman College of Computing, Daniel Huttenlocher; assert that AI '*augurs a revolution in human affairs*' (Kissinger et al, 2021). Our world is being rapidly and irreversibly changed by AI: the risk is that AI could quickly gain senior decision making powers over human systems and so take the future of humanity out of human hands (Kissinger et al, 2021). AI and associated technologies are incredibly powerful and are expected to change our world in ways we cannot yet imagine. We must consider the implications of these technologies now to secure the prosperity and peace that we have enjoyed over the past decades for the decades to come.

AI and related technologies are automating the repetitive and cognitively simple tasks in the economy, from supermarket checkouts, to surveying windmill blades for damage, to driving mining trucks, to analysing data. As a result, the baseline conditions that determine the relative value of human skill sets are changing (Bughin et al, 2018). The value of repetition, pattern-prediction and recognition, memorization, or any skills connected to collecting, storing, and retrieving information are in relative decline in the human workforce (Owen, 2017; Muro et al. 2019; Tata Communications, 2019; Zhao and Watterston, 2021). Tasks that are beyond the capabilities of AI and related technologies, such as creativity, curiosity, complex problem solving, transferring knowledge across domains, human connection, and social-emotional perception are becoming relatively more valuable. The ‘revolution in human affairs’ (Kissinger et al, 2021) is happening at a much greater speed than previous industrial revolutions and is all but inevitable due to the inescapable forces of geopolitical competition (Gawdat, 2021). The speed and extent of the changes have reduced our time horizon: there are almost no knowledge or skills that can be guaranteed to meet the needs of the unknown, uncertain, and constantly changing future (Zhao and Watterston, 2021). In this historically novel paradigm, we must agree upon what we want from our human intelligence (HI), how HI and AI can best complement each other, and as a consequence what new knowledge and skills the workforce needs (Luckin and Issroff, 2018). As Luckin (2018, p124) points out: “*Any failure to recognize and address the urgent and critical teaching and training requirements precipitated by the advancement and growth of AI is likely to result in a failure to galvanise the prosperity that should accompany the AI revolution*.”

There is a plethora of suggestions for which skills and aptitudes will best enable humans to add value in an AI augmented workforce. Some of the most prevalent suggestions are: creativity (Beghetto, 2017; Kaufman and Beghetto, 2009), elements of character like perseverance, curiosity, conscientiousness, optimism, and self-control (Tough, 2012), communication and collaboration skills (Partnership for 21st Century Skills, 2007; Trilling and Fadel, 2012), critical thinking (Bughin, et al 2018), innovation skills (Wagner, 2008; Wagner, 2012), entrepreneurial skills (Zhao, 2012), happiness (Seligman, 2006, 2011), physical well-being and self-determination (Ryan and Deci, 2017), social and emotional well-being (Wentzel, 1991; WEF 2016a), and mind-set (Dweck, 2006). In large part, these skills represent domains where humans are likely to retain a competitive advantage against AI, at least into the medium-term future.

Some authors have put forward sets of *interrelated* competencies that will help us to work with AI. Luckin, for example, in her book, *Machine Learning and Human Intelligence*, suggests seven interwoven intelligences: academic, social, epistemic, metacognitive, metacubjective, and metacontextual intelligence with perceived self-efficacy (2018). At the base of Luckin’s argument is a critique of our educational culture’s obsession with measurement and the observation that it is leading us to oversimplify and undervalue human intelligence. For all of its remarkable powers, AI remains a bounded intelligence; the interwoven human intelligences are unbounded and collaborative, and are therefore of infinitely higher value to humankind (Luckin, 2018).

As well as working alongside AI, humans will have to live and work in a world redefined by it. Berkowitz and Miller summarise privacy, human dignity, concentration of economic power, algorithmic bias, and system reliability as the major ethical concerns arising from an AI augmented world (2018). AI and related technologies will interact with environmental sustainability, urbanisation, rising inequality, globalisation, demographics, and political instability in ways we cannot predict (Bakhshi et al, 2017). With all these dynamics in flux, the OECD, a club of mostly rich countries, predicts that young people will have to invoke ‘transformative competencies’, including innovation, responsibility, and awareness, in order to thrive within a changing world (OECD, 2018).

Deloitte defines cognitive diversity as ‘*educational and functional diversity, as well as diversity in the mental frameworks that people use to solve problems*’ (Bourke, 2018). Cognitively diverse teams acting in an environment of psychological safety (Reyonlds and Lewis, 2018) show improved problem solving, increased innovation, and make more accurate predictions- all of which lead to better performance and results (Bell, 2007; Page, 2017; Reynolds & Lewis, 2017). Demographic diversity, for its part, helps teams tap into complementary networks, knowledge, and behaviours (Bourke, 2021). Team diversity is increasingly being recognised by business as a valuable asset.

The foundation of our modern economy is the division of labour. Specialisation is becoming more important as AI and related technologies automate an increasing proportion of the repetitive and cognitively simple tasks in the economy. Employers are increasingly seeking out well-developed, high order skills. Some businesses, such as GCHQ for example, are preferring applications from people with dyslexia on the basis of their superior pattern recognition abilities and creativity (Addisson and Cooke, 2019). In the words of Sir Jeremy Flemming, Director of GCHQ, ‘*I want to show young people that thinking differently is a gift. It is only with the right mix of minds that they can solve seemingly impossible problems, just like we do at GCHQ*’ (Knowles, 2021). Within increasingly dynamic job markets, specialist skills retain relevance for a shorter period of time, and so the effective cost of specialisation increases. This report speculates that the increased cost of specialisation will increase the demand for affordable and continual education and assessment.

2.2.2: Agreeing upon what matters in education

What is measured in education represents what society considers important. What gets measured becomes what society expects its citizens to be equipped to do, and what schools, colleges, universities, teachers, parents, governments, and students pursue. Consequently, what gets measured has a large impact upon the entirety of the educational system and the knowledge, skills, and aptitudes of its graduates (Zhao et al, 2019). One likely implication of AI’s ability to offer dependable measurement of softer character traits like determination or kindness, is that their relative value in the workplace will increase. Another implication is that this ability will offer us a deeper understanding of the relative value of the output of education.

The problems in education, like the problems of climate change, social injustice or public health, cannot be clearly defined and are highly resistant to resolution; social scientists term these ‘wicked problems’. Conventional linear analytic approaches often lead to more problems because many factors work at the same time and are highly interactive. In the case of implementing a national educational policy, there is no immediate and ultimate test of the impact of the solution. We cannot know if what is achieved is better than what would have been achieved had we pursued a different policy, nor can we verify in the present if the output will actually matter in the future (Zhao et al, 2019).

In modern societies, the decision regarding what to measure in education has been made by an authority, most often by a group of supposedly representative experts, in which the winner decides the curriculum and exams for all (Zhao et al, 2019). What works for some learners will not work for all and therefore any curriculum that obligates everyone to achieve the same standard will inevitably provide an optimal learning experience for only a minority of students. At worst, a curriculum that is ill-matched to the aptitudes and interests of a learner will harm their learning. Some types of learning have been shown to depress other types of learning; for example, encouraging conformity depresses creativity (Zhao, 2018). Therefore, an educational model that is designed to result in excellent outcomes for *all* learners must optimise educational experiences at the individual level; not a class, school, or national one (Basham, Hall, Carter, and Stahl, 2016; Tomlinson, 2014; Kallio and Halverson, 2020).

2.2.3: The legacy education system is not equipping graduates with the skills, character, and aptitudes they need for life and work in the 21st century

The legacy education system is based upon a model of schooling that was designed to equip students for the industrial age: students are divided into age cohorts; learning is divided into subject areas; one teacher teaches many students in a designated room; students are allowed one or two breaks a day to play, socialise, and eat; and the year is divided into three semesters allowing students time off schooling to fit around the harvest and religious calendar. Learners graduate within expertise in a defined subject that are meant to last them a lifetime. Of course, we are no longer in the industrial age, and the mismatch between the requirements of learners and what the legacy education system is providing them with is causing problems.

Cognitive development is *enhanced* when learners interact with different age groups in the classroom, yet the legacy education system segregates learners into age cohorts. Concepts are ‘learned’ when the learner connects them to relevant aspects of their own prior knowledge and experience (a process known as constructivism in educational philosophy). All learners have different prior knowledge, strengths and weaknesses, yet the legacy education system introduces all learners to the same concepts at the same time. The result is a highly inefficient system of teaching and learning that encourages conformity over creativity and taking responsibility for one's own learning. Persisting with a one-size-fits all approach when learners have diverse knowledge and experience is one reason why despondency, boredom, and disengagement is so common in our schools.

Innovative ideas are often created from the synthesis of unrelated ideas in different areas of human knowledge and experience; yet the legacy education system is based entirely on a model of teaching and assessing knowledge and skills *within* a subject; not the ability to make connections *between* them. This decision to silo knowledge into subject areas constrains innovation and learning. The siloed approach to pedagogy in the legacy education system may be contrasted with, for example, the integrated and holistic approach of the Waldorf educational system.

Play is a highly effective and innate way to learn. Yet the legacy primary education system relegates play to the periods between formal classes. Within the classroom, sitting still, being quiet, and listening to instructions is rewarded; whilst spontaneous, self-directed play is mostly disciplined. Instead of utilising play as an aid to learning, the legacy education system relegates play to the times between formal learning.

Failure has been proven to be a more effective driver of learning than instructional teaching, yet the legacy education system continues to practise instructive teaching as its primary method. Similarly, conformity has been proven to suppress creativity and innovation, yet conformity remains a dominant ideology in our schools and colleges.

It is well understood that different students feel comfortable in different settings and learn best at different times of the day, yet the legacy education system requires all learners to be in the same place at the same time.

Our legacy educational assessment system produces millions of graduates with qualification profiles that offer little to distinguish between them and are a poor at accounting for the skills and aptitudes that really matter to employers in the twenty-first century; namely creativity, curiosity, complex problem solving, transferring knowledge across domains, human connection, and social-emotional perception. We must recognise that the world has changed and realign our system of educational assessment accordingly.

This report asserts the interdependence of education and enterprise. Education drives enterprise; and enterprise pays for education. Outdated education and assessment systems are constricting enterprise and public affairs alike. The issue is of national and international importance and the need for solutions is urgent.

The job market of the near future will place a high value on a heterogenous, diverse workforce; one that is composed of workers who think differently, have different but complementary skills and knowledge, can innovate and problem solve, and work well together. Yet the legacy education system assesses everyone on the same knowledge, and accordingly we teach them the same knowledge; this approach is inappropriate for the 21st century. We spend the majority of our time in schools, colleges, and universities consuming old knowledge rather than producing new insights, we strive for correctness instead of novelty. The entirety of our system encourages us to do what a few decision makers believe is the best thing for all of us to do, instead of finding out what matters to us most and how our aptitudes and interests could be developed to provide the most value to ourselves, our communities, and the workplace.

Inflexible, ‘one-size-fits’ all curricula are one of the major out-of-date and inappropriate features of the legacy education system. We impose national curricula, ultimately, because of the limitations of the human mind. After graduation, learners need to authoritatively communicate their abilities to strangers. Exams are used to assess learners’ abilities and exam certificates used to prove abilities. Until now, humans have had to administer the exams. However, because a human isn’t capable of assessing an unlimited number of skills, characters, and attributes, we constrain learning with curricula. Examiners need only understand the curricula to assign a mark to a certificate. Critically with regards to the argument of this report, we are no longer so constrained by the limitations of the human mind in the assessment of human abilities.

The development of AI-based systems of assessment that offer distinct and authoritative certificates of a candidates ‘full suite’ of skills, attributes, and character is, technologically speaking, within our grasp. The implications for education are revolutionary. AI assessment systems can now assess a vast range of human abilities and therefore we no longer need to demand that all learners follow the same curriculum. We no longer need to enforce adherence to a one-size-fits all curriculum.

Prior to the advent of AI, the process of teaching and assessing a curriculum was constrained to human beings. This constraint meant that teachers were obliged to teach and assess. This constraint has now been lifted, and the implications for the roles of teachers are revolutionary.

Ai has changed the fundamental requirements of schools and teachers and made possible the re-design of legacy systems of education and assessment. As the 21st century continues to increase in complexity and the market increasingly demands different skills, characters, and attributes than the ones that the legacy education system is providing them with, we should grasp the opportunity that AI offers to revolutionise our assessment systems with both hands.

2.2.4: Towards a system of education fit for the 21st century

We should foster the knowledge, skills, aptitudes, and character that are appropriate for the world we live in. The legacy education system focuses on the transfer of known knowledge. Precisely because the increasing speed of technological development has rendered the future unpredictable, we have to refocus our education system to teach adaptability, resilience, and creativity. The skills that will be most valuable to individuals and to employers in the 21st century are creativity, critical thinking, problem solving, the capacity to learn, communication and collaboration (Trilling and Fadel, 2012; WEF, 2016b). Education systems across the world have remained inflexible in the face of a rapidly changing world; and the result is a grave and growing graduate skills gap across the world (Abayadeera and Watty, 2014; Abbasi, Ali, and Bibi, 2018; Belwal, Priyadarshi, and Al Fazari, 2017; Bowers-Brown and Harvey, 2004; Malik and Venkatraman, 2017; Moore and Morton, 2015; Pillai et al, 2019; Verma et al, 2018). We will enable future generations to grasp the vast opportunities offered by embracing AI and related technologies if and only if we arrange our education system to adequately prepare society to work alongside these new technologies.

Jobs in the 21st century will need diverse workers and teams to solve complex problems. Therefore, a curriculum fit for the 21st century should promote heterogeneity by being ‘personalisable’. There are minimum standards in literacy, numeracy, and cultural fluency that every person needs to function in modern societies; these standards are relatively low. Over and above these standards, students should be free to pursue the knowledge and skills that interest them most and which play to their natural strengths (Basham et al. 2016; Zhao and Tavangar 2016). Society is best served by exploiting human capital as efficiently as possible, and this is best achieved by focussing the components of that capital, the individuals, upon participating in society where they deliver the greatest benefit. The optimisation of human potential is the most compelling reason to enable students to choose and curate their learning because it strikes at the heart of what drives civilisation forward, namely the development of strengths and cooperating in groups. Additional reasons for curating one’s own learning are that it would improve the wellbeing, metacognition, innovation, and personal responsibility of learners- all of which are important in the 21st century. Again, the only reason why we oblige learners to follow the same curricula, regardless of whether or not it is optimal for the individuals in the 21st century, is because, until now, we couldn’t administer a national system of assessment which could assess learners on whatever aptitude, capability, or knowledge that they wish. Technologically speaking, that ability is within our grasp.

Technology is already changing the face of classrooms. The covid epidemic proved unequivocally that the education system can change rapidly when it needs to (Dhawan, 2020). Online learning and blended learning can be effective (Dhawan, 2020; Tucker, 2020; Means et al, 2013; Rudestam and Schoenholtz-Read 2010; Bishop and Verleger 2013), as can flipped classrooms (Bishop and Verleger, 2013). There are many educational models currently in use that offer insights and inspiration to a society looking to renew its system of education.

Curricula should be evolving and adaptable to time and place because institutions and systems that exhibit versatility and adaptability are more resilient and productive in times of change. A curriculum that prepares learners to live and work in such a complex and rapidly changing world should promote cognitive diversity and collaborative problem solving because the fresh perspectives and varied approaches to change brought about by cognitively diverse teams help them solve problems better and faster (Bell, 2007; Reynolds &

Lewis, 2017). Curricula should imbue the learner with the ability to personalise their learning in accordance with their own goals, interests, and strengths. This would not only improve motivation to learn but also result in a cognitively diverse graduate pool (Seldon and Abidoye, 2018). Curricula should require learners to understand how they have come to their positions and the contextualised nature of others' positions, and encourage interdisciplinary exchanges so that collaborative problem solving comes naturally to workers in the 21st century. Retaining the legacy systems of assessment that oblige learners to demonstrate the *same* knowledge or skills will prevent humanity from creating the versatile, adaptable workforces that the technologies of the 21st century demand (Zhao and Watterston, 2021). We must embrace the opportunities offered by AI and related technologies to create flexible, personalisable, objective, and authoritative systems of national assessment. It is the contention of the authors that if these advanced, automated assessment systems are not designed and funded at a national level, then private equity will inevitably build automated assessment systems and the wealthy will have exclusive access to them, widening social inequality.

The technologies of the information age have enabled widespread access to expert knowledge at exceptionally low cost. The technologies of the coming age will reshape our economies just as the technologies of preceding ages did. defining, will Technologically speaking, it is no longer necessary for teachers to be the sole directors of learning. Teachers spend the majority of their time administering and assessing progress against a defined curriculum. It is now possible to develop a system that relieves teachers of the burden of administering a defined curriculum; teachers could instead serve other more important roles such as curators of personalised learning environments and experiences, counsellors to students, community organisers, motivators, and project managers of students' learning (Zhao and Watterston, 2021). Allowing and embracing change in the role of a teacher would make it infinitely more rewarding, interesting, and ultimately effective.

Our education system is not adequately preparing learners for the world to come. We have a choice to make. Preparing our children for success and happiness in adulthood is arguably humanity's most elemental task. Dr Phil Hammond, NHS doctor, broadcaster, comedian and commentator, has said that education is more important than health (2021). Deciding to retain our legacy education system would be to decide to fail our children. We must recognise that AI and related technologies are ushering in a new world paradigm. The benefits that new technologies will bestow upon humanity are potentially massive, but education and assessment systems have to change in order to grasp the benefits; populations who do so early will benefit most; those who do so late or never will be consigned to relative poverty.

Early moving or pioneering educational establishments that embrace AI and related technologies are going to create a massive advantage for their community or country. The authors of this report contend that this is not 'if' but 'when'. If such educational assessment systems were to be developed and deployed in a spirit of egalitarianism and progressivism on national or international scales, the authors contend that the result would be to enliven our education systems and economies. It could move mid-ranking, developed nations, such as Scotland, to pioneering and potentially world leading ones; the benefits of which are myriad.

Section 3:

AI-enabled continuous assessment is key to unlocking education fit for the 21st century

AI-enabled assessment systems

High-stakes examinations remain central to legacy education systems across the world, despite the fact that there is little evidence for their validity, reliability or accuracy (Miao et al, 2021). National exams administered by humans require the same knowledge to be transferred to all students. The 'one-size-fits-all' nature of the legacy education system is one of the major reasons why the system is failing learners in the 21st century (Hill and Barber, 2014; Luckin et al, 2016; Miao et al, 2021 Seldon and Adiobye, 2018).

The AI revolution creates an innovation imperative in education: as humans live and work alongside increasingly smart machines, our education systems will need to revolutionise to meet the scale of the challenge (Luckin et al, 2016). Labour markets are increasingly thirsty for creative, innovative, self-aware, and effective team workers with *particular* talents. Legacy education systems must change to afford learners the opportunity to live a fulfilling life in the 21st century, part of which requires responding to the skills that markets increasingly demand. To revolutionise the education system, we must revolutionise assessment.

AI technologies are currently being used to improve legacy elements of the education system, such as taking students through a set curriculum, or verifying the identity of exam candidates. These are useful developments but ultimately fall far short of the scale of change required in education (Luckin et al, 2016). G*reenfield* applications of AI-based technologies are required in education to meet the challenges that the 21st century demands. As of 2022, greenfield systems of AI-enabled continuous assessment are yet to be fully researched and commercialised at scale (Miao et al, 2021); however, the logic of international competition suggests that they soon will be. Subsequently, and due to its overwhelming advantages, AI-enabled continuous assessment is likely to replace high-stakes exams as the dominant form of assessment in formal education and professional development.

As we use the internet, kitchen appliances, online maps, emails, social media, library cards, travel cards, mobile phones, entertainment devices, and so on, we leave large amounts of digital data in our wake. The ability of AI to sort through and identify otherwise indetectable patterns in the data that surrounds our everyday interactions offers a unique opportunity to revolutionise assessment. Where legacy assessment systems are limited to assessing progress against a relatively tiny set of knowledge in a snapshot of time, AI assessment systems can, in theory, reveal changes in innumerable aspects of skill, character, attributes, and abilities over a lifetime. The establishment of AI-enabled continuous assessment systems will free up teachers to focus on teaching, provide employers with significantly more valuable information about candidates, and improve life-long learning in general and, most importantly, self-knowledge.

AI and related technologies afford us the opportunity to make an exceptionally broad assessment of a learner's skills, aptitudes, and character, far beyond that which traditional exams are able to. For example, response times, emotional fluency, determination, physical dexterity, will be measured alongside traditional metrics such as knowledge retention and analytical skills. Given a long enough period, large enough data sets, and appropriate sensors, AI can, in practical terms, assess much more than a traditional exam can. When an AI-enabled continuous assessment system can assess and mark anything, it becomes unnecessary to write an exam, because it won't be left to humans to mark them; and therefore illogical to 'teach' to the exam, because there will be no exams. Learners will be free to study, to engage their curiosity and creativity, and be assessed on the skills, aptitudes, and characters that are most appropriate for them, because they will no longer be constrained by the limitations of human-administered assessment systems.

Continuous and real-time assessment would benefit learners, teachers, and employers. AI-enabled assessment systems will accurately assess a learner's progress towards stated goals and take account of relevant factors such as a learner's capabilities, particular strengths and weaknesses, emotional and physical states, environment, etc. The assessment 'results' will be presented in such a way as to effect maximum motivation for continued learning; assessment will become default formative. AI-enabled continuous assessment will be both more authoritative and informative than legacy exam systems, and will therefore empower employers and job seekers to make better decisions in a complex labour market.

AI technologies, such as face and voice recognition, keyboard dynamics, text forensics, and automatic essay scoring systems, are increasingly being used to verify the identity of remote exam candidates (Miao, 2021). Applying these techniques in continuous assessment would significantly reduce fraud and protect against 'gaming' the system, making assessment fairer, more trust-worthy, informative, and authoritative.

AI-enabled continuous assessment will provide not just an account of a learner's ability, but also an insight into the manner in which a learner developed and gained their understanding, and the factors that affected learning. For example, how many hours of studying and practice were involved, how much effort was made, what were the circumstances under which the learning took place, how did sleep, concentration, attitude, emotion, exercise, etc, affect outcomes, are all questions that could theoretically be answered. This information will be incredibly valuable. Learners may use this information to improve their self-knowledge and perceived self-efficacy. Teachers may use the information to more effectively distribute resources amongst learners and justify their reasons for doing so. For employers, the information will prove critical in judging which candidates are most suited to vacancies, particularly when elements of character, such as determination, grit, persistence, humour, ability to learn, and values, are becoming increasingly salient in modern workforces.

The challenges of developing AIEd

Whilst continual assessment by AI offers numerous advantages over legacy assessment systems, its development and adoption poses considerable technical, ethical, practical, institutional, legal, and social issues (Miao et al, 2021). Global awareness and training in the interaction between humans and AI need to be prioritised to enable the participation of all and ensure the alignment of AI systems with societal values and principles.

True progress towards a national system of AI-enabled assessment will require the development of an AIEd infrastructure. It is highly unlikely that the AIEd infrastructure within a nation state will be one, centralised system because that would require the mobilisation of national resources at a scale previously unseen since perhaps the establishment of the NHS, and nowhere in the international order is there the political will for that to happen. Rather, the infrastructure is likely to resemble the current day marketplace for smartphone apps: thousands of individual AIEd components, developed by cross disciplinary teams of educators, technologists, product managers, and investors; conforming to uniform, international standards (Luckin et al, 2016). Within AIEd, the adoption of international standards would facilitate system-level data collection and analysis from across the educational sector at a scale and detail previously unseen, and so facilitate the rapid development of the technologies, policies, and user behaviours, and understanding of the efficacy of different educational systems and approaches (Luckin et al, 2016).

Unfortunately, many of the best ideas in AIEd don’t make it past the laboratory. AIEd is hampered by a funding system that encourages siloed research and shies away from dealing with the essential messiness of education contexts (Luckin et al, 2016). Given that AI-enabled continuous assessment and e-portfolio systems are yet to be fully researched and commercialised, the initial financial costs of doing so will be high. The authors of this report contend that the moral imperative and economic and social gains offered present ample reasons to fully commit to research and commercialisation now. The steady application of Moore’s law- the exponential increase in the power of computers- and wise investments will diminish the cost of AIEd over time, allowing for the mass adoption of AIEd technologies sooner than we anticipate (Luckin et al, 2016).

E-portfolios and lifelong learning

The amount of highly detailed, objectively assessed and credible information that could be stored on e-portfolios would be unprecedented, and incredibly valuable. Immense power would be granted to individuals, communities, and nations, because the data sets could be used to reveal an untold number of hitherto unrecognised relationships between seemingly unconnected variables in our lives. There would be a commensurate risk to personal, communal, national, and global safety, health, and wellbeing from those who would wish to cause harm. It is clear that very effective safeguards will have to be developed.

Lifelong e-portfolios do not yet exist, but the logic of international competition suggests that it is imminent. Employees who are better able to authoritatively demonstrate their credentials will be more attractive and a safer hire- those who use lifelong e-portfolios will have an advantage in the labour market. Simultaneously, employers who use e-portfolios effectively will recruit better, reduce hiring costs and increase value, giving employers an advantage over their competitors.

AI-enabled assessment must focus on human intelligence

There are many different visions of what schools should teach. In summary, most focus on skills that will remain the preserve of humans and enable us to compliment AI in life and work.

This report presents the ideas of Professor Luckin of UCL because her work displays a sensitive understanding of both the similarities and differences that lie at the heart of the relationship between AI and humans. Professor Luckin describes seven interwoven elements of human intelligence, six of which remain, and seem likely to remain in the medium-term future, the preserve of humans (Luckin, 2018). The intention of presenting Luckin's ideas is to highlight the types of factors that assessment systems will need to focus on in the 21st century. There are, of course, many other voices in this space.

The first of Luckin's seven elements of human intelligence is *academic intelligence*. Academic intelligence concerns knowledge and the ability to learn and recall facts and experiences and apply them in useful ways. Both humans and AI demonstrate academic intelligence but AI is vastly superior at it. For this reason, it is unlikely that a world attuned to the threats and opportunities of AI would retain academic intelligence as the primary element of intelligence fostered by human education (Luckin, 2018); to do so would condemn humans to the economic status of 'second-rate computers' (Owen, 2017).

The second element of human intelligence, *social intelligence*, is the basis of conscious, individual thought and communal intelligence. It concerns the fundamental ways in which we communicate with one another and ourselves. Social intelligence in humans is far superior to that in AI (Luckin, 2018).

The third element of human intelligence, *meta-knowing intelligence*, is about understanding how we know what we know. We are able to question what we know, and in accordance with our conclusions, build a personal epistemology. AI systems cannot explain how they have come to know what they know; they do not understand their own perspective; nor those of other intelligent beings (Luckin, 2018). In general, our education systems have not prioritised the development of effective interpersonal epistemologies amongst humans, but they could, with or without AI. Scott (2008) and D'Souza (2013) found that debate was an excellent means of developing personal epistemologies.

The fourth element of human intelligence, *metacognitive intelligence*, allows us to interpret and manage our own ongoing mental activity effectively. It means being able to plan and allocate our mental resources, explain differences in performance over time and context, and check-in with ourselves. Metacognitive intelligence concerns things like choosing to relax, hype ourselves up, or seek comfort in others. AI is not capable of metacognitive intelligence (Luckin, 2018).

The fifth element of human intelligence, *metasubjective intelligence*, allows us to balance our inner states and intentional behaviour with the external environment and emotions of others. The result is an effective means to navigate a complex world. Managing self-belief, determination, positive mindset, self-esteem, and motivation are all part of metasubjective intelligence. Ai is not capable of metasubjective intelligence (Luckin, 2018).

The sixth element of human intelligence, *metacontextual intelligence*, involves the appreciation of physical and mental ‘situatedness’ in the world. Humans live within multiple and overlapping contexts which each affect our state or influence our behaviour in different ways. Our ability to recognise and interpret our reactions to different contexts helps us to think and act in appropriate ways. AI can only practise a limited form of metacontextual intelligence (Luckin, 2018).

The seventh and final element of human intelligence, *perceived self-efficacy*, is one of the most important abilities in the 21st century. Perceived self-efficacy requires an accurate, evidence-based judgement about our knowledge, understanding, emotions, motivations, and personal context. It is concerned with how people relate to tasks, challenges and goals. It is intimately related to the awareness of what we know and don’t know; what we are good and not good at; and when and how to get help should we need it. For example, we may learn some knowledge or skills more readily or effectively than others, and this knowledge is critical to the efficient deployment of mental and physical effort within a team or community. Self-awareness is strongly correlated with perceived self-efficacy and is increasingly recognised as a catalyst for changing behaviour and personality (Eurich, 2017; Roberts et al, 2017; Stieger et al, 2021); the plasticity of which is a valuable trait in rapidly changing times. A strong sense of self is slightly less correlated with perceived self-efficacy. People who show a strong sense of self are more likely to be: promoted (Bass & Yammarino, 1991); regarded as capable (Church, 2005); satisfied with their job (Sy, Tram, & O’Hara, 2006); productive among direct reports (Moshavi, Brown, & Dodd, 2003); and better at decision making (Fallon et al., 2014). However, multiple studies suggest that most people, across cultures, overestimate their competencies (Dunning, 2011; Dunning, Johnson, Ehrlinger, & Kruger, 2003; Zell, Strickhouser, Sedikides, & Alicke, 2019). Perceived self-efficacy should be the primary goal of our education and training (Luckin, 2018).

Using education to develop the elements of intelligence that AI does not possess will enable humanity to complement AI in the economy; rather than be outcompeted by it. Our curricula should focus less on academic intelligence and more on promoting learning within and between the other six elements of intelligence, and in particular, perceived self-efficacy. Teaching and learning methods should develop learners across all elements of intelligence, and allow learners to concentrate on developing the elements of their own intelligence profiles that suit them best. Whilst AI is not capable of many forms of intelligence it can be used to help humans identify and develop the forms of intelligence that are unique to humans.

The promise of AI-enabled continuous assessment

Improving education is what researchers call a wicked problem- a complex problem which evades ‘solving’ because it is impossible to fully isolate cause from effect and one can never be sure what would have happened had a different intervention been attempted. Of ninety, major educational interventions in US schools evaluated in randomised control trials commissioned by the US Institute of Education Sciences between 2002-2013, 88% were found to have weak or no positive effects (Coalition for Evidence-Based Policy, 2013). Early reading has been found to be associated with early education success (The Annie E. Casey Foundation, 2013); but also with poor long-term outcomes including less overall educational attainment, worse teenage and adult adjustment, and increased alcohol use (Kern & Friedman, 2009). Regardless of the validity of the arguments either way, it is clear that, despite thousands of years of history of written language, there remains vigorous debate around the most effective way of teaching people to read. Throughout history, we have been unable to *definitively* ascertain what matters in education and this has been a major impediment to the improvement of pedagogy. AIEd may be about to tip the scales in favour of providing definitive answers.

The future of educational assessment rests on the question ‘How do we train the formidable data processing power of AI on all the data we collect on ourselves to help develop the elements of intelligence that are unique and beneficial to humans?’. This question has deep implications that go to the heart of what we are seeking to assess. AI is more than the technology that implements it- above all, it is about how we analyse problems and specify solutions. The questions we ask influence the type of data that needs to be collected, and the types of answers that we can expect. (In educational terminology, we need a progression model against which success can be measured).

At the heart of AIEd is the scientific goal to unveil the implicit forms of educational, psychological and social knowledge that underpin the act of teaching and learning. AI-enabled assessment will open up what is sometimes referred to as the ‘black box of learning’. AI-enabled assessment will present us with the ability, for the first time, to track learner progress against different teaching and learning approaches in fine detail in a transparent, objective manner. Objectivity is important given that conscious and unconscious bias and unfairness in human-administered assessments are inevitable and permeate our grades and experience of formal education (Tversky and Kahnmen, 1974). AI-enabled assessment will reveal the complex, fine-grained interactions between the innumerable factors that influence the efficacy of learning. Critically, we will be able to identify the factors that are both salient and mutable (in that changing them would affect a significant improvement) and use this knowledge to improve the design and delivery of effective systems of education (Zunger, 2017). AI-enabled assessment will offer us the ability to make authoritative decisions regarding the age-old question of what makes for a good education (Luckin et al, 2016). And the results could have a massive impact upon the quality and efficacy of formal education and teaching, as well as improve economies and quality of life.

Visions of the future of learning

AIEd in general promises to make learning more personalised, flexible, inclusive, and engaging. In contrast to legacy education tools, AIEd provides learners and teachers with the ability to respond not only to what is being learned but also to *how* it is being learned and how students *feel* about it (Luckin et al, 2016). We are increasingly exposed to digital devices- AIEd could gather data about our interactions with the world from these devices and use it to expose the evidence that we use to build our knowledge of the world. Evidence describing how our emotions, environment, motivations, and subjective experience, are affecting our learning would be invaluable. In particular, it could prove invaluable in supporting learners to develop their perceived self-efficacy- regarded as one of the most important skills for the 21st century (Luckin, 2018). AI is neither inherently good nor bad; but it is very powerful (Seldon & Adobe, 2018). Commensurate ethical standards and protection against those who would use the technology to do harm will be essential if the technology is to be adopted at scale (Luckin, 2018).

There are currently no commercial AI-driven lifelong learning products available, and little research (Miao et al, 2021). In theory, smart phones and related technologies could be leveraged to create AI-driven learning companions that could accompany individual learners throughout their lives. Rather than setting out to take learners through pre-defined curricula, the companion could provide personalised and continuous support that builds on the learner’s current abilities, is sensitive to their interests, and aligned with their short and long term goals. In theory, data from the entirety of a learner's lifetime could be tracked and used to optimise the pathway in the present, and the systems could tailor its guidance to the changing moods and environment of the learner.

Many AIEd applications are deployed online; they are not constrained by physical buildings or school opening times in the way that many educational tools are. This inbuilt capacity to support learning anytime, anywhere, opens possibilities to reimagine what formal learning looks like (Luckin et al, 2016). For example, learners would be free to attend specialist or different ‘schools’ concurrently. Learners could, for example, take six months out to attend a course in something that interests them, or participate remotely in lessons with students from across the world. Ideas concerning the reimagining of education are not new. For example, in 1993, Alison King suggested that time in the classroom would be better spent developing understanding of concepts; rather than passive information transfer (1993). In 1997, Eric Mazur advocated for taking the construction of knowledge outside the classroom, and turning the classroom into a place for assimilation and debate (1997). AI presents a historic, greenfield opportunity to reimagine education because it fundamentally changes the value of human work within the economy and the logic of how teacher time is best spent (Zhao, 2020).

Collaborative learning has been shown to provide better learning outcomes than learning alone (Dillenbourg et al, 1995). Collaborative learning encourages learners to explain their own thinking, consider different perspectives, resolve differences, and build shared meaning. Whilst collaborative learning improves motivation to learn, it does not necessarily occur spontaneously (Slavin, 2010) and so AIEd is being developed to help encourage it. For example, ‘adaptive group formation’ uses AI and knowledge about multiple learners’ individual learning styles, strengths, and weaknesses to suggest optimal groupings of individuals for the completion of group tasks (Muehlenbrock, 2006). Groups could be formed according to similar interests or goals, to promote cooperation or conflict, or any other way that accords with the intended learning outcomes. AI could play the role of expert facilitator, utilising voice recognition, natural language processing technologies, and other technologies, providing interactive support and guiding the group in effective collaboration (McLaren et al, 2010). Intelligent virtual agents could actively participate within groups of human learners, playing different ‘roles’ within the group as required. For example, intelligent virtual agents could act as mediator, guiding members through difficult interaction; peer, introducing subtle challenges or novel ideas; or ‘a struggling friend’, providing learners with opportunities to teach and in so doing improve their own understanding of the content (Luckin, 2016). Virtual agents could also be placed within virtual reality environments, with learners supported to traverse the environment by the agents. Many studies have identified positive learning outcomes coming from immersion in virtual reality environments (Hassani et al, 2013). AI moderation could provide human tutors or learners with transcripts or summaries of group discussions. AI moderation would be particularly useful for keeping track of what many groups are discussing in real time.

Visions of the future of teaching

Seldon and Abidoye (2018) list five major tasks of teachers in legacy education systems:

1. Preparation of learning material
2. Setting and marking assignments
3. Preparation for terminal exams and writing summative reports
4. Organisation of the classroom
5. Ensuring all students are engaged in learning

AIEd work with combinations of pedagogical, subject domain, and behavioural models. The fields of neuroscience, neurology, psychiatry, and psychology are leading the development of our understanding of long and short term memory, how the brain can most effectively absorb information, and how the mind's effectiveness may be increased (Seldon and Abidoye, 2018). It is this synthesis of knowledge, combined with progress in AI technologies, that are converging in the development of AIEd technologies. AIEd will drastically change the role of the teacher in formal education. It is surmised that the first three major tasks of teachers as listed by Seldon and Abidoye (2018), namely, the preparation of learning material, the setting and marking of assignments, and preparation for terminal exams and writing summative reports, will completely disappear, and the final two, namely, organising the classroom and ensuring all students are engaged with learning, will be heavily augmented by AI, and so transformed.

Change is needed within the teaching sector. Teachers across Singapore, Canada, the US, and UK work an average of 50 hours a week (Bryant et al, 2020). Teachers in the UK are amongst the longest working in Europe (Hall, 2022), whilst 81% of UK teachers are considering leaving the profession because of the high workload (Bryant et al, 2020). Yet McKinsey and Co estimate that 20-40 percent of teacher hours are spent on activities that could be automated with existing technology, meaning that 13 hours per week could be redirected to activities that promote student learning and job satisfaction (Bryant et al, 2020). Teacher workforce issues are even more severe in other countries. By 2030, 33 countries are predicted to not have enough teachers to provide every child with a primary education. The shortfall equates to 25.8 million teachers across the globe (UNESCO, 2015). From a historical perspective, the cost of providing comprehensive education has generally increased year-on-year, because whilst teacher wages have risen to keep pace with wages in more productive sectors of the economy, the number of people they can teach has not. Health and social care, two other labour intensive sectors, suffer from the same dynamic. Demography adds to the problem. In the UK, by 2030, there will be 4.4 million over-80s, up from 3 million at the moment. The state spends around £20,000 per year on each child of school-age, but about £40,000 per year on each person in their late 80s (The Economist, 2022). Low productivity improvement rates in labour-intensive services, combined with ageing populations, pose significant challenges to the future viability of national welfare provision.

The future of teaching rests partially on the future of learning/teaching technologies. Intelligent tutoring systems (ITS) provide intelligent, personal tutors for every learner. ITS use algorithms, combined with pedagogical, domain, and learner models (including behavioural, social, environmental, meta-cognitive models) to present learners with personalised learning stimuli in accordance with a chosen curricula (Luckin et al, 2016). ITS can be designed to promote different types of learning; for example, to encourage learners to take control of their learning and promote self-regulation skills, or to apply pedagogical strategies to challenge and support learners (Luckin, 2016). ITS capture data regarding how learners are interacting with the system, process the data, and feed it back into their algorithms and models to enable dynamic, real-time responses to the learner. Learning is significantly influenced by how we feel (Lindgren and Johnson-Glenberg, 2013). ITS will capture data about the learner's emotional and physical state. This information will further improve what we know about how emotions affect learning, and provide teachers with real-time information regarding how their learners are feeling, thereby helping teachers to provide appropriate and timely interventions (Luckin et al, 2016).

ITS incrementally improve as they are used, building increasingly sophisticated models about personal learning styles, and potentially revealing hitherto unknown learning patterns and behaviours (Luckin, 2018). Some ITS present learner and teacher with an open learner model, making the learning and teaching process explicit, aiding transparency, promoting trust, and providing continual assessment. (Luckin et al, 2016; Luckin, 2018).

The role of teachers will evolve in the face of ITS and AIEd. ITS and AIEd will assume the majority of responsibility for presenting appropriate learning material and conducting continuous assessment; and partial responsibility for guiding learners through learning material, organising the learning environment, and ensuring engagement with learning (Luckin et al, 2016). ITS do not get tired or impatient, and are increasingly consistent, reliable, personalised, and effective. If the role of the teacher remains focussed on 'teaching to the test', it seems likely that ITS will soon 'outcompete' teachers. Teachers have had a central role in education throughout history; in a short to medium term future augmented by AI, the role of the teacher will become more important; not less (Luckin, et al 2016). AI will not be able to emulate the things that make good teachers great: inspiring students, building positive school and class climates, resolving conflicts, creating connection and belonging, seeing the world from the perspective of individual students, and mentoring and coaching students (Bryant et al, 2020). The elements of human intelligence are grounded in the physical, spiritual, and social experience of being human. If teachers are not to be 'outcompeted' by AI, education and assessment must be separated. Teachers should be freed to focus their teaching through what makes them human; allowing ITS and related technologies to augment their work, and refocusing their work around the fostering of 21st century skills.

Accordingly, the structure of classroom learning in the legacy education systems that we are used to seems likely to break down. Teachers will cease to manage the transfer of knowledge, and will instead coach learners, analyse data on personal learning, help learners to interpret learning data, and curate communal learning environments and opportunities.

Critically, teachers will need to develop new skills. Of particular importance will be the development of: (1) a sophisticated understanding of what different AIEd systems do to enable an informed evaluation of new AIEd products; (2) research and data skills to enable the effective use of AIEd-derived data; and (3) new team working, coaching, and interpersonal skills that compliment AIEd systems (Luckin et al, 2016).

Learning and teaching will become student-centred, inquiry based, authentic, and purposeful. New forms of pedagogy will emerge that focus on student-initiated explorations of solutions to relevant, unsolved, and significant problems. Student 'voice and choice' will take centre stage; instructional time will be re-prioritised around students' interests, agency, and working in teams; and teachers will work within idiosyncratic technology ecosystems that distribute teaching and learning tasks (Kallio and Halverson, 2020). The cumulative effect of these changes will be a reconceptualisation of the experience of formal teaching.

The role of senior teaching staff will likely change too because of the power that AIEd will offer them for real-time, system level measurement. AIEd will offer a detailed picture of teaching and learning across subject, class, college, district, or country levels. Staff will need to be nimble and open minded to take advantage of these new abilities. Synergistically, AIEd systems may well provide the scaffolding to enable leaders and policy makers to develop these new skills and abilities (Luckin et al, 2016).

Professional development amongst teachers broadly focuses on learning how to assess the impact of actions on learners, how to provide feedback on learner progress and how to motivate learners (Fullan and Donnelly, 2013). The lack of time resource within the teaching profession often results in inadequate professional development. This is despite the fact that developing teacher expertise and addressing teacher retention issues are critical issues within the profession across developed countries. In the same manner that AIEd could offer personalised learning and assessment to learners; so it could do the same for teachers and indeed to everyone (Luckin et al, 2016).

Advocating for the reimagining of education is not to advocate for the complete removal of teaching and learning from classrooms, nor for the dissolution of schools as we know them. As was shown in the covid pandemic, home environments play a much more significant role in learning when schools are closed, accentuating differences between students and increasing inequality (Zhao, 2020). AIEd could provide relevant information to teachers about a learner's home environment or experiences on a given day, and therefore help teachers to support learners better. At the same time, real time information about how learners are thinking and feeling in the classroom could help the teacher curate and manage better learning environments. Schools provide valuable services alongside teaching and learning, such as childcare, health care, free meals, physical setting for friendship and socialising, collection of trained education professionals, and other social services (Zhao, 2020). Higher educational institutions are important centres of research, teaching, and learning. Whatever happens, teachers and the teaching profession must participate in the development of AIEd to ensure that the new technologies are embraced by the sector.

Factors that will affect the AI-enabled assessment, AIEd, and the AI revolution, and ultimately, us.

For AI to augment human societies in productive and symbiotic ways, everyone needs to possess a sufficient amount of knowledge about AI so that all parts of society can be involved in the design and creation of AI systems- including AIEd. One risk of only a small section of society being involved in AI development is that the small cohort may inevitably capture the majority of the benefits afforded by AI. A greater risk is that without the full attention that humanity can bring to bear on such a powerful technology, AI could well outpace humanity's ability to guide and direct its development, and quickly grow beyond humanity's control (Kissinger et al, 2021).

Society needs a baseline number of professionals who are able to develop and improve AI systems, and a baseline number of teachers who are able to teach the skills. Developers of AI need to understand that AI is as much about the technology and methods that underlie the systems as it is about specifying appropriate problems and matching them with appropriate technology (Luckin, 2018). Teachers must be equipped with knowledge and skills related to data literacy and learning sciences that will enable them to skillfully wield AIEd tools. The education sector must recognise that the nature of human intelligence consists of multiple elements. AI systems can learn faster and recall information more accurately than humans can, but this ability represents only one element of human intelligence. New education systems should exploit AI's academic intelligence to help us develop the other elements of our intelligence that AI does not yet possess and seems unlikely to possess in the coming century (Luckin, 2018).

There is an issue, specific to machine learning and assessment that requires attention: there is often a difference between what one wants to measure and what it is technically possible to measure. Where there is a difference, proxy measures will be used, and machine learning models will become good at predicting the proxy, not the quantity for which the proxy was intended (Zunger, 2017). This is one example of many of how AI assessment systems will raise new issues around bias, whilst simultaneously resolving old biases.

There is often a mismatch between the factors we expect to provide a good measure of performance and those which actually do. Personality assessments often make more accurate predictions of job performance than do interviews, resumés, or educational certificates (Deeper Signals, 2022). At the US Army's West Point Military Academy, 'grit' and strength of will, turned out to be a better predictor of who would persist through the first difficult summer than West Point's own 'Whole Candidate Score' (Perkins- Gough, 2013). Extracurricular activities were found to be a stronger predictor of creative expression in college applicants than traditional admissions factors, such as grades and high school rank (Cotter, Pretz, & Kaufman, 2016). AI assessment systems will excel at unveiling hitherto unrecognised connections between apparently disparate aspects of ourselves.

There is a 'very human' problem at the heart of designing and creating AI systems. Our norms of interaction and egos are awash with white lies, contradictions, self-deceptions, unspoken rules, and unexamined assumptions. Our free will is itself a black box- it is not clear to us why we want what we want. Navigating these internal inconsistencies is second nature to humans and therein lies the problem. AI will only go along with polite fictions, for example, if we explicitly show them how to lie to us beforehand (Zunger, 2017). AI can help us act in our best interests if we accept that we are often either ignorant of, or don't want to act in, our best interests. AI can help us achieve what we want if we acknowledge that we often don't really know what we want, and don't want to admit what we really want. Writing AI programs forces us to be very explicit about our goals, in a way that almost nothing else does- and sometimes, we will find it hard to be that honest with ourselves (Zunger, 2017).

The inherently contradictory nature of human thinking leads to a second, related problem in AI. Machine learning systems are very smart within the confines of their domain, but know nothing at all about the broader world in which they function, unless they learn or are taught about it. Given that AI systems are often powerful and cannot yet fully explain how they are interacting with the world around them, we must be incredibly careful when 'exposing' AI systems to the real world because we just don't know what will happen. One form of protection against unintended consequences is a recently encoded EU law that states that any decisions regarding AI that could have serious consequences for people should be sanity-checked by a human and that human override mechanisms should be built in as standard. (Zunger, 2017). EU law is just the start- we will need much stronger legal frameworks going forward. Dealing with our own inconsistencies and the unintended consequences of new technologies are not new challenges for humanity in historical terms. What is new is the unflinching and unrelenting gaze that AI obliges us to focus on the aspects of ourselves that we have until now been happy to avoid. As noted by Zunger (2017) the honesty that building AI systems forces upon us may be the most valuable gift our new technology can give us.

Nation states and international organisations will have a significant role to play in the development of AI. National governments and international bodies are recognising their responsibility to facilitate the development of AI technologies, mediating competition and cooperation, and protecting public interests. The first ever internationally agreed document offering guidance and recommendations on how best to harness AI technologies for achieving the UN's *Education 2030 Agenda* was published by UNESCO, a United Nations agency with the aim of promoting international cooperation, in 2019. The document is called *The Beijing Consensus on Artificial Intelligence (AI) and Education* and, according to Stefania Giannini, Assistant Director-General for Education at UNESCO, has been designed "*to improve livelihoods, to reduce inequalities and promote a fair and inclusive globalisation*" (UNESCO, 2019). The OECD, a club of mostly rich countries, published *The OECD AI Principles* in 2019, a document which outlines a common aspiration for member countries to promote human-centric, trustworthy AI (OECD, 2019). The European Commission proposed the first ever legal framework on AI design to govern the use of AI in the European Union based on an assessment of risk, in 2021 (European Commission, 2021).

Nations that harness the tremendous power of AI early will position themselves for future global competitiveness. Subsequently, many nation states are jostling to differentiate themselves and become leaders in specific fields of AI (Walch, 2021). The UK is currently ranked third in terms of its investment, innovation, and implementation of AI, in a global index by the journalistic media company Tortoise; only the US and China are ahead (2022). The UK Government's *National AI Stra*tegy sets out its ambition to become '*a computer science and AI superpower*' (2021). The UK's superb home-grown researchers, healthy start-up scene, and history of innovation in computing, contribute to its high ranking; but its highly inefficient patent regime, and apparent difficulties in moving innovations past the proof-of-concept phase hampers its rating. On current predictions, China will surpass the US within the next 5 to 10 years, and Canada, Germany, and France, may well overtake the UK soon (Clark et al, 2019). For its part, the Scottish Government has laid out its strategy to '*become a leader in the development and use of trustworthy, ethical and inclusive AI'* (The Scottish Government, 2021; Scottish AI Alliance, 2022a; Scottish AI Alliance, 2022b).

Lastly, the development of AI heralds a historic juncture in human history. Research suggests that within this century a computer AI could be as "smart" as a human being (Bostrom, 2015)- and what then?! Holden Karnofsky, founder of charity evaluator GiveWell and foundation Open Philanthropy argues that the 21st century may be the most important century ever. AI will fundamentally change the nature of human work in the 21st century; but the implications of how we react to this proposition will be felt far beyond the 21st century. Assuming that humans do not go extinct in the near future, many more humans will exist in the future than have already existed in the past; and the 21st century will be the *first* of many centuries in which AI and humanity co-exist. Given the exponential nature of the growth of AI, the choices that we make about

AI in this century will reverberate through the millennia to come. Human society should give AI the attention it, and we, deserve.

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