Gonski Institute for Education

Research Report

Education, work and Australian society in an AI world

A review of research literature and policy recommendations

May 2018

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Executive summary

This review addresses three key questions:

1. What is education itself going to look like in an AI world?
2. How do we prepare people to work in an AI world?
3. How do we prepare Australian society to adjust to an increasingly AI world?

Artificial Intelligence (AI) describes the use of computers to do the kinds of things that minds can do. There are two main goals for AI: (1) developing computer systems to do intelligent things and (2) using computer systems to model and learn about minds. AI is already part of media that we use in everyday life, but it is rapidly becoming more powerful and pervasive.

The current organisation of education will shape how new AI technologies are adopted, but corporate interests and technological advances will also shape this adoption. Like other areas of social and political life, decisions about the uses of AI in education need to be enlarged beyond considerations of what is technically possible. AI in education will bring with it profound normative and ethical challenges to the social, economic and political purposes of education, including what is learnt and how we teach.

The future of education could be one of atomised 'personalisation', but the role of schools and universities is likely, at least in the near future, to remain important as physical sites that are locally based organisations, with important community building functions. It is already evident that technological changes associated with AI could exacerbate inequalities in education. *We must also entertain the possibility that in an AI world our conception of learning and education will change*, in response to new insights into how minds work, as could our perception of the world and ourselves through our engagement with AI embedded in new media.

Finally, while we have good research evidence relating to past and current trends in education, work and technology, the nature of our emerging AI world requires us to consider a very diverse set of possible future scenarios, and it also requires us to acknowledge inherent limitations on our capacities for prediction and planning.

What is education itself going to look like in an AI world?

The major shift in education, across sectors, will be toward 'personalised learning' that will involve new interactive and adaptive learning environments. The combination of AI and robotics may include new opportunities and challenges for students with a range of disabilities. With the increasing prominence of the 'learning sciences', adaptive learning systems will cover not only content and analytical tasks, but will also provide feedback and interaction based on the affective aspects of learning.

Teaching currently has a low risk of being automated as an occupation, but AI will substitute for mundane tasks and may well lead to a requirement for fewer teachers and ancillary staff. In higher education, increased use of Learning Management Systems will continue, with the use of 'bots' as teaching assistants. Students in K-12 and post-secondary education are likely to encounter automated basic communications. *Automated systems will also be used to identify and manage students who are 'at-risk'*. Students will encounter computing systems that are increasingly intertwined with biology, including the broadening collection and use of biodata. What counts as educational data is likely to continue to change and expand.

How do we prepare people to work in an AI world?

There are two main issues to consider in relation to this question: (1) how work will change in an AI world and (2) how we should prepare people for this work.

How work will change is heavily debated. One view among labour economists is that AI will *substitute* for many occupations leading to substantial increases in unemployment (around 50%). Another view is that certain tasks will be automated, while other tasks will require *complementary* skills and will continue to be performed by human workers. From this perspective, anxieties about machine substitution of human labour are often over-stated, because routine tasks susceptible to automation cannot always be easily separated from non-routine tasks.

To prepare people for work in an AI world it will be important to focus on education in (1) science, technology, engineering and mathematics (STEM) subjects and (2) 21st century skills required for non-routine tasks, including critical thinking, interpersonal skills and collaborative problem solving. However, even in scenarios where lower risks of automation are predicted, the number of people faced with re-training, and obstacles to the provision of this training, indicate that substantial policy challenges lie ahead.

The role of formal and informal education will be important, with a growing diversification of educational provision including more online and on-demand options that will facilitate flexible, lifelong education.

How do we prepare Australian society to adjust to an increasingly AI world?

There is much uncertainty about the extent to which AI will reshape society in the next few decades and there is clearly a need to consider more extreme possibilities of disruption caused by exponential growth in computational and algorithmic power.

Based on current trends, however, *there is a clear need to develop people's capacities to understand AI (at least in non-technical terms, in order to engage with it competently and critically in everyday life), and to consider and act upon the ethical implications of AI.* This will include considerations of what types of citizenship are desirable and necessary in an AI world. Additionally, it will require an assessment of the regulatory changes, and limitations, that will be required to enable organisations to flexibly adapt to different contexts of education provision, and employment.

As is becoming more evident in contemporary examples of automated systems and data, there are considerable policy issues to address around privacy, trust and transparency. This includes the requirement to address what happens when data is used in AI, who owns it and who has access, including issues of the role of technology corporations in education systems. There are already *calls for some AI systems that are opaque to not be allowed in 'high risk' domains such as education and health*, and a recognition that issues of bias and discrimination must be addressed before AI is used in these domains.

Recommendations

Recommendation 1: Establish a cross-sector representative body to provide advice on the development of AI in Australian education systems.

Recommendation 2: Establish guidelines for the introduction of adaptive and personalized learning to ensure a focus on educational and equity principles.

Recommendation 3: Consult with the teaching profession, teacher educators and industry to formulate professional development strategies that help educators manage the introduction of AI into their workplaces.

Recommendation 4: Develop a set of procurement guidelines that encourage the ethical design and transparency of AI systems purchased by Australian education systems.

Recommendation 5: Review data protection legislation internationally to develop an approach for Australian education systems.

Recommendation 6: Increase access to resources that help educators and learners to develop AI-complementary skills, including 21st century skills.

Introduction

Artificial Intelligence (AI) will significantly reshape social, political, economic and technological domains of life. In this literature review, we consider: (1) the potential implications of AI on educational provision; and, (2) how education will need to prepare people for an 'AI world'. Over the past 100 years, education institutions have largely assimilated technological developments (Koschmann & Kolodner, 1997) and have been relatively stable and very slow to change (Jónasson, 2016). However, as the influential 'historian of the future', Yuval Noah Harari, has suggested the important questions for education today concern whether this trend will continue and whether we can predict what to teach in an AI world:

> We're in an unprecedented situation in history in the sense that nobody knows what the basics about how the world will look like in 20 or 30 years. Not just the basics of geopolitics but what the job market would look like, what kind of skills people will need, what family structures will look like, what gender relations will look like. *This means that for the first time in history we have no idea what to teach in schools*. (quoted in de Freytas-Tamura, 2018, March 19; see also Harari, 2015)

This point serves as an important caveat for the following review of the research on AI and education. While we have good evidence relating to past and current trends in education, work and technology, the nature of our emerging AI world requires us to consider a very diverse set of possible future scenarios, and it also requires us to acknowledge inherent limitations on our capacities for prediction and planning.

John McCarthy coined the term 'artificial intelligence' in 1955. AI describes a heterogenous set of techniques and tasks, rather than a single 'thing', and we do not have a clear idea of what AI *is* (for example, MIT prefers the term 'extended intelligence', while UNSW AI-expert Toby Walsh favours 'augmented intelligence') or what it will *become*. However, Boden (2016, p. 1) has provided a simple definition of artificial intelligence as describing the field that seeks 'to make computers do the sorts of things that minds can do'. Successful development of new AI capacities often results in the exclusion of these technologies from what is considered to be the domain of AI. Greg Corrado from Google Brain underscores this focus in AI research on new challenges: 'It's not about what a machine 'knows' or 'understands' but what it 'does,' and — more importantly — *what it doesn't do yet*' (quoted in Lewis-Kraus, 2016).

There have been two main aims of AI research: (1) modelling intelligence in living minds and (2) using computers to act on the world in intelligent ways (Boden, 2016). This involves efforts to produce 'systems that think like humans, systems that act like humans, systems that think rationally, systems that act rationally' (Russell & Norvig, 2016). Writing about AI in education, Luckin et el. (2016, p. 14) defines AI as:

> computer systems that have been designed to interact with the world through capabilities (for example, visual perception and speech recognition) and intelligent behaviours (for example, assessing the

available information and then taking the most sensible action to achieve a stated goal) that we would think of as essentially human.

We can ascribe intelligence to any device that can achieve specified goals in a wide range of environments (Legg & Hutter, 2007), although human intelligence has provided a guiding ideal for the field. The different techniques employed in AI research include, for example, symbolic approaches (good old-fashioned AI, or GOFAI) and artificial neural networks, which have been in ascendance recently due to Google's pioneering work with this approach for image recognition and translation purposes. Other areas of AI development include robotics and the modelling of biological life.

Popular discussion about AI often conflates the term with Artificial General Intelligence (AGI), or 'strong AI'. While strong AI continues to be the focus of AI research, it is unlikely that it will significantly impact education in the next decade. Whether it does so after that is very uncertain and subject to much debate (Walsh, 2016; Yampolskiy, 2017). The focus of this review is on 'weak AI' or intelligent agents that enable the automation of specific and narrow tasks. This form of AI builds upon and intensifies previous forms of automation and we already live in a world where it is ubiquitous. However, AI's presence in our daily lives is often invisible because it is embedded in other media, such as smart phones or streaming services. Intelligent agents are already *acting* within education and a primary focus of this review is on the growing body of research evidence in this area. We consider predictions about the potential impact that AI will have on education, work and society over the next three decades.

The aim of AI research to model minds also has implications for our conception of human learning and our understanding of human brain function. Our conceptions of machine intelligence, human minds and learning (human and non-human) are increasingly interconnected, with changes in one domain having potential impacts on thinking about the others. It is important to note that AI itself also needs to learn. Computer-based intelligent agents, particularly those based on artificial neural networks, are "machine learners" (Mackenzie, 2017) that are trained on patterns in big data sets and reinforce these patterns in their actions. So, we must entertain the possibility that in an AI world our conception of learning and education could change, as could our perception of the world and ourselves through our engagement with AI embedded in new media. Our review tentatively considers these wider potential implications of AI for education where reasonable evidence is available.

A note on the evidence comprising this review. We have included few references to grey literature produced by organisations such as consultancy companies, or the rapidly growing body of popular books in this area, generally deeming this not to constitute research evidence. However, we have relied on non-academic sources in relation to areas where little research is available.

The review is organised into three sections that respond to the following key questions:

1. What is education itself going to look like in an AI world?
2. How do we prepare people to work in an AI world?

3. How do we prepare Australian society to adjust to an increasingly AI world?

Section 1: What is education itself going to look like in an AI world?

Introduction

This section examines what education will look like in an AI world. The first part addresses teaching and learning issues. the second part deals with the provision and governance of education. Most of the references focus on formal sectors of education (from Early Childhood to Post-Secondary).

The discussion in this section draws upon the following research fields: (1) AIEd, in which most work focussing on AI-driven pedagogical adaptation around teaching, learning and interaction is undertaken; and (2) other fields such as computing sciences, humanities and social sciences that augment knowledge and delivery of AI within education.

Teaching and learning

Students and personalised learning

The major shift in students' experience of education will be the move toward 'personalised learning'. Differentiation and personalised learning plans have long been part of educational practice and pedagogical theories (Mastropieri & Scruggs, 2017). However, with the introduction of AIEd, personalisation will involve new (interactive and adaptive) learning environments. In these environments, new non-human agencies will perform in the role of teacher:

> Intelligent tutoring systems, Cognitive Tutors, and adaptive learning environments are all variations of the same common theme: instructional systems that contain empirical models of the student to predict student behaviors and knowledge, and to act upon these predictions to make pedagogical moves as students progress towards gaining expertise and mastery of the target domain. (Arroyo et al., 2014, p. 388)

Intelligent Tutoring Systems (ITS) have been incorporated in parts of education for at least the last 20 years (e.g., Polson & Richardson, 1988). With the adoption of AI technologies, key issues for ITS were: (a) technological barriers, such as computer systems that had been primarily designed for business and personal use rather than education (Timms, 2016); and, (b) that AI in the classroom was previously seen as something that would be incommensurate with teachers' beliefs and pedagogical models (Nye, 2016, p. 757). These issues are now arguably in the process of being resolved; the technological barriers are being addressed in the domain of the computing sciences, and the problem of pedagogical models in the domain of educationalists. New expertise in education has become focused on the modelling and design of learning and learners in the 'learning sciences' (Dupoux, 2018; Kim & Baylor, 2016). Notably: 'In addition to the learner, pedagogical and domain models, AIEd researchers have also developed models that represent the social, emotional, and meta-cognitive aspects of learning' (Luckin et al., 2016, p. 21).

One outcome of the increased use of adaptive learning will will be the capacity for AI systems to serve students across schools, and for AI to evaluate multiple learning models across and within schools (Nye, 2016). Additionally, since there is ‘an inextricable link between attention and learning’ (D'Mello, 2016) adaptive tutors can be implemented to help ‘motivate students’ (Terracina & Mecella, 2015) and will be able to provide feedback, not only on whether students have accurately completed a set task, but also by gathering information for teachers and students on ‘affective aspects of learning’ and feedback (Balaam, Luckin, Good, & Harris, 2009; Moridis & Economides, 2009; Woolf et al., 2009).

One further contribution that adaptive computing, alongside robotics, may make is an increase in personalised learning for students with disabilities (Cuji, 2017). However, there will have to be ethical discussions about the use of autonomous robotics with these students (Bricout, Sharma, Baker, Behal, & Boloni, 2017).

Teachers

Schools and classrooms are likely to remain largely the same in terms of physical structures (ongoing investment is so large that personalisation will likely be incorporated in existing classrooms). However, the embodied presence of the teacher *may not* be required (Thompson & Cook, 2017) to the same extent. This may also be the case in the creation of new learning materials and even the planning of the curriculum. Both design and delivery of courses and programs could be assisted by AI (with slightly more sophisticated versions of the algorithms that are currently used by Netflix or YouTube algorithms that suggest what to view next) (Tomei, 2013).

K-12 education systems

In predictions of professions under threat from automation, teachers have been identified as being at the lowest risk of all (Nedelkoska & Quintini, 2018). This does not mean that teaching roles will stay the same. Education provision, especially K-12, is increasingly focused on the ‘learning sciences’, which identify and replicate aspects of teaching and learning using AI capabilities. As AI based on pedagogical models is combined with ‘on-screen teaching’ to underpin adaptive learning (du Boulay & Luckin, 2016; Kim & Baylor, 2016) the role of the teacher will change.

Some aspects of teaching will be automated that would previously seem *the purview of human teachers*, such as giving feedback on student collaboration (Floryan, Dragon, Woolf, & Murray, 2010). AI will also substitute in the performance of mundane tasks which may well lead to a requirement for fewer teachers in the profession. Until then, AI (and indeed teachers) must evolve to develop ‘21st century skills such as creativity, critical thinking, communication, collaboration, information literacy, and self-direction’ (Terracina & Mecella, 2015).

Post-secondary education

In post-secondary education, especially higher education (HE), the role of the teacher has already begun to shift due to the use of Learning Management Systems (LMS). LMS allow for the structured and/or flexible delivery of a wide variety of media and communicational forms. Content/learning packages offered using LMS now include text, recorded audio/video and recently 360 degree/VR lectures and other interactive materials, quizzes and discussion boards using various electronic resources. Content can be drawn from diverse sources, opening the system to provision external to HE institutions, both formal and informal (with all the tensions this brings to current HE providers).

LMS are easily combined with AI-based analytic techniques such as machine learning (Aher & Lobo, 2013; Iqbal, Saleem, Naseer, & Kim, 2018). A new possibility is the use of AI bots as teaching assistants (Mhatre, Motani, Shah, & Mali, 2016). To get a sense of how AI may change teaching in post-secondary environments, LMS could be seen as transitional, as they provide a kind of pre-automation of learning and an existing portal for further automation. However the aim is for LMS, AI and nonlinear teaching strategies to be 'learner-centred emphasizing autonomy and guided discovery' (Tan, Choo, Kang, & Liem, 2017).

Knowledge

Much of the developing knowledge in education will be informed by the overlap of computer science, neuroscience and cognitive science (Laird, Lebiere, & Rosenbloom, 2017). This overlap will both underpin AI itself and provide the rationale for the need for, and take up of, AIEd. This parallels Boden's (2016) argument that AI is about modelling the mind and then AI acting on the mind as modelled by cognitive science and neuroscience. This involves a computational rationality that 'offers a potential unifying framework for the study of intelligence in minds, brains, and machines' (Gershman, Horvitz, & Tenenbaum, 2015, p. 278). It also involves aspects that overlap with AI such as learning about robotics and programming 'bots' (Bat'ko, 2017; Bezgodov, Karsakov, Mukhina, Egorov, & Zakharchuk, 2015). The take up of these ideas in education has been identified as important in addressing the future curriculum development of education systems.

Provision and governance of education

Provision and mobility

While personalization will change the way education is delivered, schools are likely to remain important as 'locally accountable organizations, committed to building viable and sustainable futures for everyone in their communities' (Facer, 2011, p. x). Due to the capacity to deliver not only content, but different pedagogical modes and assessment, it is likely that there will be a focus on mobile learning connected to new forms of collaboration. 'Learning communities, networking, collaboration software, and mobile and ubiquitous computing are being used to create seamless social learning' (Woolf et al, 2013, pp.72-3). Challenges will include making decisions about equity of provision, and regulations that will be necessary for delivery and for credentialing. However, many of these issues will be able to draw on existing regulations concerning home-schooling and on-line forms of schooling, such as on-line charter schools (Barbour & Reeves, 2009).

Student management systems

Students in K-12 and, especially, post-secondary education are likely to encounter automated basic communications. Student management systems have already been established in both K-12 and higher education to collect and provide readable data (often in the form of data dashboards). This will continue but will be combined with new forms of predictive analytics and data visualisations (Alexandru, Tirziu, Tudora, & Bica, 2015). In data centres in education, such as the NSW DEC's Centre for Education Statistics and Evaluation, the use of these aspects are part of current strategic plans for information management[i]. In higher education, LMS are already open to these developments, enabling the combination of program and course administration with content provision, and can be further integrated with other systems, including: university administration and student records, ongoing program audit, disability services and special consideration. (Hoffait & Schyns, 2017).

There will be emphasis on using AI for the identification and management of students who are 'at-risk' either with a focus on their retention or on their progress academically (Martinho, Nunes, & Minussi, 2013). Data will include not only simple metrics like attendance, or even their movement around a campus, such as visiting the library (or not), but also in-class engagement (attention, interaction and motivation) (Subramainan, Mahmoud, Ahmad, & Yusoff, 2016) and the affective aspects of learning, in conjunction with adaptive learning. (Avramides & du Boulay, 2009).

Overlap with data science and the role of data

Crucially, AI is dependent on data. Thus, many AIEd researchers point to the need for stable, standardised, and richly interconnected data sets (Luckin et al., 2016). The increasing dependence on data and computational forms of governance enabled by machine learning, premised on the overlap of data science with other cognate fields, is likely to continue (Gulson & Webb, 2017; Solo, 2011; Williamson, 2016; Zeide, 2017).

It is also likely that students will encounter computing systems that are increasingly intertwined with biology (Floryan et al., 2010; Miglino, Gigliotta, Ponticorvo, & Nolfi, 2008). This will include broadening of the collection and use of biodata, such as biometrics. Issues here include the role of commercial vendors (e.g. SoccerGenomics[ii]) and the ethics associated with using biodata to personalise learning (Murphy, 2014; Qu & Johnson, 2005).

Conclusion

It is important to see that AI in education will be shaped as much by the features of contemporary education – including existing inequities - as by AI techniques and tasks. The history of technology in education is one in which the institutions have assimilated technological change such that schooling has remained relatively stable over the past 100 years (Koschmann & Kolodner, 1997). It is not yet clear whether this stability will endure with the introduction of AI, but it is likely, as educational institutions are very slow to change (Jónasson, 2016).

Section 2: How do we prepare people to work in an AI world?

Introduction

This section examines (1) how work may change in an AI world and (2) how we should prepare people for this work. Research evidence in this area is both limited and speculative. The National Academies of Sciences, Engineering, and Medicine (2017) observes that 'while improvements in and diffusion of IT have had profound effects on many aspects of the workforce, the future effects of these advances on the workforce and the broader economy are difficult to predict' (National Academies of Sciences Engineering and Medicine, 2017). We are thus limited to evidence-informed predictions or 'best guesses' about how to prepare people for work in an AI world.

Two main types of sources are surveyed here: (1) academic publications and (2) reports published by non-university research bodies such as the Organisation for Economic Cooperation and Development (OECD), which has an active Future of Work initiative, and national research bodies such as the US National Academies of Sciences, Engineering and Medicine.

The discussion is divided into three main sections that address the following sub-questions:

1. What will work look like in an AI world?
2. What education and skills will be needed for this work?
3. How can this education and these skills be provided?

What will work look like in an AI world?

Historically, there have been many periods of concern about automation and technological unemployment and the past five years has witnessed renewed anxiety about this issue. Autor et al. (2003) argues that 'computer technology substitutes for workers in performing routine tasks that can be readily described with programmed rules, while complementing workers in executing non-routine tasks demanding flexibility, creativity, generalized problem-solving capabilities, and complex communications' (p.1322). This explains why demand for, and the earnings of, college educated workers increased from 1970 to 1998. However, Autor (2015) suggests that anxieties about machine substitution of human labour are often over-stated because routine tasks that are susceptible to automation often cannot be easily separated from non-routine tasks that require 'interpersonal interaction, flexibility, adaptability, and problem solving' (p.5). Based on Autor's (2015) analysis,

> the issue is not that middle-class workers are doomed by automation and technology, but instead that human capital investment must be at the heart of any long-term strategy for producing skills that are complemented by rather than substituted for by technological change. (p. 27)

This is the *complementarity* position on the risks of automation and it highlights the need to help people to develop new kinds of AI-complementary skills.

The OECD have employed a task-based approach to predict the risks of automation. Arntz et al. (2016) found that across 21 OECD countries an average of 9% of jobs are automatable. Arntz et al. are skeptical about predictions of mass unemployment but do emphasise the disproportionate impact on low-skill workers and the need to facilitate re-training to address the risk of growing inequality. Building on this work, Nedelkoska and Quintini (2018) found that 14% of jobs across 32 OECD countries are highly automatable (equating to 66 million workers) and a further 32% have a high risk of automation (50% – 70%), and they also found the risk of automation is unequally distributed. Thus, even in scenarios where lower risks of automation are predicted, the number of people faced with re-training, and obstacles to the provision of this training, indicate that substantial policy challenges will be created by automation.

Frey and Osbourne (2017) have argued that improvements in machine learning are changing the potential for non-routine tasks to be automated (Brynjolfsson & McAfee, 2014). Focusing on the risk of automation at the occupation level, in contrast to the OECD's task-based approach, Frey and Osborne predict that 47% of US jobs would be susceptible to automation. The figure provided for Australia is 44% and a separate study estimates that 59% of jobs are at risk of automation in Germany (Brzeski & Burk, 2015). A CSIRO report on changes for Australia's workforce in the next twenty years gives serious consideration to this possibility that AI-driven automation will have a significant disruptive impact on jobs (Hajkowicz et al., 2016). Estimates that around half of all jobs are at high risk automation underpin the view that automation may substitute for large numbers of workers. These predictions also support the view of Randall Collins, an influential sociologist, that significant technological unemployment produced by automation, combined with a break-down of the longstanding relationship between credentials and earnings, will result in a crisis for capitalist society (Collins, 2013). This is the *substitution* position on the risks of automation.

What education and skills will be needed for this work?

Most technological change during the 20th century was skill-biased (Katz & Autor, 1999) and this may be due to the increased supply of skilled workers accelerating skill-complimentary technologies (Acemoglu, 2002). This lead to a polarisation and growing wage inequalities between 'lovely' and 'lousy' jobs as technological change produced:

> …rising relative demand in well-paid skilled jobs (that typically require non-routine cognitive skills) and in low-paid least skilled jobs (that typically require non-routine manual skills) and falling relative demand in the 'middling' jobs that have typically required routine manual and cognitive skills. (Goos & Manning, 2007)

Preparation for work in an AI world will require the development of non-routine skills that cannot be easily automated. While the risk of automation declines with level of education (Nedelkoska & Quintini, 2018), this does not necessarily mean that work in an AI world will generally require higher levels of formal education. Indeed, obtaining more and higher educational qualifications has become an increasingly competitive strategy for gaining positional advantage in 'hollowed out' labour markets, rather than always being a means for obtaining specific skills actually required for high-paying jobs (Brown, 2003).

As such, a more nuanced approach than broadly increasing overall levels of educational attainment, such as moving toward mass higher education, will be required. The US National Academies of Science, Engineering and Mathematics (2017) observes that '… it is easy to support the idea of education that prepares the workforce for future dynamism in employment opportunities and enables lifelong learning. It is much more difficult to answer the question of what specifically to teach, and how, in order to achieve that educational goal' (p.113). However, it will be important to provide people with non-routine skills that (a) enable them to work with AI in complimentary ways and (b) are not at high risk of automation. These include both cognitive and non-cognitive skills. Hajkowicz et al. (2016) highlight a number of new areas of work where there is likely to be significant demand for workers in Australia, including: big data analysts, complex decision support analysts, remote controlled vehicle operators, customer experience experts, personalized preventative health helpers, online chaperones. These jobs will require, in different proportions, a mix of high level technical skills in STEM areas, people skills and digital skills.

Formal education and training will continue to be important in an AI world (Hajkowicz et al., 2016) and educational attainment does strongly predict earnings, health and civic engagement (National Research Council, 2012). Berger and Frey (2016) show that many new jobs created in an AI world will require high level cognitive and technical skills that are obtained from higher education. In relation to STEM education, the recent 2015 PISA study (OECD 2018) found that disadvantaged students would benefit from additional, targeted resources to improve their scientific literacy, while all students would benefit from more limited application of policies that sort students into streams and from programmes designed to motivate students to study science (Nedelkoska & Quintini, 2018).

Nearly four decades ago, Jencks found that non-cognitive skills had a positive impact on labour market success (Jencks, 1979). There is now a growing body of evidence showing that non-cognitive skills have a positive effect on earnings (Bowles, Gintis, & Osborne Groves, 2001) and that soft skills predict and influence success in both economic and social life (Borghans, Duckworth, Heckman, & ter Weel, 2008; Heckman & Kautz, 2012). Deming has shown that there is growing demand and reward for social skills because 'computers are still very poor at simulating human interaction' (Deming, 2017). The National Academies for Science, Engineering and Mathematics (2017) found that 'as IT continues to complement or substitute for many work tasks, workers will require skills that increasingly emphasize creativity, adaptability, and interpersonal skills over routine information processing and manual tasks' (pp. 8-9). Frey and Osborne (2017) argue that creativity and social intelligence will be important future skills required by jobs that are not able to be automated. Berger and Frey suggest that workers at risk of technological unemployment should 'strive to develop skills such as assisting and caring for others, creativity, or persuasion-skills that are likely to remain resilient in the face of further technological advances' (Berger & Frey, 2016). Critical thinking, flexibility, social skills and developing the capacity for lifelong learning are highlighted as important areas for development by the National Academies for Sciences, Engineering and Medicine (2017). Focusing specifically on Australia, Hajkowicz et al. (2016) have shown that, since 1991, jobs requiring people skills have grown by 43% more than average, and there is clearly consensus about a need to develop non-cognitive personal and social skills.

Together, this combination of *non-routine* cognitive and non-cognitive skills are now commonly described as *21st century skills* and the need to develop these skills has been on national education policy agendas since the 1990s (Adamson & Darling-Hammond, 2015). Ananiadou and Claro (2009) show that most OECD countries now integrate 21st century skills into their school curricula, although this integration is uneven and much more work is needed. The US National Research Council (2012) reviewed the literature on 21st century skills and found that there is 'statistically significant, positive relationships of modest size between various cognitive, intrapersonal, and interpersonal competencies and desirable adult outcomes' (p. 37). There are many different frameworks for 21st century skills and a detailed survey is beyond the scope of this review. However, there are a number of recent analyses that have synthesized existing frameworks.

The Assessment and Teaching of 21st Century Skills (ATC21S) project conducted at the University of Melbourne from 2009 to 2012 developed an important synthesis of previous work in this area (Griffin & Care, 2015; Griffin, Care, & McGaw, 2012). In a white paper prepared for the project, Binkley et al. (2012) conducted an analysis of 12 skills frameworks, including frameworks from Australia, the UK, the USA, the EU and the OECD. This review was used to generate the Knowledge and Skills, and Attitudes, Values and Ethics (KSAVE) framework, which brings together a set of 21st century cognitive and non-cognitive skills (see Table 1) (Binkley et al., 2012).

Ways of thinking	**Ways of working**	**Tools for working**	**Living in the world**
Creativity and innovation	Communication	Information literacy (includes research on sources, evidence, biases)	Citizenship – local and global
Critical thinking, problem solving, decision making	Collaboration (teamwork)	ICT literacy	Life and career
Learning to learn, metacognition			Personal and social responsibility (including cultural awareness and competence)

Table 1. The KSAVE model of 21st century skills (Binkley et al. (2012)

Voogt and Roblin (2012) have also undertaken a comparative analysis of eight major 21st century skills frameworks, including the one above, and found that there is convergence on a common set of skills, including: ‘collaboration, communication, ICT literacy, and social and/or cultural competencies (including citizenship)’ (Voogt & Roblin, 2012). The OECD also highlights the importance of ICT functional skills (‘skills relevant to mastering the use of different ICT applications’) and ICT skills for learning (‘skills that combine both cognitive abilities or higher-order thinking skills with functional skills for the use and management of ICT applications’) (Ananiadou & Claro, 2009). Developing these IT skills will include teaching people about AI. Beyond ICT skills, the OECD has outlined a set of 21st century skills that includes the following: information literacy, media literacy, research and inquiry, creativity and innovation, problem solving, decision making, critical thinking, collaboration and team-working, communication, flexibility and adaptability, responsibility, and digital citizenship.

How can this education and these skills be provided?

In one of the first reports on AI in education, Luckin et al. (2016) warn against being seduced by new technology and argue for sustaining a strong focus on pedagogy. Hajkowicz et al. (2016) argue that to meet future workforce challenges Australian society will need to provide young people with the right skills for current and future demands, as well as providing workplace and lifelong learning to facilitate re-training. Here we briefly consider approaches within formal and informal modes of education for developing 21st century skills, as well as highlighting some broader social policy implications.

Formal education

In a summary of his extensive and widely influential studies on human capital development, Heckman (2011) shows that ‘ … policies that provide early childhood educational resources to the most disadvantaged children produce greater social and economic equity’ (p.32). He also emphasises the need for new 21st century models of skills that include ‘attentiveness, perseverance, impulse control, and sociability’ (p. 33). Early investment in the development of cognitive and non-cognitive skills can have a significant economic and social benefit for societies and are an efficient means of investing in human capital (Kautz, Heckman, Diris, Weel, & Borghans, 2014).

Developing 21st century skills in schools will require the ability to drive reform centrally, having good ICT access in schools, the provision of support for teachers with professional development and classroom-ready resources, and embedding 21st century skills into curricula and large-scale assessments (e.g. collaborative problem solving in PISA 2015) (Adamson & Darling-Hammond, 2015). The US National Research Council (2012) found that deep learning can help to develop cognitive, *intrapersonal* and *interpersonal* 21st century skills and enable transfer of these skills beyond the classroom. The following research-based teaching methods facilitate deep learning: ‘using multiple and varied representations of concepts and tasks’, ‘encouraging elaboration, questioning, and explanation’, ‘engaging learners in challenging tasks’, ‘teaching with examples and cases’, ‘priming student motivation’, and ‘using formative assessment’ (National Research Council, 2012, p.10). Woods et al. (2015) argue for a similar developmental approach and have demonstrated how the ACT21S KSAVE framework of 21st century skills can be translated into learning progressions, lesson plans and assessments.

Beyond curricula and pedagogies for 21st century skills, Luckin et al. (2016) point to a range of AIEd applications that may be able to support the development of both cognitive and non-cognitive skills and argue for creating structures and incentives to drive the development of the field of AIEd. Luckin et al. also stress the importance of: involving teachers, students and parents in the development of AIEd applications; testing in real world contexts; and addressing ethical issues relating to data collection, sharing and use.

In the context of higher education, Burton et al. (2017) argue for the integration of ethics courses into computer science, engineering and other areas that prepare professionals who will develop and use AI. There will also be a need to integrate basic introductions to AI across a range of courses to ensure that the development of a non-technical understanding is part of a wider range of undergraduate degree programs.

Informal education (re-training, lifelong learning)

Automation will affect routine, low-skill jobs more significantly than previous automation and some workers will need re-training and re-qualification. Nedelkoska and Quintini (2018) have found that the challenge of providing re-training is complicated by the fact that 'workers with the highest risk of automation [are] about twice less likely to participate in formal education and 3.5 times less likely to take part in distant learning' (p.9). There will be a need to develop mentoring and workplace learning to respond to changing demand for skills in ways that meet the needs of these workers (Anderson & Rainie, 2017). We are also likely to see a growing diversification of educational provision including more online and on-demand options that will facilitate flexible, lifelong education (National Academies of Sciences, Engineering and Medicine, 2017).

Social policy

The policy response required to help formal and informal education systems prepare people for work in an AI world will need to be broad. Autor (2015) argues that 'rapid automation may create distributional challenges that invite a broad policy response' (p.8), and McAfee and Brynjolffson (2016) argue that 'a radical reshaping of work will call for new policies to protect the vulnerable while reaping the gains of the new age'. These policies will need to address socioeconomic inequality. Condron (2011, 2013) has shown that egalitarian countries have higher educational achievement, more highly skilled students and fewer low-skilled students. His findings suggest that policies designed to create more egalitarian economic systems can have positive effects on skills.

Conclusion

There is consensus that automation will substitute for some tasks and workers, although the nature and extent of this substitution varies according to the assumptions and methodologies used to model the risks. However, even in low risk scenarios substantial disruption is likely and there will be a need to address the unequal impacts of automation by developing policies that provide: (1) education and re-training with non-routine, AI-complimentary 21st century knowledge and skills; and (2) fair distribution of the wealth generated by automation-driven increases in productivity.

Many frameworks of 21st century skills have been identified in the research literature and in national curricula. However, there appears to be some consensus regarding the broad categories of skills that are important, which include the kinds of cognitive skills that have traditionally been emphasized in formal education along with non-cognitive skills (both *inter-* and *intrapersonal*) and skills that enable people to interact effectively with information and communication technologies. We need more (1) research into these skills, in terms of both teaching and assessment, as well as (2) policies and programs designed to support the acquisition of these skills (National Research Council, 2012).

Section 3: How do we prepare Australian society to adjust to an increasingly AI world?

Introduction

The degree of adjustment that an increasingly AI world will require from Australian society over the next 20 years could vary substantially. Some scenarios suggest current trends continuing. Other scenarios suggest technological change causing significant disruption to employment and exacerbating social inequalities, perhaps even leading to civil unrest (Hajkowicz, 2016). People will need to be prepared for changing labour markets and to engage competently and critically with new media and technologies, both in work and everyday life. Even in a milder scenario, if current trends continue, the increasing prevalence of AI could also exacerbate or ameliorate present social problems, including in education, depending on how it is developed, implemented and regulated. A series of ethical, regulatory and legislative challenges will need to be met to increase the likelihood that AI will have positive impacts on Australian society. There are also questions about what kinds of AI will be taken up, how it will be organised, and who will provide and run AI systems. In more disruptive scenarios, a similar series of ethical and regulatory challenges will need to be met, although with greater urgency and higher stakes.

Luckin (2017) has provided a map of what is required to prepare society for an AI world with two courses of action: using AI to address educational challenges and educating people about AI.

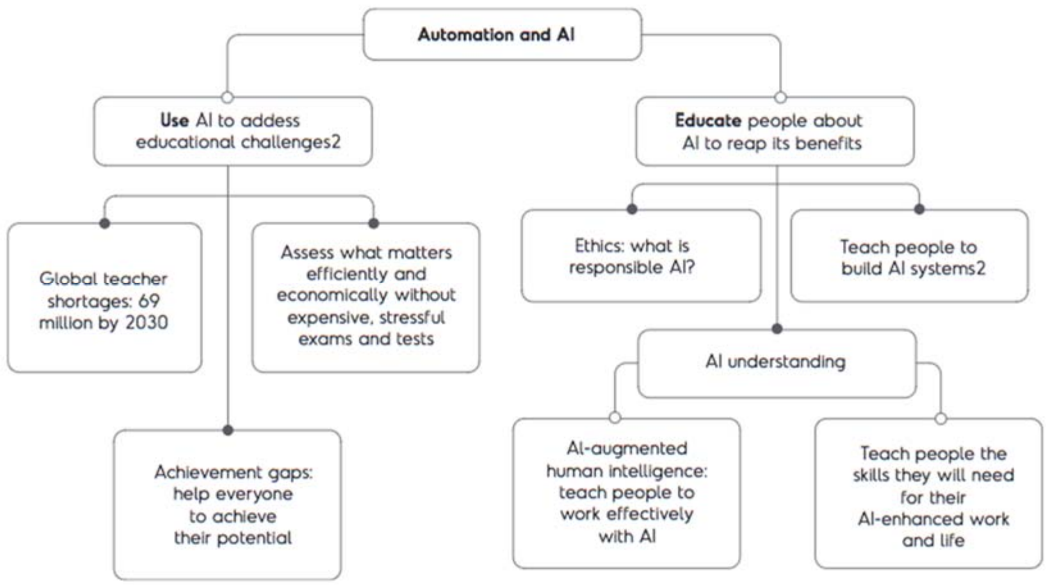

Figure 1: The AI and Education Knowledge Tree (Luckin, 2017)

Being prepared for an AI world will mean having a basic education in AI and this basic education could influence the social hierarchies that are produced in the future. One clear area of preparation will be educating people in the domain of human values that provide a context for the creation and use of AI. An AI world will be shaped by, and will in turn reshape, the social contexts from which it emerges. As Campalo et al. (2017) explain,

> AI is not impartial or neutral. Technologies are as much products of the context in which they are created as they are potential agents for change. Machine predictions and performance are constrained by human decisions and values, and those who design, develop, and maintain AI systems will shape such systems within their own understanding of the world. (p. 18)

Current research indicates that establishing norms is key in relation to AI, from individual decisions about what ought to be done with AI to codes of conduct, regulations and legislation, as ‘differences in moral codes or religious standards between different communities would mean that a system deemed safe in one community may be considered dangerous/illegal in another’ (Yampolskiy, 2016). Additionally, there will also be very significant challenges to the management of infrastructure (Rossiter, 2017), to the organisation of work and of more general responses to both continuing and new social needs. As such, it will be important to ensure that social institutions are sufficiently flexible to evolve with an increasingly AI world (Brynjolfsson & McAfee, 2016).

This section is divided into two parts. The first focuses on ethical issues relating to (1) the development of AI and (2) addressing its impacts on society. The second part discusses regulatory and legislative issues such as data privacy, the incorporation of AI into the governance of societies, and measures that may need to be taken to address growing inequalities.

Sustaining strong societies in an AI world

As Campolo et al. (2017) observe, the ‘[e]thical questions surrounding AI systems are wide-ranging, spanning creation, uses and outcomes’ (p.30). Here we focus on two clusters of issues: (1) the ethical development and use of AI; and (2) preparing citizens for an AI world.

Ethics and AI

Five major ethical issues created by the growth of AI are: risks to jobs; the ethics of machine learning and algorithms (including questions of liability); thinking about the moral status of AI and robots; lethal autonomous weapons (‘killer robots’); and low probability/high risk scenarios in which advanced AGI or superintelligence emerges (Bostrom & Yudkwosky 2011; Burton et al. 2017).

It will be important to increase the ethical reasoning of computer scientists and other professionals involved in the development of AI. Burton et al. (2017) argue that educators of computer scientists, engineers and other relevant professions will have a responsibility to teach ethics in AI classes. Additionally, educators have expressed concerns about de-humanizing effects of introducing robots into classrooms, as well as potentially encouraging authoritarian or dependent attitudes among children. There will be a need to consider whether new forms of AI-driven pedagogies may work at cross-purposes to curricula focused on human values, including the question of ethical uses of AI itself (Serholt et al., 2017).

It is already important to broaden the types of professionals involved in developing AI (Campolo et al., 2017). Lack of diversity among developers will need to be addressed through strategies for improving the gender imbalance in STEM education (OECD, 2018). Luckin (2017) has called for educationalists to work with AI developers, writing that 'everyone needs to be involved in a discussion about what AI should and should not be designed to do' (p. 121). There will be a need to include scientists, ethicists, lawyers and others in the development of AI from a social perspective. As Campalo et al. (2017) observe, 'training data, algorithms, and other design choices that shape AI systems may reflect and amplify existing cultural assumptions and inequalities' (p. 4). Education, health and other social policy areas are 'high stakes' domains for the implementation of AI and it will be important to take measures to avoid biases in decision-making in relation to determining capacity to learn, risk of disease, medical diagnoses and so on.

Preparing citizens for an AI world

The 21st century skills developed for work overlap significantly with the competencies that have been identified as important for Global Citizenship Education (GCED), including empathy, critical thinking/problem solving, and the ability to communicate and collaborate with others (Brookings, 2017). GCED 'aims to be transformative, building the knowledge, skills, values and attitudes that learners need to be able to contribute to a more inclusive, just and peaceful world' (UNESCO, 2015, p. 15). Importantly, the competencies developed for this purpose are 'germane to the broader landscape of success in learning and life and not specific to global citizenship alone' (Brookings, 2017, p. 4). Global citizenship education comprises both instrumental dimensions (21st century skills and cosmopolitan learning) and normative dimensions (citizenship and social justice purposes) (Marshall, 2011), and focusing on developing these capacities will be increasingly important in societies disrupted by AI that will create new technical and social demands.

An increasingly AI world will also involve significant organisational change and place new demands on infrastructure, requiring organisational and regulatory flexibility (McAfee and Brynjolffson, 2016). Employment relationships will change as the number of workers engaged in alternative forms of work increases (e.g. 'Uberization') (Katz & Krueger, 2016), and the AI-driven platforms that manage labour will change relationships between employers and employees, including through increased use of data to manage performance (Campalo et al. 2017). Changing employment relations will require new classifications of workers, new regulations to protect workers in the 'gig economy', and balancing the protection of full-time jobs with policies to support workers' transition into new work arrangements where this is not possible or prefereable (MacAfee & Brynjolffson, 2016).

Other cognate concerns include aspects of workplace management and surveillance, such as whether existing laws are adequate to cover issues of transparency and protection of employees (Bernstein, 2017). While these areas have not covered employees in educational systems, it is clear that this will be a significant issue. This has begun to be explored in the US and it will need to be investigated in Australia as well to see if there are any stringent legal limits on workplace surveillance – which, presently, in the US is not the case (Ajunwa, Crawford, & Schultz, 2017).

Regulation

As machine learning and algorithms are increasingly embedded in the mediated infrastructure of everyday life, we will need mechanisms to increase transparency, regulation and algorithmic literacy, and also ways to monitor what algorithms are doing in practice and create effective accountability mechanisms (Annany, 2016). This will include identifying areas of regulation that either need revising or creating.

Data privacy and literacy

As corporations provide and manage data systems in education (Williamson, 2017), key issues are: what happens to student, parent and other forms of data when it is used in systems, including who owns data; and who has access (Zeide, 2017). Some suggestions point to the importance of individual ownership of data and opt-in rather than op-out programs (Tene & Polonetsky, 2012). Overall, there is a need to review existing legal and governance frameworks for the educational data involved in managing both performance and administration. AI is already challenging existing frameworks as it changes the idea of what can be done with different kinds of data when put together. Additionally, there is a need for humans to understand how AI systems work with and access data, because '[p]art of the promise of predictive techniques is to make accurate, often intimate deductions based on a seemingly-unrelated pieces of data or information' (Campalo, Sanfilippo, Whitaker, & Crawford, 2017, p. 29).

Use of AI in public agencies

Much of the provision of automated systems is done under the proprietary knowledge of corporations and there has been a call for core public agencies, such as those responsible for criminal justice, healthcare, welfare, and education (e.g. "high stakes" domains) '…[to] no longer use "black box" AI and algorithmic systems' (Campalo et al., 2017, p. 1).

It is clear that as some decision making becomes automated, there needs to be an acknowledgement of the narrowness that can emerge from automation if it lacks context. That is, system and school based administrators 'will need to rethink how they formulate goals and use data, while acknowledging the limits and risks of automated systems' (Campalo et al., 2017, p. 13), especially the possibility of missing important contextual details that go into making complex social areas like education. The latter may be able to be addressed by using diverse data inputs (Luca, Kleinberg, & Mullainathan, 2016).

The issue of developer and platform bias and decisions made by algorithms has become a key concern in AI, especially around gender and racism (AI Now Institute, 2018). This is unlikely to abate and while it is important that developers are made aware of these issues (Elish & boyd, 2017), there have been suggestions that '[t]echnical approaches that look for a one-time "fix" for fairness risk oversimplifying the complexity of social systems.' (Campalo et al., 2017, p. 2).

Inequality and redistribution

While the predictions concerning the impact of automation on jobs vary significantly, it is important to begin considering how redistribution can be undertaken in scenarios where productivity increases but employment decreases. In education, automation may not have a substantial impact on teaching occupations, but automation is likely in areas of administration and teaching assistant work. One policy for dealing with a world in which automation leads to large-scale unemployment is Universal Basic Income (UBI) (Ford, 2015). There are a number of trials of UBI schemes underway in North America, Europe, Africa and Asia, but the findings are not yet generalisable to whole societies (Campalo et al., 2017, p. 13). While concerns that basic income would be misspent or exacerbate social problems are not supported by current evidence (Evans & Popova, 2017), there is reason to be sceptical about whether UBI could be 'universally implemented' (Brynjolffson & McAffee, 2016). Another possible mechanism is Earned Income Tax Credits (EITC), which provides additional top-up income to workers and has been shown to increase people's work hours (Chetty, Friedman & Saez, 2013).

Conclusion

Debate about how AI will reshape society in the next few decades focus upon the question of whether technological change will be different this time, as compared to previous periods of significant disruption. There is clearly a need to consider more extreme possibilities of disruption caused by exponential growth in computational and algorithmic power, although the very nature of these scenarios makes planning difficult. However, based on current trends it is clear that there is a need to develop people's capacities to understand AI (at least in non-technical terms, [G. Thompson, personal correspondence]), to consider and act upon the ethical implications of AI, and to consider regulatory change that will be required to enable organisations to flexibly adapt to different contexts of production and employment, as well as protecting people's privacy, ensuring good governance and addressing potential increases in social inequalities.

Recommendations

These recommendations reflect the views of the research report team.

Recommendation 1: Establish a cross-sector representative body to provide advice on the development of AI in Australian education systems.

All areas of education are likely to be impacted by the use of AI and all stakeholders need opportunities to shape the implementation of AI in Australian education systems.

A representative cross-sector body could include members from government, higher education (both STEM and HASS disciplines), schooling and early childhood sectors (including diverse range of students for all sectors), the education technology industry, teacher associations and parent groups. The body should be established to: (1) oversee the development of AI in Australian education with a focus on public A.I. development; (2) produce regular issue-specific publications for the groups it represents; and, (3) maintain a set of iteratively revised guidelines for the field.

NOTE: The subsequent recommendations could be actioned by this body. Additionally, key potential stakeholders are identified below who could be part of implementing these recommendations as discrete actions.

Recommendation 2: Establish guidelines for the introduction of adaptive and personalized learning to ensure a focus on educational and equity principles.

Ensuring broad access to new technologies within existing education institutions, or in newly established publicly funded hubs (public libraries may be an institution that can expand already existing work in technology access and training), will be important to minimise the unequal use and benefits of AI in Australian education systems. Any introduction of adaptive and personalised learning or robotics for students with disabilities should be done in consultation with appropriate representative bodies.

Potential key stakeholders: Government; Students from across sectors; Advocacy groups

Recommendation 3: Consult with the teaching profession, teacher educators and industry to formulate professional development strategies that help educators manage the introduction of AI into their workplaces.

The introduction of AI across all education sectors will change the roles of teachers and other staff and will affect industrial conditions. Teacher and tertiary unions, and the relevant associations from the different schooling sectors, should sit on any working groups or statutory authorities that will deal with the introduction of AI into Australian education systems.

Potential key stakeholders: Government; Employers; Teacher educators; Teaching unions/ associations

Recommendation 4: Develop a set of procurement guidelines that encourage the ethical design and transparency of AI systems purchased by Australian education systems.

AI-driven education technologies should meet minimum requirements as part of procurement processes. In public policy areas such as education, AI products should be accompanied by material that allows the customer and other users to understand how the product makes decisions and how these decisions might affect people. The aim should be to provide intelligible AI through a combination of technical operability and general explanations. AI is trained with existing data and there should also be systematic training of designers and users to prevent the use of data sets that will reinforce existing inequalities.

Potential key stakeholders: Government; Education technology companies

Recommendation 5: Review data protection legislation internationally to develop an approach for Australian education systems.

AI requires large amounts of data and data protection legislation that is specifically tailored to education should outline what data is collected and set limits on the types of data to be collected, how it is collected, and how it will be used. Examples such as the EU's General Data Protection Regulation (GDPR) should be examined as possible models. This legislation will need to reflect national data sharing protocols, including the work of the National School Interoperability Program, and should recognise that users own the rights to their data.

Potential key stakeholders: Government

Recommendation 6: Increase access to resources that help educators and learners to develop AI-complementary skills, including 21st century skills.

Working with AI in education should reflect the changing nature of working with AI in general. Teachers, administrators and students should be familiar with current best practices. Educational practice should aim to develop complementary approaches to 'working-with' AI using non-routine skills, including 21st skills, to support the current and future needs of students, to support and extend the capacities of teachers, and to enhance the flexible administration education organizations. Curricula, pedagogies and organisational strategies that rely on and promote routine skills will increase the risk of technological unemployment for teachers, students and administrators.

Potential key stakeholders: Government; Teacher unions/ associations; Teacher educators

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[ii] https://www.soccergenomics.com